Bitcoin Market Segmentation and Regulatory Effect

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November 15, 2024

Abstract

This paper examines the long- and short-term effects of cryptocurrency regulation on price deviations in the Bitcoin market, focusing on regulatory implementation rather than announcements. We construct a unique database of regulations across 28 countries since 2009, categorized into seven types. Using Bitcoin price data since September 2013, we employ an ARDL Error Correction Model to assess both short- and long-term regulatory impacts. Our findings indicate that the Law of One Price does not hold in the Bitcoin market. Contrary to initial conjectures, more regulated markets exhibit higher price convergence with the USD benchmark. Implementing regulations has no significant influence in the short-term. Regulations enhancing reliability and transparency, such as the expansion of securities laws, banking and payment regulations, and the implementation of regulatory sandboxes foster price convergence. In contrast, partial bans exacerbate price divergence. AML/CFT laws reduce local prices regardless of USD price level. Markets with cheaper Bitcoins are found to be isolated from bubbles occurring in the USD market.

1 Introduction

"He ignored me royally," Christine Lagarde said in November 2023, referring to her son's 60% loss on his cryptocurrency investments. Even the advice of the ECB president herself could not protect him from the intense volatility of cryptocurrency prices.

Cryptocurrencies, with a market capitalization of 1.83 trillion USD as of November 2024, are establishing increasingly tight links with traditional finance. The Hacibedel and Perez-Saiz (2023) highlights multiple channels through which disruptions in cryptocurrency markets could amplify into systemic risk. Sharp cryptocurrency price declines can weaken the financial health of users, raising default risks in other financial products. This effect is heightened by the use of cryptocurrencies as collateral. Systemic risks are further exacerbated by market concentration—Bitcoin alone accounts for over 60% of cryptocurrency market capitalization, and the emergence of dominant firms, along with operational and cybersecurity vulnerabilities. Regulation, therefore, becomes essential to mitigate the sector's escalating risks.

Policy approaches, however, can vary significantly across countries. Some countries promote sector development and innovation (e.g., Switzerland, the United Arab Emirates, El Salvador), while others push for bans on trading or usage (e.g., Algeria, China, Iraq). What effects do these differing regulatory stances produce? As an asset traded internationally but regulated within national borders, can cryptocurrency regulations ultimately influence the global market?

The literature on the effect of regulation on Bitcoin prices primarily focuses on regulatory announcements in the media, with little attention to the impact of regulation once implemented. This literature thus addresses short-term announcement effects, rather than the longer-term influence of regulation on the market. Additionally, studies generally examine only the USD price of cryptocurrency, capturing global trends while potentially overlooking local effects of certain regulations. The case of the United Arab Emirates illustrates this well. Figure 1 shows Bitcoin price difference in Arab Emirates Dirham (AED) compared to the USD price. It is important to note that trading restrictions exist between countries, meaning, for instance, that European residents cannot purchase Bitcoin on UAE platforms. Nevertheless, we observe no price deviation before March 13, 2023. After this date, the AED price drops below the dollar price, followed by a more significant and persistent deviation beginning on October 19, 2023. These two dates align with the public announcement and implementation of the RAK Digital Assets Oasis, the largest regulatory-free zone for crypto-related firms. This case is particularly notable because of the fixed exchange rate between the AED and USD, ruling out exchange rate effects on price deviations. This phenomenon underscores the importance of studying the impact of policy implementation on local markets.

The first contribution of this paper is its examination of regulatory implementation effects rather than regulatory announcements. To do this, we developed a database of cryptocurrency regulations across 28 countries from 2009, categorized into seven types: AML/CFT laws, virtual asset service provider regulations, banking and payment regulations, securities law expansion, regulatory sandboxes, liberalisation/legalisation of crypto-related investments, and partial bans.

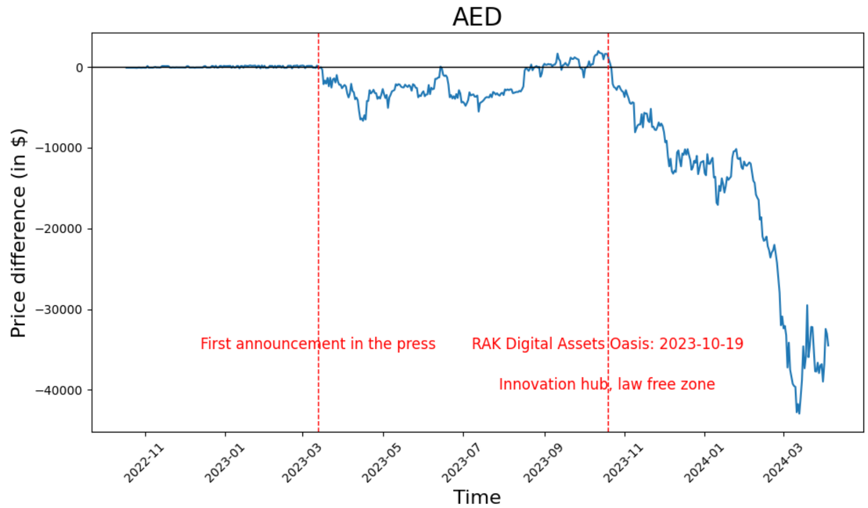

Figure 1: Price difference between Arab Emirates Dirham (AED) Bitcoin price expressed in USD and USD Bitcoin price

The second contribution is the focus on price deviation rather than global price alone. This approach allows for the study of local regulatory effects while controlling for global trends and exchange rate effects.

The third contribution involves analysing financial bubbles in Bitcoin prices to explain price deviations. Makarov and Schoar (2020) noted that deviations increase during Bitcoin price appreciations. This paper extends their findings by examining if investor behaviour remains consistent between countries during bubble periods.

This study uses Bitcoin price data from 22 countries since September 1, 2013, applying an ARDL Error Correction Model to assess both short- and long-term regulatory impacts. A country fixed effect is included to account for inherent country-specific barriers. Findings indicate that the Law of One Price does not hold in the Bitcoin market. Regulation is not a primary driver; instead, results show that greater regulation correlates with smaller price deviations from the USD benchmark, particularly when local prices exceed USD prices. Thus, regulations are associated with price convergence, with evidence suggesting that regulatory effects on price convergence partly stem from price reductions when local prices exceed USD levels.

By categorizing regulations, we show that price convergence induced by increased regulation is driven by regulations on the banking and payment systems, expansion of securities laws, regulatory sandboxes, and the liberalization of crypto-related investments. No significant effects are observed for VASP regulations. AML/CFT laws are associated with price convergence when local prices exceed USD prices but lead to divergence otherwise. Countries with more AML/CFT laws have lower local prices, underscoring Bitcoin's use in criminal activities. Partial bans, however, cause price divergence, driven by local price increases when above USD prices and decreases when below. These effects are observed in the long term, with no short-term impact from regulation implementation found.

The presence of bubbles in cryptocurrency markets correlates with increased price deviations when local prices are below USD prices, suggesting potential market isolation with lower local prices.

The remainder of this paper proceeds as follows: Section 2 introduces the cryptocurrency market microstructure. Section 3 reviews relevant literature. Section 4 addresses the empirical validation of the Law of One Price. Section 5 examines the impact of regulation on price deviations. Section 6 covers robustness checks, and Section 7 concludes.

2 Microstructure of the Cryptocurrency Market

Satoshi Nakamoto, an anonymous person or group of persons, introduced cryptocurrency and blockchain technology with the aim of establishing a decentralized monetary system independent of central banks or financial institutions. Central to this system is the blockchain, a distributed ledger accessible to all network participants, enabling collective verification and updating. This decentralized design ensures equal access, preventing any single entity from exerting undue influence. Understanding the blockchain's and the international cryptocurrency trading mechanics are crucial for understanding cryptocurrency price dynamics. This section therefore provides basic knowledge on the functioning of cryptocurrency.

2.1 The Blockchain

The blockchain serves as a comprehensive ledger of Bitcoin transactions. Each block within the chain encapsulates multiple transactions, documenting changes to the ledger. Upon transaction recording, the network constructs and validates a block, subsequently appending it to the existing chain. This continuous chain links all blocks since the blockchain's inception, ensuring their authentication.

The block validation process is perform by miners, which creates a block containing several transactions, checks whether the owner has sufficient bitcoins, and then validates the block through the resolution of sophisticated mathematics problem. Then, the other miners verify the solution and accept or not the new block. The resolution process can be described as follows (Biais (2018)): the miner draws with replacement solution at random from an urn containing many balls, one of which contains the solution while the others contain no information. This is performed by computer, and the more powerful the computer is, the greater the number of possible solutions that the miners draws each second ("hash rate"). After finding the solution, the other miners verify the solution and accept or not the new block. These steps are time (and electricity) consuming, and delay arises to include transactions in the blockchain. According to the "buycryptoworlwide" website, in most cases, bitcoin transactions need one or one hour and a half to complete. For each transaction the bitcoin owner set a fee that the miner will receive for confirming the transaction. The time that the transaction takes therefore depends on the fee; the higher the fee, the faster the transaction, as more miners will be interested in solving the problem. Therefore, considering the high volatility of bitcoin price, the owner faces a trade-off: he can set high fee for the transaction to be included in the blockchain rapidly reducing price risk, or set low fee to not erode its profit.

2.2 Cryptocurrency Exchanges

Transactions described pertain to peer-to-peer marketplaces or decentralized exchanges, directly connecting with the blockchain using private keys. Nonetheless, the primary avenue for buying, selling, and trading cryptocurrencies is centralized exchanges, analogous to traditional stock exchanges but for digital assets. These exchanges are a third-party intermediary that facilitate cryptocurrency trading. While most limit transactions to cryptocurrency-for-cryptocurrency trades, the largest platforms often support cryptocurrency-to-fiat exchanges. Research by Makarov and Schoar (2020) and Borri and Shakhnov (2023) reveal price differentials across exchanges and countries. Notably, price deviations are more pronounced across countries than within them.

Each exchanges have their own order book and trades can occur with only customers of the exchange. Transactions are not recorded in the blockchain, they are in the exchange ledger instead. Therefore, only the exchange possesses a wallet with their own private keys, which are used when a customer wants to transfer cryptocurrency to its own wallet or to another exchange. In this case, the transaction is recorded in the blockchain. Using centralised exchanges therefore leads to additional fees and delays.

Usually, customers can only trade in local currency (Makarov and Schoar, 2020). The fiat currency used for crypto purchases on an exchange is restricted to the transaction country's fiat money. This limitation partly stems from requirements to maintain bank and crypto trade accounts in the registering country. For instance, even if an exchange operates across multiple countries, a Japanese customer can only purchase cryptocurrencies using Japanese Yen. Despite observed price differentials between countries, suggesting potential arbitrage opportunities across regions, Makarov and Schoar (2020) indicate that these overlapping exchanges do not significantly influence cross-regional arbitrage correlations.

Consequently, structural barriers such as additional fees, transfer delays, and exchange currency constraint hinder cross-regional arbitrage and delineate market boundaries.

3 Literature Review

3.1 Price Deviation and the Law of One Price

In cryptocurrency research, the predominant focus lies in explicating and forecasting the price of the most widely traded cryptocurrencies, typically denominated in US dollars. Conversely, there is a relative scarcity of studies investigating price discrepancies across exchanges or geographical regions. Traditional financial markets studies often employ the Law of One Price (LOP) to analyse price disparities for commodities or the Covered (or Uncovered) Interest Parity for assets influenced by interest rates.

Despite ongoing debates regarding the classification of cryptocurrencies as a medium of exchange or a novel asset class, they predominantly function as digital commodities without yield-bearing future payments. Consequently, existing literature on cryptocurrency price discrepancies predominantly employs the LOP framework, drawing parallels with gold and commodity markets.[1]

[1]It is worth noting the existence of security tokens, digital tokens on a blockchain representing ownership or

The LOP states that identical goods traded in different countries should be priced equivalently when expressed in a common currency. This principle relies on the arbitrage mechanism to ensure price convergence. In the absence of transaction costs and for freely tradable goods, arbitrage opportunities incentivize investors to sell in markets with higher prices and buy in markets with lower prices, thereby narrowing price differentials until no more profit can be derived from arbitrage. As cryptocurrency is a fungible and highly internationally traded asset, this market should be a study case of the LOOP. Nevertheless, persistent and significant price differentials across Bitcoin markets establish a consensus among economists.

Price deviations in cryptocurrency markets occur both within and across regions. Makarov and Schoar (2020) conducted an analysis on 34 exchanges spanning 19 countries, revealing that bitcoin price deviations are more pronounced between regions than within them. They observed an increase in these deviations during periods of bitcoin appreciation. Furthermore, their research underscores the significant role of capital controls in influencing the variability of price deviations. The underlying mechanism can be explained as follows: customers transacting on exchanges are typically constrained to the fiat currency of their registration country. Consequently, profits obtained from selling cryptocurrency in a jurisdiction with higher prices are denominated in the local fiat currency. Severe capital controls can impede or delay the repatriation of these profits, thereby constraining arbitrage opportunities and fostering price discrepancies across countries with different fiat currencies. Building on this foundation, Borri and Shakhnov (2023) extended the analysis by examining 135 exchanges encompassing 39 bitcoin-to-fiat pairs. Their findings highlight that location-specific factors account for more than 50 percent of the price deviation variability in fiat pairs. Specifically, they identified a significant association between price deviations and local supply and demand, as proxied by mining activity and Google search volumes, respectively.

Another strand of the literature delves into the price deviations of US-denominated cryptocurrency across exchanges and the underlying determinants. Krückeberg and Scholz (2020) discover that the arbitrage spread between 2017 and 2018 yields profits substantial enough to offset transaction costs. Given that this period coincides with periods of market bubbles, their findings raise questions on potential correlations between market bubbles and price discrepancies. Similarly, Kroeger and Sarkar (2017) examine six exchanges and identified several factors influencing price deviations. They observe a positive correlation between price deviations and bid-ask spreads, order book depth, and volatility, while noting a negative relationship with trading volume. Additionally, institutional factors, capture through exchange-pair fixed effects, exert a significant influence on price deviations. Utilizing a Vector Error Correction Model (VECM), they confirm the existence of a long-run equilibrium in the speed of adjustment of price deviations across exchanges. Lastly, Pieters and Vivanco (2017) explore the relationship between price deviations and regulatory policies, specifically focusing on Anti-Money Laundering (AML) and Know-Your-Customer (KYC) regulations. These policies impact customer anonymity, and their analysis reveals that exchanges with lax AML and/or KYC implementations exhibit distinct price patterns compared to more compliant exchanges.

fractional ownership of a financial asset. Designed as financial securities, these tokens confer legal and economic rights to their holders. However, this paper focuses solely on cryptocurrencies initially conceived as mediums of payment, omitting the discussion on security tokens traded on distinct exchanges.

3.2 Regulations and Cryptocurrencies

The literature exploring the influence of regulations on cryptocurrency markets has predominantly focused on regulatory events on press articles, characterized by official announcements pertaining to cryptocurrency policies, primarily through the event study methodology. To our knowledge, Auer and Claessens (2018) were the first to conduct a quantitative analysis of the impact of cryptocurrency regulation. They analyse the global cryptocurrency market, encompassing both price and transaction volume of cryptocurrencies. Regulatory events were categorised into five classes: legal status, anti-money laundering measures, interoperability with regulated financial entities, official warnings, and statements regarding Central Bank Digital Currencies (CBDCs). Their findings indicated that regulatory news events, particularly those related to general bans on cryptocurrencies and their treatment under securities laws, had a significant positive influence on Bitcoin prices. Consequently, they concluded that investors in the Bitcoin market value a clear cryptocurrency legal status. Furthermore, the authors drew attention to a potential market segmentation across different jurisdictions. Although cryptocurrencies are traded globally, regulations are typically implemented on a local scale, sometimes resulting in significant price disparities among jurisdictions (Krückeberg and Scholz, 2020). These disparities could potentially create cross-border arbitrage opportunities.

In a related vein, Park et al. (2020) examined the segmentation of the global Bitcoin market in response to regulatory events. Their analysis extended to both price and volume changes in major markets, including the United States, Japan, China, South Korea, Europe, and the United Kingdom, encompassing 16 regulation-related events. Utilizing the event study methodology, they focused on cumulative abnormal returns and cumulative abnormal volumes as variables of interest. Their findings indicated that volumes reacted negatively to regulatory changes, contrasting with the positive price response. Consequently, they argued that investors exhibited a global perspective and were not restricted to localized markets, emphasizing the presence of cross-border arbitrage opportunities. This paper also raises the interesting question of a potential heterogeneous impact according to the type of announcement, whether the announcement is a communication or a direct intervention. Their estimates are still robust after controlling for the type of announcements, inducing that a communication has the same influence than direct intervention.

Feinstein and Werbach (2021) also delves into the impact of regulatory announcements on local trading activity. However, their conclusions diverged from those of Park et al. (2020). They constructed a comprehensive database comprising 89 regulatory events categorized into seven groups, spanning aspects such as cryptocurrency treatment (as securities or currencies), Anti-Money Laundering (AML) regulations, anti-fraud measures, and the development of cryptocurrency-specific regulatory regimes. Their analysis encompassed trading activity data from various markets, including China, Hong Kong, Japan, South Korea, Russia, the United Kingdom, and the United States. Employing the event study methodology, they found no significant impact of regulatory announcements on local abnormal trading volumes. Therefore, their results did not provide specific evidence that regulatory measures incentivise traders to flee or enter said jurisdictions. According to their results, the cryptocurrency market is not segmented by jurisdiction, as results do not present change in the trading behaviour. However, when extending their analysis to a global scale, their results surprisingly aligned with those of Auer and Claessens (2018), suggesting that regulatory events affect global cryptocurrency prices and trading volumes.

This latter result is also consistent with that of Shanaev et al. (2020), which analyses 120 regulatory events on global cryptocurrency prices. Their contribution lay in the examination of an aggregated cryptocurrency portfolio. They found that regulations concerning bans and legal status had a negative impact on cryptocurrency prices, while the influence of exchange-related and state-backed issuance regulations yield less robust results. Importantly, they observed no significant impact on cryptocurrency valuations following authorities' announcements regarding cryptocurrency concerns.

In line with the above-mentioned literature, Chokor and Alfieri (2021) conducted an investigation into the impact of regulatory events on cryptocurrency markets, spanning both short-term and long-term horizons. Drawing from a dataset comprising 63 relevant events sourced from the FACTIVA database, the authors employ the event study method, wherein the abnormal returns of 30 distinct cryptocurrencies serve as the dependent variable for the short-term analysis. In contrast, the long-term analysis is carried out through a performance model, which encompasses different performance metrics. Their findings corroborate a negative reaction by investors to regulatory events, both in the short term and the long term. The authors explain this result by the intrinsic characteristics of decentralization and lack of regulation of cryptocurrency markets, which initially attracted investors. Consequently, the introduction of regulatory measures acts as a deterrence factor, leading investors to respond unfavourably to regulatory news in the short, and the long-term.

Within the filed of cryptocurrency regulation analysis, a significant focus has emerged on China's regulatory actions (Borri and Shakhnov, 2020; Griffith and Clancey-Shang, 2023; Zhang et al., 2023). These regulations, triggered by concerns over capital flight and currency depreciation, culminated in the 2017 and 2021 reforms, ultimately resulting in a comprehensive ban on cryptocurrencies in China. The 2017 reform prohibited initial coin offerings (ICOs) and domestic operations of cryptocurrency exchanges, while the 2021 reform extended its scope to encompass cryptocurrency ownership, mining, and all related transactions, even those involving offshore exchanges serving Chinese citizens. The significance of these reforms is intensified by China's status as a global cryptocurrency market leader.

Borri and Shakhnov (2020) scrutinized the 2017 regulation, revealing a substantial reduction in local cryptocurrency trading volume. Moreover, they found that domestic regulations exerted significant global impacts on volume and prices, underlining heterogeneous spillovers across markets.

Griffith and Clancey-Shang (2023) delved into the repercussions of the 2021 ban on cryptocurrency markets. Their research unveiled a decline in cryptocurrency prices and diminished liquidity, with these effects persisting over time. A comparative analysis of the 2021 and 2017 bans indicated that the former had a more pronounced impact.

Zhang et al. (2023) assessed the influence of Chinese regulatory announcements during the COVID-19 pandemic on market volatility. Their findings revealed that investors generally perceived regulatory policy events as “bad news”, resulting in increased volatility of price, volatility of liquidity, and volatility of return. Contrary to prior research by Auer and Claessens (2018), **?**, and Feinstein and Werbach (2021), they identified risk warnings as one of the driving factors behind this effect. However, their study also highlighted that regulations had a positive impact on the market during periods of elevated enthusiasm, as measured by the cryptocurrency fear-greed index. Consequently, the authors underscored the importance of strategic regulatory policies in mitigating excessive investor greed and recommended regulators deploy such policies strategically to stabilize the market, particularly during periods of heightened investor enthusiasm.

In summary, a consistent result emerges from the existing literature: regulatory news events, particularly those involving bans, the classification of cryptocurrency as securities, and the implementation of Anti-Money Laundering measures, are consistently linked to significant declines in cryptocurrency prices. Conversely, warnings issued by authorities do not seem to have a discernible impact (Auer and Claessens, 2018; Shanaev et al., 2020; Feinstein and Werbach, 2021). Regulatory news is consistently perceived as ”negative news,” exerting a negative influence on the cryptocurrency market, both in the short and long term (Chokor and Alfieri, 2021). However, the effects on local trading volumes, which can impact market segmentation across jurisdictions, exhibit greater nuance and vary depending on the analytical model and specific regulatory events and cryptocurrency datasets employed (Park et al., 2020; Feinstein and Werbach, 2021). Notably, Chinese regulatory measures have a pronounced impact on both the domestic and global cryptocurrency markets, attributable to the scale of the restrictive reforms implemented and China’s large market share in the cryptocurrency landscape (Borri and Shakhnov, 2020; Griffith and Clancey-Shang, 2023; Zhang et al., 2023). These regulations also appear to introduce market instability, except during periods of high investor enthusiasm. This latter finding underscores the pivotal role of cryptocurrency policies in maintaining financial stability and raises questions regarding potential influence during speculative bubbles.

3.3 Cryptocurrency Bubbles

In line with the asset pricing approach, a bubble is characterized as a period during which an asset’s price exceeds its fundamental value. The fundamental value of a financial asset is derived from its anticipated future dividends, profits, or earnings. However, this method cannot be applied to cryptocurrencies, as they do not generate such income, which gives rise to a debate among economists on their fundamental value. Cheah and Fry (2015) assert that the fundamental value of cryptocurrencies is zero, while a subset of studies postulate that the cost of mining (the cost associated with cryptocurrency production) and cryptocurrency prices are cointegrated, thereby implying that mining costs reflect their fundamental value (Hayes, 2019; Gottschalk, 2022). As enunciated by Bouri et al. (2019), the challenge in identifying the fundamental value underscores the need for caution when using the term "bubble" concerning the cryptocurrency market. The uncertainty surrounding cryptocurrency fundamentals raises questions about whether elevated prices are driven by increased fundamental value. Consequently, some research articles opt for the term "explosivity" to account for this ambiguity.

To overcome the uncertainty of cryptocurrency fundamental value, a prevailing approach employed across literature is the Phillips, Shi and Yu (PSY) methodology, introduced in Phillips et al. (2015), to identify bubbles (Corbet et al., 2018; Geuder et al., 2019; Cheung et al., 2015; Bouri et al., 2019; Agosto and Cafferata, 2020; Haykir and Yagli, 2022). This method, based on the detection of explosive prive movement, allows to dates-stamp multiple bubble episodes within a given cryptocurrency price time-series. To a lesser extent, the econophysics log-periodic power law (LPPL) method introduced by Filimonov and Sornette (2013) is also utilised (Geuder et al., 2019; MacDonell et al., 2014; Bianchetti et al., 2018). The LPPL method enables the detection of the critical point in a bubble, the bubble burst after which the asset price declines.

Across all the aforementioned studies, consensus emerges regarding the presence of bubble episodes in various cryptocurrencies. Figure 1 illustrates the bitcoin bubbles identified by the literature. It is worth noting that the analysed time intervals typically conclude prior to 2022, with prices beyond this date remaining unexplored. Notably, the literature reveals two major bitcoin bubbles, one in 2017 and a subsequent one in 2021.

By analysing multiple cryptocurrencies, researchers also reach a consensus on the co-explosivity phenomenon among these digital assets (Bouri et al., 2019; Agosto and Cafferata, 2020; Haykir and Yagli, 2022). This co-explosivity reveals that explosive price episodes within one cryptocurrency are linked to and can potentially trigger similar explosive movements in other cryptocurrencies. Agosto and Cafferata (2020) focus further into this interconnectedness of the bubbles burst. Their analysis demonstrates that when a bubble bursts in one cryptocurrency, it increases the probability of a bubble burst occurring in other cryptocurrencies. Importantly, Bouri et al. (2019) contributes to our understanding of these dynamics by revealing that the interdependence of cryptocurrency prices is not contingent on the size or market capitalization of the cryptocurrency.

Few research articles focus on the determinants of cryptocurrency bubbles. In a parallel to their impact on traditional financial assets, herding behaviour emerges as a driving force behind the pricing dynamics of cryptocurrencies (Vidal-Tomas et al., 2019; Susana et al., 2020; Papadamou et al., 2021). However, the findings of Haykir and Yagli (2022) suggest a nuanced relationship between herding behaviour and cryptocurrency bubbles. Specifically, their research indicates that herding behaviour tend to decrease during periods of uncertainty and explosivity. This observation aligns with the findings of Da Gama Silva et al. (2019), who show that herding behaviour tends to manifest during normal periods but gives way to adverse herding in extreme periods.

Furthermore, Enoksen et al. (2020) investigate the significance of cryptocurrency-specific and market-specific factors in predicting bubbles, with a particular emphasis on uncertainty variables. They analyse eight cryptocurrency markets through panel and time-series probit models. Their analysis reveals that uncertainty surrounding legislation and regulation, measured through the Economic Policy Uncertainty index, demonstrates a positive relationship with bubble occurrence, whereas uncertainty in financial markets, as represented by the VIX index, exhibits a negative relationship with the onset of bubbles. They also find that the volume and the volatility are positively associated with the occurrence of bubbles. However, no significant effect is found concerning google searches. Findings of Haykir and Yagli (2022) corroborate those of Enoksen et al. (2020) concerning the importance of trading volume and volatility.

4 Demonstrating The Law of One Price

4.1 Empirical Strategy

The LOP states that the price of a commodity expressed in a common currency should be the same in two countries. To test this law, we follow the literature on the failure of the LOP in the usual commodity market (Ardeni 1989 ; Baffes, 1991 ; Pippenger and Philips 2007) and focus on the long-run relationship between prices by exploring time series properties.

By taking the USD-denominated Bitcoin price as reference, for the LOP to hold, the regression of the local Bitcoin price expressed in USD on USD-prices must show a significant slope coefficient equals to one:

$$log(p_{i,t}e_{i,t}) = \beta log(p_{US,t}) + \epsilon_{i,t} \tag{1}$$

Where $p_{i,t}$ is the local Bitcoin price of country i and at day t, $e_{i,t}$ is the exchange rate of country's i against USD. To disentangle the price effect from the exchange rate effect, we include the exchange rate as a regressor. Equation (1) is equivalent to:

$$log(p_{i,t}) = \beta_0 log(e_{i,t}) + \beta_1 log(p_{US,t}) + \epsilon_{i,t} \tag{2}$$

For the LOP to hold, coefficients β_0 and β_1 must be equal to -1 and 1 respectively, ensuring that local price is appropriately adjusted by the exchange rate, and and equal to the USD price when expressed in USD terms.

According to cointegration theory of Engle and Granger (1987), regressions of cointegrated and non-stationary time series can result in spurious results. Therefore, we first need to analyse stationarity of our panel series, and, according to the order of integration, employ the adequate test for cointegration. If cointegration is found, residuals of (1) must be stationary, meaning that there might be a stationary linear combination of $log(p_{i,t} * e_{i,t})$ and $log(p_{US,t})$ and consequently a long-run equilibrium relationship between them. Finally, we estimate β_0 and β_1 which capture the long-run relationship to validate or not the LOP.

To test for stationarity, we use first-generation tests, as the Levin-Lin-Chu (2002) test (LLC), the Im-Pesaran-Shin test (2003) (IPS), the Harris-Tzavalis (1999) test (HT), the Breitung (2000) test (B) and the Karavia and Tzavalis (2014) test (KT), as well as second-generation tests, namely the cross-sectionally independent IPS (CIPS ; Peseran, 2007) and ADF test (CADF ; Pesaran, 2003). All of them test the null hypothesis of a unit root in each panel. First generation tests assume cross-sectional independence, assumption that does not likely hold in our panel data.

These tests allow us to determine the order of integration of our variables and three cases can appeared:

- variables are stationary in levels (integrated of order 0, I(0)). In this case, we can use the OLS estimator, assuming that prices are not simultaneously endogenous.
- There is a mix of I(0) and I(1) (stationary in first difference). In this case, we employ the Westerlund and Pedroni tests.
- Series are I(1). In this case, we apply the Johansen (1995) trace cointegration test.

If the variables are cointegrated, we then estimate the model according to the following cases:

- if one time series is stationary in level (intergated of order 0) and the other is stationary in first difference (integrated of order 1), we apply a panel Autoregressive Distributed Lag Error Correction model (ARDL ECM).
- if both series are stationary in first difference, we apply a Vector Error Correction model (VECM) through the Lagrange Multiplier test for correcting autocorrelation in residuals.

For the LOP to be validated, we follow **?** with the 99% confidence intervals around β_0 and β_1, leading to interpret $\beta_0 \in [-1.03; -0.97]$ and $\beta_1 \in [0.97; 1.03]$ as a valid LOP [2].

4.2 Data

Bitcoin prices are extracted from the Cryptocompare.com website in 29 different currencies (including USD prices). For each currency we attribute a country (or region for the Euro). Table 8 lists the currencies/country analysed. Dara were extracted on April 4, 2024. The start dates varies across countries.The USD has the longest series, starting on July 17, 2010, while the HKD has the shortest, beginning on October 18, 2022. To ensure a balanced panel, we limit the sample to 22 currencies from September 1, 2013, excluding AED, ARS, HKD, INR, KZT, PHP and USD.

Exchange rate of currencies against the USD are extracted from the BIS.

4.3 Results

Table 9 of the annexes presents results of the unit root tests for local Bitcoin prices and exchange rates. Based on the first and second generation tests, local prices are found to be stationary in level, while exchange rates are found to be stationary in first difference. Investigation on cointegration is therefore necessary.

[2] A 95% and 90% confidence lead to a $\beta_1 \in$ [0.9772, 1.0228] and [0.9808, 1.0192] respectively.

Results of cointegration test of Pedroni and Westerlund are presented in Table 10 of the annexes. In a robust manner, we find that local prices, USD prices and exchange rates are cointegrated, in both Pedroni and Westerlund tests.

According to the different order of integration of our variables, we estimate a panel ARDL Error Correction Model (ARDL ECM) to capture long- and short-run dynamics. This method has the advantage to be designed for series that ca be either I(0) or I(1). The general form of ARDL model is defined as follows:

$$p_{i,t} = \alpha_0 + \sum_{j=1}^{p} \gamma_j log(p_{i,t-j}) + \sum_{j=0}^{q} \delta_j log(e_{i,t-j}) + \sum_{j=0}^{r} \phi_j log(p_{US,t-j}) + \epsilon_{i,t} \tag{3}$$

The Error Correction Term captures the deviation from the long-run equilibrium. It is derived from the $\epsilon_{i,t}$ of original long-run relationship (equation (1)), and is defined as follows:

$$ECT = log(p_{i,t-1}) - \beta_0 log(e_{i,t-1}) - \beta_1 log(p_{US,t-1}) \tag{4}$$

The Error Correction Model (ECM) incorporates both the short-run dynamics and the correction to the long-run equilibrium. It is written as:

$$\begin{aligned}\Delta \log(p_{i,t}) =& \lambda(\log(p_{i,t-1}) - \beta_0 \log(e_{i,t-1}) - \beta_1 \log(p_{US,t-1})) + \sum_{j=1}^{p-1} \gamma_j \Delta \log(p_{i,t-j}) + \sum_{j=0}^{q-1} \delta_j \Delta \log(e_{i,t-j}) \\ &+ \sum_{j=0}^{r-1} \phi_j \Delta \log(p_{US,t-j}) + \epsilon_{i,t}\end{aligned} \tag{5}$$

To estimate the model, we employ two different approaches: pooled mean-group (PMG) and dynamic fixed effects (DFE). The PMG approach allows for heterogeneous short-term dynamics across cross-sectional units but assumes homogeneity in the long-term equilibrium. This estimator therefore assumes that β_0 and β_1 are the same across countries, but that the other coefficients vary across countries. The DFE assumes homogeneity in both short- and long-run relationships, but capture unit-specific heterogeneity. All the coefficients are therefore the same across countries.

To account for the interconnectedness of countries, we also estimate a cross-sectionally augmented ARDL model, by including cross-sectional averages of the dependent and independent variables. This captures the common factors influencing all countries.

Table 1 presents estimations of coefficients of interest, namely the long-run coefficients β_0 and β_1, and of the error correction term (ECT). The entire results can be found in Table 11 in the Appendices section. The ECT measures the speed at which the system corrects itself to return to equilibrium after a short-term shock. In all specifications, we find a negative ECT, which is crucial for the system to adjust back to the equilibrium over time. At the maximum, we find an ECT equal to -0.01, meaning that only 1% of the deviation from the long-run equilibrium is corrected the following day.

Concerning the coefficients of interest, we observe that the *USD price* coefficient is significant at the 1% level and is within the range [0.97;1.03] in all specifications. This means that local price of Bitcoin in other countries closely follows the price expressed in USD, which is a key feature of the LOP. However, we observe that the coefficient of *Exchange rate* does not fall in the range of [-1.03;-0.97] in a robust manner. Therefore, the exchange rate does not fully offset price differentials. Hence, results suggest that the LOP does not hold in the Bitcoin market. Bitcoin is a global commodity, as its price in USD tend to align across countries. However, the exchange rate does not fully explain local prices, indicating that other factors may influence local Bitcoin prices. The next section aims to determine whether cryptocurrency regulations can explain these price deviations controlling for other factors.

	In Level				In Growth Rate	
Exchange rate	-0.872***	-0.848***	-1.062***	-1.061***	-7.001***	-7.009***
USD price	1.003	1.002	0.994	0.993	1.002	1.002
ECT	-0.010	-0.010	-0.007	-0.006	-0.078	-0.078
Country FE	No	No	Yes	Yes	Yes	Yes
Cross sectionally augmented	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.97	0.97	0.99	0.99	0.99	0.99
Nb of obs	74250	74250	74250	74250	74250	74250
Nb of countries	22	22	22	22	22	22
Nb of days	3375	3375	3375	3375	3375	3375

Standardized beta coefficients. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The null hypothesis is beta equal to 1. The optimal number of lags is chosen according to the Akaike Information Criterion (AIC). Panel ARDL EC Model using Dynamic Fixed Effect (DFE) and Pooled-Mean-Group (PMG) estimations. In growth rate regressions, all variables are introduced in growth rate.

Table 1: Long run coefficients of the panel ARDL EC model

5 Price Deviation and Regulation

The previous section highlighted price deviations in Bitcoin markets, suggesting a market segmentation driven by country-specific factors or varying exposure to global forces. Here, we examine the role of cryptocurrency regulations in this segmentation, focusing on whether, and which types of regulations, contribute to price deviations, controlling for global and country-specific factors.

5.1 Data

5.1.1 Dependent Variable

We use the same Bitcoin data as in the previous section. However, we now use price deviation as dependent variable. To consider the case where local price are lower than USD price as a higher price deviation, the dependent variable is: defined as follows:

$$price\_deviation_{i,t} = \log\left(1 + \left|\frac{p_{i,t}e_{i,t}}{p_{USD,t}} - 1\right|\right) \quad (6)$$

To understand which variables are responsible for a lower or higher price compared to the USD one, we split our sample between the case where local price higher than USD price, and local price lower than USD price. Similarly to the previous section, we also regress local price on exchange rate and USD price to disentangle the effect of regulation on these variables.

5.1.2 The independent variables

The independent variables capture the implementation of national cryptocurrency regulations. We created a new dataset covering the effective date of these regulations across 28 countries. The primary data source is the Global Legal Insights web site [3], supplemented by national law registers and press articles data. The dataset includes the regulation's effective date, type (guidance or new/modified law), and category. Seven categories of laws are defined:

- Anti-Money Laundering and Combatting the Financing of Terrorism (*AML/CFT*): this category outlines regulatory measures and guidelines focused on anti-money laundering (AML) and counter-terrorist financing (CTF) in the context of cryptocurrencies. It refers to policies that foster transparency and integrity of the cryptocurrency market and the monitoring of transactions and client identity. This encompasses notably licensing, Know-Your-Client (KYC) procedures, transaction reporting, AML/CFT regulatory extension.

- Regulatory Framework: this category refers to the definition and associated requirements of cryptocurrency products and parties. It encompasses laws that clarify the regulatory perimeter of the cryptocurrency market, licensing requirements, and rights and obligations of parties. We create three subcategories according to the entity or sector concerned:

  - Virtual Asset Service Providers (*VASPs*): it refers to laws aiming at regulating virtual assets and service providers. Such regulations include for example licensing requirements, minimum capital, secure management system, assessment of business activity, etc.
  - Financial sector laws (*Securities*): such regulations expand financial sector regulatory framework to cryptocurrency. It encompasses the definition of some tokens as a security and the application of financial sector regulations to crypto-related entities.
  - Banking and payment laws (*Banking*): this category of regulations expand banking and payment laws to the cryptocurrency sector. This encompasses supervision of monitoring of crypto-related payment services, consumer protection in payment services, the prohibition of cryptocurrency advertisement, or by the safeguarding of consumer assets. These laws should build trust in crypto-related institutions and payment platforms.

  It is important to notice that some regulations can be assigned to several of these subcategories.

[3] https://www.globallegalinsights.com/practice-areas/blockchain-laws-and-regulations/

- Development: this category refers to regulations aiming at developing the cryptocurrency market and fostering its use. We collected data on two types of regulations:
  - *Regulatory sandbox*: a regulatory sandbox is a framework that allows companies to be exempted from specific regulations to test innovative products, services or businesses. This category therefore includes regulatory sandboxes, as well as innovation hubs, created for the cryptocurrency and blockchain sector.
  - Cryptocurrency-related investment legalisation (*Acceptance*): these regulations encompass the legalisation of cryptocurrency ETF or cryptocurrency investment by funds for example. They indicate increasing acceptance and integration of cryptocurrency into traditional financial markets.
- *Ban*: Total ban are not included in this category as no data on Bitcoin prices would be found for these countries. These regulatory measures rather reflect efforts by central authorities to restrict the involvement of financial institutions and intermediaries in cryptocurrency transactions. This encompasses for example the prohibition of banks to transact in cryptocurrency with their client, the prohibition to use credit cards to purchase cryptocurrencies or the prohibition to use cryptocurrencies as a means of payment for goods and services.

Mining and taxation regulations were also included in the dataset but are not considered in the analysis, as too few regulations were found with their effective date. In the empirical framework, each category and sub-category corresponds to a variable that measures the number of laws passed in a specific country i at day t.

Finally, the independent variables are defined as cumulative counts of implemented regulations across the seven categories: *AML/CFT*, *Banking*, *VASP*, *Securities*, *Acceptance*, *Sandbox*, and *Ban*. Each variable represents the cumulative number of regulations introduced in each category in country i by date t, reflecting the regulatory intensity in that area. An overall regulatory index, *Regulation*, is computed as the sum of these seven variables, providing a measure of the aggregate regulatory framework.

Hypotheses

Following Vivanco and Pieters (2016), we expect AML/CFT regulations to reduce price deviations, driven by lower local demand. Bitcoin's association with illicit activities and its appeal for anonymity may diminish with stricter regulations. Moreover, heightened compliance costs for exchanges can increase user costs, further reducing demand.

The impact of regulatory framework is less clear. While increased regulation may raise costs and reduce demand, it could also improve market confidence. Despite variations in national regulatory frameworks, we anticipate a convergence of prices between regulated countries, leading to reduced price deviations.

Development regulations, particularly regulatory sandbox, we anticipate that the creation of such environment is coupled with an increase in Bitcoin price. Cornelli et al. (2020) corroborate this hypotheses.Their findings show that sandbox entry has a significant positive effect on innovation, which can stimulate market activity and raising demand. Moroever, by allowing firms to experiment without full regulatory pressure, sandboxes reduce the uncertainty associated with unclear or evolving regulations. This can attract new participants and capital to the market, further boosting Bitcoin's appeal and potentially raising prices. This latter mechanism also applies to the legalisation of crypto-related product. However, the effect on price deviations may be ambiguous. While local Bitcoin prices may rise due to increased demand in countries adopting sandboxes, global prices may also be affected by the introduction of new products, creating both upward price pressures.

Finally, based on Griffith and Clancey-Shang (2023), demonstrating that average crypto prices fell after the establishment of Chinese ban partial, we expect that bans negatively impact local and global prices. Such countries being less attractive for foreign investors, we anticipate that the local price decline will exceed the global impact, suggesting a positive relationship between the ban variable and price deviation.

5.1.3 Controls

Control variables are both country-specific and global, including macro-financial, regulatory and market factors, which influence Bitcoin price.

Exchange rates and USD Bitcoin price are added as control variables, as they are directly involved in the computation of our dependent variable. Moreover, when a domestic currency appreciates against the dollar, it takes fewer units of domestic currency to purchase the same amount of Bitcoin, leading to a decrease in the domestic bitcoin price. Also, such appreciation makes Bitcoin more expensive for foreign buyers, whose currency has depreciated. This can reduce demand for Bitcoin from these buyers, potentially leading to lower Bitcoin price. Finally, if Bitcoin is viewed as a safe haven asset, an appreciating currency makes Bitcoin less attractive, leading to a decrease in demand and drop in Bitcoin price. We then expect a negative relationship between exchange rate and Bitcoin prices. To avoid perfect multicolinearity with the dependent variable, we do not include current values.

USD Bitcoin price intervenes as a proxy for global demand for Bitcoin. We expect that local Bitcoin price follows the USD one, leading to a positive relationship between local and USD Bitcoin price.

Following Di Casola et al. (2023), we control for financial factors at country and global level. These variables control for the link between traditional financial markets and the Bitcoin market. We include the Chicago Board Options Exchange's Volatility Index (VIX), as a proxy of the global level of stress in the stock market. Cryptocurrencies being a diversification asset, Bitcoin price increases during times of investor's fear (Akyldirim et al., 2020). Due to this change of behaviour during periods of stress, we therefore expect a positive relationship between prices and fear in the stock market.

We also control for local macroeconomic and financial development, proxied by domestic stock exchange indices growth. Higher development may stimulate the use of Bitcoin as method of payment. However, considering the negative relationship between tradition financial markets and the cryptocurrency market (Akyldirim et al., 2020), the demand of Bitcoin may decrease during stock market growth. The expected sign is therefore ambiguous. Inflation rate is also introduced, as a high inflation rate encourages the use of Bitcoin as a reserve of value. We then expect that an increase in inflation rate is associated with higher BTC price. We also include the Dow Jones index to control the global economic and financial development. The same mechanism as for domestic stock exchange applies.

Additionally, we control for liquidity in local Bitcoin markets and in foreign exchange markets. As in Di Casola et al. (2023), we include the bid-ask spread for each currency, to control for the liquidity in traditional foreign exchange markets. Higher spread increases conversion costs, that can delay arbitrage of traders taking advantage of price differences between markets. This wider spread reflect therefore higher risk in the local currency, which can lead to a premium on Bitcoin prices in that currency. To control for Bitcoin market liquidity risk, we follow Borri and Shakhnov (2023), by calculating the local trading volume normalised by the total supply of Bitcoin (number of coins in the economy). We expect that low liquidity leads to higher volatility, resulting in higher price deviations.

To account for price attractiveness, we include google trend as variable, computed at country-level. We expect a positive relationship between google trends and Bitcoin price.

As institutional variables, we include a measure of capital controls. Makarov and Shoar (2020) shows that capital account closeness limits arbitrage across countries, as it acts as a barrier to outflow of the fiat currency and generated profits. As in Di Casola et al. (2023), access to financial institutions and level of remittances are also included, as weak access to financial institutions and higher level of remittances to the country may encourage the use of cryptocurrencies.

Following the result of Makarov and Schoar (2020), observing an increase in price deviations during period of Bitcoin appreciation, we also control for periods of bubble in the USD Bitcoin market with a dummy variable. To determine such periods, we follow the methodology of explosivity identification of Phillips et al. (2015), based on the GSADF and BSADF tests. We account for bubble with a minimum duration of three days. The methodology is detailed in Annexes 2. A positive and significant coefficient for this variable would mean that local traders have amplified reactions compared to those in the USD market.

5.2 Empirical Strategy

This section outlines the empirical strategy employed to analyze the impact of regulations on Bitcoin price deviation and local price levels.

As in the previous section, the data for Bitcoin prices form a long panel structure, and thus the same methodology is applied to assess time series properties such as stationarity and cointegration. Given the nature of regulatory data, we do not assess their stationarity directly, as shifts in mean and variance in these variables are more likely driven by the occurrence of regulatory events rather than inherent time-series dynamics.

The stationarity and cointegration tests reveal a mix of I(0) and I(1) variables, suggesting the use of a panel ARDL Error Correction (EC) model to accommodate both stationary and integrated series. We incorporate both regulatory and control variables in the following model:

$$\begin{aligned}\Delta \log(price\_deviation_{i,t}) =&\lambda(\log(price\_deviation_{i,t-1}) - \beta_0 Regulation_{i,t} + \beta_1 X_{i,t} + \beta_2 X_t) \\ &+ \sum_{j=1}^{p-1} \gamma_j \Delta \log(price\_deviation_{i,t-j}) + \sum_{j=0}^{m-1} \alpha_j \Delta Regulation_{i,t-j} \\ &+ \sum_{j=0}^{n-1} \theta_j \Delta X_{i,t-j} + \sum_{j=0}^{k-1} \psi_j \Delta X_{t-j} + \epsilon_{i,t}\end{aligned} \tag{7}$$

Here, $price\_deviation_{i,t}$ denotes the price deviation between Bitcoin in country i and USD price on day t, *Regulation* refers to our regulatory variables (included either individually or as an aggregate), $X_{i,t}$ represents country-specific control variables, and X_t includes global control variables. To avoid multicollinearity issues, we exclude *VIX* and *FIA* due to high VIF values.

This model is also estimated using local price, $p_{i,t}$, as an alternative dependent variable to examine the effect of regulations on the local market. For this specification, the exchange rate and USD price are included:

$$\begin{aligned}\Delta \log(p_{i,t}) =&\lambda(\log(p_{i,t-1}) - \beta_0 \log(e_{i,t-1}) - \beta_1 \log(p_{USD,t-1}) + \beta_2 Regulation_{i,t} + \beta_3 X_{i,t} + \beta_4 X_t) \\ &+ \sum_{j=1}^{p-1} \gamma_j \Delta \log(p_{i,t-j}) + \sum_{j=0}^{q-1} \delta_j \Delta \log(e_{i,t-j}) + \sum_{j=0}^{r-1} \phi_j \Delta \log(p_{USD,t-j}) + \sum_{j=0}^{m-1} \alpha_j \Delta Regulation_{i,t-j} \\ &+ \sum_{j=0}^{n-1} \theta_j \Delta X_{i,t-j} + \sum_{j=0}^{k-1} \psi_j \Delta X_{t-j} + \epsilon_{i,t}\end{aligned} \tag{8}$$

$p_{i,t}$ represents the local Bitcoin price in country i on day t, $e_{i,t}$ is the exchange rate between the country's currency and USD.

To address trade barriers, a dynamic fixed effects estimator is used, and the sample is split based on whether the local price is below or above the USD price.

5.3 Results

Table 14 presents the results of stationarity tests for the dependent and control variables. The null hypothesis of non-stationarity is rejected for most variables in levels, with the exception of *Inflation*, *Remittances* and *FIA*, which exhibit stationarity only in first differences. *Capital account openness* is also non-stationary in levels, with mixed results in first differences, likely due to its low time-series variability.

Because variables are a mix of I(0) and I(1), we perform a Pedroni and a Westerlund cointegration tests. While the Pedroni test tests for residuals non-stationarity, the Westerlund one is based on the significance of the error correction term. Both test the null hypothesis of no cointegration. Table 15 presents the results of these tests with price deviations and local prices as dependent variables. Concerning Pedroni test, in the two cases where common (panel) or different (group) autoregressive coefficient across the cross-sections is assumed, the null hypothesis of cointegration is rejected at the 1% level of significance. The same result is found with the Westerlund test.

Based on these results, we use a Panel ARDL EC Model, as previously employed in the demonstration of the failure of the LOP section.

Table 2 reports the results of regressions of price deviation and local price on the aggregate regulatory variable *Regulation*. To account for trade barriers, we directly display results using the fixed effect estimator. For each dependent variable, regressions are estimated first on the full sample, then the sample is split according to whether the local price (expressed in USD) is below or above the USD price (note: observation of local price equalising USD price does not occur).

The Error Correction Term (ECT) is consistently significant and negative across specifications, supporting a long-run equilibrium relationship between price deviations and explanatory variables across countries. The magnitude of the ECT reflects the speed of adjustment toward equilibrium. For example, a coefficient of -0.203 suggests that 20,3% of deviation from the long-run equilibrium is corrected the next day.

Regulation is found to be negatively associated with price deviation in the full- and split-sample-regressions at the 1% level of significance. The more regulated the country is, the more converging local and USD prices are. Focusing on regressions with local price as dependent variable, we find that *Regulation* displays a significant negative coefficient in the full-sample regression. However, in the segmented samples, we observe that the coefficient is positive when local price is above USD price, and becomes negative in the opposite case. This suggests that the price convergence resulting from implementations of regulations may be attributed to a local effect on price. Cryptocurrency regulations make therefore the market more integrated. They also allow to stabilise Bitcoin prices when local prices are above global prices.

Bubble shows a significant association with price deviation only when local price is below USD price, with a positive coefficient significant at the 1% level. This suggests that, in this context, during period of bubbles in the USD market, USD prices are likely inflating faster than local prices. This results is in line with results of regressions with local price as dependent variable, as we see that *Bubble* does not present a significant coefficient in such context. This may indicate a degree of insulation in this local market from speculative behaviour in the USD market. This isolation would not concern markets where local price is above USD price, given the lack of significance of *Bubble* in regression on price deviation, and its positive coefficient on local price when local price is above USD price.

Capital account openness shows a significant negative association with price deviation in the full-sample regression and in the regression where local price is above USD price, at the 1% level. The more opened capital account of a country is, the more convergent Bitcoin prices are. This result is consistent with findings of Makarov and Shoar (2020), as opened capital account makes profits repatriating possible. This effect is accompanied by a reduction in the local price. Interestingly, this relationship does not hold when local prices fall below USD prices, likely because such markets would not attract foreign arbitrageur to sell Bitcoins.

Both *Stock growth* and *Inflation* exhibit significant positive associations with price deviation, suggesting that increased stock performance and inflation may amplify local price premiums over the USD Bitcoin price. Conversely, *Remittances* is found to be negatively associated with price deviation at the 1% level of significance. The higher the level of remittances received, the lower price deviation is. This result underscores the use of Bitcoin as mean of international money transfer, making prices converging.

In the short term, *Bubble* is found to have a positive effect on price deviation when local price is below USD price, and a negative effect in the opposite case, at the 1% level of significance. Moreover, no significant effect on local price is found when local price exceed USD price, whereas a significant positive effect is found on the opposite case. These results corroborates the potential insulation of markets with prices lower than international price.

		Dep var: price deviation			Dep var: local price		
		all sample	local price $\leq$ USD price	local price $\geq$ USD price	all sample	local price $\leq$ USD price	local price $\geq$ USD price
Long-Term							
	Exchange rate				-0.999***	-1.384***	-0.991***
	USD price				0.996***	0.970***	0.989***
	Regulation	-0.01***	-0.006***	-0.015***	-0.009***	0.018*	-0.008***
	Bubble	0.005	0.040***	-0.002	0.004	-0.024	0.023**
	Capital account openness	-0.024***	-0.000	-0.040***	-0.020***	0.016	-0.051***
	Stock growth	0.466***	0.0497	0.967***	0.457	-0.312	1.624***
	Inflation	0.001***	-0.001	0.002***	0.002***	-0.004	0.002***
	Google trend	0.000	-0.000**	0.000	0.000**	-0.000	0.000
	Liquidity BTC	-0.546	-2.045	-0.459	0.014	7.212	-1.200
	Liquidity FX	-0.000	0.000	-0.000	-0.000	-0.001	0.000
	Remittances	-0.038***	-0.050***	-0.037***	0.031***	0.080***	-0.031***
	ECT	-0.203***	-0.131***	-0.176***	-0.161***	-0.072***	-0.126***
Short-Term							
	D.Exchange rate				-0.526***	-0.707***	-0.605***
	D2.Exchange rate				0.283***	0.212	0.187***
	D.USD price				0.547***	0.716***	0.474***
	D2.USD price				-0.096***	-0.182***	-0.106***
	D3.USD price				0.041***	0.052***	0.068***
	D.Regulation	-0.003	-0.003	-0.004	0.006	0.011	0.002
	D.Bubble	-0.003	0.009***	-0.010***	0.012***	0.004	0.018***
	D.Capital account openness	-0.028*	0.028	-0.005	0.028	-0.001	-0.009
	D.Stock growth	0.013	-0.001	0.046	0.042	-0.008	0.117***
	D.Inflation	0.000	0.000	0.000	-0.002	-0.004	0.000
	D.Google trend	-0.000	0.000	-0.000	0.000	-0.000	0.000
	D.Liquidity BTC	-0.041	-0.162	-0.042	-0.119	0.313	-0.258
	D.Liquidity FX	0.000	0.000	0.000	-0.000	-0.000	-0.000
	D.Remittances	-0.002	-0.004	0.000	0.024	-0.024	-0.002
FE		Yes	Yes	Yes	Yes	Yes	Yes
cross sectionally augmented		No	No	No	No	No	No
Obs		103501	37911	65590	103501	31911	65590

* p<0.10, ** p<0.05, *** p<0.01. Lower value of price deviation 2 indicates divergence between USD converted local price and USD price. Dynamic fixed effect estimator. Optimal lag determined via AIC.

Table 2: Regression Results: Impact of Aggregated Regulations on Price Deviation and Local Price

Table 3 presents results of regressions with the breakdown of regulations as independent variable. The methodology and the layout of this table are the same as in Table 2.

AML/CFT is found to increase price deviation when local prices are below USD prices and reduce it when local prices exceed USD prices, significant at the 1% level. This effect is likely driven by a reduction in local prices in response to stricter AML/CFT regulations, which mitigate the use of Bitcoin for illicit activities by enforcing stricter monitoring and reporting requirements, in line with Vivanco and Pieters (2020).

Banking show a negative relationship with price deviation, significant at the 1% level. These regulations appear to promote price convergence by improving the safety and reliability of the Bitcoin market, facilitating arbitrage. The observed effect stems from a reduction in local prices when they exceed international prices, but no significant increase in local prices is seen when they are below international levels.

VASP show no significant impact on price deviation but are positively associated with local price, suggesting that the regulatory environment for virtual asset service providers has an upward pressure on local Bitcoin prices.

Securities exhibit a negative effect on price deviation, leading to price convergence with the USD benchmark. This effect is accompanied by an increase in local prices. The expansion of securities laws fosters a more regulated, transparent trading environment, enhancing investor confidence and facilitating cross-border arbitrage, thereby reducing price deviations.

Regulatory are associated with a negative effect on price deviation at the 1% significance level, along with a positive effect on local price. By reducing regulatory uncertainty and fostering innovation, sandboxes contribute to market growth and improved trading infrastructure, which enhances market integration and facilitates price convergence.

Legalisation exhibits a negative relationship with price deviation at the 5% level of significance and a negative one with local price et 10%. Hence, integrating cryptocurrency in the traditional financial market makes the Bitcoin market more compliant with the LOP. Interestingly, the local Bitcoin price lowers.

Ban is found to be positively associated with price deviation at the 1% level. Partial bans therefore trigger price divergence in Bitcoin prices, by creating regulatory barriers that restrict cross-border arbitrage. This divergence can also be due to the perceived scarcity or uncertainty due to these bans. Moreover, countries implementing partial bans often do not implement a strong regulatory framework, further preventing market integration. We observe also an increase in local price when it is above the USD benchmark. However, on the whole, countries implementing partial bans are associated with lower local prices.

Finally, improving the regulatory framework of the cryptocurrency market enhances its integration and fosters price convergence between countries in the long term. Implementing reform does not however influence local market in the short term. For banking and payment system regulations, securities laws, and regulatory sandboxes, this convergence is accompanied by upward pressure on local prices. In contrast, AML/CFT regulations exert downward pressure on local prices, regardless of the USD price level, indicating Bitcoin's use for illicit activities. Partial bans, on the other hand, increase price divergence and reduce market integration, with countries implementing more bans generally associated with lower local prices. Together with the bubble effect, these findings suggest that such countries are more insulated from bubbles in the USD market.

		Dep var: price deviation			Dep var: local price		
		all sample	local price ≤ USD price	local price ≥ USD price	all sample	local price ≤ USD price	local price ≥ USD price
Long-Term							
	Exchange rate				-1.037***	-1.477***	-0.989***
	USD price				0.993***	0.963***	0.988***
	AML/CFT	-0.002	0.022***	-0.002***	-0.063***	-0.137***	-0.028***
	Banking	-0.039***	-0.035***	-0.055***	0.004	0.091	-0.050***
	VASP	-0.003	0.012	0.009	0.030**	0.062	0.026
	Securities	-0.010***	-0.013***	-0.013**	0.012**	0.103***	-0.002
	Sandbox	-0.020***	-0.020***	-0.017***	0.015**	0.033	-0.001
	Legalisation	-0.015**	-0.003	-0.017	-0.024*	0.016	-0.029
	Ban	0.021***	-0.001	0.014	-0.058***	-0.041	0.031**
	Bubble	0.006*	0.039***	-0.000	0.006	-0.011	0.024***
	Capital account openness	-0.022***	-0.005	-0.036***	-0.016**	0.053	-0.043***
	Stock growth	0.458***	0.012	0.961***	0.455	-0.123	1.59***
	Inflation	0.001***	-0.001	0.01***	0.002***	-0.007	0.002***
	Google trend	0.000	-0.000***	0.000	0.001***	0.000	0.000
	Liquidity BTC	-0.462	-1.771	-0.460	-0.417	2.400	-1.227
	Liquidity FX	0.000	0.000	0.000	-0.000	-0.001	0.000
	Remittances	-0.043***	-0.052***	-0.043***	0.036***	0.077***	-0.034***
	ECT	-0.205***	-0.133***	-0.177***	-0.163***	-0.074***	-0.127***
Short-Term							
	D.Exchange rate				-0.537***	-0.717***	-0.605***
	D2.Exchange rate				0.284***	0.214	0.186***
	D.USD price				0.545***	0.717***	0.474***
	D2.USD price				-0.094***	-0.182***	-0.105***
	D3.USD price				0.041***	0.052***	0.068***
	D.AML/CFT	-0.002	-0.007	-0.000	0.006	0.016	0.004
	D.Banking	0.001	-	0.011	-0.006	-	-0.011
	D.VASP	-0.001	-0.018	-0.003	-0.006	-0.036	-0.005
	D.Securities	-0.004	-0.001	-0.005	0.007	0.017	0.001
	D.Sandbox	0.013	0.008	0.004	0.020	0.008	0.006
	D.Legalisation	-0.006	0.008	-0.011	0.010	-	0.013
	D.Ban	-0.040*	-0.004	-0.083	-0.002	0.032	-0.008
	D.Bubble	-0.003	0.008***	-0.010**	0.012***	0.004	0.018***
	D.Capital account openness	-0.029*	0.029	-0.004	0.028	-0.001	-0.008
	D.Stock growth	0.013	-0.004	0.046	0.043	-0.002	0.116***
	D.Inflation	0.000	0.000	0.000	-0.002	-0.003	0.000
	D.Google trend	-0.000	0.000	-0.000	0.000	-0.000	0.000
	D.Liquidity BTC	-0.033	-0.149	-0.044	-0.154	0.102	-0.260
	D.Liquidity FX	0.000	0.000	0.000	-0.000	-0.000	-0.000
	D.Remittances	-0.002	-0.004	-0.000	0.024	-0.030	-0.002
FE		Yes	Yes	Yes	Yes	Yes	Yes
cross sectionally augmented		No	No	No	No	No	No
N		103501	31911	65590	103501	31911	65590

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Lower value of price deviation 2 indicates divergence between USD converted local price and USD price. Dynamic fixed effect estimator. Optimal lag determined via AIC.

Table 3: Regression Results: Effects of Regulations (breakdown) on Price Deviation and Local Prices

6 Robustness checks

To ensure the reliability of our findings, we conduct robustness checks by examining the effects of different model specifications and estimation methods.

Firstly, due to the lack of short-term impacts of regulatory variables, we estimate a dynamic fixed effects model, omitting short-run variables. Although the panel ARDL model's lag structure mitigates autocorrelation, its standard errors are not adjusted for heteroscedasticity. We therefore use Driscoll-Kraay standard errors, which address both heteroscedasticity. While introducing a country fixed effect in a dynamic model can introduce Nickell bias, the bias is reduced here due to the long time dimension of our data. To avoid spurious regressions, we introduce *Inflation* and *Remittances* as first-differenced variables.

To further test robustness, we assess whether our results are sensitive to the functional form of price deviation. Specifically, we redefine price deviation as follows:

$$price\_deviation_{i,t} = \left| \frac{p_{i,t} * e_{i,t}}{p_{USD,t}} - 1 \right| \tag{9}$$

Additionally, we examine the growth rate of price deviation, calculated as the log difference:

$$price\_deviation\_growth_{i,t} = \log(price\_deviation_{i,t}) - \log(price\_deviation_{i,t-1}) \tag{10}$$

Tables 4, 5, 6, and 7 present the results of the effect of *Regulation* on price deviation and local price, both in level and growth rate. Our findings indicate that results for price deviation (in level) remain consistent across specifications, including when excluding short-run variables, when not applying the logarithmic transformation to the dependent variable, and when using Driscoll-Kraay standard errors.

Our findings remain robust when the growth rate of price deviation is used as the dependent variable. Negative coefficients for *Banking*, *Securities*, and *Sandbox* indicate that these regulations accelerate the convergence of local prices to the USD benchmark, fostering faster market integration.

Bubble keeps its significance in markets where local prices are below USD prices, with a positive coefficient in both level and growth rate regressions.

For regressions with local price as the dependent variable, results for *Regulation* are consistent in both level and growth rate. The breakdown of regulations yields even more significant results with consistent signs. However, for most regulations, the effects are not robust in growth rate regressions.

	Dep var: price deviation (abs)			Dep var: price deviation (growth rate)		
	all sample	local price ≤ USD price	local price ≥ USD price	all sample	local price ≤ USD price	local price ≥ USD price
L.Price deviation	0.739***	0.628***	0.738***	-0.208***	-0.311***	-0.203***
Regulation	-0.003***	-0.000	-0.004***	-0.002***	-0.000	-0.002***
Bubble	0.002	0.010**	-0.001	0.002	0.007***	0.000
Capital account openness	-0.002***	-0.001	-0.011***	-0.005***	-0.001	-0.006***
Stock growth	0.067	0.018	0.097	0.074**	0.027	0.102**
D.Inflation	0.000**	-0.001***	0.001***	0.000***	-0.001***	0.000***
Google trend	0.000	-0.000*	0.000	0.000	-0.000**	0.000
Liquidity BTC	-0.108**	-0.262**	-0.01	-0.081**	-0.194***	-0.077*
Liquidity FX	-0.000	0.000	-0.000	-0.000	0.000	-0.000
D.Remittances	-0.013***	-0.018***	-0.013***	-0.008***	-0.012***	-0.007***
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.58	0.57	0.57	0.11	0.20	0.10
Obs	74250	27437	46813	74250	27437	46813

* p<0.10, ** p<0.05, *** p<0.01. All regressors are introduced with a lag.
Growth rate of the dependent variable is computed as the log difference.

Table 4: Regression Results: Effects of *Regulation* on Price Deviation using Dynamic Fixed Effect Estimator and Dricoll-Kraay Standard Errors

	Dep var: price deviation (abs)			Dep var: price deviation (growth rate)		
	all sample	local price ≤ USD price	local price ≥ USD price	all sample	local price ≤ USD price	local price ≥ USD price
L.Price deviation	0.738***	0.621***	0.737***	-0.211***	-0.317***	-0.204***
AML/CFT	0.001	0.011***	-0.006***	0.000	0.007***	-0.004***
Banking	-0.013***	-0.011**	-0.017***	-0.008***	-0.008***	-0.009***
VASP	-0.000	0.001	0.006	-0.000	0.002	0.003**
Securities	-0.003***	-0.003	-0.003***	-0.002***	-0.001*	-0.002***
Sandbox	-0.007***	-0.006**	-0.007***	-0.004***	-0.004***	-0.004***
Legalisation	-0.004***	-0.002	-0.002	-0.003***	-0.001	-0.001
Ban	0.009***	0.007**	0.006*	0.005***	0.003*	0.003
Bubble	0.001	0.010**	-0.000	0.002	0007***	0.001
Capital account openness	-0.008***	-0.002	-0.009***	-0.005***	-0.002**	-0.005***
Stock growth	0.067	0.015	0.097	0.074***	0.026	0.103**
D.Inflation	0.000	-0.001***	0.001**	0.000*	-0.001***	0.000***
Google trend	-0.000	-0.000**	-0.000	-0.000	-0.000***	0.000
Liquidity BTC	-0.078	-0.186**	-0.099	-0.067*	-0.148**	-0.083*
Liquidity FX	0.000	0.000	0.000	0.000*	0.000*	0.000
D.Remittances	-0.016***	-0.021***	-0.015***	-0.009***	-0.013***	-0.008***
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.58	0.57	0.57	0.11	0.21	0.10
Obs	74250	27437	46813	74250	27437	46813

All regressors are introduced with a lag. Growth rate of the dependent var mean difference of log

* p<0.10, ** p<0.05, *** p<0.01. All regressors are introduced with a lag.
Growth rate of the dependent variable is computed as the log difference.

Table 5: Regression Results: Effects of Regulations (breakdown) on Price Deviation using Dynamic Fixed Effect Estimator and Dricoll-Kraay Standard Errors

	Dep var: local price			Dep var: local price (growth rate)		
	all sample	local price ≤ USD price	local price ≥ USD price	all sample	local price ≤ USD price	local price ≥ USD price
Exchange rate	-0.988***	-1.073***	-0.984***	-0.374***	-0.589*	-0.339***
USD price	0.997***	0.996***	0.995***	0.068***	0.104***	0.065***
Regulation	-0.009****	0.002	-0.007***	-0.000	0.003***	-0.001***
Bubble	-0.015**	-0.023**	-0.001	0.008***	0.011***	0.008***
Capital account openness	-0.018**	0.009	-0.034***	-0.001	0.001	-0.001
Stock growth	-0.020***	-0.033	-0.047	0.005	0.043	-0.002
D.Inflation	0.004***	0.004***	0.002***	0.000	-0.001**	0.000***
Google trend	0.001***	0.000	0.000***	-0.000	0.000	-0.000***
Liquidity BTC	0.493***	1.100***	0.136	0.074	0.267	-0.000
Liquidity FX	-0.000	-0.000	-0.000	0.000	-0.000	0.000**
D.Remittances	0.032***	0.092***	-0.027***	-0.000	0.000	0.000
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.99	0.99	0.99	0.01	0.01	0.01
Obs	74250	27437	46813	74250	27437	46813

* p<0.10, ** p<0.05, *** p<0.01. All regressors are introduced with a lag.
Growth rate of the dependent variable is computed as the log difference.
24 countries. In growth rate regressions, exchange rate and US price are expressed in growth rate (log difference)

Table 6: Regression Results: Effects of *Regulations* on Local Price using Dynamic Fixed Effect Estimator and Dricoll-Kraay Standard Errors

	Dep var: local price			Dep var: local price (growth rate)		
	all sample	local price ≤ USD price	local price ≥ USD price	all sample	local price ≤ USD price	local price ≥ USD price
Exchange rate	-1.026***	-1.135***	-0.980***	-0.374***	-0.585*	-0.338***
USD price	0.993***	0.991***	0.994***	0.068***	0.106***	0.065***
AML/CFT	-0.059***	-0.073***	-0.015***	-0.000	0.006***	-0.003***
Banking	0.002	0.057***	-0.037***	0.000	-0.003	0.001
VASP	0.032***	0.021**	0.007	-0.000	0.001	0.005***
Securities	0.012***	0.031***	-0.003*	-0.000	0.010***	-0.000
Sandbox	0.015***	0.033***	-0.009***	0.000	-0.007***	-.005***
Legalisation	-0.020***	0.003	-0.017***	-0.000	0.000	0.007***
Ban	-0.057***	-0.068***	0.021***	-0.000	0.010***	-0.002
Bubble	-0.017**	-0.018*	-0.000	0.008***	-0.001	0.008***
Capital account openness	-0.016***	0.019***	-0.029***	-0.001	0.042	0.000
Stock growth	-0.054	-0.022	-0.048	0.004	-0.001**	-0.001
D.Inflation	0.004***	0.002**	0.002***	0.000	0.000	0.000***
Google trend	0.001***	0.000	0.000***	-0.000	0.357**	-0.000***
Liquidity BTC	0.181	0.548**	0.153	-0.074	-0.000	-0.045
Liquidity FX	-0.000	-0.003**	0.000	0.000**	-0.000	0.000*
D.Remittances	0.037***	0.097***	-0.032***	-0.000	0.000	0.000
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.99	0.99	0.99	0.01	0.01	0.01
Obs	74250	27437	46813	74250	27437	46813

* p<0.10, ** p<0.05, *** p<0.01. All regressors are introduced with a lag.
Growth rate of the dependent variable is computed as the log difference.
24 countries. In growth rate regressions, exchange rate and US price are expressed in growth rate (log difference)

Table 7: Regression Results: Effects of Regulations (breakdown) on Local Price using Dynamic Fixed Effect Estimator and Dricoll-Kraay Standard Errors

7 Conclusion

This article investigates whether cryptocurrency regulations are responsible of Bitcoin market segmentation. To this end, after examining whether the Law of One Price (LOP) holds in this market, we study the impact of regulations on price deviation. To capture the local effect of regulations, we also study the impact on local prices controlling for USD Bitcoin price and exchange rate. A database of cryptocurrency regulations of 28 countries since 2009 were build to this end, defining 7 categories of regulations.

This study shows that even if the local price closely follows that in USD, the exchange rate does not fully compensate for the LOP to hold. This result highlights the presence of market barriers for cross-border trading. Observing price deviations and different policy orientations, we conjectured that regulations could explain part of this market segmentation, making some countries more attractive or more closed compared to others.

This study rejects the conjecture, as a more regulated country is found to be associated with higher price convergence with the USD benchmark, with an overall lower local price. Regulations aiming at increasing reliability and transparency (expansion of securities laws and banking and payments laws) as well as regulatory sandbox makes enhance market integration in terms of price convergence, while partial bans exacerbate price divergence. Price divergence is also amplified by the weak cryptocurrency regulatory framework that accompanies countries implementing partial bans. AML/CFT laws reduces local prices, regardless on the level of USD price. Implementing such regulations therefore increases price divergence even if local price is already below that in USD. This result underscores the use of Bitcoin as a mean circumvent AML/CFT laws in the traditional financial sector.

These findings suggest that an international framework is crucial to address anti-money laundering, the financing of terrorism and fiscal fraud. Moreover, policies that create a regulatory framework makes the market more reliable, however, it also makes it more vulnerable to disruption beyond borders.

This study takes the USD price as benchmark, which is restrictive as an investor is not limited to this market. Considering a bidimensional data would improve the analysis. Adding the MiCAR European Regulation as well as the introduction of the introduction of US Bitcoin ETF.

As the cryptocurrency market continues to grow, understanding the role of regulation in shaping market dynamics will remain crucial to fostering a sustainable financial market. Hence, further analysis are needed to understand the link between regulations and the stability in the cryptocurrency market.

8 Annexes 1

Currency	Country	Start Date	End Date
AED	ARE	2022-10-18	2024-04-04
ARS	ARG	2019-04-19	2024-04-04
AUD	AUS	2011-09-02	2024-04-04
BRL	BRA	2013-03-18	2024-04-04
CAD	CAN	2011-09-27	2024-04-04
CHF	CHE	2011-09-03	2024-04-04
COP	COL	2013-07-08	2024-04-04
CZK	CZE	2013-04-10	2024-04-04
EUR	EUR	2011-08-27	2024-04-04
GBP	GBR	2011-09-06	2024-04-04
HKD	HKG	2022-10-18	2024-04-04
IDR	IDN	2013-05-14	2024-04-04
ILS	ISR	2013-03-15	2024-04-04
INR	IND	2017-05-16	2024-04-04
JPY	JPN	2011-08-27	2024-04-04
KRW	KOR	2013-08-08	2024-04-04
KZT	KAZ	2020-01-28	2024-04-04
MXN	MEX	2013-03-11	2024-04-04
MYR	MYS	2013-06-26	2024-04-04
NZD	NZL	2011-09-27	2024-04-04
PHP	PHL	2022-10-18	2024-04-04
PLN	POL	2011-09-02	2024-04-04
RUB	RUS	2011-09-11	2024-04-04
SGD	SGP	2011-09-18	2024-04-04
THB	THA	2011-10-13	2024-04-04
TRY	TUR	2013-08-29	2024-04-04
UAH	UKR	2013-08-21	2024-04-04
USD	USA	2010-07-17	2024-04-04
ZAR	ZAF	2013-04-13	2024-04-04

Table 8: Currencies, associated countries and temporal availability of data

	LLC	IPS	HT	B	CIPS	CADF	Order of Integration
				Level			
Local prices (log)	-4.666***	-4.931***	0.989***	-7.933***	-5.003***	-5.327***	I(0)
Exchange rates (log)	-0.951	-1.867**	0.997	2.069	-2.365	-2.569	?
				1st Difference			
Local prices (log)							I(0)
Exchange rates (log)	-490***	-340***	0.031***	-98.248***	-6.420***	-6.420***	I(1)

For all tests, the null hypothesis is that some panels contain unit roots. All models contents trend and constant. Breitung and CIPS tests allow for cross-sectional dependence. Lags are choosen via the AIC. LLC refers to the Levin-Lin-Chu test, IPS to the Im-Pasaran-Shin test, HT to the Harris-Tzavalis test, B to the Breitung test, KT to Karavias and Tzavalis (2014) test, and CIPS to the cross-sectionally independent IPS test.

Table 9: Panel unit root tests of local Bitcoin prices and exchange rates

Pedroni		Westerlund	
Statistic	Value	Statistic	Value
panel ν	188.1***	Gt	-11.892***
panel ρ	-1058***	Ga	-505.525***
panel t	-149.9***	Pt	-42.702***
panel ADF	-18.78***	Pa	-335.729***

The null hyptoheses is "no cointegration". Test includes trend and constant. Lags are selected via AIC.

Table 10: Panel cointegration tests with local prices, USD prices and exchange rates

	In Level				In Growth Rate	
			Long run			
Exchange rate	-0.872***	-0.848***	-1.062***	-1.061***	-7.001***	-7.009***
USD price	1.003	1.002	0.994	0.993	1.002	1.002
			Short run			
Local prices (t-2)	0.491	0.491	0.495	0.495	0.469	0.469
Exchange rate (t-1)	-0.309	-0.309	-0.316	-0.316	-0.009	-0.008
Exchange rate (t-2)	0.229	0.228	0.188	0.188		
USD price (t-1)	0.611	0.611	0.617	0.617	0.923	0.923
USD price (t-2)	-0.420	-0.420	-0.425	-0.424	-0.470	-0.470
USD price (t-3)	0.073	0.073	0.074	0.074		
ECT	-0.010	-0.010	-0.007	-0.006	-0.078	-0.078
Country FE	No	No	Yes	Yes	Yes	Yes
Cross sectionally augmented	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.97	0.97	0.99	0.99	0.99	0.99
Nb of obs	74250	74250	74250	74250	74250	74250
Nb of countries	22	22	22	22	22	22
Nb of days	3375	3375	3375	3375	3375	3375

Standardized beta coefficients. * p<0.10, ** p<0.05, *** p<0.01. The null hypothesis tested is beta equal to 1. Panel ARDL EC Model using Dynamic Fixed Effect (DFE) and Pooled-Mean-Group (PMG) estimations. The optimal number of lags is chosen according to the Akaike Information Criterion (AIC). In growth rate regressions, regressors are included in growth rate.

Table 11: Validation of the LOP - ARDL EC Model

Variable	Definition	Source
country-specific variables		
exchange_rate	Exchange rates against USD (log)	BIS
stock_growth	main national stock index (growth rate)	LSEG
inflation_rate	inflation rate, average consumer price index	IMF
liquidity_FX	bid-ask spread for each currency, taking the exchange rate against USD	LSEG
liquidity_BTC	Trading volume normalised by total supply of Bitcoin	LSEG and cryptocompare.com
FIA	Financial Institutions Access Index (compiles data on bank branches per 100 000 adults and ATMs per 100 000 adults)	IMF, Financial Development Index database
remittances	Personal transfers made or received by resident to or from non residents households (%GDP)	World Bank
google_trend	Index based on searches of the word "Bitcoin"	Google trend
kaopen	Chinn-Ito index, a de jure measure of financial openness (until 2021)	Chinn and Ito (2008)
global variables		
US_price	USD-nominated Bitcoin price (log)	cryptocompare.com
VIX	Cboe VIX of VIX Index	CBOE [4]
dow_jones	Dow Jones Industrial Average (in USD)	WSJ markets [5]

Table 12: Description of control variables

Country	Stock Index	Country	Stock Index
AED	DFM General Index	JPY	Nikkei 225 Index Close
ARS	S&P Merval Index	KRW	Korea SE Kospi 200 Index
AUD	S&P/ASX 200	KZT	KASE Index
BRL	Sao Paulo SE Bovespa Index	MXN	S&P/Bmv Ipc
CAD	S&P/TSX Composite Index	MYR	FTSE Bursa Malaysia KLCI Index
CHF	Swiss Market Index	NZD	S&P/NZX 50 Index
COP	Coleqty Index	PHP	PSEi Index
CZK	PX Prague SE Index	PLN	Warsaw SE WIG Poland Index
EUR	FTSE Eurotop 100 Index	RUB	MOEX Russia Index
GBP	FTSE 100 Index	SGD	FTSE Straits Times Index
HKD	Hang Seng Index	THB	SET 100 INDEX
IDR	Jakarta SE Composite Index	TRY	BIST 100 Index
ILS	Tel Aviv 35 Index	UAH	PFTS Index
INR	S&P BSE Sensex Index	ZAR	FTSE/JSE SA Top 40 Companies Index

Table 13: National stock indices

	LLC	IPS	HT	B	CIPS	CADF	Order of Integration
			Level				
country-specific factors							
Price deviation (log)	-100***	-110***	0.659***	-4.562***	-6.183***	-6.223***	I(0)
Stock growth	-510***	-360***	-0.021***	-110***	-6.420***	-6.420***	I(0)
Inflation	0.997	1.426	0.999	2.571	-1.576	-1.583	?
EPU index	-2.996***	-9.881***	0.986***	-6.696***	-5.451***	-5.464***	I(0)
Google trend	-2.206**	-13.086***	0.990***	-4.028***	-4.850***	-4.842***	I(0)
Capital account openness	16.271		0.998	-0.639	0.258	0.258	?
Liquidity BTC	-120***	-120***	0.531***	-33.731***	-5.118***	-6.420***	I(0)
Liquidity FX	-140***	-140***	0.912***	-13.129***	-5.554***	-6.186***	I(0)
FIA	-1.084	1.119	0.998	-0.779	-2.147	-2.149	?
Remittances	-1.098		0.998	0.412	-2.043	1.700	?
Global factors							
USD Bitcoin price	-5.922***	-2.273**	0.997***	-1.020			I(0)
VIX	-98.305***	-80.603***	0.835***	-16.172***			I(0)
			1st Difference				
country-specific factors							
Price deviation (log)							I(0)
Stock growth							I(0)
Inflation	-530***	-370***	-0.000***	-81.334***	-6.420***	-6.420***	I(1)
EPU index							I(0)
Google trend							I(0)
Capital account openness	-220***		-0.000***	-82.91***	-1.253	-1.153	?
Liquidity BTC							I(0)
Liquidity FX							I(0)
FIA	-540***	-370***	-0.004***	-100***	-540***	-6.420***	I(1)
Remittances	-510***		-0.000***	-67.076***	-6.067***	-6.067***	I(1)
Global factors							
USD Bitcoin price							I(0)
VIX							I(0)

For all tests, the null hypothesis is that some panels contain unit roots. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. All models contents trend and constant. Breitung and CIPS tests allow for cross-sectional dependence. Constant values in time series are responsible for the absence of result in the IPS column. Lags are choosen via the AIC.
LLC refers to the Levin-Lin-Chu test, IPS to the Im-Pasaran-Shin test, HT to the Harris-Tzavalis test, B to the Breitung test, and CIPS to the cross-sectionally independent IPS test.

Table 14: Panel stationary tests of dependent and control variables

	Pedroni			Westerlund	
	price deviation	price		price deviation	price
panel $\ni$	-9.08***	-9.13***	Gt	-52.40***	3.44***
panel ρ	-386.97***	8.21***	Ga	-301.07***	2.38***
panel t	-70.11***	15.55***	Pt	-49.33***	2.23***
panel ADF	-98681.76***	-5685.57***	Pa	-288.90***	1.05***
group ρ	-284.57***	19.37***			
group t	-62.56***	27.99***			
group ADF	-36.84***	9.37***			

The null hypotheses is "no cointegration". * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Test includes trend and constant. Lags are selected via AIC. ECT means Error Correction Term.

Table 15: Cointegration tests with explanatory and control variables

9 Annexes 2 - Technical Support for Identifying and Measuring Explositivity

9.1 Identifying Explositivity

To date price explosiveness in the cryptocurrency market, we use the generalised supremum augmented Dickey-Fuller (GSADF) test of Phillips et al. (2015). The authors created an econometric test to detect market exuberance, without the need to observe the fundamental values. The GSADF test is an extension of the supremum Augmented Dickey Fuller test, which is a repeated right-tailed unit root test on a sequence of forward expanding samples based on the following recursive regression (Bouri et al., 2019):

$$y_t = \mu + \beta y_{t-1} \sum_{i=1}^{p} \delta_{r_w} \beta y_{t-i} + \epsilon_t \tag{11}$$

where y_t is the cryptocurrency price, μ, β, δ are parameters estimated using OLS, p is the number of lags, $r_w = r_2 - r_1$ is a rolling interval window that starts and ends respectively with a fraction r_1 and a fraction r_2. The null hypothesis describes a unit root, where $\beta = 1$, and the alternative describes an explosive root, where $\beta > 1$. The SADF statistic is the following with $r_1 = 0$ and $r_2 \in [r_0, 1]$:

$$SADF(r_0) = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2} \tag{12}$$

The GSADF test implements a repeated SADF regressions subsample windows varying by the starting point. The GSADF statistic is the following:

$$GSADF(r_0) = \underset{r_2 \in [r_0,1], r1 \in [0, r_2 - r0]}{sup} \left\{ ADF_{r1}^{r_2} \right\} \tag{13}$$

Because this test faces difficulty in detecting multiple bubbles after the first, Phillips et al. (2015) recommends, after using the GSADF test, to perform a double recursive test called Backward SADF test (BSADF). This test is a SADF test on a backward expanding sample sequence, where the endpoint of each sample is fixed to r_2 and the window size expands from r_0 to r_2. The BSADF statistics is then as follows:

$$BSADF_{r_2}(r_0) = \underset{r_1 \in [0, r_2 - r_0]}{sup} \left\{ ADF_{r_1}^{r_2} \right\} \tag{14}$$

A date is defined as a bubble phase if its BSADF statistic exceeds the critical value, with a significance level usually set at 5%. We use the *exuber* package of R, that directly gives the start, the peak and the end dates of each bubble identified in the crypto price time series.

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