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Price Discovery in Cryptoasset Exchanges: An Empirical Analysis Across Market Conditions and Investor Positions Using Transaction-Level Data From Thailand

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Abstract

This study investigates the price discovery process on Thailand's largest cryptoasset exchange, uniquely leveraging high-frequency transaction data and investor portfolio positions from 2020 to 2022. By applying a vector error correction model (VECM), we compare local price dynamics of BTC, ETH, and XRP against a global benchmark (Kraken). Our findings reveal a significant lag, with local prices taking approximately 30 to 60 minutes to align with global movements. This convergence process notably slows during periods of high market volatility, irrespective of market direction. Such patterns, particularly the varied investor reactions based on their profit/loss status, suggest the influence of behavioral biases like inertia and the disposition effect among predominantly retail investors. These insights into how local market participants react to global price shocks contribute to a deeper understanding of cryptoasset market microstructure. The results carry actionable implications for regulatory policy, including the potential for enhanced market quality benchmarks and targeted investor education to mitigate behavioral inefficiencies.

Keywords: cryptoasset, Bitcoin, price discovery, market microstructure.

1. Introduction

In the rapidly evolving financial markets, cryptoasset trading stands out as a distinctive and fertile ground for exploring investor behavior, diverging significantly from the well-trodden paths of traditional asset classes, such as stocks. The inherent accessibility of cryptoassets, coupled with their high volatility and relative nascency, presents a unique set of challenges and opportunities that profoundly influence investor decision-making. Unlike traditional markets, where decades of empirical research have shed light on the price dynamics, cryptoassets remain a nascent field ripe for exploration.

This study leverages the rich yet largely untapped dataset of cryptoasset trading activities to delve into how cryptoasset prices behave in an environment characterized by less regulation and higher uncertainty. Our collaboration with the Securities and Exchange Commission of Thailand presents a unique opportunity to explore the intricacies of intraday cryptoasset price dynamics on a prominent local cryptoasset exchange. By leveraging high-frequency price data, detailed order books, and investor portfolio positions, we can conduct an in-depth analysis during the critical period of 2020 to 2022.

Through this lens, we aim to unravel the complex interplay between global market movements and localized trading behaviors in the crypto domain. This analysis is particularly salient given the distinctive features of cryptoasset markets, including the 24/7 trading cycle, the diversity of participants, and the impact of global events on local trading dynamics. Focusing on cryptoassets enhances the broader comprehension of the price discovery process. Additionally, we shed light on the relationship between investor portfolio positions and the rate of price response on the local exchange to global market price movements.

Conventional economic theory posits that, under the no-arbitrage assumption, local market bids and offers should rapidly converge to global price levels.

However, our observations of lagged responses in these bids and offers across varying market conditions suggest that investors' trading behavior can differ significantly during market upturns and downturns. This deviation from theoretical expectations is particularly intriguing in cryptoasset markets, which are known for their volatility and the predominance of retail investors, a demographic often susceptible to behavioral anomalies.

Our study employs intraday bid-offer quotes at high frequency. We analyze trading volume, bid-offer spreads, and quote movements to understand the price discovery process under diverse market conditions. Our study focuses on the three most liquid cryptoassets, Bitcoin (BTC), Ether (ETH), and Ripple (XRP), utilizing 30-minute interval limit order book data from Thailand's largest cryptoasset exchange, which is also the largest by trading volume. This exchange, which commands a market share of approximately 87% and an average daily trading volume of around 2.7 billion baht (approximately $75 million), provides a robust platform for our analysis.

Selecting Thailand's cryptoasset market as the focus of this study is important for several reasons. First, the market is predominantly composed of retail investors, providing a unique opportunity to analyze their trading behavior and its influence on price dynamics. Second, order execution in this market is largely driven by global price movements rather than local information, offering a clear framework for examining investor responses. Third, the bid-ask spreads observed in the local exchange primarily reflect retail trading activity, as opposed to market-maker interventions. Ultimately, the global interconnectedness of cryptoasset prices provides a valuable context for evaluating the efficiency of price discovery and the persistence of arbitrage opportunities.

These insights are especially relevant for regulators aiming to enhance market efficiency through targeted policy interventions. The findings from this study can help regulators understand the intraday price dynamics of cryptoassets and assess the degree of price efficiency on specific exchanges. If cryptoasset prices are weakly inefficient in the short term, it could indicate price manipulation, malpractice, or suspicious trading activities by market participants. It has been widely discussed that cryptoasset prices can be manipulated since many cryptoasset exchanges are unregulated (Cong et al., 2023; Dhawan & Putniņš, 2023; Le Pennec et al., 2021).

In addition to prioritizing anti-money laundering (AML), counter-financing of terrorism (CFT), and know-your-customer (KYC) requirements, regulators must also develop a deeper understanding of the price formation process in cryptoasset markets. Such insight is crucial for understanding how local market participants interpret real-time information and respond to global price fluctuations. Without this understanding, it becomes challenging to justify the inclusion of cryptoassets as viable alternative asset classes for portfolio diversification by financial institutions.

Moreover, our findings enable investors to understand the price dynamics of cryptoassets on the local exchange and identify trading opportunities arising from the price discovery process. The insights can help clear arbitrage opportunities, increasing market efficiency over time.

Our empirical analysis identifies two distinct phases in the local market's price adjustment to global cryptoasset movements. In the initial 30-minute window, prices adjust by approximately 98–99% to global levels, with this adjustment nearing full convergence (close to 100%) in the following hour. Among the assets studied, BTC demonstrates the fastest rate of adjustment. Further analysis across different market conditions reveals that investors are generally hesitant to revise their bids and offers during periods of significant price fluctuations. Additionally, there is some evidence suggesting that local offer quotes tend to undercut global price levels during market uptrends. These patterns suggest the presence of behavioral biases among retail investors, including inertia, cognitive dissonance, and status quo bias.

The structure of this paper is as follows: Section 2 reviews the existing literature on the price discovery process and return predictability of cryptoassets. Section 3 outlines the characteristics of cryptoasset markets in Thailand. Section 4 details the analytical framework for examining the price discovery process and introduces the hypotheses tested in this study. Section 5 presents the empirical results and provides insights into investor behavior in Thailand's cryptoasset exchanges. Finally, Section 6 summarizes the key findings and concludes the paper.

2. Literature Review

In recent decades, cryptoasset and traditional financial markets have undergone significant transformations, including the development of algorithmic trading, high-frequency trading, electronic limit order books, and extended trading hours. There has been exponential growth in interest in cryptoasset investments, with cryptoassets increasingly being included as a distinct asset class in both individual investors' portfolios and corporate investment strategies (Koutmos et al., 2021).

Recent literature has predominantly focused on the predictability of returns for cryptoassets, often employing the theoretical framework of the capital asset pricing model in their analyses. For instance, Dunbar and Owusu-Amoako (2022) found that market risk exposure is a key determinant of future cryptoasset returns, leading investors to demand a higher market risk premium. Similarly, Liu et al. (2022) demonstrated that the risk factors influencing cryptoassets closely resemble those affecting equities. Zhang and Li (2023) identified idiosyncratic volatility, downside risk, and liquidity as significant drivers of returns on cryptoassets. Meanwhile, Bianchi et al. (2023) suggest that investor attention plays a crucial role in shaping the returns of cryptoassets. Yaravaya and Zieba (2022) further highlighted that BTC trading volume and volatility are primary market risk factors influencing the predictability of returns for other cryptoassets.

However, cryptoasset markets remain distinct from traditional financial markets due to their global fragmentation, with hundreds of small exchanges operating in each country. Although most global cryptoasset exchanges, such as Coinbase, Kraken, and Bitstamp, operate under licenses provided by regulators, they are not subject to the same level of regulatory oversight as traditional financial asset exchanges. Additionally, numerous unregulated cryptoasset exchanges exhibit high trading volumes. This situation can result in the same cryptoassets being traded at different price levels, causing their price dynamics to deviate to some extent in the short term. Therefore, cryptoasset markets provide a unique opportunity to explore the price discovery process of identical assets traded across different exchanges.

The pioneering study in this area was conducted by Garbade and Silber (1979). They examined the prices of US securities traded on the New York Stock Exchange (NYSE) and smaller regional exchanges, using a linear regression technique to analyze the relationship between security prices on one market and lagged prices on other markets. Their findings indicated that prices on regional exchanges tend to follow those on the NYSE. Later, Engle and Granger (1987) and Johansen (1988) introduced the concepts of co-integration and error correction. Although the prices of assets may diverge in the short term, the co-integrating relationship will cause their prices to converge to an implicit long-term equilibrium. This concept inspired Hasbrouck's (1995) study, which introduced the information share measurement derived from co-integration and error correction estimation. Similarly, Gonzalo and Granger (1995) proposed a new measure known as the component share.

Unlike stocks, cryptoasset prices provide a fertile ground for asset pricing research. For example, Urquhart (2016) used price data from 2010 to 2016 and found that the efficient market hypothesis could not be confirmed. Nadarajah and Chu (2017) also found that BTC returns are weakly efficient.

However, examining a longer period, Tran and Leirvik (2020) observed that the price efficiency of cryptoassets has improved over time since 2017. Chayutthana and Thepmongkol (2024) also propose economic models that explain the relationship between the bubble state of cryptoassets and the degree of risk aversion among market participants.

In the context of studying the price discovery process in cryptoassets, Brandvold et al. (2015) conducted the first investigation into the price dynamics of cryptoassets traded across seven exchanges from 2013 to 2014. At that time, BTC trading volume represented approximately 90% of the entire cryptoasset market. Their findings revealed that BTC prices on Mt.Gox led other markets. Researchers often focus on BTC, given its dominance. Pagnottoni and Dimpfl (2019) analyzed the price discovery of BTC from 2014 to 2017 across six exchanges, considering exchange rate movements for BTC prices traded in USD, RMB, and EUR. They found that Chinese spot exchanges, specifically OKCoin and BTC China, led the price discovery process, which was weakly influenced by exchange rate movements.

Later studies expand the scope of cryptoassets. For example, Dimpfl and Peter (2021) examined five cryptoassets (Bitcoin, Ether, Ether Classic, Litecoin, and Monero) across three exchanges (Bitfinex, Kraken, and Poloniex). They found that prices on Bitfinex led the price discovery process, even after accounting for microstructure noises on those exchanges. Giudici and Polinesi (2021) applied random matrix and minimum spanning tree methodologies to examine the formation of BTC prices across various exchanges. Their findings indicate that the largest and least volatile exchanges, such as Bitstamp, play a central role as primary price setters in the market.

Another stream of research on price discovery focuses on comparing the pricing of cryptoassets across decentralized exchanges (DEXs) and centralized exchanges (CEXs). Capponi et al. (2024) found that trades executed on DEXs with high transaction fees tend to carry more informational content, as investors are more deliberate in placing their orders. Han et al. (2021) confirmed the existence of short-term arbitrage opportunities between Binance and Uniswap, attributing them to large, short-term order flows. Additionally, Klein et al. (2023) demonstrated that trading activity by liquidity providers on DEXs contains valuable information that significantly influences price dynamics on CEXs.

In addition to studies on spot prices across different markets, some research investigates the price discovery process between spot and futures prices. For instance, Corbet et al. (2018) analyzed BTC and CBOE BTC futures using one-minute data frequency and found that spot prices tend to lead futures. Baur and Dimpfl (2019) used 15-minute price data and found that spot prices on Bitstamp lead futures prices on the CBOE and CME markets. They concluded that spot markets exhibit higher trading volumes and contain more information. Hung et al. (2021) also found similar results, showing that increased trading activities of hedgers in the futures market lead to faster price discovery. Alexander and Heck (2020) confirmed that prices implied in CME futures, a regulated market, follow prices in semi-regulated spot exchanges. This contrasts with the findings of Robertson and Zhang (2022) and Wu et al. (2021), who demonstrated that CME BTC futures consistently lead price formation in unregulated exchanges.

To the best of our knowledge, no studies have investigated the price discovery process across different market conditions and investors' portfolio positions. We use granular price data, limit order books, and investor portfolio positions. Our collaboration with the SEC enables us to understand the dynamics of cryptoasset prices on local exchanges in Thailand in comparison to those on global exchanges and to examine how information is transmitted between exchanges through the price discovery process.

While previous research, such as Brandvold et al. (2015), Dimpfl and Peter (2019), and Urquhart (2016), identified price formation across leading global markets,[1] we look at the lead-lag analysis between a prominent local exchange in Thailand and Kraken (representing global market price), not to ascertain market leadership in price formation but to gauge the efficiency of price discovery in the local market and to interpret how this price discovery process varies in different market conditions.

We use price data from Kraken to represent global cryptoasset prices, as Kraken ranks among the top 10 exchanges worldwide by trading volume. The platform offers a wide range of products, including spot trading, derivatives, and index trading. Elmandjra (2020) shows that Kraken is among the top three exchanges with the lowest bid-offer spreads, reportedly as low as 0.0011%. Additionally, Kraken demonstrates strong market depth, with price adjustments of only 0.16% to 0.21% in response to market buy or sell orders as large as $1 million.

3. Background on the Thai Cryptoasset Market and Data Used

Cryptoassets are an alternative asset class that attracts a particular type of investor. For Thailand, ranked 8th in the 2022 Global Crypto Adoption Index by Chainalysis, over 70% of investors are between 18 and 24 years old (Scholle, 2026). The Thai market presents a sharp contrast to that of the United States, where Aiello et al. (2023) found that cryptoasset investors span all income levels, and households tend to treat cryptoassets similarly to traditional financial assets.

[1] Brandvold et al. (2015) show that Mt. Gox is the leading market for BTC spot prices, where BTC prices in other exchanges will follow. Dimpfl and Peter (2019) incorporate microstructure noises using the methodology proposed by Putniņš (2013) and find that trading in Bitfinex leads prices in Kraken and Poloniex. In a related study, Urquhart (2016) employs statistical tests to prove that cryptoasset markets across the globe appear to be more efficient over time.

During our analysis period, five cryptoasset exchanges were approved by Thailand's Securities and Exchange Commission (SEC). As of December 2022, there were approximately 2.9 million accounts across all five cryptoasset exchanges, which is relatively high compared to the 5.14 million stock trading accounts on the Stock Exchange of Thailand. Across the five exchanges, 191 cryptoassets are available for trade. The trading volume of the largest exchange accounted for nearly 90% of the total daily trading volume, which stood at around 3.23 billion baht per day (approximately $92 million). The exchange grew rapidly, from just 60,000 accounts at the beginning of 2020 to almost one million at the end of 2022, with around 20–30% of the accounts trading at least once a week.

Despite the growing global acceptance of cryptoasset investment, the integration of these assets into the portfolios of institutional investors remains nascent. Consequently, retail investors constitute approximately 84% of trading activities on the authorized cryptoasset exchange examined in this study, making the cryptoasset market a suitable venue for investigating the impact of retail investors' trading on asset price dynamics. The characteristics of the local exchange used in this analysis are detailed in Table 1.

Table 1. Key characteristics of the local exchange in Thailand

	2020	2021	2022
Number of listed cryptoassets	54	94	109
Number of trading accounts	60,340	924,601	989,865
Number of domestic accounts	56,752	915,125	979,499
Number of foreign accounts	3,602	9,491	10,440
Trading value per day (unit: million baht)			
Mean	565.18	4,581.53	2,751.80
Standard deviation	309.62	2,958.46	1,777.56
Min	112.64	888.61	257.98
Max	1,580.40	25,542.89	13,225.26
Trading value per account per day (unit: baht)			
Mean	12,464.18	5,895.77	5,528.39

Standard deviation	52,428.84	30,551.93	28,521.39
Min	0.01	0.01	0.01
Max	7,549,668.99	20,517,059.20	14,962,500.11
Proportion of retail investors			
% of the number of accounts	99.97	99.99	99.98
% of trading value	91.74	94.28	84.06
Proportion of juristic investors			
% of the number of accounts	0.03	0.01	0.02
% of trading value	8.26	5.72	15.94
Market share of trading volume (unit %)	88.92	80.59	87.07

Although the cryptoasset markets in Thailand are regulated by the SEC, the trading rules differ significantly from those of stock markets. Cryptoasset markets operate without regulatory constraints on bid-offer spread limits, minimum tick sizes, or caps on daily price fluctuations. Additionally, cryptoasset exchanges are entirely digital. These features enable rapid adjustments to spreads and prices. The market price is a culmination of the evolution of bid-offer quotes and the timing of order execution. The observable bid-offer quotes represent public information, while executed trades reflect the actions of investors acting on private information, as outlined by Glosten and Milgrom (1985) and Kyle (1985).

Unlike traditional assets, such as stocks and bonds, which are typically confined to specific exchanges due to regulatory and logistical frameworks, cryptoassets are characterized by their ability to be traded across various global exchanges. This unique feature stems from the decentralized nature of cryptoassets and the absence of central authority oversight. The global network of crypto exchanges facilitates diverse trading opportunities and provides a broader scope for price discovery and arbitrage. However, it also introduces complexities in tracking and understanding market dynamics, underscoring the significance of our study in deciphering price dynamics within this multifaceted landscape.

Our study utilizes anonymized, transaction-level data from participants trading cryptoassets on Thailand's largest licensed digital asset exchange, which operates under Thai regulations. Following the Notification of the Securities and Exchange Commission No. GorThor. 26/2562, these exchanges are required to report customers' trading activities to the SEC from November 2020. Thus, our dataset spans from November 2020 to December 2022. While the data for regulatory purposes is updated with the SEC regularly, the authors only had clearance to use data up to 2022. Data management and handling were conducted by authors affiliated with the SEC, adhering strictly to the SEC's data protection protocol.

The dataset encompasses detailed information on buy and sell transactions, including the date and time of trade execution, cryptoasset types, execution prices, trading volume, pseudonymized customer identifiers, and account types. Using limit order book data, we construct 30-minute bid and ask prices for Bitcoin (BTC), Ether (ETH), and Ripple (XRP), the primary cryptoassets in Thailand and globally. In 2024, BTC and ETH are the only cryptoassets the US SEC approved for institutional investors to establish ETFs. Table 2 summarizes the weekly trading volume and account holdings for each cryptoasset over the sample period.

Table 2. Characteristics of accounts trading BTC,
ETH, and XRP in Thailand's largest cryptoasset exchange

	BTC	ETH	XRP
Weekly trading volume (unit: million baht)			
Average	2,807.70	2,110.33	875.21
SD	1,625.20	1,298.18	1,111.64
Min	338.57	200.12	71.17
Max	8,483.33	6,695.16	7,075.35
Number of accounts holding the cryptoasset			
Dec 2020	14,406	5,513	7,539
June 2021	100,326	79,584	57,748
Dec 2021	177,804	137,637	86,247
June 2022	225,577	170,475	94,081

Dec 2022	218,680	164,030	90,747

The bid-offer spreads on the Thai exchange (Figure 1) and Kraken (Figure 2) show several interesting patterns. First, bid-offer spreads on Kraken are substantially narrower, often more than ten times lower, compared to those on the Thai exchange. Second, while spreads on Kraken remain relatively stable throughout the day, the Thai exchange exhibits a pronounced increase in spreads after midnight, peaking around 5 a.m. local time.

Figure 1. Bid-offer percentage spreads on the Thai exchange

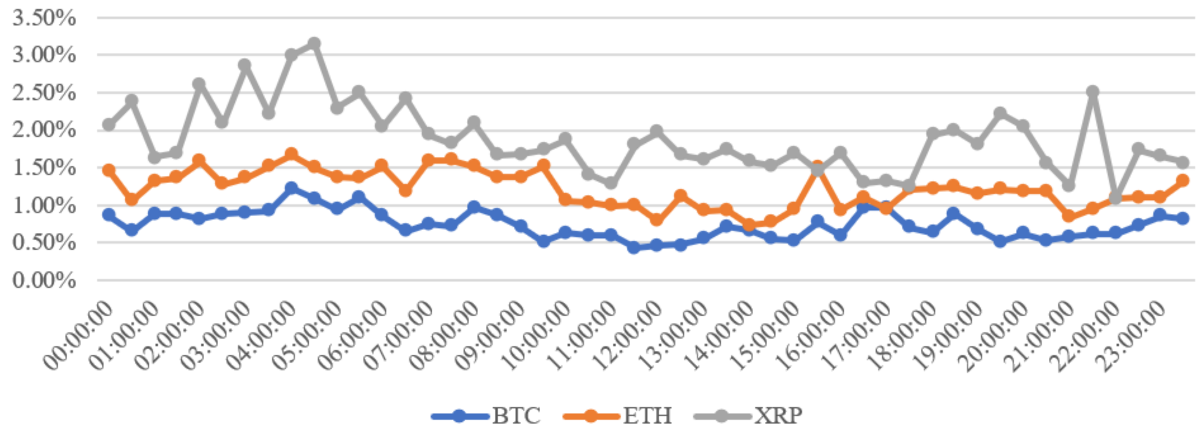
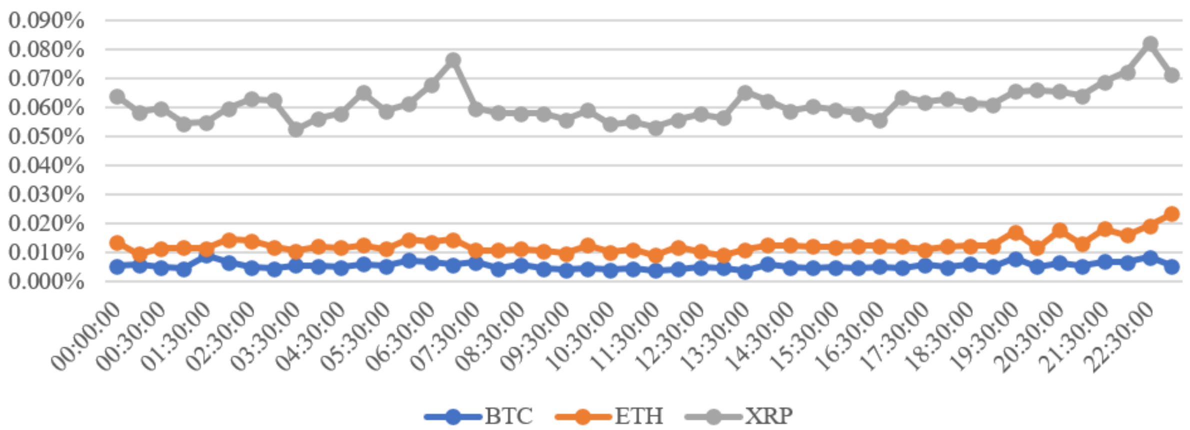


Figure 2. Bid-offer percentage spreads in Kraken



Factors such as inventory costs, transaction costs, and particularly adverse selection costs are known to influence the magnitude of spreads in certain conditions. Previous studies have established that adverse selection costs tend to escalate during new information announcements, overshadowing other costs (Harris, 1986; McInish & Wood, 1990; Foster & Viswanathan, 1993). Additionally, these studies commonly observe a U-shaped pattern in bid-offer spreads throughout the trading day, attributed to heightened trading volume and price volatility during market opening and closing times.

In addition, we regress bid-offer spreads on time dummies, trading volumes within each 30-minute interval, and volatility levels. For volatility, we adopt the measure proposed by Rogers and Satchell (1991), which differs from the traditional standard deviation approach. This method estimates volatility directly using the four observed price points within each short time frame: (1) opening price, (2) lowest price, (3) highest price, and (4) closing price. Unlike standard deviation-based measures, the Rogers-Satchell volatility does not require the specification of a lookback window, making it particularly suitable for high-frequency data. The results, presented in Table 3, show a statistically significant positive relationship between volatility and bid-offer spreads. These findings suggest that higher volatility leads to wider spreads and that volatility may be a key factor in explaining the price discovery process. We will explore this issue further in Sections 4 and 5.

Table 3. Regression results of bid-offer percentage spreads on exchange characteristics

	Bid-offer percentage spreads of BTC	Bid-offer percentage spreads of ETH	Bid-offer percentage spreads of XRP
Ln of trading value	0.00039***	-0.00021***	0.00046***
	(0.00003)	(0.00005)	(0.00007)
Volatility	3.96***	5.91***	1.54***
	(0.151)	(0.146)	(0.076)
Constant term	0.00117**	0.01408***	0.00935***
	(0.00057)	(0.00081)	(0.00117)
R-squared	0.063	0.080	0.049
Time dummies	Yes	Yes	Yes

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4. Price Discovery Analysis and Hypotheses Development

Price discovery refers to the process through which markets assimilate new information and adjust prices accordingly (Hasbrouck, 1995, 2003; Booth et al., 2002; Huang, 2002). Studies of the price discovery process assume that the prices of the same asset should converge to a common equilibrium value. Temporary deviations from this long-term equilibrium can occur due to market frictions, price pressure from trading volume imbalances, transaction costs, and bid-ask spreads. While short-term price deviations typically correct themselves to revert to the implicit long-term equilibrium, the speed of this correction depends on market efficiency and regulatory frameworks.

Price discovery analysis involves identifying the market that most effectively incorporates new information, which in turn influences the pricing of identical assets in other markets. Seminal work in this area (e.g., Hasbrouck, 1995; Gonzalo & Granger, 1995) stipulates the processes governing price movements across various stock exchanges. The principle of no arbitrage suggests that the price of identical assets should be aligned across different trading venues. Thus, the price series across different markets should be co-integrated.

It is important to distinguish between co-integration and correlation. While correlation measures the degree to which two price series move together in the short term, co-integration assesses whether two time series share a common long-term equilibrium relationship. Even if prices diverge temporarily due to short-term stochastic trends, co-integration implies that they will eventually revert to a shared long-term trend. In our context, the co-integration of BTC prices across different exchanges suggests that a common underlying factor, consistent with the economic rationale of arbitrage elimination across markets, drives these price processes.

We use the vector error correction model (VECM) to detect the co-integration relationships between cryptoasset prices. The model is implemented by regressing one return series against the leading and lagging intervals of another. To illustrate the VECM, suppose $P_{A,t}$ is the price of BTC in Market A and $P_{B,t}$ is the price of BTC in Market B, and the two prices are co-integrated by the error correction term η_t. Then, the co-integration equation can be written as:

$$P_{A,t} = \beta_0 + \beta_1 P_{B,t} + \eta_t \tag{1}$$

$$\eta_t = P_{A,t} - \beta_1 P_{B,t} - \beta_0 \tag{2}$$

$P_{A,t}$ and $P_{B,t}$ should be integrated of order 1, denoted I(1). Thus, the price process could be expressed by an autoregressive process, where i can be for market A or B. $\nu_{i,t}$ is the error terms of the relationship.

$$P_{i,t} = \phi_{i0} + \phi_{i1} P_{i,t-1} + \nu_{i,t} \tag{3}$$

With recursive substitution and the co-integration equation, it can be shown that the differenced price series can be written as:

$$\Delta P_{A,t} = \alpha_A \eta_{t-1} + \sum_{k=1}^{p} \gamma_A \Delta P_{A,t-k} + \sum_{k=1}^{p} \delta_A \Delta P_{B,t-k} + \epsilon_{A,t} \tag{4}$$

$$\Delta P_{B,t} = \alpha_B \eta_{t-1} + \sum_{k=1}^{p} \gamma_B \Delta P_{A,t-k} + \sum_{k=1}^{p} \delta_B \Delta P_{B,t-k} + \epsilon_{B,t} \tag{5}$$

η_{t-1} in equations 4 and 5 is the error correction term, and p is the lag. One key aspect of our model is the flexibility in choosing the data frequency, which ranges from seconds to minutes, offering a granular view of price dynamics. The coefficient estimations derived from the VECM can reveal the patterns of price discovery and the interplay between local and global markets.

Hasbrouck (1995) utilized the VECM with two price series, demonstrating that the co-integration relationship consists of a stationary component and a random-walk component. When new fundamental information causes a permanent price adjustment in one market, the co-integrating relationship facilitates the flow of information to other markets, leading to the adjustment of prices for the same asset across different markets to a new efficient price.

Our primary goal is to identify the speed at which prices converge to a long-term equilibrium rather than estimating causal linkages between lagged factors and a dependent variable. Consequently, we did not apply the Granger causality technique. Additionally, using only Vector Autoregressive (VAR) models is not suitable for this analysis because VARs do not include a co-integrating equation. Additionally, VECM incorporates a disequilibrium term that determines the speed of price reversion toward the long-term trend.

We focus on the best bid and offer prices within 30-minute intervals between November 2020 and December 2022. The rationale behind this choice is supported by findings from Cao et al. (2009) and Pascual and Veredas (2010), which suggest that using the midpoint can lead to a loss of critical information, particularly in assessing investors' buying and selling intentions. In granular timeframes, examining separate bid and offer quotes provides valuable insights into price movements, reflecting how investors place their bids and offers.

We chose 30-minute intervals to minimize the influence of microstructure noise in the data. Using shorter intervals would result in too many short-lived price deviations caused by noise rather than accurately reflecting the price formation process. To align the data from the global exchange with the local context, we convert cryptoasset values into the local currency using the prevailing exchange rates for each timeframe. We also performed unit root tests to assess the stationarity of all price series included in the analysis. The results, presented in Table 4, indicate that the price series are integrated of the same order. This finding suggests that the prices of the same cryptoasset traded across different markets may share a common long-run equilibrium relationship, which we further investigate using VECM.

Table 4. Unit root tests of bids and offers for BTC, ETH, and XRP in the analysis

Variables	Levels (intercept without trends)		1st Differences (intercept without trends)		Order of integration
	ADF t-stat	P-value	ADF t-stat	P-value	
Local exchange					
BTC bid	-2.067	0.2580	-235.288	0.0000	I(1)
BTC offer	-2.026	0.2753	-238.258	0.0000	I(1)
ETH bid	-2.413	0.1382	-243.024	0.0000	I(1)
ETH offer	-2.429	0.1337	-251.039	0.0000	I(1)
XRP bid	-2.179	0.2141	-246.069	0.0000	I(1)
XRP offer	-2.254	0.1872	-272.568	0.0000	I(1)
Kraken exchange					
BTC bid	-1.527	0.5203	-196.363	0.0000	I(1)
BTC offer	-1.539	0.5142	-211.323	0.0000	I(1)
ETH bid	-1.891	0.3362	-211.277	0.0000	I(1)
ETH offer	-1.901	0.3317	-304.462	0.0000	I(1)
XRP bid	-2.374	0.1492	-198.629	0.0000	I(1)
XRP offer	-2.393	0.1436	-271.985	0.0000	I(1)

Note: All the variables have the Dickey-Fuller critical values equal to -3.430 for 1%, -2.860 for 5%, and -2.570 for 10%.

Our analysis of VECM includes three lagged periods because, at this number of lags, the information criterion is minimized. The coefficients derived from these leads and lags for the entire study period, along with the error correction terms, are presented in Table 5.

When the price differences in the local exchange are the dependent variable, the result suggests that global exchange prices (across all three analyzed cryptoassets) significantly precede local exchange prices by 1 to 2 lags. This delay indicates the time for local exchange prices to align with new global price levels. Our VECM estimation results are consistent with the expectation that Thai exchange prices follow global market trends.

In contrast, the coefficients associated with most lags of price differences in the local exchange are statistically insignificant when the global exchange's price differences are used as the dependent variable. Although a few lagged price differences from both the local and global exchanges show statistical significance, their economic impact is negligible. This finding suggests that price information from the local exchange does not contribute meaningfully to global price discovery. It supports the view that retail investors in the Thai market primarily engage in reactive trading behavior, mirroring global market movements rather than generating new information. Consequently, there is no evidence of information flow from the local exchange to the global market.

For both local and global exchanges, the negative coefficients of past returns on the same exchange suggest that there is a short-term reversal in the market.

Table 5. VECM estimations between the Thai exchange and Kraken

Panel A: Bitcoin (BTC)

	Constant term	Co-integration term	Price differences in the Thai exchange			Price differences in Kraken		
		First lag	First lag	Second lag	Third lag	First lag	Second lag	Third lag
BTC bid quote								
Dependent variable: price differences in the Thai exchange								
Coefficient	-0.0482	-0.0333***	-0.5328***	-0.2880***	-0.0743***	0.6775***	0.5797***	0.2940***
Standard errors	34.9104	0.0017	0.0051	0.0051	0.0038	0.0050	0.0060	0.0063
Dependent variable: price difference in Kraken								
Coefficient	0.2930	-0.0055***	-0.0017	-0.0048	-0.0109***	-0.0272***	-0.0167	0.0020
Standard errors	38.7371	0.0019	0.0057	0.0056	0.0042	0.0056	0.0067	0.0070
Co-integrating equations								
	Constant term	Price in the Thai exchange	Price in Kraken					
Coefficient	19,785.34	1.0000	-1.0252***					
Standard errors			0.0024					
BTC offer quote								
Dependent variable: price differences in the Thai exchange								
Coefficient	-0.0573	-0.0317***	-0.5324***	-0.2950***	-0.0715***	0.6655***	0.5426***	0.2842***
Standard errors	34.4686	0.0016	0.0051	0.0051	0.0038	0.0049	0.0059	0.0061
Dependent variable: price difference in Kraken								
Coefficient	0.4003	-0.0045**	-0.0192***	-0.0068	-0.0002	-0.0408***	0.0010	0.0069

Standard errors	39.0102	0.0018	0.0058	0.0058	0.0043	0.0056	0.0067	0.0070
Co-integrating equations								
	Constant term	Price in the Thai exchange	Price in Kraken					
Coefficient	21,306.45	1.00	- 1.0300***					
Standard errors			0.0025					

Note: *** p<0.01, ** p<0.05, * p<0.1.

Panel B: Ether (ETH)

	Constant term	Co-integration term	Price differences in the Thai exchange			Price differences in Kraken		
		First lag	First lag	Second lag	Third lag	First lag	Second lag	Third lag
ETH bid quote								
Dependent variable: price differences in the Thai exchange								
Coefficient	-0.0011	-0.0881***	-0.3763***	-0.1701***	-0.0497***	0.3746***	0.3349***	0.1467***
Standard errors	3.3930	0.0025	0.0053	0.0052	0.0045	0.0052	0.0056	0.0054
Dependent variable: price difference in Kraken								
Coefficient	0.8569	-0.0001	0.0168***	0.0087	-0.0057	-0.2306***	-0.0605***	-0.0218***
Standard errors	3.8519	0.0029	0.0060	0.0059	0.0051	0.0059	0.0064	0.0061
Co-integrating equations								
	Constant term	Price in the Thai exchange	Price in Kraken					
Coefficient	703.15	1.00	-1.0169***					
Standard errors			0.0011					
ETH offer quote								
Dependent variable: price differences in the Thai exchange								
Coefficient	-0.0191	-0.0740***	-0.4195***	-0.1990***	-0.0690***	0.5378***	0.3645***	0.1678***

Standard errors	3.3045	0.0023	0.0052	0.0053	0.0043	0.0062	0.0068	0.0068
Dependent variable: price difference in Kraken								
Coefficient	0.6827	-0.0021	-0.0062	0.0037	-0.0130***	-0.0187***	-0.0039	-0.0001
Standard errors	3.0185	0.0021	0.0048	0.0048	0.0040	0.0057	0.0062	0.0063
Co-integrating equations								
	Constant term	Price in the Thai exchange	Price in Kraken					
Coefficient	618.90	1.00	-1.0209***					
Standard errors			0.0013					

Note: *** p<0.01, ** p<0.05, * p<0.1.

Panel C: Ripple (XRP)

	Constant term	Co-integration term	Price differences in the Thai exchange			Price differences in Kraken		
		First lag	First lag	Second lag	Third lag	First lag	Second lag	Third lag
XRP bid quote								
Dependent variable: price differences in the Thai exchange								
Coefficient	0.0000	-0.0855***	-0.4885***	-0.2349***	-0.0768***	0.6422***	0.5206***	0.2326***
Standard errors	0.0014	0.0027	0.0053	0.0052	0.0039	0.0059	0.0067	0.0068
Dependent variable: price difference in Kraken								
Coefficient	-0.0001	-0.0085***	-0.0002	-0.0097*	-0.0208***	-0.0451***	-0.0393***	-0.0051
Standard errors	0.0014	0.0027	0.0053	0.0052	0.0039	0.0060	0.0067	0.0069
Co-integrating equations								
	Constant term	Price in the Thai exchange	Price in Kraken					

Coefficient	0.45	1.00	-1.0282***					
Standard errors			0.0015					
XRP offer quote								
Dependent variable: price differences in the Thai exchange								
Coefficient	0.0000	-0.1111***	-0.5089***	-0.2716***	-0.0955***	0.5511***	0.4972***	0.2704***
Standard errors	0.0018	0.0032	0.0054	0.0054	0.0043	0.0074	0.0079	0.0080
Dependent variable: price difference in Kraken								
Coefficient	-0.0001	-0.0050**	-0.0044	-0.0109***	-0.0018	-0.0434***	-0.0351***	-0.0038
Standard errors	0.0014	0.0025	0.0042	0.0042	0.0034	0.0058	0.0062	0.0063
Co-integrating equations								
	Constant term	Price in the Thai exchange	Price in Kraken					
Coefficient	0.4433	1.00	-1.0358***					
Standard errors			0.0015					

Note: *** p<0.01, ** p<0.05, * p<0.1.

The estimated coefficients shown in Table 5 can be used to formulate the price impulse response function. This function quantifies the rate at which local exchange prices respond to price impulses from the global exchange.

To support our interpretation of the coefficients presented in Table 5, Figures 3 through 5 illustrate the bid-offer price responses to one-standard-deviation innovations in the system's residuals. These impulse response functions are derived from the VECM estimations reported in Table 5, using the full sample period from November 22, 2020, to December 24, 2022. The figures provide a visual representation of how bid and offer prices adjust over time in response to shocks, offering further insight into the dynamics of price discovery across exchanges.

The left panels of Figures 3 to 5 display the price responses in the local market following a price impulse in the global market, while the right panels illustrate the reverse scenario. On average, bid-offer quotes on the local exchange take approximately 1 to 1.5 hours to adjust to new global price levels. Among the assets analyzed, BTC exhibits the fastest response, likely due to its higher trading volume and liquidity. In contrast, price impulses originating in the Thai exchange do not elicit any significant response in global market prices. This asymmetry suggests that trading activity on the Thai exchange does not convey new information that can influence the fundamental value of cryptoassets in the global market.

Figure 3. Bitcoin (BTC) price response in the Thai exchange (left)
and in Kraken (right) from a one standard deviation price impulse

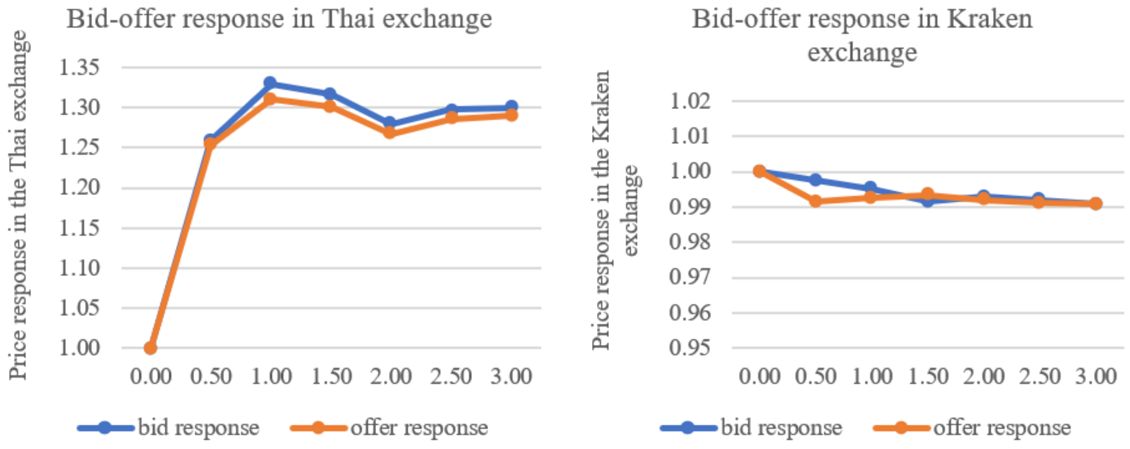


Figure 4. Ether (ETH) price response in the Thai exchange (left)
and in Kraken (right) from a one standard deviation price impulse

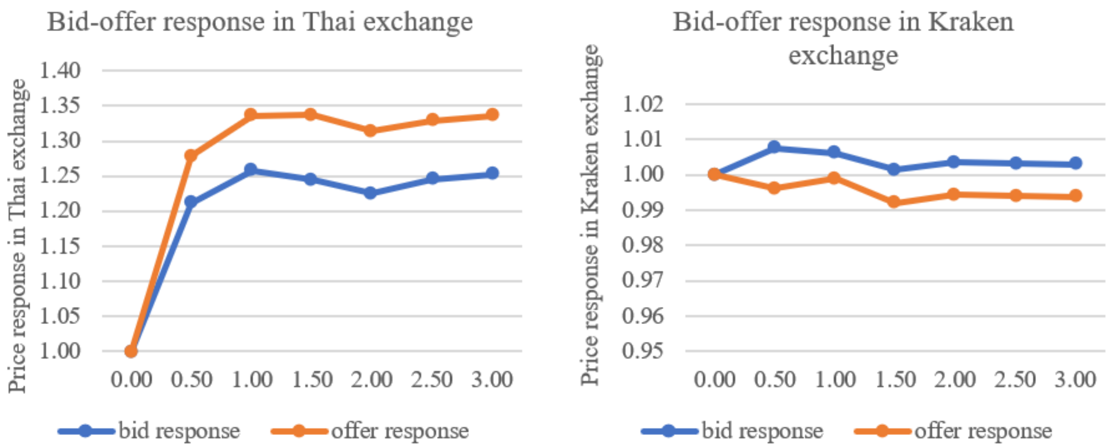
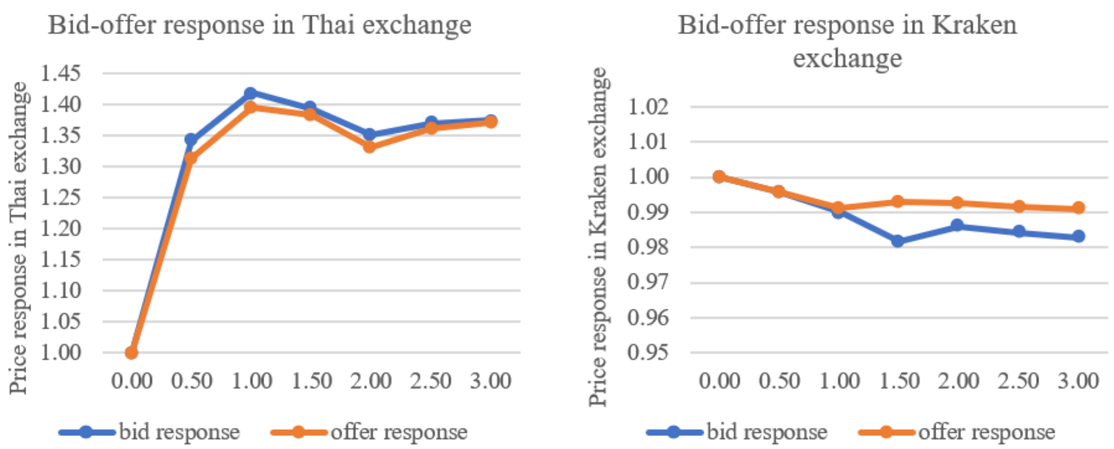


Figure 5. Ripple (XRP) price response in the Thai exchange (left)
and in Kraken (right) from a one standard deviation price impulse



To aid in interpreting price impulses, we define 'relative quote value' (RQV) as follows:

$$Relative\ Quote\ Value_t = \frac{Quote\ in\ the\ Local\ Exchange_t}{Price\ Impulse\ Level\ in\ the\ Global\ Exchange_0} \tag{6}$$

Our analysis of bid-offer responses is predicated on market reactions to global price changes, independent of whether local exchange investors possess superior information. The dynamics of bids and offers following global market movements do not necessarily reflect differential information among market participants. Thus, if the bid and offer quotes do not promptly adjust to global price levels, and RQV exhibits significant variation between portfolios with positive and negative returns, it would imply that investors in the local exchange behave differently in different market conditions.

In an efficient market, RQV should adjust immediately, reaching 100% in response to the shock. However, if the adjustment occurs gradually, it indicates a delayed price response, suggesting the presence of inefficiencies in the local exchange.

One potential source of inefficiency in the local exchange may stem from investor behavioral biases. A common bias is inertia, where investors are slow to adjust their bid and offer prices even in the presence of new information that alters the fundamental value of financial assets. This behavior can be explained by cognitive dissonance, as described by Festinger (1957), where individuals give disproportionate weight to their prior beliefs and selectively attend to information that aligns with their existing views while discounting or ignoring new, conflicting information.

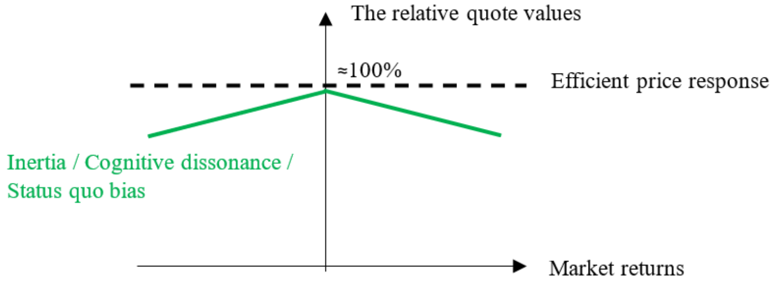
A growing body of literature suggests that cognitive dissonance among investors can significantly influence asset prices. For instance, Antoniou et al. (2013) argued that negative news tends to diffuse more slowly in markets with positive sentiment, as investors are reluctant to adjust their expectations. Similarly, Argentesi et al. (2010) found that investors often disregard information that contradicts their existing beliefs, which affects trading behavior during corporate financial announcements. Bernard and Thomas (1989) also provided evidence that equity prices respond sluggishly to earnings announcements, further supporting the notion that psychological biases can delay the incorporation of new information into asset prices.

The tendency of investors to persist with their existing decisions is closely linked to status quo bias, which stems from a general reluctance to embrace change. This bias reflects a perception that change entails costs, both psychological and financial, and that potential benefits must significantly outweigh these costs before action is taken. Numerous studies have suggested that deviations from the status quo can heighten feelings of regret, particularly when losses result from new actions rather than from inaction. In such cases, investors may experience greater regret from losses incurred through change than from equivalent losses resulting from maintaining their current position (Kahneman, 2003; Gilovich & Medvec, 1994; Boninger et al., 1994). This psychological tendency helps explain why investors often hold onto familiar investments for extended periods, even when those investments consistently underperform.

Due to behavioral biases such as inertia and status quo bias, investors may be hesitant to adjust their bid and offer prices in response to large swings in global prices. This reluctance can result in a delayed price response, as observed through the VECM estimation. Specifically, when market returns are high (both positive and negative), RQV is expected to be lower, indicating slower adjustment.

This hypothesis is visually represented in Figure 6. The figure illustrates an asymmetric relationship: When returns are negative, we expect a positive correlation between market returns and RQV, as investors gradually adjust their quotes downward when prices decline significantly. Conversely, when returns are positive, a negative correlation is expected, reflecting a slower upward adjustment in quotes. This pattern highlights the role of behavioral frictions in determining the speed and direction of price discovery on the local exchange.

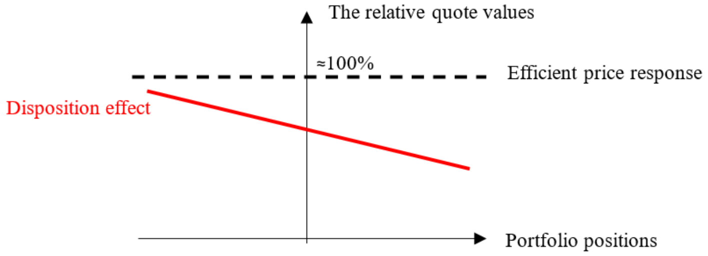
Figure 6. Illustration of the relationship between the relative quote values and market returns according to the proposed hypothesis related to the inertia, cognitive dissonance, and status quo bias



Another prominent behavioral bias observed among investors is explained by prospect theory, which challenges the assumptions of rational decision-making outlined in the Von Neumann-Morgenstern utility framework. Prospect theory posits that individuals exhibit concave utility functions for gains and convex utility functions for losses, leading to risk-averse behavior in the domain of gains and risk-seeking behavior in the domain of losses. Kahneman and Tversky (1979) encapsulate this phenomenon, stating, "…a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise" (p. 287). This insight suggests that investors may become more aggressive in their trading behavior during periods of significant portfolio losses, as they seek to recover losses, compared to periods of gains when they are more likely to preserve their positions.

Furthermore, prospect theory underpins the disposition effect, where investors are inclined to sell profitable assets while hesitating to realize losses (Shefrin & Statman, 1985; Odean, 1998). In this context, when investors are in profits, the bid-offer setting is likely to lag behind global price movements. Specifically, on the bid side, investors may exhibit reluctance to place bids at newly elevated prices due to increased risk aversion when in profit. Conversely, on the offer side, they might set lower offers relative to global prices to increase the tendency to take profits. Hence, RQV during a portfolio's gain is expected to be lower compared to the situation when most investors are in losing positions. This is visually represented in Figure 7, where a negative correlation is anticipated between RQV and the proportion of investors in profits.

Figure 7. Illustration of the relationship between the relative quote values (RQV) and portfolio positions according to the proposed hypothesis related to the disposition effect



In this study, our analysis of bid-offer responses focuses exclusively on how the local market reacts to global price movements, without assuming that investors on the local exchange possess superior information. The observed dynamics of bids and offers in response to global market changes are not necessarily indicative of informational asymmetries among participants. Therefore, if bid and offer quotes fail to adjust promptly to global price levels, and if the relative quote value varies significantly between portfolios with positive and negative returns, this would suggest the influence of behavioral biases. A detailed examination of these findings is presented in Section 5.

5. Results and Discussion

To test the differences in bid-offer responses under different market conditions, we conduct the VECM analysis on a weekly basis, starting each Sunday. For each week, there are 336 observations of the 30-minute bid-offer prices. This results in 109 distinct estimations for each cryptoasset over 109 weeks, encompassing the period from November 22, 2020, to December 24, 2022.

After obtaining the VECM estimations for each week, we calculate the RQV from price responses to one-standard-deviation shocks across five time intervals (30 minutes, 1 hour, 1.5 hours, 2 hours, and 2.5 hours) and compare them to market conditions and investors' portfolio positions.

Summary statistics are presented in Table 6. At the 30-minute mark, RQV ranges between 93% and 101%, increasing to 95% and 102% after one hour, and stabilizing thereafter. Among the assets analyzed, BTC demonstrates the fastest adjustment to global price movements, likely due to its high trading volume and broad investor participation. In contrast, XRP exhibits the slowest and most variable price response, which may be attributed to its relatively low number of trading accounts and transaction volume, as previously shown in Table 2.

Table 6. Relative quote values (RQV) from a one standard deviation shock in the system

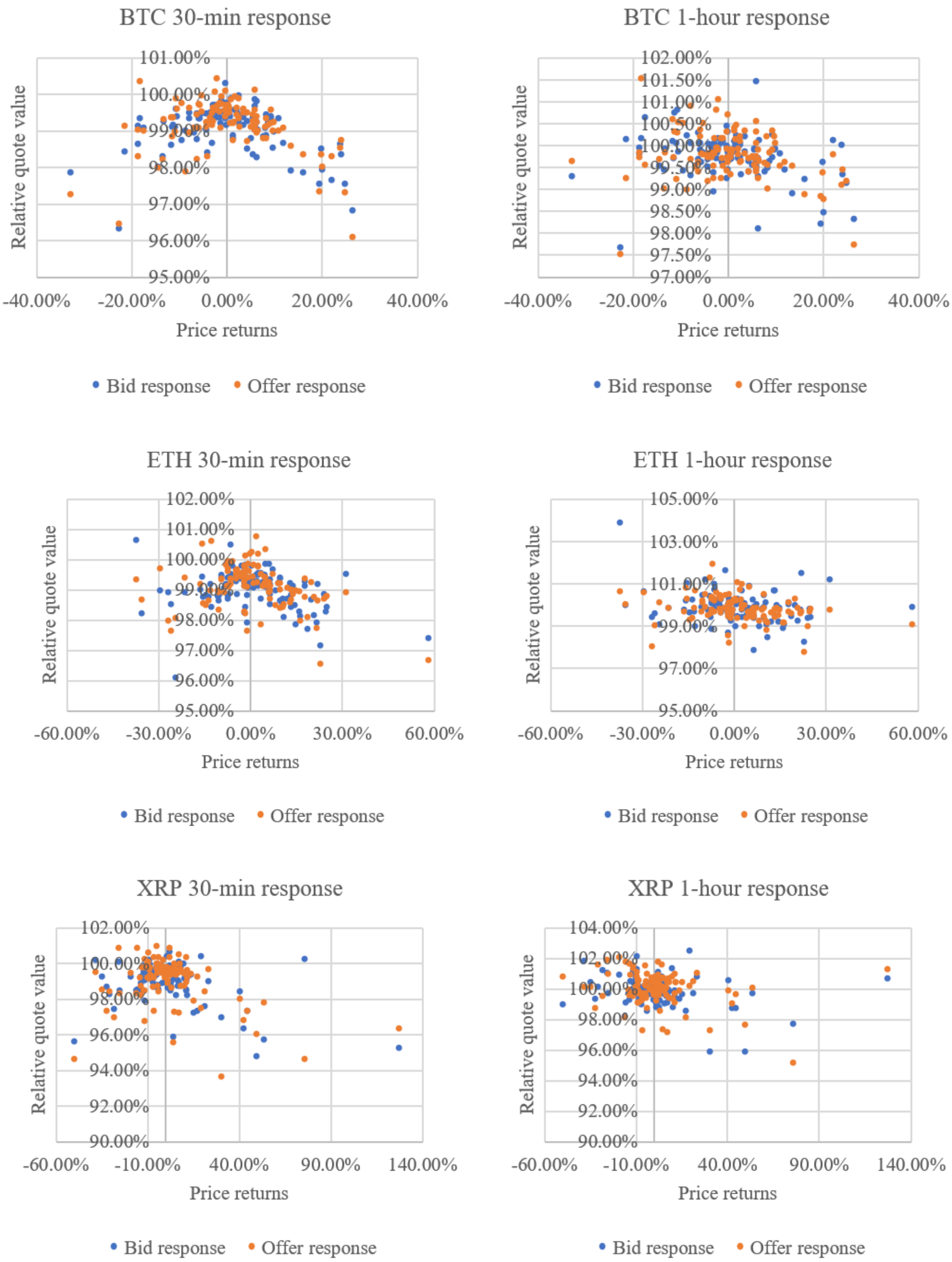
	Relative quote value at different timeframes				
	30-minute	1-hour	1.5-hour	2-hour	2.5-hour
BTC-bid					
Mean	99.06%	99.72%	99.65%	99.48%	99.58%
SD	0.65%	0.51%	0.58%	0.59%	0.63%
Min	96.30%	97.65%	97.62%	97.21%	97.46%
Max	100.28%	101.44%	101.46%	100.97%	101.27%
BTC-offer					
Mean	99.14%	99.76%	99.73%	99.59%	99.73%
SD	0.71%	0.56%	0.60%	0.63%	0.67%
Min	96.09%	97.52%	97.46%	97.11%	97.35%
Max	100.41%	101.51%	101.46%	101.06%	101.67%
ETH-bid					
Mean	98.99%	99.83%	99.73%	99.51%	99.66%
SD	0.64%	0.72%	0.77%	0.93%	0.96%
Min	96.07%	97.82%	96.99%	97.28%	97.92%
Max	100.59%	103.85%	102.84%	105.20%	105.53%
ETH-offer					
Mean	99.08%	99.78%	99.85%	99.65%	99.83%

SD	0.71%	0.61%	0.78%	0.75%	0.74%
Min	96.54%	97.70%	97.53%	97.45%	97.84%
Max	100.73%	101.90%	102.21%	101.75%	101.89%
XRP-bid					
Mean	98.92%	99.74%	99.54%	99.25%	99.44%
SD	1.07%	0.93%	0.94%	1.11%	1.23%
Min	94.70%	95.79%	96.17%	95.62%	95.08%
Max	100.59%	102.48%	103.31%	103.49%	103.55%
XRP-offer					
Mean	98.97%	99.92%	99.93%	99.65%	99.88%
SD	1.30%	1.07%	1.35%	1.07%	1.14%
Min	93.61%	95.09%	95.58%	96.56%	96.72%
Max	100.91%	101.99%	108.42%	102.44%	103.64%

Over longer time horizons, the RQV of all cryptoassets tends to converge toward global price levels. The remaining discrepancies are largely attributable to the wide bid-ask spreads previously discussed in Figure 1 and Table 3. Notably, the approximately one-hour lag in local price adjustment may be explained by the absence of market makers in the local exchange. Unlike more mature financial markets, cryptoasset exchanges, particularly in emerging markets like Thailand, often lack dedicated market makers, especially during their early stages of development. At the time of this study, regulatory frameworks for cryptoasset trading were still evolving under the supervision of the Thai SEC. As a result, most bid and offer quotes were submitted by retail investors, whose trading behavior tends to be slower and less responsive to global price changes. The elevated bid-offer spread at 5 a.m. in Figure 1 is consistent with reduced local liquidity during off-peak Thai hours.

To examine the variation in bid-offer responses during market upturns and downturns, Figure 8 plots relative quote values at the 30-minute and 1-hour intervals against cryptoasset returns. Across all three cryptoassets, a clear asymmetry is observed: RQV exhibit a strong negative correlation with returns during market upturns and a strong positive correlation during downturns. Notably, this pattern persists even at the 1-hour timeframe, suggesting that investor behavior and market friction continue to influence price adjustments well beyond the immediate response window.

Figure 8. Bid-offer responses and market conditions



We further ascertain this relationship between RQV and cryptoasset returns by controlling for trading value and price volatilities in a regression framework. We also test the relationship between cryptoasset weekly returns and RQV by adding an interaction term between the weekly return and a dummy variable indicating return sign. The empirical results in Table 7 indicate a positive correlation when returns are negative and a negative correlation when returns are positive. For BTC and ETH, these correlations are statistically significant at the 1% level. However, the results for XRP are not statistically significant, which may be due to its relatively low trading volume and the frequent absence of trades during certain 30-minute intervals.

Table 7. Regression results of relative quote values (RQV) on cryptoasset returns

	Relative quote value at 30-minute timeframe		Relative quote value at 1-hour timeframe	
VARIABLES	BTC bid	BTC offer	BTC bid	BTC offer
Constant	1.002***	1.009***	0.964***	0.971***
	(0.016)	(0.018)	(0.017)	(0.018)
BTC weekly returns	0.057***	0.052***	0.018**	0.015
	(0.008)	(0.009)	(0.009)	(0.009)
BTC weekly returns x dummy of positive returns	-0.130***	-0.124***	-0.059***	-0.057***
	(0.014)	(0.016)	(0.015)	(0.016)
Ln of BTC trading value	0.000	-0.001	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
BTC weekly volatility	-0.015	-0.064*	0.019	-0.084**
	(0.028)	(0.032)	(0.030)	(0.032)
R-squared	0.571	0.527	0.191	0.242
VARIABLES	ETH bid	ETH offer	ETH bid	ETH offer
Constant	0.978***	1.032***	0.971***	1.027***
	(0.019)	(0.018)	(0.022)	(0.019)
ETH weekly returns	0.021**	0.014	-0.01	-0.002
	(0.009)	(0.009)	(0.011)	(0.009)
ETH weekly returns x dummy of positive returns	-0.057***	-0.054***	0.001	-0.015
	(0.014)	(0.014)	(0.016)	(0.014)
Ln of ETH trading value	0.001	-0.002**	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)

ETH weekly volatility	-0.009	-0.044	0.088***	0.014
	(0.029)	(0.028)	(0.033)	(0.029)
R-squared	0.234	0.377	0.172	0.109
VARIABLES	XRP bid	XRP offer	XRP bid	XRP offer
Constant	0.963***	1.012***	0.937***	1.01***
	(0.021)	(0.025)	(0.022)	(0.025)
XRP weekly returns	-0.001	0.017	-0.003	0.008
	(0.011)	(0.013)	(0.012)	(0.013)
XRP weekly returns x dummy of positive returns	-0.022	-0.045**	-0.016	-0.033*
	(0.015)	(0.018)	(0.016)	(0.018)
Ln of XRP trading value	0.002	-0.001	0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
XRP weekly volatility	-0.093***	-0.076***	0.010	0.075***
	(0.021)	(0.026)	(0.022)	(0.026)
R-squared	0.434	0.432	0.162	0.142

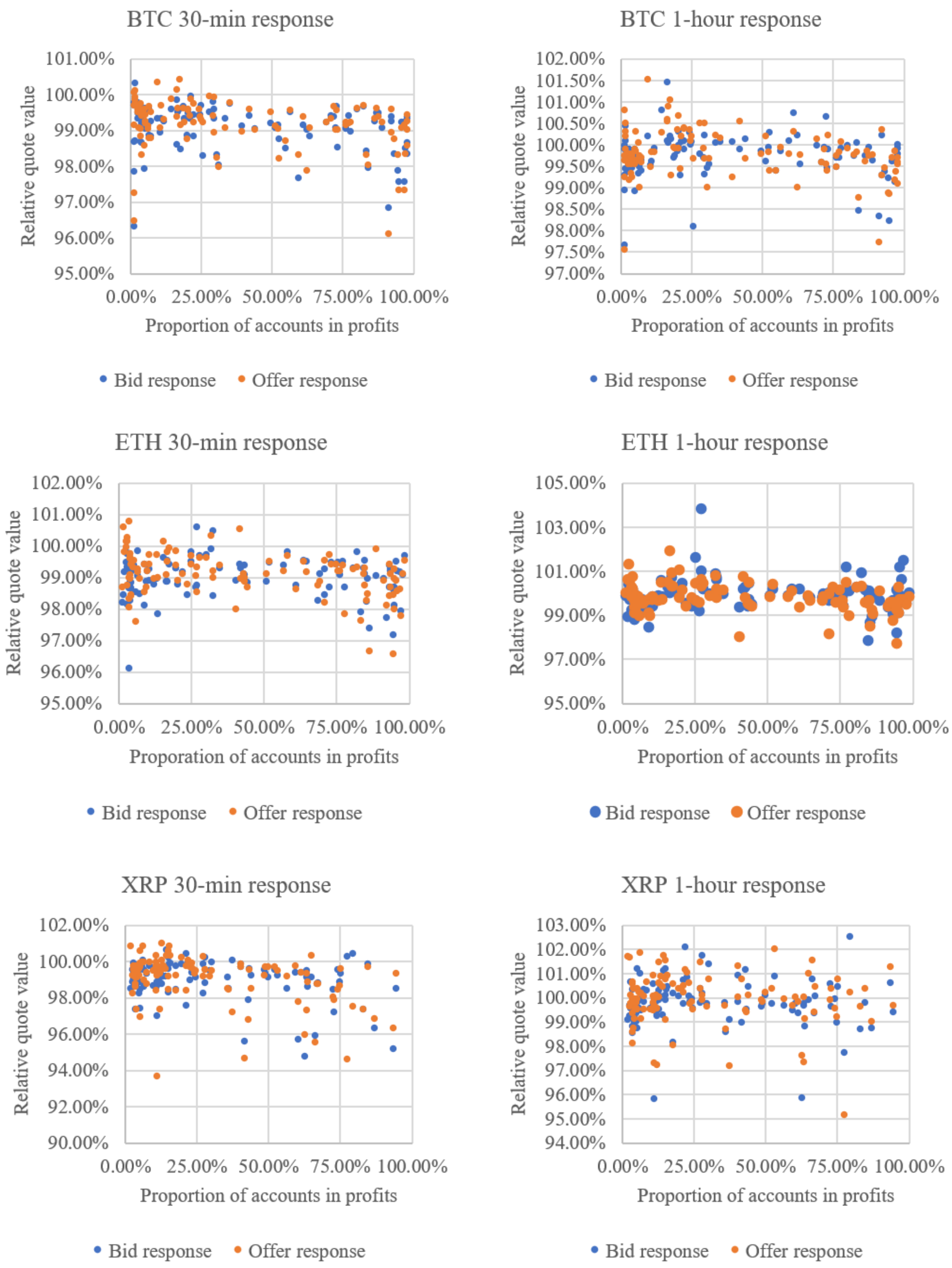
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The results presented in Table 7 support the hypothesis that retail investors on the Thai local cryptoasset exchange exhibit a high degree of inertia and status quo bias. These investors tend to maintain their initial bids and offers, showing reluctance to adjust their orders in response to significant market movements. When examining the absolute value of the slope, it appears slightly steeper when returns are positive compared to when they are negative. This provides some evidence of the disposition effect, where investors are more inclined to realize gains during upward market movements. However, this behavior diminishes over a 1-hour timeframe, suggesting that investors on the local exchange require time to process new information before modifying their orders.

In addition to investigating the relationship between the rate of price convergence and market conditions, we also analyze how prices in the local exchange move when individual investors' portfolios are in profits and losses. The regulatory data we received from the SEC includes gains and losses on individual investors' positions. Thus, we can compute the proportion of accounts with gains in each week as a proxy for investors' portfolio positions.

We report the results in Figure 9 and Table 8. We find negative relationships between relative quote values and the proportion of accounts with gains. Our findings indicate that local bids and offers converge with the global prices slightly quicker when most investors are in loss positions. This evidence suggests that retail investors might exhibit loss aversion when their positions are at a loss, as they aggressively adjust their bids and offers to follow the market downturn. Conversely, their slower response when in profit suggests a higher risk aversion, with a preference to realize gains by undercutting global prices during market upturns. This pattern also persists in the 1-hour interval following a price impulse.

Figure 9. Bid-offer responses and proportion of accounts with gains



To better illustrate the results, Table 8 presents the statistical test comparing the means of RQV across different groups based on the proportion of accounts in profit. The data is divided into four groups: 0–25%, 25–50%, 50–75%, and 75–100% of accounts in profit. A Tukey HSD (Honestly Significant Difference) test is conducted to compare group means. The results show that the difference in RQV between the 0–25% and 75–100% groups is statistically significant at the 5% level in most cases. However, the economic magnitude of this difference is relatively small, at approximately 0.5%.

Table 8. Mean differences analysis among different groups of the proportion of accounts in profits by using Tukey HSD mean comparison

BTC bid movement – 30 min. response					
		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Mean value of relative quote value		0.992	0.9914	0.9897	0.9878

Mean differences of relative quote value		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Proportion of accounts in profits	0-25%	0			
	25-50%	0.0006 (0.0019)	0		
	50-75%	0.00232 (0.00185)	0.00172 (0.00235)	0	
	75-100%	0.00426** (0.00151)	0.00366 (0.0021)	0.00193 (0.00205)	0

BTC offer movement – 30 min. response					
		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Mean value of relative quote value		0.9934	0.9918	0.9898	0.9879

Mean differences of relative quote value		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Proportion of accounts in profits	0-25%	0			
	25-50%	0.00158 (0.00205)	0		
	50-75%	0.00354 (0.00199)	0.00196 (0.00254)	0	
	75-100%	0.00542***	0.00383	0.00188	0

		(0.00163)	(0.00226)	(0.00221)	

ETH bid movement – 30 min. response				
	Proportion of accounts in profits			
	0-25%	25-50%	50-75%	75-100%
Mean value of relative quote value	0.9892	0.9935	0.9912	0.9882

Mean differences of relative quote value		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Proportion of accounts in profits	0-25%	0			
	25-50%	-0.00433* (0.00174)	0		
	50-75%	-0.00196 (0.00191)	0.00237 (0.00223)	0	
	75-100%	0.00101 (0.00145)	0.00534** (0.00186)	0.00298 (0.00202)	0

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

ETH offer movement – 30 min. response				
	Proportion of accounts in profits			
	0-25%	25-50%	50-75%	75-100%
Mean value of relative quote value	0.9929	0.9921	0.9917	0.9864

Mean differences of relative quote value		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Proportion of accounts in profits	0-25%	0			
	25-50%	0.00073 (0.00185)	0		
	50-75%	0.00117 (0.00203)	0.00044 (0.00237)	0	
	75-100%	0.00649*** (0.00154)	0.00576** (0.00197)	0.00532* (0.00214)	0

XRP bid movement – 30 min. response	
	Proportion of accounts in profits

	0-25%	25-50%	50-75%	75-100%
Mean value of relative quote value	0.9912	0.9907	0.9833	0.9836

Mean differences of relative quote value		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Proportion of accounts in profits	0-25%	0			
	25-50%	0.00054 (0.00284)	0		
	50-75%	0.00789** (0.00272)	0.00734 (0.00348)	0	
	75-100%	0.00761 (0.0039)	0.00706 (0.00446)	-0.00028 (0.00439)	0
XRP offer movement – 30 min. response					

	Proportion of accounts in profits			
	0-25%	25-50%	50-75%	75-100%
Mean value of relative quote value	0.9933	0.9873	0.9852	0.9761

Mean differences of relative quote value		Proportion of accounts in profits			
		0-25%	25-50%	50-75%	75-100%
Proportion of accounts in profits	0-25%	0			
	25-50%	0.006 (0.00332)	0		
	50-75%	0.00813* (0.00318)	0.00213 (0.00407)	0	
	75-100%	0.01723*** (0.00457)	0.01123 (0.00523)	0.0091 (0.00514)	0

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Due to the weak evidence of a negative correlation between RQV and the proportion of accounts in profit, the regression results presented in Table 9 show that most coefficients for the dummy variables representing the proportion of accounts in profit are not statistically different from zero. In the few models where statistically significant effects are observed, the economic impact remains minimal, with effect sizes ranging from approximately 0.3% to 0.5%.

Table 9. Regression results of relative quote values (RQV) on proportion of accounts with gains

	Relative quote value at 30-minute timeframe		Relative quote value at 1-hour timeframe	
VARIABLES	BTC bid	BTC offer	BTC bid	BTC offer
Constant	1.048***	1.035***	0.977***	0.957***
	(0.027)	(0.028)	(0.022)	(0.023)
% account BTC in profits				
0–25% proportion	0.002	0.004**	0.003*	0.005*
	(0.002)	(0.002)	(0.001)	(0.001)
25–50% proportion	0.003*	0.003*	0.002	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
50–75% proportion	0.003	0.003	0.004**	0.003***
	(0.002)	(0.002)	(0.002)	(0.002)
Ln of BTC trading value	-0.003**	-0.002	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
BTC weekly volatility	-0.062	-0.119***	-0.007	-0.118***
	(0.039)	(0.041)	(0.033)	(0.034)
R-squared	0.187	0.25	0.063	0.188
VARIABLES	ETH bid	ETH offer	ETH bid	ETH offer
Constant	1.003***	1.030***	0.996***	1.021***
	(0.022)	(0.022)	(0.023)	(0.021)
% account ETH in profits				
0–25% proportion	0.001	0.005***	-0.001	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)
25–50% proportion	0.006***	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
50–75% proportion	0.003	0.005**	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Ln of ETH trading value	-0.001	-0.002*	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ETH weekly volatility	-0.044	-0.079***	0.105***	0.006
	(0.027)	(0.027)	(0.029)	(0.026)
R-squared	0.122	0.29	0.224	0.124
VARIABLES	XRP bid	XRP offer	XRP bid	XRP offer

Constant	0.935***	0.970***	0.888***	0.974***
	(0.031)	(0.038)	(0.032)	(0.038)
% account XRP in profits				
0–25% proportion	0.003	0.009*	0.009***	0.010**
	(0.004)	(0.005)	(0.004)	(0.005)
25–50% proportion	0.002	0.005	0.007	0.007
	(0.004)	(0.005)	(0.004)	(0.005)
50–75% proportion	-0.005	0.004	0.000	0.006
	(0.004)	(0.005)	(0.004)	(0.005)
Ln of XRP trading value	0.003*	0.001	0.005***	0.001
	(0.001)	(0.002)	(0.002)	(0.002)
XRP weekly volatility	-0.123***	-0.121***	-0.014	0.043*
	(0.019)	(0.023)	(0.019)	(0.022)
R-squared	0.384	0.376	0.131	0.076

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The 75–100% proportion of accounts in profit is the reference group.

To assess the robustness of the relationship between RQV and market returns, additional regressions were conducted to examine whether weekly return variables might be confounded by the proportion of accounts in profit. Table 10 shows that the coefficients on weekly returns are positive and highly significant for both bids and offers. The interaction terms for positive returns are also large and negative, indicating a slower adjustment of bid and offer quotes when prices rise. Similar to Table 9, the profit-proportion dummies are small and mostly insignificant. Taken together, these results suggest that investors tend to maintain their original orders or place new orders anchored to previous price levels, rather than promptly adjusting to new market prices.

Table 10. Regression results of relative quote values (RQV) on returns and proportion of accounts in profit

	Relative quote value at 30-minute timeframe		Relative quote value at 1-hour timeframe	
VARIABLES	BTC bid	BTC offer	BTC bid	BTC offer
Constant	0.996***	0.985***	0.955***	0.935***
	(0.020)	(0.023)	(0.022)	(0.022)

BTC weekly returns	0.058***	0.056***	0.020**	0.021**
	(0.009)	(0.010)	(0.009)	(0.009)
BTC weekly returns x dummy of positive returns	-0.130***	-0.124***	-0.058***	-0.057***
	(0.014)	(0.016)	(0.015)	(0.015)
% account BTC in profits				
0–25% proportion	0.001	0.003*	0.001	0.004***
	(0.001)	(0.002)	(0.001)	(0.002)
25–50% proportion	0.001	0.001	0.000	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
50–75% proportion	0.001	0.001	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.002)
Ln of BTC trading value	0.000	0.000	0.002**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
BTC weekly volatility	-0.018	-0.076**	0.009	-0.101***
	(0.029)	(0.033)	(0.031)	(0.032)
R-squared	0.573	0.542	0.216	0.301
VARIABLES	ETH bid	ETH offer	ETH bid	ETH offer
Constant	0.992***	1.019***	0.995***	1.017***
	(0.020)	(0.020)	(0.023)	(0.021)
ETH weekly returns	0.022**	0.022**	-0.011	0.003
	(0.009)	(0.009)	(0.011)	(0.009)
ETH weekly returns x dummy of positive returns	-0.057***	-0.057***	0.004	-0.018
	(0.013)	(0.013)	(0.016)	(0.014)
% account ETH in profits				
0–25% proportion	0.000	0.004***	-0.002	0.003**
	(0.001)	(0.001)	(0.002)	(0.002)
25–50% proportion	0.005***	0.005***	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
50–75% proportion	0.001	0.003*	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Ln of ETH trading value	0.000	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ETH weekly volatility	-0.007	-0.042	0.091***	0.014
	(0.028)	(0.027)	(0.032)	(0.029)
R-squared	0.302	0.445	0.247	0.16
VARIABLES	XRP bid	XRP offer	XRP bid	XRP offer
Constant	0.947***	0.978***	0.897***	0.983***
	(0.028)	(0.036)	(0.031)	(0.037)

XRP weekly returns	0.001	0.018	0.001	0.009
	(0.011)	(0.014)	(0.012)	(0.014)
XRP weekly returns x dummy of positive returns	-0.030**	-0.047***	-0.022	-0.033*
	(0.015)	(0.019)	(0.016)	(0.019)
% account XRP in profits				
0–25% proportion	-0.006	0.002	0.002	0.003
	(0.004)	(0.005)	(0.004)	(0.005)
25–50% proportion	-0.007*	-0.002	-0.001	0.000
	(0.004)	(0.005)	(0.005)	(0.005)
50–75% proportion	-0.012***	-0.003	-0.006	0.000
	(0.004)	(0.005)	(0.004)	(0.005)
Ln of XRP trading value	0.003**	0.001	0.005***	0.001
	(0.001)	(0.002)	(0.001)	(0.002)
XRP weekly volatility	-0.097***	-0.082***	0.005	0.071***
	(0.020)	(0.026)	(0.022)	(0.026)
R-squared	0.503	0.448	0.217	0.154

Note: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The 75-100% proportion of accounts in profit is the reference group.

6. Conclusion

This study offers valuable insights into the price discovery process within Thailand's largest cryptoasset exchange, highlighting the market's reliance on global price movements and, crucially, the significant role of investor behavior and portfolio positions in shaping price adjustments. Our empirical analysis confirms that while local prices eventually converge with global benchmarks, this process is characterized by a lag of approximately 30–60 minutes and is notably slower during periods of large price swings, both upward and downward. This suggests that behavioral biases such as inertia, status quo bias, and anchoring effects are prevalent among the predominantly retail investor base, leading to hesitant adjustments in bids and offers in response to substantial global price shifts.

A key contribution of this research is the novel analysis of how price discovery varies with investors' portfolio positions, using unique regulatory data on gains and losses. We find evidence that local market participants exhibit slightly more aggressive trading behavior when the majority are in loss positions, potentially reflecting loss aversion, compared to a more cautious, gain-preserving stance when in profit. This differentiated response underscores the complex interplay between market conditions and individual investor psychology in this nascent asset class.

The findings carry important implications for regulators and market participants. Beyond prioritizing transaction costs and preventing malpractice, our results suggest that regulators should consider establishing benchmarks for market quality, such as acceptable ranges for bid-offer spreads and speed of price convergence, potentially with enhanced surveillance during periods of high global volatility. Furthermore, understanding the tendency of retail investors toward inertia and behavioral biases could inform the development of targeted investor education campaigns focusing on common pitfalls in volatile markets, thereby fostering more efficient market behavior.

While this study provides a detailed analysis, certain limitations should be acknowledged. Our findings are based on Thailand's largest exchange and three major cryptoassets (BTC, ETH, XRP); dynamics on smaller local exchanges or for less liquid cryptoassets might differ. Although Kraken serves as a robust global price proxy, the global crypto market has multiple price discovery venues. Additionally, our definition of market conditions using weekly returns is a practical proxy that may not capture all intra-week sentiment or volatility nuances. Finally, while our results are consistent with behavioral biases, we do not directly test them.

Future research could build upon these findings by directly testing specific behavioral biases using experimental methods or more granular account-level trading data. Comparative studies across different local exchanges, or for a broader array of cryptoassets with varying liquidity profiles and investor bases, would also be valuable. Investigating the impact of specific market events, such as major regulatory announcements in Thailand or technological developments in the crypto space, on price discovery efficiency and investor behavior presents another fruitful avenue for extending this research.

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