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Price Delay and Market Efficiency of Cryptocurrencies: The Impact of Liquidity and Volatility during the COVID-19 Pandemic

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Abstract: The rise of cryptocurrencies as alternative financial investments, with potential safe-haven and hedging properties, highlights the need to examine their market efficiency. This study is the first to investigate the combined impact of liquidity and volatility features of cryptocurrencies on their price delays. Using a wide spectrum of cryptocurrencies, we investigate whether the COVID-19 outbreak has affected market efficiency by studying price delays to market information. We find that as liquidity increases and volatility decreases, cryptocurrencies demonstrate stronger market efficiency. Additionally, we show that price delay differences during the COVID-19 outbreak increase with higher levels of illiquidity, particularly for highly volatile quintiles. We suggest that perceived risks and high transaction costs in illiquid and highly volatile cryptocurrencies reduce active traders' willingness to engage in arbitrage trading, leading to increased market inefficiencies. Our findings are relevant to investors, aiding in improving their decision-making processes and enhancing their investment efficiency. Our paper also presents significant implications for policymakers, emphasizing the need for reforms aimed at enhancing the speed at which information is incorporated into cryptocurrency returns. These reforms would help mitigate market distortions and increase the sustainability of cryptocurrency markets.

Keywords: cryptocurrency; market efficiency; liquidity; volatility; COVID-19; price delay

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1. Introduction

The market efficiency of cryptocurrencies has been a highly controversial research topic over the past few years. Such research has important implications for market participants and policymakers due to the emergence of cryptocurrencies as alternative financial investments that might present safe-haven and hedging properties. The cryptocurrency market is known for its price fluctuations, and several studies have shown that its efficiency is unstable and can be time-varying. Previous studies have assessed the market efficiency of cryptocurrencies under the weak-form efficient market hypothesis (Urquhart 2016; Wei 2018). Others have considered the adaptive market hypothesis (AMH) that expands the static approach of the EMH by arguing that the market efficiency of cryptocurrencies evolves over time and depends on changes in market conditions (Chu et al. 2019; Naeem et al. 2021).

A growing body of empirical literature also addresses the impact of cryptocurrencies' features on the efficiency of this market. For instance, Wei (2018) and Brauneis and Mestel (2019) show that return predictability decreases as the liquidity of cryptocurrencies increases. Dong et al. (2022) argue that the illiquidity of cryptocurrencies generates anomalous returns, which prevents the development of an efficient cryptocurrency market. Zaremba et al. (2021) find that illiquid cryptocurrencies exhibit daily short-term price reversals, whereas liquid ones display daily momentum. Mensi et al. (2019) present evidence that the persistence levels of both returns and volatility decrease when controlling for the long memories of cryptocurrencies and switching states. Katsiampa et al. (2019) suggest that future research on the interlinkages between price volatility and changes in the liquidity of cryptocurrencies is becoming crucial. In the same line, Leirvik (2022) argues that cryptocurrency traders are exposed not only to the risks concerning the levels of liquidity, but also to the volatility of these levels.

The study of Al-Yahyaee et al. (2020) is the only research in the current literature that investigates both the volatility and the liquidity of cryptocurrencies as driving variables of market efficiency. Using MF-DFA and the quantile regression approach, the authors investigate the multifractality and the long-memory properties of six major cryptocurrencies and show that higher liquidity improves the efficiency of cryptocurrencies while a higher volatility weakens it, depending on the quantiles. Our paper complements the scarce literature on this topic by exploring a different innovative approach that assesses the combined impact of the liquidity and the volatility features on the market efficiency of a large cross-section of cryptocurrencies. Specifically, the market efficiency is assessed by examining the price delays of cryptocurrencies to market news. To date, we are not aware of any paper dealing with the link between cryptocurrencies' price delays and their liquidity and volatility features before or during the COVID-19 pandemic. While Köchling et al. (2019) explored the determinants of price delay in cryptocurrencies by highlighting the liquidity feature, none of the current literature assesses the dual impact of liquidity and volatility features on cryptocurrency market efficiency gauged specifically using price delay metrics. This paper addresses this research gap and contributes to the debate over the market efficiency of the cryptocurrency market during the era of the cryptocurrency market situated within the COVID-19 pandemic. The outbreak of the COVID-19 crisis created a chaotic financial environment, and thus it seems crucial to investigate how the pandemic affects the efficiency of this immature market. This study thereby aims to investigate whether the outbreak of COVID-19 adversely affected the efficiency of the cryptocurrency market by assessing the change in the speed of cryptocurrencies' price responses to the information embedded in the market or whether this market remains resilient by presenting safe-haven features during the pandemic period.

We find that the price delay differences are more pronounced as illiquidity increases and become more significant for highly volatile cryptocurrency quintiles before and during the COVID-19 pandemic. Our findings suggest that higher perceived levels of risk along with higher transaction costs in illiquid and volatile cryptocurrency markets reduce the incentives of active traders to act quickly and readily to new information, resulting in market inefficiencies. We also show that the speeds of price responses to the information embedded in the market are the highest for the most liquid and the least volatile quintile group of cryptocurrencies during the different sample periods, thus suggesting stronger market efficiency and safe-haven benefits for this group. These findings are robust when using different proxies of liquidity and when controlling for randomness using a battery of statistical efficiency tests. This study also highlights the impact of the volatility features and the effect of investors' senses of panic on the determinants of the price delays of cryptocurrencies, which has not been adequately explored in the existing literature. Our findings suggest that price delays are strongly positively linked to the volatility and to the illiquidity of cryptocurrencies and negatively linked to their size. Our results are pronounced and robust during periods of high panic levels and heightened implied volatility in the financial market, suggesting greater inefficiencies under these extreme market conditions.

The findings of this paper are valuable for financial market regulators and authorities in their efforts to improve the financial stability of the cryptocurrency market and to decrease price delays within it, especially during crisis periods where evidence of inefficiencies in equity markets are proven (Liao et al. 2019; Naeem et al. 2021). Financial reforms are thus needed to encourage active cryptocurrency traders to arbitrage any signs of return predictability, which can enhance the informational efficiency of the cryptocurrency market. Our results are also beneficial for investors' risk management and allocation decisions during periods of financial turbulence. Investors should therefore consider volatility and liquidity features when estimating the return predictability and the risk premiums required on cryptocurrencies, as our findings suggest that these features can alter their informational efficiencies. This paper is organized as follows: Section 2 describes the literature review. Section 3 explains the data and methodology. Section 4 outlines our results. Finally, the study is concluded in Section 5.

2. Literature Review

Cryptocurrencies are one of the newest and most controversial financial instruments available. The controversy stems from the inability to clearly define their intrinsic values (Bhambhwani et al. 2019; Biais et al. 2023; Detzel et al. 2020; Liu et al. 2020). The rise in popularity of the cryptocurrency market can be attributed to various factors, such as its limited correlation with traditional investment assets (Baur et al. 2018; Corbet et al. 2019; Makarov and Schoar 2020; Griffin and Shams 2020), its lower transaction expenses compared to conventional currencies, its perceived potential as a safe-haven (Bouri et al. 2017) and its hedging properties during economic instability (Conlon and McGee 2020; Corbet et al. 2020). Despite these advantages, the cryptocurrency market has encountered hurdles due to regulatory ambiguity and a lack of transparency, leading to excessive price fluctuations. This creates various risks, including illiquidity and volatility risks.

For traditional assets, market efficiency is often perpetuated by liquidity, as it increases the ability of traders to quickly execute transactions at fair prices. As bid–ask spreads become narrower, indicating an increase in liquidity, predictability in short-term returns of financial instruments is diminished (Chordia et al. 2008), with variance ratio tests suggesting prices becoming closer to random walk benchmarks. The role of liquidity has been extended as a driver of market efficiency in the cryptocurrency market as well. Zhang and Li (2023) observe a negative relationship between liquidity and returns for a sample of cryptocurrencies with capitalization over USD 1 million in a dataset ranging from 2014 to 2019. For any given week, cryptocurrencies with greater liquidity tend to have smaller returns in the subsequent week. However, no significant intertemporal relationship was found between liquidity and expected returns for Bitcoin, Ethereum and Ripple. Leirvik (2022) documents a positive relationship between the volatility of liquidity and the expected returns of the five largest cryptocurrencies. The author suggests based on their use of the Corwin and Schultz (2012) liquidity measure that liquidity is time-varying and is improving overall, as spreads are become tighter. Brauneis and Mestel (2018) find that the efficiency of cryptocurrencies is positively related to their liquidity levels. Wei (2018) finds a lesser ability to predict cryptocurrency returns as liquidity increases. The author highlights a strong inverse relationship between liquidity and volatility, consistent with the notion that higher liquidity leads to increased price efficiency resulting in lower volatility. In the same line, Sensoy (2019) reports a significant positive relationship between liquidity and Bitcoin price efficiency, as well as a strong negative relationship between volatility and price efficiency.

Moreover, the volatility of cryptocurrencies has an influence not only on the returns generated but also on their efficiency. Doumenis et al. (2021) investigate the volatility of Bitcoin versus that of the S&P 500, gold and treasury bonds in the timeline of 2014–2021 and find that the volatility of Bitcoin is higher than that of the other assets, both before and after the COVID-19 outbreak. Evidence also suggests that Bitcoin is more of a speculative asset rather than a store of value due to its lack of a relationship with the 30-year US treasury bills. Ahmed (2020) uses multiple volatility proxies to assess the risk–return trade-off of Bitcoin and shows a significant and negative contemporaneous relationship between returns and volatility. Conrad et al. (2018) find significant evidence that higher realized volatility in the US stock market leads to a decrease in the Bitcoin volatility in a dataset ranging from 2013 to 2017, while other factors, such as notable news searches on Google Trends, also coincide with large weekly price swings in Bitcoin. Zhang and Li (2020) demonstrate a positive relationship between idiosyncratic volatility and expected returns in a sample of 500 cryptocurrencies spanning the period from 2014 to 2019. This is confirmed by Bouri et al. (2022), who demonstrate a positive relationship between idiosyncratic volatility and returns, highlighting that additional risk is priced into nearly 2000 cryptocurrencies. However, this relationship is mostly pronounced for more illiquid currencies.

Higher volatilities may cause significant price fluctuations over a short period of time, creating higher noise in the market. This can obscure the intrinsic value of assets, making it harder for market participants to accurately evaluate market conditions and make informed decisions. In an efficient market, volatility will not persist, resulting in a quicker dissipation of its impact. Yaya et al. (2021) investigate the market efficiency of some of the most prominent cryptocurrencies and the fluctuation in their volatilities, with evidence of market efficiency in most currencies being found while testing for randomness in returns. This opposes the consensus of the inefficiency of the cryptocurrency market that has long been observed, with Bitcoin being found to be inefficient in earlier studies (Urquhart 2016; Jiang et al. 2018).

Cryptocurrencies exhibiting high volatility and illiquidity features may lead to inefficiencies in the market, such as price discrepancies between different trading platforms. We argue that cryptocurrencies with low liquidity may present thin-order books and wide bid–ask spreads, making it challenging for traders to execute large transactions without affecting prices. This lack of liquidity can worsen market inefficiencies. Moreover, cryptocurrencies with high volatility levels can hinder market participants' ability to promptly and accurately interpret new information. As a result, we argue that cryptocurrency prices may not be able to fully adjust to impacts of the latest news in a timely manner. This effect can be exacerbated during crisis periods. During times of crisis, market uncertainty tends to increase, and investors often exhibit risk-averse behavior and seek to invest in safe-haven assets. The role of cryptocurrency as a safe-haven during the pandemic was highlighted through the sharp increase in liquidity in the period following the COVID-19 outbreak (Corbet et al. 2022), as price shocks that indicated higher volatility were found to be coupled with sharp liquidity shifts after multiple prominent cryptocurrencies were examined in the period before and after the start of the pandemic.

We argue in this paper that both volatility and liquidity features may delay the incorporation of new market information into prices. As a result, it may take longer for the market to fully adjust to new information, leading to delays in price adjustments. No existing work has explored the relationship between cryptocurrency price delays and their liquidity and volatility characteristics both before and during the COVID-19 pandemic. This study aims to fill this gap in research and contribute to the ongoing debate on the efficiency of the cryptocurrency market. Our study thus seeks to determine whether the COVID-19 outbreak negatively affects the efficiency of the cryptocurrency market by examining changes in the speed of price responses to market information. Furthermore, it aims to assess whether the cryptocurrency market exhibits resilience by displaying safe-haven attributes during the COVID-19 crisis.

3. Materials and Methods

This section is devoted to outlining our research methodology. First, we introduce the data covered by this study, and then we delve into the construction of variables related to cryptocurrency returns, illiquidity, volatility and price delay metrics. Finally, we present the efficiency tests conducted.

3.1. Data

The data employed in this study was collected from www.coinmarketcap.com (accessed on 1 July 2022) and covers 409 cryptocurrencies for the period 28 April 2014 to 9 August 2021, representing more than 80% of the overall cryptocurrency market. We deliberately chose the period from 2014 to 2021 to include data before and after the emergence of the COVID-19 pandemic, as our study focuses specifically on the impact of the COVID-19 crisis. The dominant portion of our sample consists of non-stable cryptocurrencies, comprising approximately 98% of the dataset, while stable coins represent only 2% of the cryptocurrencies included in our study[1]. However, Data was selected based on the availability of complete observations, specifically requiring full price and aggregate volume data history throughout the entire period.

3.2. Construction of Variables

3.2.1. Returns Estimation

Each individual cryptocurrency's log returns are estimated as follows:

$$r_{i,t} = [\ln{(P_{i,t}\ /P_{i,t-1})}] \times 100 \tag{1}$$

where ln ($P_{i,t}$) and ln ($P_{i,t-1}$) are the natural logs of the daily prices of cryptocurrency i at time t and $t-1$.

3.2.2. Illiquidity Measure

We employ in this paper the illiquidity measure developed by Amihud (2002) that focuses on the relationship between the returns of cryptocurrencies and their trading volume. This illiquidity proxy provides insights about the sensitivity of cryptocurrencies' prices to changes in trading activity, and it is measured as follows:

$$Illiquidity = \frac{1}{D_T}\sum\nolimits_{\mathrm{t}=1}^{D_T}\frac{|r_{i,t}|}{V_{i,t}P_{i,t}} \tag{2}$$

where D_T is the number of traded days in year T. On day t, $\mid r_{i,t} \mid$ is the absolute value of the daily return, $V_{i,t}$ is the daily traded volume and $P_{i,t}$ is the closing price of cryptocurrency i.

To test for robustness, we compute the Corwin and Schultz (2012) bid–ask spread as an additional proxy for the liquidity of cryptocurrencies as follows:

$$CS = \frac{2(e^{\alpha}-1)}{1+e^{\alpha}} \tag{3}$$

where

$$\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}} \tag{4}$$

$$\beta = \left[\ln\left(\frac{H_i}{L_i}\right)\right]^2 + \left[\ln\left(\frac{H_{i+1}}{L_{i+1}}\right)\right]^2 \tag{5}$$

$$\gamma = \left[\ln\left(\frac{H_{i,i+1}}{L_{i,i+1}}\right)\right]^2 \tag{6}$$

where H_i denotes the high price and L_i denotes the low price in subinterval i, while $H_{i,i+1}$ and $L_{i,i+1}$ are the high and low prices of two adjacent subintervals i and $i+1$, respectively. In the above equations, α represents the difference between the adjustments of a 1-day and a 2-day period, β denotes the adjustments in daily high and low prices relative to the high price and γ represents the adjustments in high and low prices over a 2-day period.

3.2.3. Volatility Measure

The volatility of cryptocurrencies is captured by the Garman and Klass (1980) volatility estimator, as follows:

$$Volatility = \sqrt{\frac{1}{n}\sum\nolimits_{t=1}^{n}\left[\frac{1}{2}\left(ln\frac{H_t}{L_t}\right)^2 - (2ln2-1)\left(ln\frac{C_t}{O_t}\right)^2\right]} \tag{7}$$

where, on day t, H_t denotes the daily high price, L_t is the daily low price, C_t is the daily closing price and O_t is the daily opening price of each cryptocurrency.

3.2.4. Price Delay Measure

The predictability of cryptocurrency returns is rigorously assessed based on the price delay measure proposed by Hou and Moskowitz (2005). The price delay captures the speed of the cryptocurrencies' price response to the information embedded in the market. The delay measure is computed using weekly returns by performing time-series regressions that are based on a rolling window of 52 weeks, as follows:

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{4} \delta_i^{(-n)} R_{\mathrm{m,t-n}} + \epsilon_{i,t} \tag{8}$$

where, in week t, $r_{i,t}$ is the rate of return of the cryptocurrency i and $R_{m,t}$ is the return on the CRIX value-weighted market index[2]. If the cryptocurrency price responds immediately to market news, none of the $\delta_i^{(-n)}$ values will differ from zero. The standard price delay ($D1$) measure is then captured as follows:

$$D1 = 1 - \frac{R^2_{\delta_i^{(-n)}=0, \forall \mathrm{n} \in\ [1,4]}}{R^2} \tag{9}$$

where R^2 and $R^2_{\delta_i^{(-n)}=0, \forall \mathrm{n} \in\ [1,4]}$ are the R-squared estimates based on the unrestricted and restricted regressions in Equation (8), respectively (i.e., restricting the coefficients of lagged underlying returns to be zero). A high value of $D1$ indicates that higher amount of a cryptocurrency's return variation comes from lagged market returns, thereby implying higher price delays to market news.

3.3. Efficiency Tests

To further investigate the predictability of cryptocurrency returns, we employ a comprehensive set of efficiency tests. First, we evaluate the autocorrelation of returns using the Ljung and Box (1978) test, which assesses whether there are significant correlations between observations at different time points. We also conduct the Runs test (also called the Wald–Wolfowitz runs test) and the Bartels test (Bartels 1982) to examine the randomness and the absence of seasonality patterns in cryptocurrency returns. Moreover, the BDS test (Broock et al. 1996) is employed to detect non-linear dependencies in our data. Following Urquhart (2016) and Wei (2018), we choose 2 to 5 embedded dimensions and report the average p-values across different specifications Additionally, following Kim's (2009) methodology, we conduct an analysis of the variance ratio test using the wild-bootstrapped AVR test. The aim of this test is to assess whether the observed variation in cryptocurrency returns over different time intervals is random or if there are predictable patterns detected in the data. Finally, we estimate the R/S (range over standard deviation) Hurst exponent test to investigate the long-memory properties of returns.

4. Results

In this study, we sort our sample of cryptocurrencies into quintiles based on the Amihud illiquidity ratio and the Garman and Klass volatility measure, where Group 11 (Group 55) represents the group of cryptocurrencies that are the most (least) liquid and the least (most) volatile. Table 1 reports the descriptive statistics for the cryptocurrency returns. Panel A shows that for the overall sample of cryptocurrencies, the mean and the standard deviation of returns significantly increase during the COVID-19 period[3], while the levels of kurtosis and the negative skewness are much greater during this period of market turmoil. The results are particularly more pronounced for the group of cryptocurrencies that are the least liquid and the most volatile, as presented in Panel B. This suggests that investors require higher risk premiums for holding cryptocurrencies that are illiquid and highly volatile, which is in line with the results presented by Leirvik (2022).

Table 1. Descriptive statistics.

Panel A					
	Mean		**Std. Dev**	**Kurtosis**	**Skewness**
Pre-COVID-19 Period	0.1133		10.811	20.438	−0.451
COVID-19 Period	0.20832		12.274	95.750	−4.980
Panel B					
Pre-COVID-19 Period	**Group**	**Mean**	**Std. Dev**	**Kurtosis**	**Skewness**
High Liquidity, Low Volatility	11	0.018	2.987	3.549	−0.626
Low Liquidity, High Volatility	55	0.097	4.402	0.967	−0.315
COVID-19 Period					
High Liquidity, Low Volatility	11	0.146	3.567	39.999	−3.757
Low Liquidity, High Volatility	55	0.266	5.312	15.537	−1.971

In this paper, we shed light on the volatility and liquidity features of cryptocurrencies, which can have direct impact on the investors' trading activities and allocation decisions. We believe that this can strongly affect the speed of cryptocurrencies' price adjustments with respect to market price movements. Therefore, we examine in Table 2 the determinants of the price delays of cryptocurrencies. The price delay metrics are shown to be positively and significantly affected by the illiquidity features of cryptocurrencies and strongly negatively impacted by their size, which is in line with the results of Köchling et al. (2019). More importantly, our findings complement and extend the analysis presented by Köchling et al. (2019) by investigating the impact of the volatility features of cryptocurrencies[4] and by exploring the interaction effects of heightened levels of panic and of implied volatility in financial markets that are best captured by the Ravenpack Coronavirus Panic Index and the CBOE Volatility Index (VIX), respectively[5]. The use of panic sentiment is based on the fact that investor sentiment significantly impacts asset pricing and market efficiencies (Economou 2016). This calls into question traditional financial models that assume that the investment decisions of rational investors are based on their informational-processing activities. Therefore, we expect that panic can alter investors' risk tolerance and asset allocation decisions, which can affect the speed of the cryptocurrencies' price responses to information embedded in the market. Our results thus contribute to the scarce literature on this topic by investigating the moderating impact of investors' senses of panic and uncertainty on the link between cryptocurrencies' features and price delays. Indeed, our findings suggest that the price delay measures are positively and significantly affected by the volatility of cryptocurrencies. The interaction terms also show robust findings and reveal that the increases in illiquidity and volatility levels are associated with higher price delays during periods of extremely heightened levels of panic and uncertainty, thus highlighting a lower efficiency in incorporating information into cryptocurrency prices.

In the same line, we further investigate in Figure 1 the evolvement of the average price delay along with the changes in the levels of market uncertainty and fear that are best captured by the CBOE Volatility Index (VIX) in Panel A and the Ravenpack Coronavirus Panic Index in Panel B. Figure 1 shows that the magnitude of the average price delay for the group of cryptocurrencies that are the least liquid and the most volatile (Group 55) is much stronger than that of the group of cryptocurrencies that are the most liquid and the least volatile (Group 11) when compared to the evolution of the VIX and of the Coronavirus Panic Indices over time.

Table 2. Determinants of price delay.

	Price Delay						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Illiquidity_{t-1}$	0.000 ***	0.000 ***		0.000 ***	0.000 ***		0.000 ***
	(2.593)	(2.632)		(2.590)	(2.619)		(2.582)
$Volatility_{t-1}$	0.234 ***		0.222 ***	0.232 ***		0.224 ***	0.234 ***
	(9.725)		(9.280)	(9.716)		(9.380)	(9.810)
$Turnover_{t-1}$	−0.002	−0.001	−0.000	−0.002	−0.001	−0.000	−0.002
	(−0.555)	(−0.252)	(−0.013)	(−0.449)	(−0.364)	(−0.113)	(−0.508)
$Size_{t-1}$	−0.034 ***	−0.036 ***	−0.034 ***	−0.034 ***	−0.036 ***	−0.034 ***	−0.034 ***
	(−5.070)	(−5.462)	(−5.752)	(−5.604)	(−5.227)	(−5.218)	(−5.932)
High_Panic_Index		−0.053 ***	−0.065 ***	−0.067 ***			
		(−10.252)	(−10.962)	(−11.067)			
Illiquidity x High_Panic_Index		0.000 **		0.000 **			
		(4.107)		(5.851)			
Volatility x High_Panic_Index			0.189 ***	0.203 ***			
			(3.166)	(3.391)			
High_VIX					−0.040 ***	−0.052 ***	−0.054 ***
					(−8.126)	(−8.962)	(−9.475)
Illiquidity x High_VIX					0.000 **		0.000 *
					(1.546)		(1.439)
Volatility x High_VIX						0.181 ***	0.216 ***
						(3.279)	(3.887)
R-squared	0.272	0.276	0.276	0.282	0.274	0.274	0.281

Note: This table shows results from ordinary least squared regressions using year fixed effects, where the dependent variable is the weekly price delay. As explanatory variables, we use the illiquidity measure of Amihud (2002); the volatility estimator of Garman and Klass (1980); the size measure, estimated as the logarithm of the cryptocurrency's market capitalization; and the turnover ratio, computed as the cryptocurrency's dollar volume divided by its market capitalization. We also capture the impact of the highest levels of market uncertainty and fear, which we refer to as High_VIX (High_Panic_Index), when the CBOE Volatility Index (Ravenpack Panic Index) exceeds the 75th percentile. We then interact these dummy variables with our variables of interest. The t-statistics shown in parentheses are based on the Huber–White robust standard errors. ***, ** and * correspond to a significance level of 0.01, 0.05 and 0.10, respectively.

Periods of financial turmoil are often associated with strong noise in financial markets and with prices with poor informational efficiency. We examine in Table 3 the price delays of cryptocurrencies, ordered based on their liquidity and volatility characteristics across different sample periods. Interesting results are reported[6]. Panel A shows that cryptocurrencies in the most illiquid and volatile quintile present higher significant price delays than those in the most liquid and least volatile quintile by 0.17 (0.26) before (during) the COVID-19 pandemic at the 1% significance level. Our results are in line with several papers that demonstrate the positive relationship between liquidity and the market efficiency of cryptocurrencies (Wei 2018; Köchling et al. 2019; Dong et al. 2022) but also complement the existing literature by highlighting the importance of assessing the combined impact of the liquidity and volatility features on the efficiency of cryptocurrencies. Panel B extends the analysis and shows that the speed of a cryptocurrency's price response to the information embedded in the market is the highest for the most liquid and the least volatile cryptocurrencies during the whole sample period. The latter group presents the lowest levels of price delay across all groups of cryptocurrencies and thereby exhibits stronger signs of efficiency. More importantly, our results suggest that the price delay differences between quintiles increase as illiquidity increases and are only significant for highly volatile cryptocurrencies. This result holds true before and after the COVID-19 outbreak. Our findings suggest that the liquidity and volatility features of the cryptocurrencies can alter traders' investment allocation decisions and thereby affect the efficiency of this market. Cryptocurrencies that are illiquid and highly volatile exhibit high transaction costs and high fluctuation risks, which creates a lack of incentives for traders to act based on the available information when they detect large deviations from fundamental values, resulting in market inefficiency. Our results complement and confirm the arguments presented by Wei (2018) since we show that the volatility and liquidity features of cryptocurrencies significantly impact the time needed for market participants to act on new information, altering the informational efficiency of these markets.

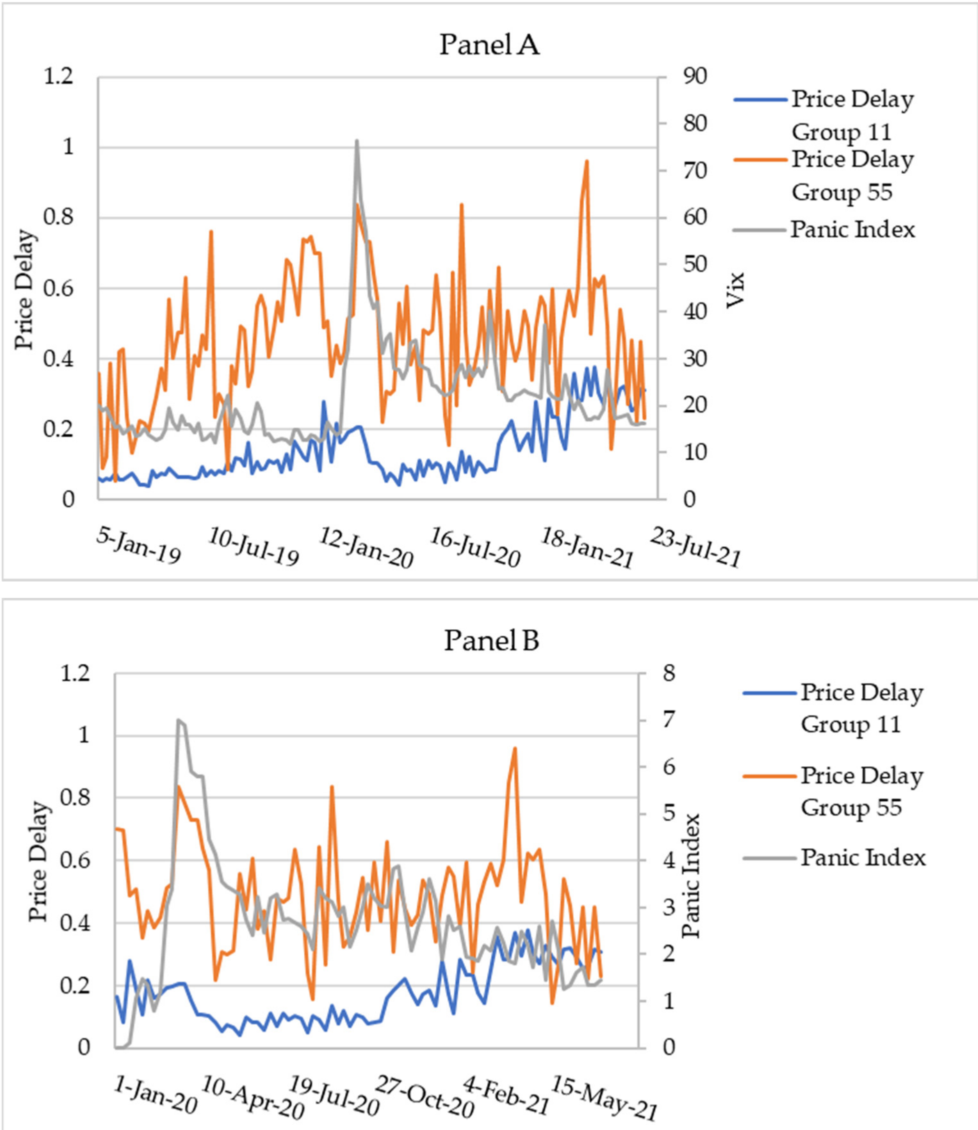

Figure 1. Evolution of the cryptocurrencies' price delays versus the VIX Index in Panel (**A**) and the Ravenpack Panic Index in Panel (**B**). Group 11 (Group 55) represents the group of cryptocurrencies that are the most (least) liquid and the least (most) volatile.

As for additional efficiency tests, we report in Table 4 the average p-values of five randomness tests that assess the predictability of cryptocurrency returns along with the average Hurst coefficients. We fail to reject the null hypotheses of randomness for the group of cryptocurrencies that present the highest liquidity and the lowest volatility features, suggesting a stronger market efficiency for this quintile. We also note that the average p-values for this group decrease during the COVID-19 subsample period but continue to exhibit consistent market efficiency. Moreover, for the highest quintile of cryptocurrencies (i.e., the group with the lowest liquidity and the highest volatility features), the R/S Hurst exponent shows evidence of anti-persistence and, on average, the null hypothesis of randomness is rejected before and during the COVID-19 pandemic.

Table 3. Price delay analysis—sorting performed based on Garman and Klass's volatility estimator and Amihud's illiquidity measure.

Panel A

	Pre-COVID-19 Period Price Delay
High Liquidity, Low Volatility Group 11	0.21
	(1.39)
Low Liquidity, High Volatility Group 55	0.38 ***
	(4.15)
Difference	0.17 ***
	COVID-19 Period Price Delay
High Liquidity, Low Volatility Group 11	0.22
	(1.46)
Low Liquidity, High Volatility Group 55	0.49 ***
	(4.37)
Difference	0.26 ***
	(4.68)

Panel B

Price Delay

Pre-COVID-19 Period

	1_High Liquidity	2	3	4	5_Low Liquidity	Quintile 5–Quintile 1
1_Low Volatility	0.21	0.22	0.25	0.23	0.24 *	0.03
	(1.39)	(1.42)	(1.37)	(1.85)	(1.92)	(1.38)
5_High Volatility	0.31 *	0.32 *	0.33 *	0.33 *	0.38 ***	0.07 **
	(2.37)	(1.64)	(1.48)	(2.91)	(4.15)	(2.10)
Quintile 5–Quintile 1	0.10 *	0.10 **	0.08 **	0.10 ***	0.14 ***	0.04 *
	(1.95)	(2.26)	(2.87)	(4.11)	(5.18)	(1.98)

COVID-19 Period

	1_High Liquidity	2	3	4	5_Low Liquidity	Quintile 5–Quintile 1
1_Low Volatility	0.22	0.23	0.25	0.25	0.26 *	0.04
	(1.46)	(1.50)	(1.47)	(1.56)	(2.15)	(0.52)
5_High Volatility	0.34 *	0.35 **	0.45 **	0.46 **	0.49 ***	0.15 ***
	(2.58)	(3.23)	(3.22)	(3.47)	(4.37)	(3.45)
Quintile 5–Quintile 1	0.12 **	0.12 ***	0.20 ***	0.21 ***	0.23 ***	0.11 *
	(3.53)	(4.36)	(4.03)	(4.17)	(4.60)	(1.86)

Note: t-statistics in parentheses. ***, ** and * correspond to a significance level of 0.01, 0.05 and 0.10, respectively.

Table 4. Market efficiency tests and R/S Hurst exponent.

Pre-COVID-19 Period

				Average *p*-Values			
	Group	**Ljung–Box**	**Runs**	**Bartel**	**AVR**	**BDS**	**Hurst**
High Liquidity, Low Volatility	11	0.51	0.75	0.14	0.16	0.02	0.522
Low Liquidity, High Volatility	55	0.01	0.02	0.00	0.00	0.00	0.428

COVID-19 Period

				Average *p*-Values			
	Group	**Ljung–Box**	**Runs**	**Bartel**	**AVR**	**BDS**	**Hurst**
High Liquidity, Low Volatility	11	0.13	0.25	0.01	0.11	0.01	0.566
Low Liquidity, High Volatility	55	0.00	0.00	0.00	0.00	0.00	0.424

5. Discussion

This study contributes to the understanding of cryptocurrency market efficiency by investigating the combined impact of liquidity and volatility features of cryptocurrencies on their return predictability and their price delay responses to market news. To our knowledge, this is the first assessment of the cryptocurrency market efficiency using price delay metrics during periods of turmoil such as the COVID-19 pandemic. Our results show that as liquidity increases and volatility decreases, cryptocurrencies demonstrate stronger price efficiency and lower price delay throughout the sample period. We also find that price delay differences are more pronounced with increasing illiquidity, and become more significant for highly volatile cryptocurrency quintiles, especially during periods of heightened market turmoil. Additionally, periods of market turbulence, such as during the COVID-19 pandemic, can induce market overreaction, leading to panic-induced asset allocation behavioral biases among investors. Such behavioral biases can result in price inefficiencies. Our study provides a more comprehensive understanding of the determinants of price delay in the cryptocurrency market, offering valuable insights and implications for policymakers and investors.

Cryptocurrencies have also witnessed a rise in their use for illicit practices (Albrecht et al. 2019). This phenomenon is driven by the decentralized structure of blockchain technology, which presents hurdles in determining territorial jurisdiction in cases of transnational crimes (Watters 2023). Policymakers are thus interested in overseeing cryptocurrency usage and mitigating its exploitation. This oversight could facilitate the acceptance of cryptocurrencies as a reliable store of value and foster their adoption as a secure medium of exchange. Overall, the incentive for policymakers to regulate the cryptocurrency market lies mainly in their pursuit of increased market efficiency, trust and transparency. Promoting stability and transparency can notably enhance investor confidence, particularly during market turbulence, thereby facilitating the sustainable growth of the cryptocurrency market.

According to our findings, we argue that implementing regulations to increase liquidity and decrease volatility in the cryptocurrency market can be beneficial in reducing price delays and improving market efficiency. These regulatory reforms are instrumental in reducing market distortions and fostering the long-term viability of cryptocurrencies. Furthermore, implementing policy reforms that reduce price delays would protect investors from significant losses resulting from unforeseen market fluctuations.

Our study is also relevant to investors, as it emphasizes the importance of considering liquidity and volatility risks in the cryptocurrency market when constructing portfolios. These factors substantially influence investment efficiency, enabling investors to navigate market complexities with greater insight and caution. Future research could investigate whether cryptocurrency traders are charging different risk premiums based on their perceived risks of various sets of cryptocurrencies that present different volatility and liquidity features.

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Appendix A

Table A1. Price delay analysis–Sorting based on Garman and Klass volatility estimator and Corwin and Schultz Bid-Ask spread estimator.

Price Delay						
Pre-COVID-19 Period						
	1_High Liquidity	2	3	4	5_Low Liquidity	Quintile 5–Quintile1
1_Low Volatility	0.19	0.19	0.21	0.21	0.23	0.04
	(1.39)	(1.35)	(1.38)	(1.65)	(1.62)	(1.35)
5_High Volatility	0.29	0.32 *	0.33 *	0.34 *	0.38 ***	0.09 **
	(1.37)	(1.95)	(1.99)	(2.15)	(3.75)	(2.75)
Quintile 5–Quintile 1	0.10 *	0.13 **	0.12 **	0.13 ***	0.15 ***	0.05 *
	(1.85)	(2.56)	(2.70)	(4.15)	(4.49)	(1.85)
COVID-19 Period						
	1_High Liquidity	2	3	4	5_Low Liquidity	Quintile 5–Quintile 1
1_Low Volatility	0.21	0.21	0.22	0.24	0.25 *	0.04
	(1.13)	(1.30)	(1.45)	(1.60)	(1.95)	(1.42)
5_High Volatility	0.33 *	0.34 **	0.37 **	0.40 **	0.46 ***	0.13 ***
	(2.45)	(2.95)	(3.11)	(3.45)	(4.27)	(3.38)
Quintile 5–Quintile 1	0.12 **	0.13 ***	0.15 ***	0.16 ***	0.21 ***	0.09 *
	(2.55)	(4.05)	(4.20)	(4.53)	(4.55)	(1.93)

Note: t-statistics in parentheses ***, ** and * correspond to a significance level of 0.01, 0.05 and 0.10 respectively.

Notes

1. While stable-coins are supposedly touted for their stability and their lower volatility compared to other cryptocurrencies, several studies show that they fail to uphold their promise of stability, demonstrating high measured volatility (Jarno and Kołodziejczyk 2021). Additionally, the volatilities of stable-coins are shown to be driven by Bitcoin's volatility (Grobys et al. 2021).
2. CRIX index data are extracted from https://www.royalton-crix.com, accessed on 1 July 2022.
3. The Wuhan Centres for Disease Prevention and Control announced the first COVID-19 case in China on 16 December 2019. Wuhan opted to shut down the entire city on 23 January 2020, and other provinces followed similar measures as a result of the sharp surge in reported cases. Following Mnif et al. (2020) and Kakinaka and Umeno (2022), we split our sample period into sub-periods: the period before (respectively, after) January 2020, is referred to as the pre-COVID-19 period (respectively, COVID-19 period).
4. Previous studies have investigated the changes in the return volatilities of cryptocurrencies over time (Mensi et al. 2019; Al-Yahyaee et al. 2020; Apergis 2022). Thus, we believe that it is also crucial to investigate how the volatility features affect the speed of cryptocurrencies' price adjustments with respect to market price movements, which has not received sufficient attention within the literature.
5. The Panic Index captures the level of news chatter that refers to panic or hysteria towards the COVID-19 pandemic. Data are extracted from https://www.ravenpack.com/, accessed on 29 October 2022. We capture the highest levels of market uncertainty and fear, which we refer to as High_VIX (High_Panic_Index), in which the CBOE Volatility Index (Ravenpack Panic Index) exceeds the 75th percentile.
6. Efficiency results are robust when using the bid–ask estimator of Corwin and Schultz (2012) as an alternative proxy for liquidity. Findings are presented in Appendix A.

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