WORKING paper

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Bitcoin Market Segmentation and Regulatory Effect

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Abstract

This paper examines the effects of cryptocurrency regulation on price deviations in the Bitcoin market, focusing on regulatory implementations rather than announcements. I construct a unique database of regulations across 28 countries since 2009, categorized into seven types, and analyse Bitcoin price data since September 2013. 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. According to the type of regulation, this result is mixed. 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—primarily targeting banks—exacerbate price divergence, underscoring the significant role of financial institutions in the Bitcoin market. Additionally, anti-money laundering/countering the financing of terrorism (AML/CFT) laws reduce local prices regardless of USD price level, suggesting the cryptoasset's use in illicit activities.

Keywords: Cryptocurrency, Cryptocurrency Regulation, Price Convergence, Law of One Price, Financial Institutions, Anti-Money Laundering, Regulatory Impact.

JEL classification: G15, G18, E42, K22.

[1] Banque de France. I thank Paola Di Casola for her excellent and helpful comments. All remaining errors are mines.

NON-TECHNICAL SUMMARY

This study explores how national regulations affect Bitcoin prices across different countries. Although Bitcoin is a global digital asset, its price often varies significantly between countries, even after adjusting for exchange rates. This challenges the economic principle known as the Law of One Price, which states that identical goods should cost the same everywhere when expressed in a common currency.

To understand why these differences occur, the paper analyses a unique dataset of cryptocurrency regulations implemented in 28 countries since 2009 and compares them with Bitcoin price data from 2013 onward. The research focuses on actual enforcement dates of regulations rather than regulatory announcements, as enforcement may also change market conditions.

The study shows that regulation plays a crucial role in shaping Bitcoin markets and reducing price disparities across countries. In general, countries with stronger regulatory frameworks tend to have Bitcoin prices that align more closely with the U.S. dollar benchmark, indicating that regulation fosters market integration. However, the type of regulation matters significantly. Measures that enhance transparency and reliability—such as banking and payment laws, securities regulations, and the introduction of regulatory sandboxes—are particularly effective in narrowing price gaps and creating a more stable trading environment. These policies build trust, encourage innovation, and facilitate cross-border arbitrage. In contrast, restrictive measures like partial bans, especially those preventing banks from engaging in cryptocurrency transactions, have the opposite effect. They increase price divergence and isolate local markets, making them less connected to global trends. Anti-money laundering and counter-terrorism financing laws also influence market dynamics by lowering local Bitcoin prices. This suggests that Bitcoin's appeal often lies in its anonymity and potential use for illicit activities, which these regulations aim to curb.

Overall, the paper concludes that well-designed regulations can make Bitcoin markets more stable and integrated internationally. However, this also means that local markets become more exposed to global shocks, creating a trade-off for policymakers between integration and vulnerability.

Segmentation de marché du Bitcoin et effet des réglementations

RÉSUMÉ

Cet article examine les effets de la réglementation des cryptomonnaies sur les écarts de prix sur le marché du Bitcoin, en se concentrant sur la mise en œuvre effective des réglementations plutôt que sur leurs annonces. Je construis une base de données unique regroupant les réglementations de 28 pays depuis 2009, classées en sept catégories, et analysé les données de prix du Bitcoin depuis septembre 2013. Les résultats indiquent que la Loi du Prix Unique ne s'applique pas au marché du Bitcoin. Contrairement à l'hypothèse initiale, les marchés les plus réglementés présentent une plus forte convergence des prix avec le benchmark en dollars américains. Selon le type de réglementation, ce résultat est nuancé. Les réglementations visant à renforcer la fiabilité et la transparence, telles que l'extension des lois sur les valeurs mobilières, les réglementations bancaires et de paiement, ainsi que la mise en place de « regulatory sandboxes », favorisent la convergence des prix. À l'inverse, les interdictions partielles — ciblant principalement les banques — accentuent la divergence des prix, soulignant le rôle essentiel des institutions financières dans le marché du Bitcoin. De plus, les lois relatives à la lutte contre le blanchiment d'argent et le financement du terrorisme (AML/CFT) réduisent les prix locaux, indépendamment du niveau du prix en dollars, ce qui suggère l'utilisation de ce crypto-acrif à des fins illicites.

Mots-clés : cryptomonnaie, convergence des prix, Loi du prix unique, institutions financières, lutte contre le blanchiment d'argent, impact réglementaire.

1. Introduction

"He ignored me royally"[1] Christine Lagarde said in November 2023, referring to her son's 60% loss on his crypto-asset investments. Even the advice of the ECB president herself could not protect him from the intense attractiveness of crypto markets.

Crypto-assets, with a market capitalization of 1.83 trillion USD as of November 2024, are establishing increasingly tight links with traditional finance. Hacibedel and Perez-Saiz (2023) highlights multiple channels through which disruptions in crypto-asset markets could amplify into systemic risk. Sharp crypto-asset 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 the crypto-asset market capitalization and dominant companies are emerging) coupled 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). As suggested by results of Auer and Claessens (2018): "cryptocurrency markets rely on regulated financial institutions to operate and are segmented across jurisdictions, bringing cryptocurrencies within reach of national regulation". This regulatory segmentation may translate in price deviations, as exemplified by the "Kimchi premium", a well-known case, highlights the persistent Bitcoin price deviation between Korean and U.S. exchanges. Studies by Makarov and Schoar (2020) and Borri and Shakhnov (2023) demonstrate that such price deviations are prevalent across exchanges and countries, but are more pronounced across countries. This raises a key question: does the national crypto-asset regulatory framework drive market segmentation, as reflected in these price deviations?

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 crypto-asset, capturing global trends while potentially overlooking local effects of certain regulations. The case of

[1] https://www.reuters.com/technology/ecb-chief-lagarde-admits-her-son-lost-crypto-cash-2023-11-24/

the United Arab Emirates illustrates the importance to consider the global and local effect of a regulation over a long time horizon. 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.

This paper's primary contribution lies in examining regulatory implementations rather than announcements. Regulatory announcements often fail to translate into actual enforcement; therefore, focusing on the date a law enters into force allows for the analysis of structural changes in the crypto-asset market rather than short-term announcement effects. This paper relates to Makarov and Schoar (2020), Borri and Shakhnov (2020) and Vivanco and Pieters (2017), which analyse the effect of capital controls, Chinese crypto trading restrictions, and AML/CFT laws respectively on price deviations or their spillovers effects on foreign markets. Contrary to this paper, a dynamic fixed effect model is estimated, controlling for both country and time fixed effects. Moreover, the analysis is extended to different types of regulations. To achieve this, I constructed a database of crypto-asset regulations across 28 countries since 2009, categorized into seven types: AML/CFT laws, virtual asset service provider regulations, banking and payment regulations, securities law extensions, regulatory sandboxes, acceptance of crypto-related investments in traditional financial markets, and partial bans.

The second contribution of this paper is the analysis of regulatory effects on price deviations and local prices through the lens of the LOP. By leveraging the LOP framework, the impact of regulations on local prices is isolated from its impact on global trends and the exchange rate.

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 analyses Bitcoin price data from 22 countries since September 1, 2013, employing a dynamic fixed-effects model to examine the regulatory impact on price deviations and local prices. Country fixed effects account for inherent country-specific barriers, while week fixed effects control for common shocks in the Bitcoin market and the evolving microstructure. The findings reveal that the LOP does not hold in the Bitcoin market. Bitcoin is therefore priced differently across countries after accounting for exchange rates and country-specific barriers. As opposed to Auer and Claessens (2018) hypothesis, results show that regulation is not the primary driver of price deviations; however, greater regulatory intensity is associated with smaller deviations from the USD benchmark, partly due to reductions in local Bitcoin prices. This result is driven by regulations enhancing banking and payment systems, expanding securities laws, introducing regulatory sandboxes, and integrating cryptocurrencies into traditional financial markets. By increasing market transparency and reliability, these measures promote greater market integration and are also linked to higher local Bitcoin prices. Conversely, restrictions on the use or trade of cryptocurrencies and laws prohibiting financial institutions to invest or to provide crypto-asset services, increase market segmentation and are associated with lower local Bitcoin prices. This result underlines the role of banks in this market. Periods of market bubbles correspond to heightened price deviations when local prices fall below USD prices. Since countries with restrictive regulations more frequently experience lower prices, this finding suggests that such policies contribute to market isolation during bubble periods as well. Our findings also show that AML/CFT laws exhibit mixed effects on price deviations but correlate with lower local prices, regardless of the USD benchmark. This finding highlights Bitcoin users' interest in its anonymity and its potential use in illicit activities. Finally, by using an Auto-Regressive Distributed Lagged Error Correction Model, we confirm the robustness of these results and show that regulation enforcement has a significant effect in the long-term, but not in the short-term.

The remainder of this paper proceeds as follows: Section 2 introduces the crypto-asset market microstructure. Section 3 reviews relevant literature. Section 4 addresses the empirical validation of the LOP. Section 5 examines the impact of regulation on price deviations local prices. Section 6 covers robustness checks, and Section 7 concludes.

2. Literature Review

2.1. Microstructure of Crypto-asset 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 cryptocurrencies. These exchanges are a third-party intermediary that facilitate crypto-asset trading. While most limit transactions to cryptoasset-for-cryptoasset trades, the largest platforms often support cryptoasset-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 crypto-asset 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.

2.2. Price Deviation and the Law of One Price

In crypto-asset 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 crypto-asset price discrepancies predominantly employs the LOP framework, drawing parallels with gold and commodity markets.[2]

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 crypto-asset is a fungible and highly internationally traded asset, this market should be a study case of the LOP. Nevertheless, persistent and significant price differentials across Bitcoin markets establish a consensus among economists.

Price deviations in crypto-asset 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 crypto-asset 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 crypto-asset 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

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

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. Utilising 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, Vivanco and Pieters (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.

2.3. Regulations and Cryptocurrencies

The literature exploring the influence of regulations on crypto-asset markets has predominantly focused on regulatory events on press articles, characterized by official announcements pertaining to crypto-asset 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 crypto-asset regulation. They analyse the global crypto-asset 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 indicate that regulatory news events, particularly those related to general bans on cryptocurrencies and their treatment under securities laws, had a significant negative influence on Bitcoin prices. Consequently, they concluded that investors in the Bitcoin market value a clear crypto-asset 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. Utilising 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 localised markets, emphasising 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 categorised into seven groups, spanning aspects such as crypto-asset treatment (as securities or currencies), Anti-Money Laundering (AML) regulations, anti-fraud measures, and the development of cryptoasset-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 crypto-asset 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 crypto-asset prices and trading volumes.

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

In line with the above-mentioned literature, Chokor and Alfieri (2021) conducted an investigation into the impact of regulatory events on crypto-asset 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 decentralisation and lack of regulation of crypto-asset 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 crypto-asset 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 crypto-asset exchanges, while the 2021 reform extended its scope to encompass crypto-asset 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 crypto-asset market leader.

Borri and Shakhnov (2020) scrutinised the 2017 regulation, revealing a substantial reduction in local crypto-asset 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 crypto-asset markets. Their research unveiled a decline in crypto-asset 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), Shanaev et al. (2020), 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 crypto-asset 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 stabilise 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 crypto-asset as securities, and the implementation of Anti-Money Laundering measures, are consistently linked to significant declines in crypto-asset 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 crypto-asset 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 crypto-asset datasets employed (Park et al., 2020; Feinstein and Werbach, 2021). Notably, Chinese regulatory measures have a pronounced impact on both the domestic and global crypto-asset markets, attributable to the scale of the restrictive reforms implemented and China's large market share in the crypto-asset 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 crypto-asset policies in maintaining financial stability and raises questions regarding potential influence during speculative bubbles.

3. Assessing The Law of One Price

3.1. 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, the empirical strategy is based on the literature on the failure of the LOP in the usual commodity market (Ardeni, 1989; Baffes, 1991; Pippenger and Phillips, 2008).

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:

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

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 and $p_{USD,t}$ is the Bitcoin price denominated in USD. To disentangle the price effect from the exchange rate effect, the exchange rate is included as a regressor. Equation (1) is equivalent to:

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

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 equal to the USD price when expressed in USD terms. The LOP is tested both in level and in growth rate. We use OLS to estimate β_0 and β_1. To account for country-specific barriers to trade and for shocks common to all countries we include a country and week fixed effect. The time dimension being large, we use the Driscoll-Kraay standard errors to control for cross-sectional dependence and to account for heteroscedasticity.

3.2. 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 Euro). Table 1 lists the currencies/country analysed. 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. Prices are available until January 1st, 2024. To ensure a balanced panel, the sample is limited to 22 currencies from September 1, 2013, excluding AED, ARS, HKD, INR, KZT, PHP and USD. These countries exhibit the largest price deviations from the Bitcoin price in USD within our sample (Table 4 in Appendices). In the case where the analysis would not validate the LOP, excluding these countries would strengthen the result.

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

3.3. Results

Table 8 presents estimations results for the validation of the LOP. We observe that in all specifications, the coefficient of *USD price* is significantly different than 1 at the 1% level of significance. The coefficient of *Exchange rate* is found to be significantly different than -1 in level when no fixed effect is included, and in specifications with variables in growth rate. This suggests that once accounting for country fixed effect, exchange rate movements are transmitted into local price adjustments. However, even when controlling for country-specific barriers, the USD price does not fully offset price differentials in both level and growth rate. Hence, results show that the LOP does not hold in the Bitcoin market.

As the USD price does not fully explain local prices, it indicates that other factors may influence local Bitcoin prices. The next section aims to determine whether crypto-asset regulations can explain these price deviations controlling for other factors.

4. Price Deviation and Regulation

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

4.1. Data - The Dependent Variable

The dependent variable in this section is the price deviation, calculated using the same Bitcoin data as in the previous section. To account for cases where the local price is lower than the USD price as higher price deviations, the price deviation is defined as:

$$price\_deviation_{i,t} = \left| \frac{p_{i,t} \cdot e_{i,t}}{p_{USD,t}} - 1 \right| \tag{3}$$

This variable reflects the degree of price divergence, with higher values indicating a greater distance between the local and USD prices.

4.2. Data - The Regulatory Variables

The independent variables capture the number of crypto-asset regulations implemented in a country. I 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, supplemented by national law registers and press articles data[3]. 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 crypto-asset market and the monitoring of transactions and client identity. This encompasses notably licensing, Know-Your-Client (KYC) procedures, transaction reporting, AML/CFT regulatory extension.

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

- Regulatory Framework: this category refers to the definition and associated requirements of crypto-asset products and parties. It encompasses laws that clarify the regulatory perimeter of the crypto-asset market, licensing requirements, and rights and obligations of parties. Three subcategories are defined according to the concerned entity or sector:

  - 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 crypto-asset. 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 crypto-asset sector. This encompasses supervision of monitoring of crypto-related payment services, consumer protection in payment services, the prohibition of crypto-asset 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 sub-categories.

- Development: this category refers to regulations aiming at developing the crypto-asset market and fostering its use. Data are collected 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 crypto-asset and blockchain sector.
  - Crypto-asset-related investment legalisation (*Acceptance*): these regulations encompass the legalisation of crypto-asset ETF or crypto-asset investment by funds for example. They indicate increasing acceptance and integration of crypto-asset into traditional financial markets.

- *Ban*: These regulatory measures rather reflect efforts by central authorities to restrict the involvement of financial institutions and intermediaries in crypto-asset transactions. This encompasses for example the prohibition of banks to transact in crypto-asset 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.

4.3. Data - Controls

4.3.1. Macroecononomic development, attractiveness and institutional factors

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 (Akyildirim 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 traditional financial markets and the crypto-asset market (Akyildirim 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 Schoar (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.

4.3.2. Bubble periods

Observing increasing price deviations during the bubble of 2014 and 2018, and following the result of Makarov and Schoar (2020) which observes an increase in price deviations during period of Bitcoin appreciation, we also control for periods of bubble in the USD Bitcoin market. In line with the asset pricing approach, a bubble is characterised 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 crypto-asset production) and crypto-asset 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 crypto-asset market. The uncertainty surrounding crypto-asset 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 crypto-asset 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 price movement through GSADF and BSADF tests, allows to dates-stamp multiple bubble episodes within a given crypto-asset price time-series. We employ this methodology to determine periods of explosivity in the USD Bitcoin market. We account for periods of explosivity with a minimum of three days. The methodology is detailed in Appendices 2. Our *Bubble* variable is therefore a dummy equal to one if explosivity is found in the USD Bitcoin market. A positive and significant coefficient for this variable would mean that local traders have amplified reactions compared to those in the USD market.

4.4. Stylised facts

Descriptive statistics on price deviations and regulatory dynamics are presented in this section. Figure 2 illustrates the distribution of annual mean price deviations, while Figure 3 focuses on price deviations below 0.25. A clear decreasing trend in price deviations emerges starting in 2014 (Figure 3), with the median and upper quartiles converging toward zero. Notably, this decline aligns with the emergence of crypto-asset regulations, as depicted in Figures 4 and 5. Additionally, our data presents variability, with the number of implemented regulations varying between 2 and 11 in 2023.

Despite the overall convergence of local and USD prices for most countries, where mean price deviations are typically below 5%, anomalies arise starting in 2019, with some countries exhibiting price deviations exceeding 100% (Figure 2). These extreme cases are further examined in Figure 6, which compares the number of implemented regulations and the mean price deviation within each year. Outliers with price deviations above 0.6 are identified as countries implementing no more than five regulations. Interestingly, the data suggests that countries implementing more regulations generally exhibit lower price deviations, although this trend does not hold for the observed outliers.

Figure 7 explores daily price deviations in 2023 relative to the number of regulations implemented by type. Countries enacting *Payment*, *VASP*, *Securities*, and *Acceptance* regulations consistently show low price deviations. Conversely, the relationship appears more ambiguous for AML/CFT regulations and regulatory sandboxes. A surprising finding is the positive relationship between the number of bans and price deviations, suggesting that restrictive regulations may, in some cases, exacerbate price disparities.

4.5. Empirical Strategy

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

To this end, a dynamic fixed effect model is employed:

$$\begin{aligned} Price\_deviation_{i,t} = {} & \beta_0 Price\_deviation_{i,t-1} + \beta_1 Regulation_{i,t-1} \\ & + \beta_2 X_{i,t-1} + \beta_3 X_{t-1} + \alpha_i + \alpha_w + u_{i,t} \end{aligned} \tag{4}$$

Here, $Price\_deviation_{i,t}$ denotes the absolute Bitcoin price deviation with the USD price of the country i at day t, *Regulation* refers to our regulatory variables (included either individually or as an aggregate), $X_{i,t}$ represents country-specific controls, X_t represents global controls, α_i and α_w are country and week fixed effects. The inclusion of country fixed effect is essential to account for trade barriers inherent to each country. Driscoll-Kraay standard errors are used to account for heteroscedasticity, autocorrelation and cross-sectional dependence. To avoid multicollinearity issues, we exclude *VIX* and *FIA* (Financial Institution Access) due to high variance inflation factor values. The sample is split based on whether the local price is below or above the USD price.

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 reduce the endogeneity problem, variables are included with a lag of 1 day.

To avoid spurious regressions, we test for stationarity with first-generation tests, as the Levin-Lin-Chu test (LLC), the Im-Pesaran-Shin test (IPS), the Harris-Tzavalis test (HT), the Breitung test (B) and the Karavia and Tzavalis 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. According to tests results (Table 11), we introduce *Inflation* and *Remittances* as first-differenced variables.

To differentiate the impact of regulations on local price from its impact on exchange rate and USD price, we refer to the LOP methodology and express the local price $p_{i,t}$ with the exchange rate $e_{i,t}$ and the price in USD $p_{USD,t}$:

$$\log\left(\frac{p_{i,t}e_{i,t}}{p_{USD,t}}\right) = \beta_0 Regulation_{i,t-1} + \beta_1 X_{i,t-1} + \beta_2 X_{t-1} + \alpha_i + \alpha_w + u_{i,t} \quad (5)$$

And we estimate the following equivalent model:

$$\begin{aligned}\log(p_{i,t}) = {} & \beta_2 Regulation_{i,t-1} + \beta_3 X_{i,t-1} + \beta_4 X_{t-1} + \beta_5 \log(e_{i,t}) + \beta_6 \log(p_{USD,t}) \\ & + \alpha_i + \alpha_w + u_{i,t}\end{aligned}$$

4.6. Results

Table 9 and 10 report results of regressions of price deviation and local price on regulatory variables respectively. To account for trade barriers, we directly display results including the country fixed effect. 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).

Regulation is negatively associated with price deviation in both full- and split-sample regressions, significant at the 1% level. Greater regulation corresponds to closer alignment between local and USD Bitcoin prices. Split-sample analysis reveals this effect is primarily driven by cases where local prices exceed USD prices, with no significant effect observed when local prices are below USD prices. We see in Table 10 that this price convergence is accompanied by a decrease in local price.

When looking at the breakdown of the *Regulation* variable, we find that *Payment*, *Securities*, *Sandbox* and *Integration* have a negative effect on price deviation at the 1% level of significance. For *Payment* and *Sandbox* this effect is found in both split samples. This price convergence is accompanied by a local price effect, with an increase in local price when local price is below USD price, and a decrease in the opposite case (Table 10).

Variables related to regulatory framework (*Payment* and *Securities*) appear to promote price convergence by improving the safety and reliability of the Bitcoin market. The expansion of securities laws and the improvement of Bitcoin payments system fosters a more regulated, transparent trading environment, enhancing investor confidence and facilitating cross-border arbitrage, thereby reducing price deviations. On the other side, by reducing regulatory uncertainty and fostering innovation, regulatory sandboxes contribute to market growth and improved trading infrastructure, which enhances market integration and facilitates price convergence. This finding is in line with Cornelli et al. (2024), showing that sandbox entry has a significant positive effect on innovation, which can stimulate market activity and raising demand. Moreover, 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.

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. These results are in line with Borri and Shakhnov (2020), demonstrating a reduced Bitcoin trading volume in Chinese markets, and an increase in volume and relative Bitcoin prices in exchange for Korean won, Japanese yen, and U.S. dollars, and on Chinese peer-to-peer exchanges. Bans therefore create a fly to more crypto-friendly regulations. Moreover, countries implementing partial bans often do not implement a strong regulatory framework, further preventing market integration. We also observe that *Ban* is associated with an increase in local price when it is above the USD benchmark, and a decrease in the opposite case. However, on the whole, countries implementing partial bans are associated with lower local prices.

Concerning *AML/CFT* variable, the effect is mixed, as a more regulated country in terms of AML/CFT laws is associated with increased price divergence when local price is below USD price, and increased convergence in the opposite case. This effect is driven by a reduction in local prices in response to stricter AML/CFT regulations. These results are in line with Vivanco and Pieters (2017). AML/CFT laws mitigate the use of Bitcoin for illicit activities or its appeal for anonymity by enforcing stricter monitoring and reporting requirements.

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 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.

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.

Inflation exhibits a significant positive association with price deviation, suggesting that increased inflation may amplify local price premiums over the USD Bitcoin price. Conversely, *Liquidity BTC* and *Remittances* are 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.

Finally, improving the regulatory framework of the crypto-asset market enhances its integration and fosters price convergence between countries. 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.

5. Robustness checks

To ensure the reliability of our findings, we conduct robustness checks by examining the effects of different model specifications and estimation methods. We first conduct the same analysis by taking the growth rate of price deviation and local price as dependent variable. Then, we estimate an Auto-Regressive Distributed Lagged Error Correction Model instead of the previous Dynamic Fixed Effect Model to validate the LOP and the influence of crypto-asset regulations on price deviation and local price.

5.0.1. Growth Rate Regressions

In this section, we test whether regulations influence price deviation and local price dynamics. The empirical strategy remains the same, except from the fact that the dependent variable is now expressed in growth rate. Tables 12 and 13 display results of regressions with price deviation growth rate and local price growth rate respectively.

We observe that our results on price deviation are robust to whether the dependent variable is expressed in level or in growth rate. *Payment*, *Securities*, *Sandbox* and *Acceptance* have negative effect on price deviation growth rate, while *Ban* has a positive effect. *AML/CFT* present mixed effect. However, findings are not robust with local price growth rate as dependent variable.

5.0.2. Moving To Another Model: Auto-Regressive Distributed Lagged Error Correction Model

Multiple papers analysing the Law of One Price or crypto-asset price determinants, look at time series properties and use Auto-Regressive Distributed Lagged and/or Error Correction Model (Kroeger and Sarkar, 2017; Vivanco and Pieters, 2017; Goczek and Skliarov, 2019; Sovbetov, 2018; Ciaian et al., 2016). These estimation strategy is based on the cointegration theory of Engle and Granger (1987), showing that regressions of cointegrated and non-stationary time series can result in spurious results. Consequently, given the long panel data of this study, instead of applying a dynamic fixed effect model, we follow the methodology of the above-cited literature to test for the LOP and to analyse the influence of crypto-asset regulations on price deviation and local price. The methodology is explained in the Appendices 3.

Table 14 of the Appendices 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. Results of cointegration test of Pedroni and Westerlund are presented in Table 15 of the Appendices. 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 Error Correction Model (ECM) incorporates both the short-run dynamics and the correction to the long-run equilibrium.

Table 17 presents regression results for the validation of the LOP. 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 significantly equal to 1 at the 1% level 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* is significantly different from -1 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 failure of the LOP is therefore robust to the use of the ARDL EC Model.

Tables 18 and 19 present regression results examining the impact of regulatory variables on price deviation and local price. Strengthening regulatory frameworks (*Regulation*, *Banking*, *Securities*, *Sandbox*) is associated with greater price convergence, whereas partial bans (*Ban*) lead to price divergence. *AML/CFT* regulations show mixed effects on price deviation but consistently lower local prices relative to international levels. Moreover, results on local price are consistent with those of the Dynamic Fixed Effect Model, as we find a positive relationship between the strength of the regulatory framework and local price, as well as a negative one with AML/CFT and Ban. Therefore, our findings remain robust under the ARDL Error Correction Model.

Interestingly, no significant short-run effects are observed for these regulatory variables.

6. Conclusion

This article investigates the link between crypto-asset regulations and 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 and based on the LOP methodology, we also study the impact on local prices controlling for USD Bitcoin price and exchange rate. A database of crypto-asset regulations of 28 countries since 2009 were build to this end, defining 7 categories of regulations.

This study show 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.

Our findings reject this 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 enhance market integration in terms of price convergence, while partial bans exacerbate price divergence. AML/CFT laws are found to reduce local prices, regardless on the level of USD price. This result underscores the use of Bitcoin as a mean to circumvent AML/CFT laws.

We also find an bubble isolation of markets with local Bitcoin prices below USD prices, translated by an increase in price deviation and a lower local price during bubble periods. Countries with partial bans exhibit this phenomenon (cheaper local Bitcoin) more frequently, suggesting that restrictions on crypto-asset markets may increase local market isolation. Further research is required to validate this finding.

This study takes the USD price as benchmark, which is restrictive as an investor is not limited to this market. Expanding the data with country-pairs price deviations would improve the analysis. Expanding the time horizon towards the implementation of the MiCAR European Regulation as well as the introduction of US Bitcoin ETF would also be interesting.

Our analysis of AML/CFT laws reveals that Bitcoin users often migrate to jurisdictions that protect or do not compromise anonymity. As a result, AML/CFT measures are ineffective in combating money laundering, terrorism financing, and fiscal fraud when implemented solely at the national level. An international AML/CFT framework or enhanced cooperation is therefore essential to address these challenges effectively.

The major result of this paper is that implementing a crypto-asset regulatory framework aligns Bitcoin prices with the USD benchmark and facilitates cross-border trading. Such policies therefore make the local market more reliable, however, it also makes it more vulnerable to international disturbances, especially during period of bubbles. Regulators must be aware of this trade-off between market integration and vulnerability when regulating the cryptocurrencies market.

7. Appendices 1

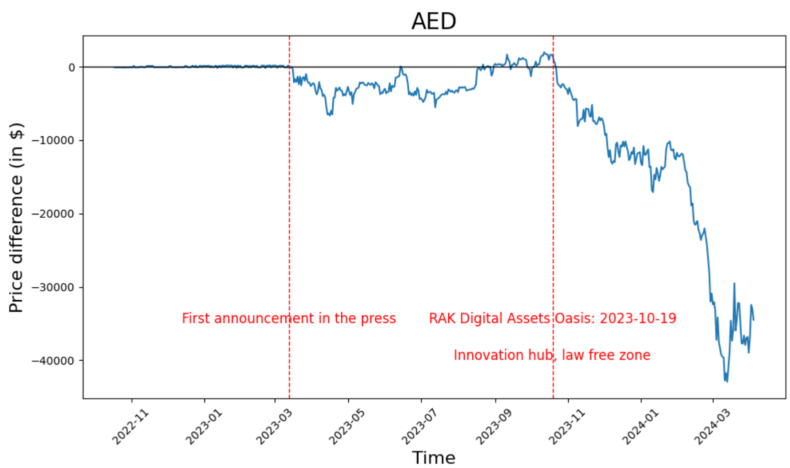

Figure 1: Price Difference Between Arab Emirates Dirham (AED) Bitcoin Price Expressed in USD and USD Bitcoin Price

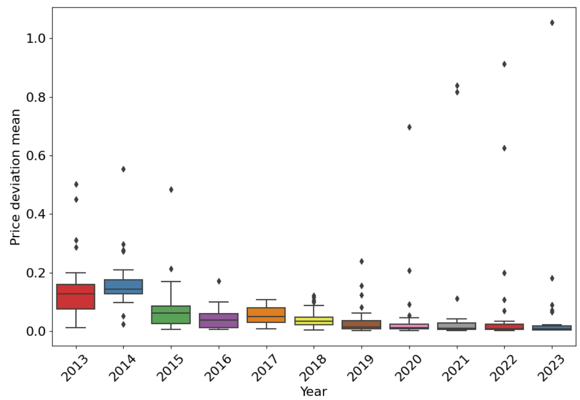

Figure 2: Distribution of Yearly Averaged Price Deviation (absolute value)

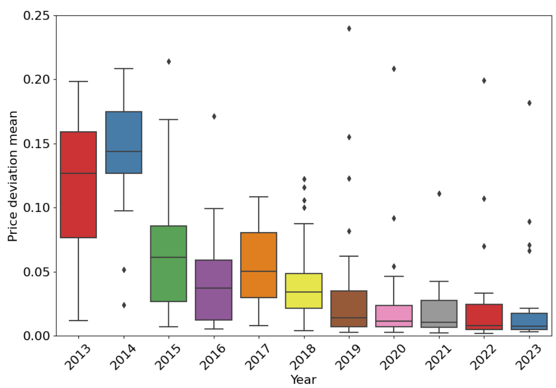

Figure 3: Distribution of Yearly Averaged Price Deviation (without deviation higher than 0.25)

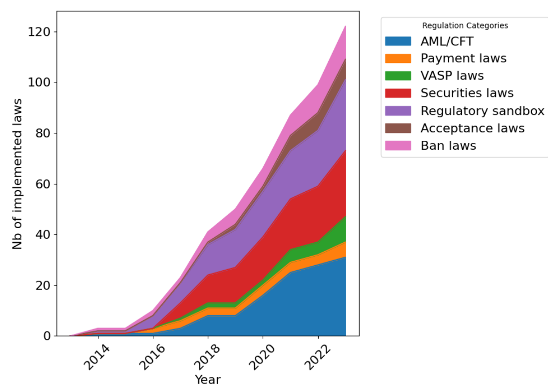

Figure 4: Number of Regulations Implemented Across All Sample Countries

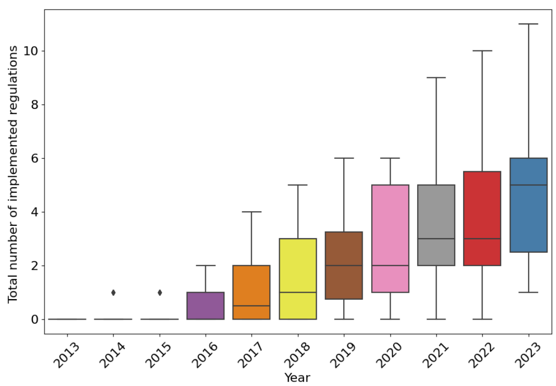

Figure 5: Distribution of the Total Number of Regulations per Year

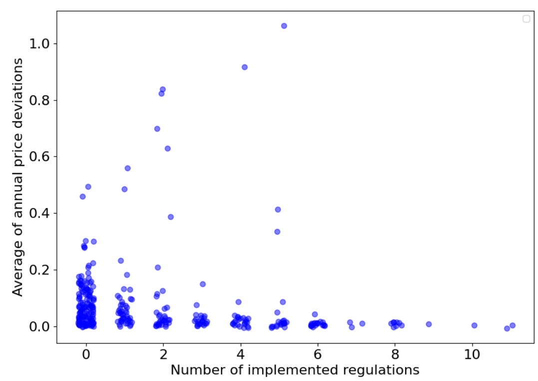

Figure 6: Scatter Plot of Yearly Averaged Price Deviation Versus Total Number of Implemented Regulations

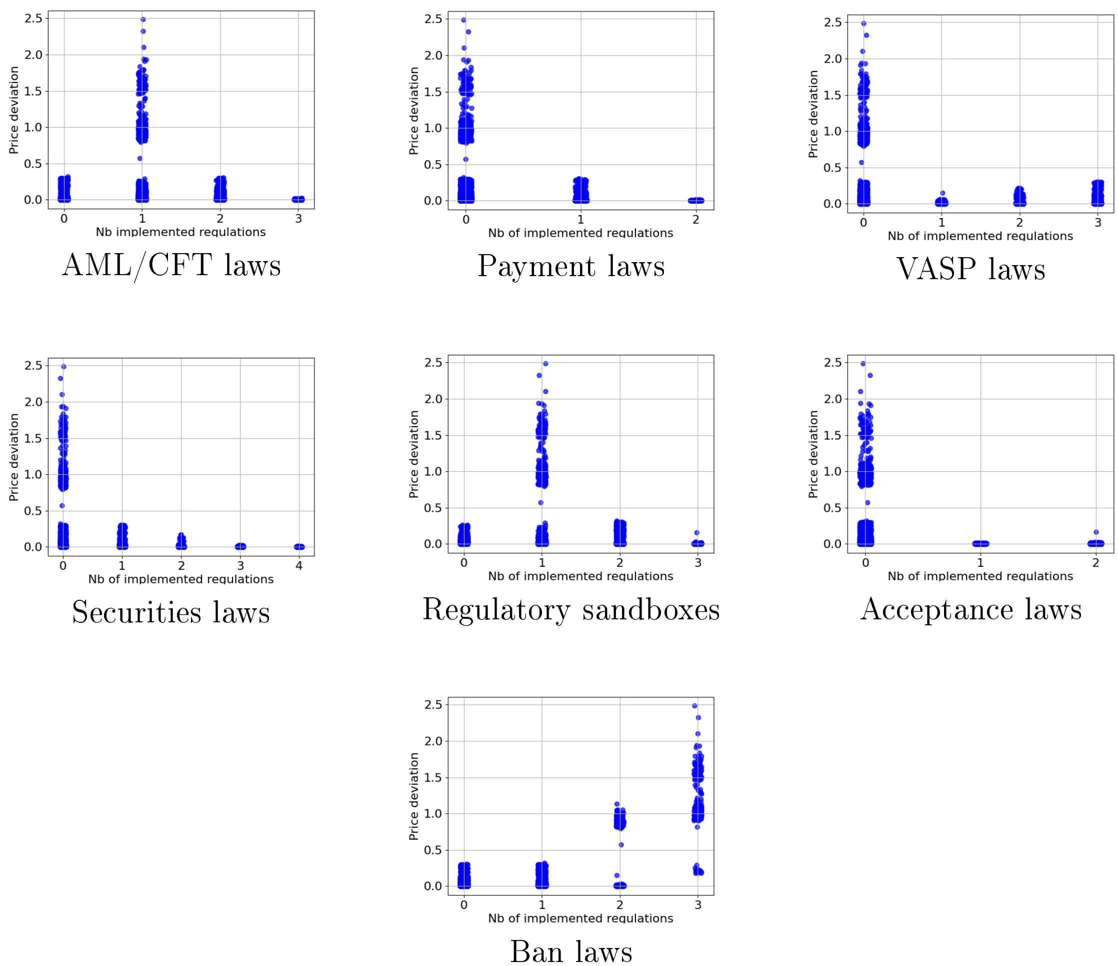

Figure 7: Relationship Between Price Deviation and the Number of Regulations by Type for the Year 2023

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 1: Currencies, Associated Countries and Temporal Availability of Data

	Count	Mean	Std	Min	25%	50%	75%	Max
all	88984	0.065	0.212	0	0.005	0.015	0.050	6.930
local price $\leq$ USD	31490	0.030	0.073	0	0.003	0.009	0.030	0.999
local price $\geq$ USD	57494	0.083	0.237	0	0.006	0.019	0.006	6.930

Table 2: Descriptive Statistics of Price Deviation (in Absolute Value)

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Count	2806	8395	8395	8395	8395	8395	8395	8395	8395	8395	8395
Mean	0.127	0.171	0.084	0.044	0.052	0.042	0.030	0.045	0.049	0.056	0.057
Std	0.0181	0.444	0.143	0.078	0.082	0.066	0.084	0.152	0.171	0.190	0.022
Min	0	0	0	0	0	0	0	0	0	0	0
25%	0.024	0.028	0.009	0.008	0.011	0.007	0.003	0.003	0.003	0.003	0.002
50%	0.065	0.065	0.033	0.022	0.029	0.020	0.009	0.007	0.007	0.006	0.006
75%	0.142	0.130	0.088	0.055	0.063	0.051	0.026	0.019	0.020	0.018	0.015
Max	1.618	6.930	2.229	1.246	2.778	0.969	0.998	1.350	1.151	1.518	2.486

Table 3: Descriptive Statistics of Price Deviation (in Absolute Value) by Year

Country	Count	Mean	Std	Min	25%	50%	75%	Max
CZK	4013	0,049	0,166	0	0,004	0,016	0,05	4,592
EUR	4605	0,008	0,02	0	0,002	0,004	0,008	1,013
MYR	3936	0,063	0,175	0	0,005	0,017	0,049	4,503
PLN	4599	0,027	0,131	0	0,004	0,009	0,018	4,488
BRL	4036	0,046	0,137	0	0,008	0,018	0,056	4,639
HKD	535	0,007	0,003	0	0,003	0,008	0,009	0,013
UAH	3880	0,092	0,193	0	0,017	0,04	0,1	4,648
INR	2516	0,321	0,318	0	0,053	0,178	0,663	0,911
ILS	4039	0,035	0,128	0	0,009	0,02	0,038	4,322
MXN	4043	0,044	0,159	0	0,004	0,011	0,043	4,496
JPY	4605	0,031	0,099	0	0,002	0,007	0,021	1,276
NZD	4574	0,066	0,161	0	0,008	0,025	0,074	4,295
AED	535	0,135	0,156	0	0,006	0,09	0,204	0,593
GBP	4595	0,012	0,026	0	0,002	0,006	0,014	0,669
PHP	535	0,01	0,006	0	0,005	0,008	0,014	0,027
CHF	4598	0,066	0,211	0	0,004	0,014	0,053	6,559
THB	4558	0,056	0,134	0	0,007	0,022	0,064	4,131
SGD	4583	0,043	0,149	0	0,003	0,008	0,032	5,047
AUD	4599	0,032	0,137	0	0,003	0,008	0,025	4,738
KZT	1271	0,147	0,08	0	0,093	0,146	0,202	0,444
CAD	4574	0,034	0,135	0	0,003	0,009	0,031	4,805
ZAR	4010	0,06	0,141	0	0,023	0,041	0,07	4,674
ARS	4004	0,492	0,426	0	0,112	0,424	0,804	6,93
TRY	3869	0,083	0,229	0	0,008	0,023	0,081	6,187
RUB	4590	0,058	0,201	0	0,008	0,019	0,044	4,74
COP	3924	0,057	0,147	0	0,017	0,04	0,072	5,001
KRW	3893	0,063	0,172	0	0,01	0,023	0,052	4,78
IDR	3979	0,052	0,173	0	0,004	0,01	0,029	4,915

Table 4: Descriptive Statistics of Price Deviation (in Absolute Value) by Country

Country	AML/CFT	Payment	VASP	Securities	Sandbox	Acceptance	Ban	Total
ARE	12/01/2020, 07/01/2023	02/07/2023	12/01/2020, 03/09/2022, 02/07/2023	02/07/2023	01/01/2019, 19/10/2023			9
ARG	07/10/2014				04/01/2022		11/01/2019, 05/05/2022, 04/05/2023	5
AUS	04/03/2018, 03/03/2018			10/29/2021, 09/01/2017	12/01/2016, 09/01/2020			6
BRA	07/01/2020		06/20/2023	10/11/2022	05/09/2018, 05/01/2020	09/19/2018, 04/26/2021		7
CAN	06/01/2020		03/29/2021, 02/22/2023	08/24/2017, 06/11/2018, 01/16/2020	08/15/2017			7
CHE	09/29/2017, 11/02/2022, 01/01/2023	09/29/2017		09/29/2017, 02/16/2018, 08/01/2021	08/01/2017, 01/01/2019	02/01/2021, 09/29/2021		11
COL	12/24/2020, 12/15/2021				01/01/2021		06/25/2014	4
CZE	06/01/2021				03/01/2022, 02/14/2023, 11/01/2019	27/10/2018		5
EUR	06/05/2015, 06/19/2018, 07/20/2021		06/01/2024		02/14/2023			5
GBR	01/10/2020			01/23/2019, 07/22/2019, 10/08/2023	10/28/2014, 05/09/2016			6
HKG	12/07/2022		11/01/2018, 11/06/2019, 06/01/2023	09/05/2017	09/27/2017	12/16/2022, 01/12/2023		8
IDN	10/29/2021	11/08/2016		12/17/2020	11/30/2017, 08/16/2018	02/01/2019, 10/29/2021	11/08/2016	8
ISR	11/14/2021			06/01/2018				2
IND	03/07/2020						01/09/2018 (end: 03/04/2020)	2
JPN	05/01/2020	06/03/2016, 01/06/2023	01/04/2017, 05/01/2020	05/31/2020	06/06/2018			7
KOR	01/30/2018, 03/06/2021		01/01/2024	02/06/2023	01/01/2019			5
KAZ					05/01/2017, 07/05/2018		04/01/2023	3
MEX	03/10/2018, 08/01/2021		03/09/2018		03/09/2018		03/09/2018, 03/08/2019	6
MYS	02/27/2018			01/15/2019	10/01/2016			3
NZL				10/01/2017				1
PHL								
POL	04/08/2021, 11/01/2021		11/01/2021		02/14/2023, 03/23/2023			5
RUS			06/20/2023	01/01/2021			01/01/2020	3
SGP	01/28/2020, 03/16/2020	01/28/2020		08/01/2017, 11/14/2017	11/16/2022		01/17/2022	7
THA	05/14/2018			05/14/2018, 07/16/2018	12/01/2016		05/01/2022	5
TUR	05/01/2021, 04/18/2022						04/20/2021	3
UKR	04/28/2020		03/17/2022	03/17/2022	04/15/2023			4
ZAF	10/19/2022			10/19/2022	01/01/2020			3
	36	6	17	27	32	9	13	140

EUR dates for AML/CFT laws correspond to directive dates and not national transpositions.

Table 5: Regulations Dates per Country and Type of Regulation

Variable	Definition	Source
	Country-Specific Variables	
Exchange rate	Exchange rates against USD (log)	BIS
Stock growth	Main national stock index (growth rate, see Figure 7 for more detail)	LSEG
Inflation	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 internet searches of the word "Bitcoin"	Google trend
Capital account openness	Chinn-Ito index, a de jure measure of financial openness (until 2021)	Chinn and Ito (2008)
	Global Variables	
USD Bitcoin 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 6: 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 7: National stock indices

Dependent variable: Local Price	In Level			In Growth Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Exchange rate	-0.999***	-1.016	-1.018	-1.021**	-1.020**	-1.021**
USD price	0.993***	0.992***	0.723***	1.001	1.001***	1.001***
Country FE	No	Yes	Yes	No	Yes	Yes
Week FE	No	No	Yes	No	No	Yes
Adj-R^2	0.99	0.99	0.99	0.99	0.99	0.99
Obs	85118	85118	85118	85096	85096	85096

The null hypothesis is beta equal to 1. Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. Driscoll-Kraay standard errors. Variables are included in log in level regressions.

Table 8: Regression results: Validation of the LOP

Dependent variable: Price Deviation	Strength of Regulation			By Type of Regulation		
	(1)	(2)	(3)	(1)	(2)	(3)
Regulation	-0.003***	-0.000	-0.004***			
AML/CFT				0.001	0.011***	-0.006***
Payment				-0.013***	-0.011**	-0.017***
VASP				-0.000	0.001	0.006
Securities				-0.003***	-0.003	-0.003***
Sandbox				-0.007***	-0.006**	-0.007***
Acceptance				-0.004***	-0.002	-0.002
Ban				0.009***	0.007**	0.006*
L.Price deviation	0.739***	0.628***	0.738***	0.738***	0.621***	0.737***
Bubble	0.002	0.010**	-0.001	0.001	0.010**	-0.000
Capital account openness	-0.002***	-0.001	-0.011***	-0.008***	-0.002	-0.009***
Stock growth	0.067	0.018	0.097	0.067	0.015	0.097
D.Inflation	0.000**	-0.001***	0.001***	0.000	-0.001***	0.001**
Google trend	0.000	-0.000*	0.000	-0.000	-0.000**	-0.000
Liquidity BTC	-0.108**	-0.262**	-0.001	-0.078	-0.186**	-0.099
Liquidity FX	-0.000	0.000	-0.000	0.000	0.000	0.000
D.Remittances	-0.013***	-0.018***	-0.013***	-0.016***	-0.021***	-0.015***
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	0.58	0.57	0.57
Obs	76412	28310	48102	76412	28310	48102

Statistical significance levels:* p<0.10, ** p<0.05, *** p<0.01. All regressors are introduced with a lag. *Regulation* is the sum of all types of regulation. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price.

Table 9: Regression Results: Impact of Regulations on Price Deviation

Dependent variable: Local Price	Strength of Regulation			By Type of Regulation		
	(1)	(2)	(3)	(1)	(2)	(3)
Regulation	-0.009****	0.002	-0.007***			
AML/CFT				-0.059***	-0.073***	-0.015***
Payment				0.002	0.057***	-0.037***
VASP				0.032***	0.021**	0.007
Securities				0.012***	0.031***	-0.003*
Sandbox				0.015***	0.033***	-0.009***
Acceptance				-0.020***	0.003	-0.017***
Ban				-0.057***	-0.068***	0.021***
Exchange rate	-0.988***	-1.073***	-0.984***	-1.026***	-1.135***	-0.980***
USD price	0.997***	0.996***	0.995***	0.993***	0.991***	0.994***
Bubble	-0.015**	-0.023**	-0.001	-0.017**	-0.018*	-0.000
Capital account openness	-0.018**	0.009	-0.034***	-0.016***	0.019***	-0.029***
Stock growth	-0.020***	-0.033	-0.047	-0.054	-0.022	-0.048
D.Inflation	0.004***	0.004***	0.002***	0.004***	0.002**	0.002***
Google trend	0.001***	0.000	0.000***	0.001***	0.000	0.000***
Liquidity BTC	0.493***	1.100***	0.136	0.181	0.548**	0.153
Liquidity FX	-0.000	-0.000	-0.000	-0.000	-0.003**	0.000
D.Remittances	0.032***	0.092***	-0.027***	0.037***	0.097***	-0.032***
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. $R^2$2	0.99	0.99	0.99	0.99	0.99	0.99
Obs	76412	28310	48102	76412	28310	48102

Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. All regressors are introduced with a lag. *Regulation* is the sum of all types of regulation. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price.

Table 10: Regression Results: Impact of Regulations on Local Price

Test	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. Statistical significance levels: * 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 11: Panel Stationary Tests of Dependent and Control Variables

Dependent variable:	Strength of Regulation			By Type of Regulation		
Price Deviation (growth rate)	(1)	(2)	(3)	(1)	(2)	(3)
Regulation	-0.002***	-0.000	-0.002***			
AML/CFT				0.000	0.007***	-0.004***
Payment				-0.008***	-0.008***	-0.009***
VASP				-0.000	0.002	0.003**
Securities				-0.002***	-0.001*	-0.002***
Sandbox				-0.004***	-0.004***	-0.004***
Acceptance				-0.003***	-0.001	-0.001
Ban				0.005***	0.003*	0.003
L.Price deviation	-0.208***	-0.311***	-0.203***	-0.211***	-0.317***	-0.204***
Bubble	0.002	0.007***	0.000	0.002	0007***	0.001
Capital account openness	-0.005***	-0.001	-0.006***	-0.005***	-0.002**	-0.005***
Stock growth	0.074**	0.027	0.102**	0.074***	0.026	0.103**
D.Inflation	0.000***	-0.001***	0.000***	0.000*	-0.001***	0.000***
Google trend	0.000	-0.000**	0.000	-0.000	-0.000***	0.000
Liquidity BTC	-0.081**	-0.194***	-0.077*	-0.067*	-0.148**	-0.083*
Liquidity FX	-0.000	0.000	-0.000	0.000*	0.000*	0.000
D.Remittances	-0.008***	-0.012***	-0.007***	-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	0.11	0.20	0.10	0.11	0.21	0.10
Obs	76412	28310	48102	76412	28310	48102

Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. Higher value of price deviation indicates divergence between USD converted local price and USD price. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price. Dynamic fixed effect estimator. Growth rate of the dependent variable computed as the log difference.

Table 12: Robustness Regression Results: Impact of Aggregated Regulations on Price Deviation Growth Rate

Dependent variable:	Strength of Regulation			By Type of Regulation		
Local Price (growth rate)	(1)	(2)	(3)	(1)	(2)	(3)
Regulation	-0.000	0.003***	-0.001***			
AML/CFT				-0.000	0.006***	-0.003***
Payment				0.000	-0.003	0.001
VASP				-0.000	0.001	0.005***
Securities				-0.000	0.010***	-0.000
Sandbox				0.000	-0.007***	-0.005***
Acceptance				-0.000	0.000	0.007***
Ban				-0.000	0.010***	-0.002
Exchange rate	-0.374***	-0.589*	-0.339***	-0.374***	-0.585*	-0.338***
USD price	0.068***	0.104***	0.065***	0.068***	0.106***	0.065***
Bubble	0.008***	0.011***	0.008***	0.008***	-0.001	0.008***
Capital account openness	-0.001	0.001	-0.001	-0.001	0.042	0.000
Stock growth	0.005	0.043	-0.002	0.004	-0.001**	-0.001
D.Inflation	0.000	-0.001**	0.000***	0.000	0.000	0.000***
Google trend	-0.000	0.000	-0.000***	-0.000	0.357**	-0.000***
Liquidity BTC	0.074	0.267	-0.000	-0.074	-0.000	-0.045
Liquidity FX	0.000	-0.000	0.000**	0.000**	-0.000	0.000*
D.Remittances	-0.000	0.000	0.000	-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	0.01	0.01	0.01	0.01	0.01	0.01
Obs	76412	28310	48102	76412	28310	48102

Statistical significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price. All regressors are introduced with a lag. Growth rate of the dependent variable is computed as the difference of current and lagged value of the variable in log. Exchange rate and US price are expressed in growth rate (log difference)

Table 13: Robustness Regression Results: Impact of Regulatory Variables on Local Price Growth Rate

Test	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 14: Panel Stationary tests of Local Bitcoin Prices and Exchange Rates

Pedroni Test		Westerlund Test	
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 hypotheses is “no cointegration”. Test includes trend and constant. Lags are selected via AIC.

Table 15: Panel Cointegration Tests on Local Prices, USD Prices and Exchange rates

	Pedroni Test			Westerlund Test	
Statistic	Price Deviation	Local Price	Statistic	Price Deviation	Local 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.

Table 16: Cointegration Tests on Explanatory and Control Variables

Dependent variable: Local Price		In Level				In Growth Rate	
Long-Term							
	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
Short-Term							
	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		
Country FE		No	No	Yes	Yes	Yes	Yes
Cross sectionally augmented		No	Yes	No	Yes	No	Yes
Adj- R^2		0.97	0.97	0.99	0.99	0.99	0.99
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. Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price. 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 17: Robustness Regression Results: Validation of the LOP - ARDL Error Correction Model

Dependent variable:		Price Deviation			Local Price		
		(1)	(2)	(3)	(1)	(2)	(3)
Long-Term							
	Exchange rate				-0.999***	-1.384***	-0.991***
	USD price				0.996***	0.970***	0.989***
	Regulation	-0.010***	-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
Obs		103501	37911	65590	103501	31911	65590

Statistical significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price. Higher value of price deviation indicates divergence between USD converted local price and USD price. Dynamic fixed effect estimator. Optimal lag determined via AIC.

Table 18: Robustness Regression Results: Impact of Aggregated Regulations on Price Deviation and Local Price - ARDL Error Correction Model

Dependent variable		Price Deviation			Local Price		
		(1)	(2)	(3)	(1)	(2)	(3)
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***
	Payment	-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
	Acceptance	-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.Payment	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.Acceptance	-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
Obs		103501	31911	65590	103501	31911	65590

Statistical significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. (1) refers to regressions using the full sample, (2) to those where the local price is less than the USD price, and (3) to those where the local price exceeds the USD price. Higher value of price deviation indicates divergence between USD converted local price and USD price. Dynamic fixed effect estimator. Optimal lag determined via AIC.

Table 19: Robustness Regression Results: Impact of Regulatory Variables on Price Deviation and Local Prices - ARDL EC Model

Dependent variable: Price Deviation				all sample			
AML/CFT	-0.008***						
Payment		-0.024***					
VASP			-0.002				
Securities				-0.07***			
Sandbox					-0.012***		
Legalisation						-0.014***	
Ban							-0.001
L.Price deviation	0.710***	0.709***	0.711***	0.709***	0.708***	0.710***	0.711***
Bubble	0.003	0.003*	0.004*	0.003	0.003	0.003*	0.004*
Capital account openness	-0.013***	-0.014***	-0.015***	-0.013***	-0.013***	-0.015***	-0.015***
Stock growth	0.082	0.081	0.082	0.082	0.083	0.082	0.083
D.Inflation	0.001**	0.000**	0.001**	0.001**	0.001**	0.000*	0.001**
Google trend	-0.000	-0.000	-0.000**	-0.000**	-0.000	-0.000**	-0.000**
Liquidity BTC	-0.012**	-0.012	-0.070	-0.071	-0.113**	-0.061	-0.072
Liquidity FX	-0.000**	0.000	-0.000	-0.000**	0.000**	0.000	-0.000*
D.Remittances	-0.014***	-0.015***	-0.015***	-0.015***	-0.014***	-0.015***	-0.015***
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj- R^2	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Obs	76412	76412	76412	76412	76412	76412	76412

Statistical significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Higher value of price deviation indicates divergence between USD converted local price and USD price.

Table 20: Regression Results: Impact of Regulatory Variables Alone on Price Deviation - All Sample - Dynamic Fixed Effect Model

Dependent variable: Price Deviation				local price ≤ USD price			
AML/CFT	-0.002						
Payment		-0.016**					
VASP			0.005*				
Securities				-0.001			
Sandbox					-0.005		
Legalisation						-0.012***	
Ban							-0.002
L.Price deviation	0.441***	0.438***	0.442***	0.441***	0.439***	0.440***	0.442***
Bubble	0.005	0.005	0.006	0.005	0.005	0.005	0.005
Capital account openness	-0.000	-0.001	-0.001	-0.001	0.000	-0.001	-0.002
Stock growth	-0.002	-0.002	-0.003	-0.003	-0.000	-0.002	-0.003
D.Inflation	-0.001***	-0.0001***	-0.001***	-.001***	-0.001***	-0.001***	-0.001***
Google trend	-0.000*	-0.000	-0.000*	-0.000**	-0.000	-0.000*	-0.000*
Liquidity BTC	-0.227**	-0.182***	-0.223***	-0.215***	-0.237***	-0.201***	-0.214***
Liquidity FX	-0.000	0.000	-0.000	-0.000	0.000	0.000	-0.008
D.Remittances	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj- R^2	0.42	0.42	0.42	0.42	0.42	0.42	0.42
Obs	28310	28310	28310	28310	28310	28310	28310

Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. Higher value of price deviation indicates divergence between USD converted local price and USD price.

Table 21: Impact of Regulatory Variables on Price Deviation - local price≤USD price - Dynamic Fixed Effect Model

Dependent variable: Price Deviation	local price $\geq$ USD price						
AML/CFT	-0.012***						
Payment		-0.031***					
VASP			-0.001				
Securities				-0.011***			
Sandbox					-0.015***		
Legalisation						-0.014***	
Ban							-0.001
L.Price deviation	0.720***	0.720***	0.722***	0.720***	0.719***	0.721***	0.722***
Bubble	0.004	0.005*	0.005*	0.004	0.004	0.005*	0.005*
Capital account openness	-0.0152***	-0.0178***	-0.018***	-0.016***	-0.017***	-0.019***	-0.002***
Stock growth	0.127	0.127	0.131	0.127	0.128	0.129	0.131
D.Inflation	0.001***	0.001***	0.001***	0.001***	0.001**	0.001**	0.001***
Google trend	-0.000	-0.000*	-0.000**	-0.000	-0.000	-0.000**	-0.000**
Liquidity BTC	-0.142**	0.006	-0.075	-0.075	-0.123*	-0.066	-0.074
Liquidity FX	-0.000**	0.000	-.000**	-0.000**	0.000**	-0.000	-0.000**
D.Remittances	-0.012***	-0.014***	-0.014***	-0.014***	-0.013***	-0.014***	-0.014***
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj- R^2	0.56	0.56	0.56	0.56	0.56	0.56	0.56
Obs	48102	48102	48102	48102	48102	48102	48102

Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. Higher value of price deviation indicates divergence between USD converted local price and USD price.

Table 22: Impact of Regulatory Variables on Price Deviation - local price$\leq$USD price - Dynamic Fixed Effect Model

8. Appendices 2 - 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.

9. Appendices 3 - Technical Support for Identifying and Measuring Explositivity

To date price explosiveness in the crypto-asset 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):

$$y_t = \mu + \beta y_{t-1} \sum_{i=1}^{p} \delta_{r_w} \beta y_{t-i} + \epsilon_t \tag{6}$$

where y_t is the crypto-asset 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 $r_2 \in [r_0, 1]$:

$$SADF(r_0) = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2} \tag{7}$$

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

$$GSADF(r_0) = \underset{r_2 \in [r_0,1], r1 \in [0, r_2 - r0]}{sup} \{ADF_{r1}^{r_2}\} \tag{8}$$

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:

$$BSADF_{r_2}(r_0) = \underset{r_1 \in [0, r_2 - r_0]}{sup} \left\{ADF_{r_1}^{r_2}\right\} \tag{9}$$

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.

10. Appendices 4 - Empirical Strategy For The Auto-Regressive Distributed Lagged Error Correction Model

10.1. Testing For the Law Of One Price

We take the equation of the LOP:

$$log(p_{i,t} e_{i,t}) = \beta log(p_{US,t}) + \epsilon_{i,t} \tag{10}$$

To avoid spurious regressions, 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 test (LLC), the Im-Pesaran-Shin test (IPS), the Harris-Tzavalis test (HT), the Breitung test (B) and the Karavia and Tzavalis 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).

According to the different order of integration of our (cointegrated) variables, we estimate a panel ARDL Error Correction Model (ARDL ECM) to capture long- and short-run dynamics. The general form of ARDL model is defined as follows:

$$p_{i,t} = \alpha_0 + \sum_{j=1}^{p} \gamma_j log(p_{i,t-j}) + \sum_{j=0}^{q} \delta_j log(e_{i,t-j}) + \sum_{j=0}^{r} \phi_j log(p_{US,t-j}) + \epsilon_{i,t} \qquad (11)$$

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:

$$ECT = log(p_{i,t-1}) - \beta_0 log(e_{i,t-1}) - \beta_1 log(p_{US,t-1}) \qquad (12)$$

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

$$\begin{aligned}\Delta \log(p_{i,t}) =& \lambda(\log(p_{i,t-1}) - \beta_0 \log(e_{i,t-1}) - \beta_1 \log(p_{US,t-1})) + \sum_{j=1}^{p-1} \gamma_j \Delta \log(p_{i,t-j}) \\ &+ \sum_{j=0}^{q-1} \delta_j \Delta \log(e_{i,t-j}) + \sum_{j=0}^{r-1} \phi_j \Delta \log(p_{US,t-j}) + \epsilon_{i,t} \qquad (13)\end{aligned}$$

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.

10.2. Influence Of Crypto-asset Regulations On Price Deviation And Local Price

As in the previous section, the data 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:

$$\begin{aligned}\Delta \log(price\_deviation_{i,t}) = {} & \lambda(\log(price\_deviation_{i,t-1}) - \beta_0 Regulation_{i,t} + \beta_1 X_{i,t} \\ & + \beta_2 X_t) + \sum_{j=1}^{p-1} \gamma_j \Delta \log(price\_deviation_{i,t-j}) \\ & + \sum_{j=0}^{m-1} \alpha_j \Delta Regulation_{i,t-j} + \sum_{j=0}^{n-1} \theta_j \Delta X_{i,t-j} \\ & + \sum_{j=0}^{k-1} \psi_j \Delta X_{t-j} + \epsilon_{i,t} \end{aligned} \tag{14}$$

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:

$$\begin{aligned}\Delta \log(p_{i,t}) = {} & \lambda(\log(p_{i,t-1}) - \beta_0 \log(e_{i,t-1}) - \beta_1 \log(p_{USD,t-1}) + \beta_2 Regulation_{i,t} \\ & + \beta_3 X_{i,t} + \beta_4 X_t) + \sum_{j=1}^{p-1} \gamma_j \Delta \log(p_{i,t-j}) + \sum_{j=0}^{q-1} \delta_j \Delta \log(e_{i,t-j}) \\ & + \sum_{j=0}^{r-1} \phi_j \Delta \log(p_{USD,t-j}) + \sum_{j=0}^{m-1} \alpha_j \Delta Regulation_{i,t-j} \\ & + \sum_{j=0}^{n-1} \theta_j \Delta X_{i,t-j} + \sum_{j=0}^{k-1} \psi_j \Delta X_{t-j} + \epsilon_{i,t} \end{aligned} \tag{15}$$

$p_{i,t}$ 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.

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