Digital Assets in Thailand:
Insights from transaction-level exchange data

Assoc. Prof.
Kanis Saengchote, Ph.D.
Chulalongkorn University

Asst. Prof.
Roongkiat Ratanabanchuen, Ph.D.
Chulalongkorn University

Asst. Prof.
Voraprapa Nakavachara, Ph.D.
Chulalongkorn University

Polpatt Vinaibodee, CFA, CIPM
Research Department,
SEC Thailand

Pongsathon Parinyavuttichai
Research Department,
SEC Thailand

Thitiphong Amonthumniyom
Research Department,
SEC Thailand

SEC 2021 CAPITAL MARKET SYMPOSIUM

Outline for Today's Talk

- Digital Assets Market in Thailand
- Exchanges: Bid-Ask Spread & Price Discovery
- Users: Disposition Effect
- Conclusions & Implications

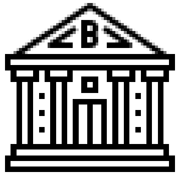
Digital Assets - Global

~77.57 Trillion baht

Market Cap.

~ 12,580

Coins



~ 413

Exchanges

As of 10 OCT 2021

Source : Coinmarketcap

Digital Assets in Thailand

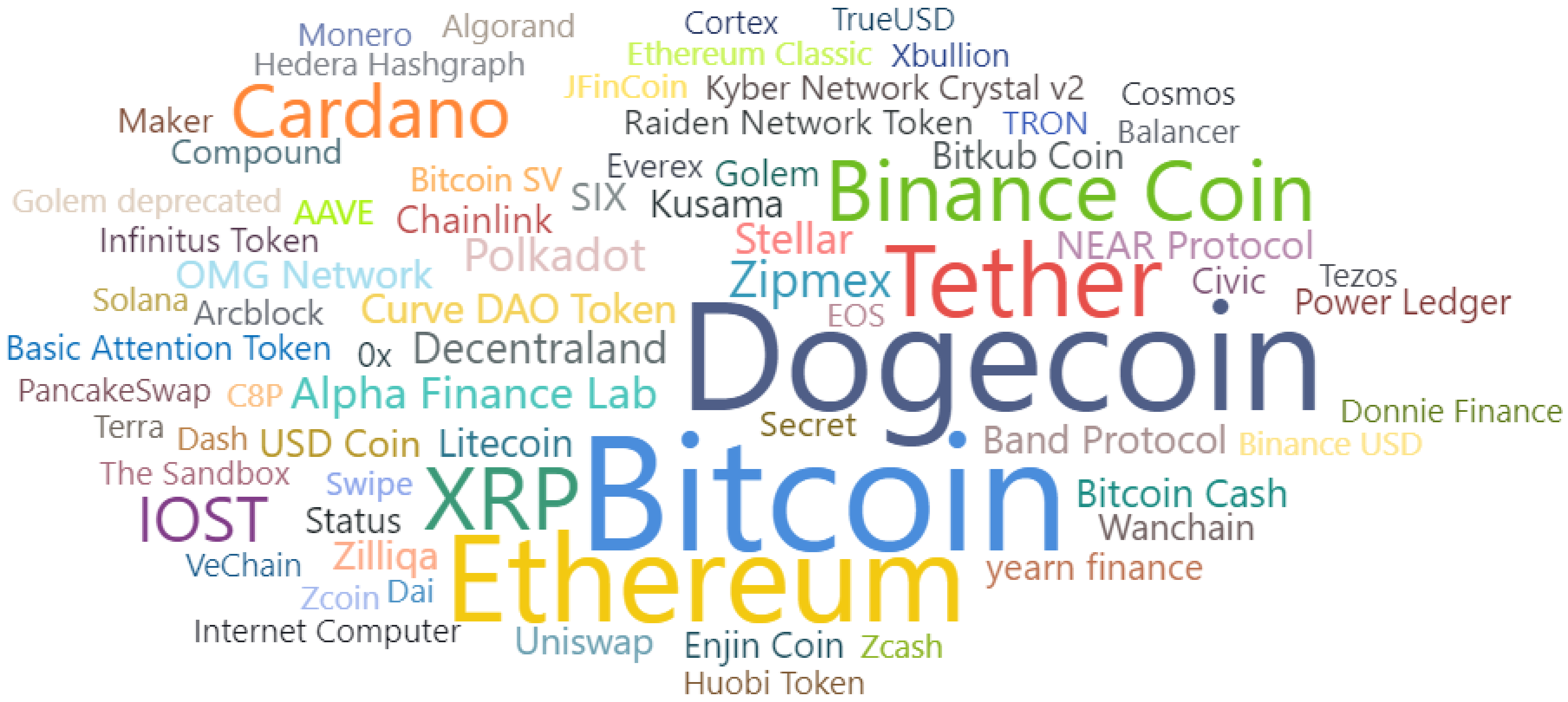
Digital Asset Exchange	Stock Exchange
~6,600MB Trading value per day	~ 89,000 MB Trading value per day
~-17.49 BN Net value by foreign investor	~ -72.16 BN Net value by foreign investor
~1.49 MN Number of accounts	~4.84 MN Number of accounts
~183 Number of coins	~582 Number of listed companies

As of 10 OCT 2021

Source : SEC

Digital Assets in Thailand

Popular Coins in Thailand (based on trading value)



Nov 2020 – Jul 2021

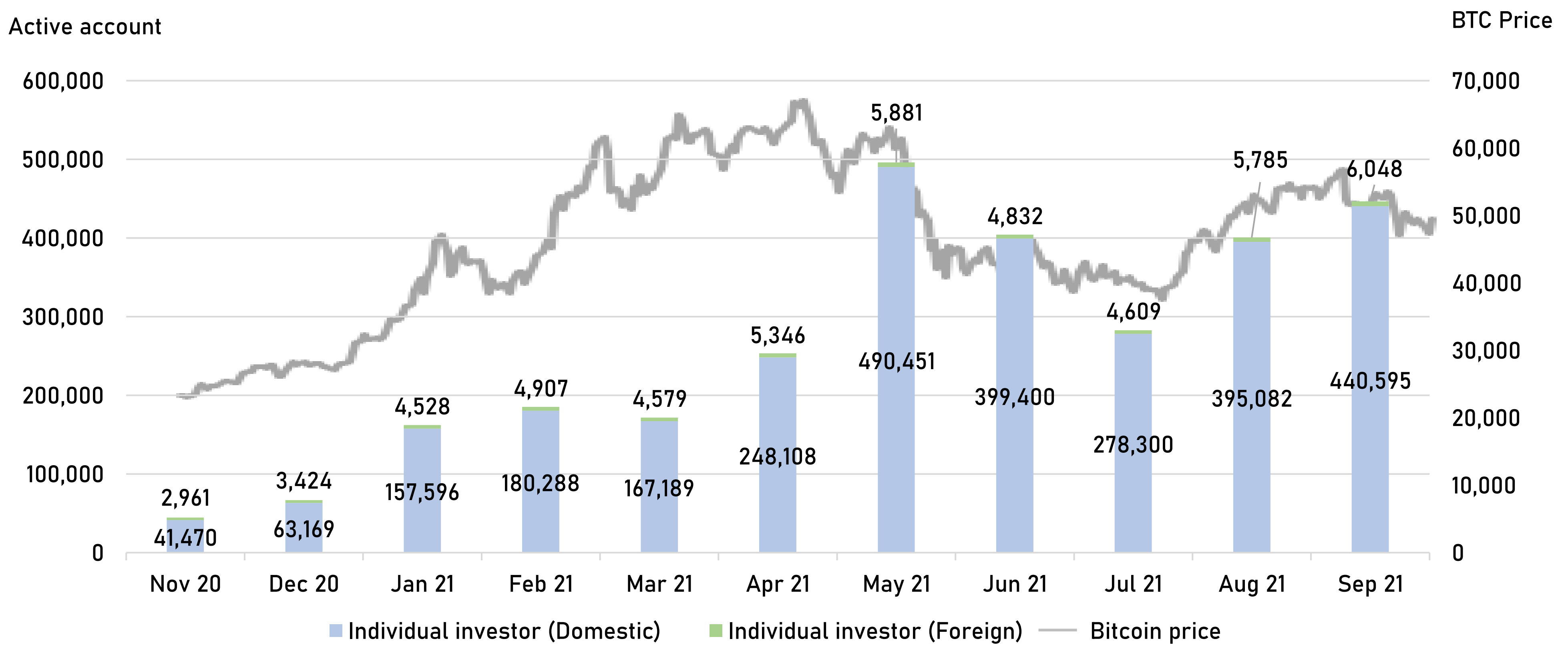
Source : SEC

Note : Bitcoin 16%, Dogecoin 15 %, Ethereum 11 %, Tether 9%, XRP 7 %, Other 30 %

Digital Assets in Thailand

Number of active accounts has grown significantly around peak

Individual investor has dominated the trading value



Nov 2020 – Sep 2021

Source : SEC

Exchanges: Bid-ask Spread and Price Discovery

Efficiency level of cryptocurrency exchange markets in Thailand

- Measurement of efficiency is proxied by 2 aspects in this study.
    1. **Bid-ask spread** – Narrow bid-ask spread is a sign of high efficiency.
    2. **Price discovery** – Fast movement of bidding and asking prices in response to the price movement in the global markets is a sign of high efficiency.
- However, the Efficient Market Hypothesis requires key assumptions to hold.
    1. Asset prices should be driven by only relevant information.
    2. Investors are required to behave rationally.
- **Therefore, the low level of efficiency may not be caused solely by the functioning of the exchange markets.**

Previous literature on the efficiency of cryptocurrency exchange markets

- Brandvold et al. (2015) is the first paper that studies the price formation process particularly in bitcoin markets, by using the econometric methodologies of Hasbrouck (1995) and Gonzalo and Granger (1995).
- Makarov and Schoar (2018) also adapt the Hasbrouck’s methodology and show that Bitcoin prices across large exchanges deviate for several hours (not minutes) on average. These price deviations exist even their study is on highly liquid exchanges such as Coinbase (US), Coinbase (UK), BitFlyer (Japan), Bitfinex (Hong Kong), and Bithumb (Korea).
- In addition, Pagnottoni et al. (2018) extend the period of analysis from Makarov and Schoar (2018) to cover the period between January 2014 to March 2017 and argue that Chinese exchanges play a crucial role in price discovery. Urquhart (2016) and Nadarajah and Chu (2017) also concludes that bitcoin prices may be ‘weakly’ efficient.

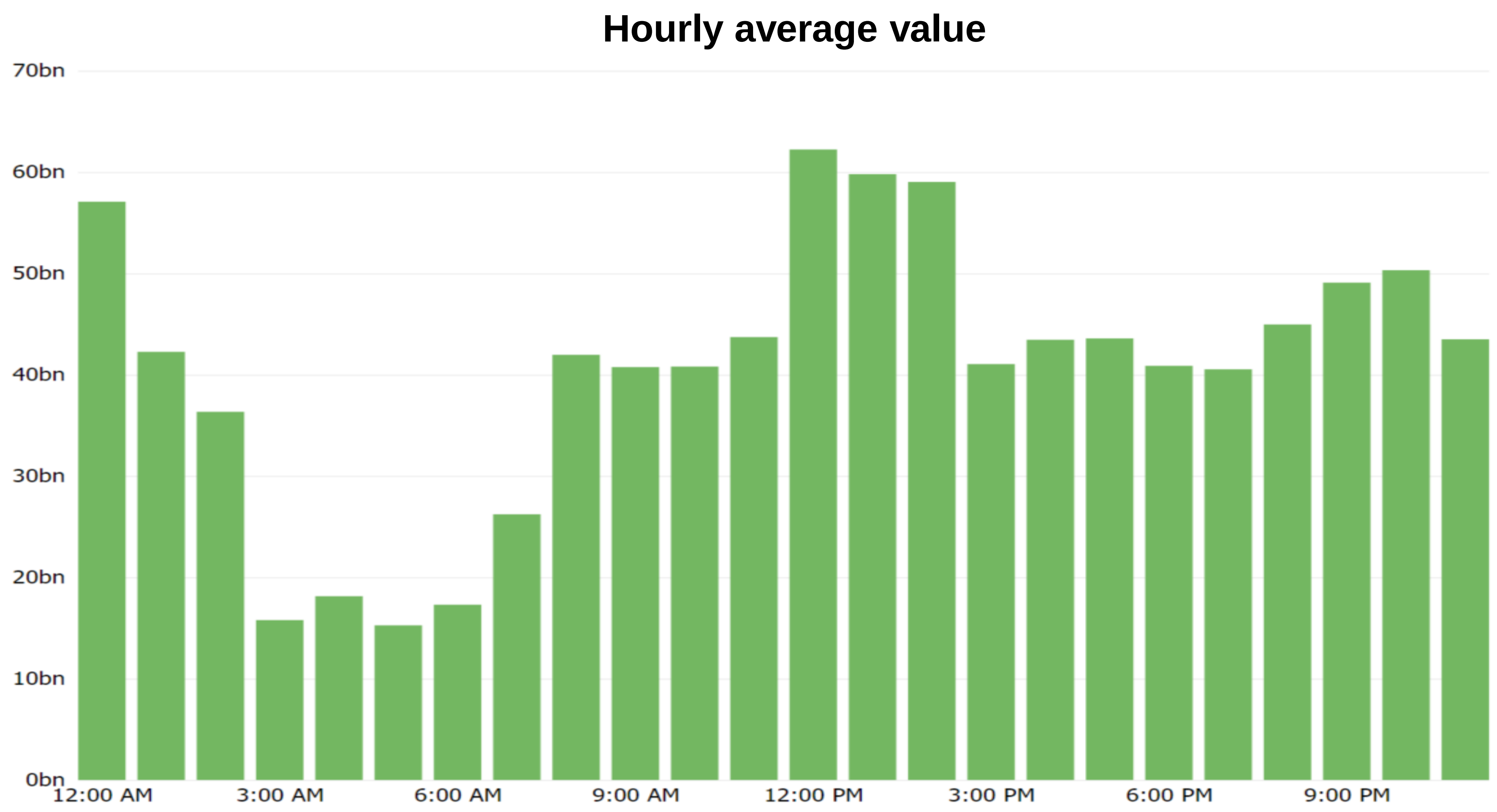
Methodologies used in this study

- **Measurement of bid-ask spreads**
  - Estimate bid-ask spread movements (BTC, ETH and XRP) using information from 5 authorized cryptocurrency exchange markets in Thailand by “a panel regression analysis”.
  - Period covered: November 2020 – July 2021.
- **Measurement of price discovery**
  - Use the theoretical concept of cointegrating relationships between non-stationary variables.
  - Estimate the vector error correction model (VECM) and develop an impulse response movements of crypto prices (BTC, ETH and XRP) in the local exchange markets.

Characteristics of 5 authorized cryptocurrency exchange markets used in this study

Exchange	Median of bid-ask spread BTC	Number of listed coin	Median of trading value per account	Sum of trading value	No. of active accounts	Individual investor – domestic (proportion)	Individual investor – foreign (proportion)
Exchange 1	7.70%	Low	High	Low	Low	Low	High
Exchange 2	0.57%	High	Low	High	High	High	Low
Exchange 3	0.35%	Low	High	High	High	High	High
Exchange 4	0.28%	High	High	Low	Low	Low	Low
Exchange 5	0.32%	High	Low	High	High	High	High

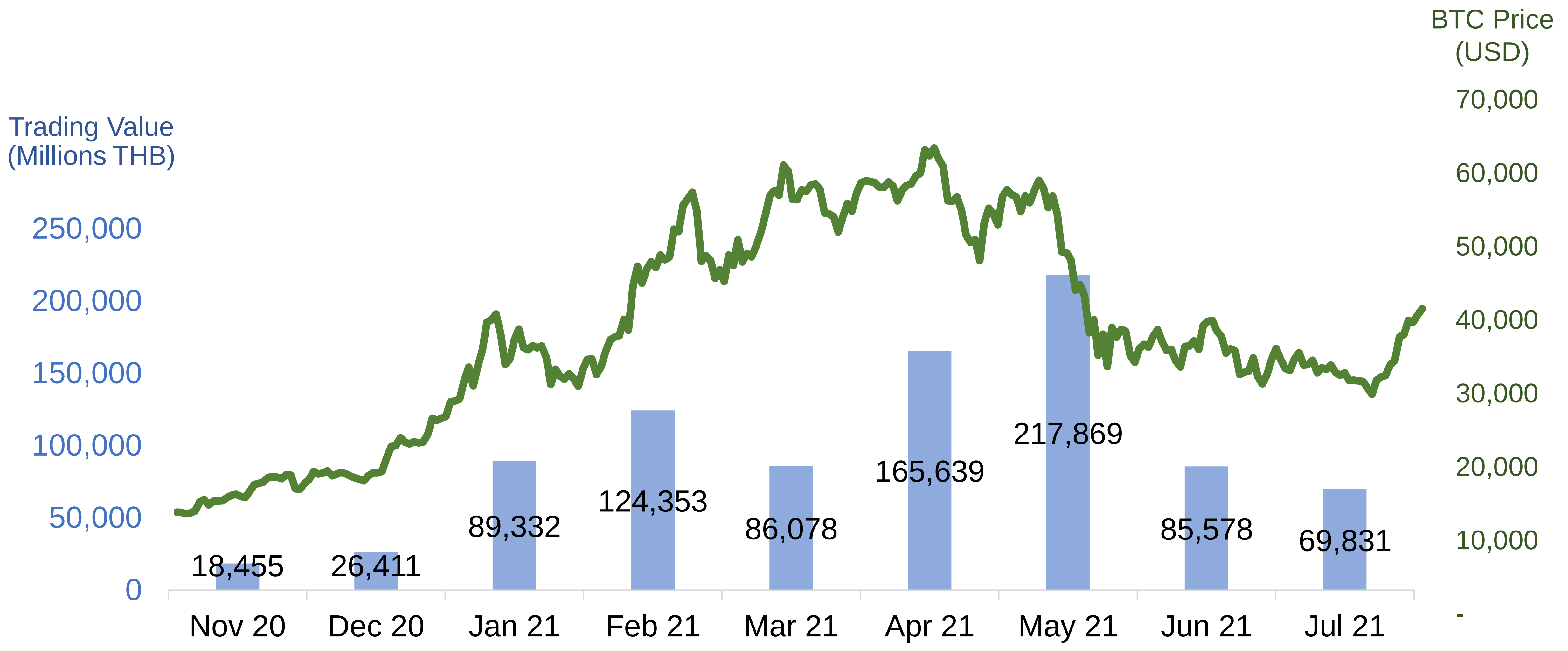
Investors normally start trading at 8.00 AM- 2.00 AM



Average of all trading days during Nov 2020 – Jul 2021

Source : SEC

Trading value has associated with BTC price



Nov 2020 – Jul 2021

Source : SEC, Kraken

Panel data regression for the analysis of bid-ask spread movements

- Panel data regression is better than just estimating the average of bid-ask spreads across different time or across different exchange markets.
- This is because the estimated effects found form the regression has been controlled for both observed and unobserved variables.
- The technique used for the panel data regression is the generalized least squares (GLS) which is good dealing with heteroskedasticity.

$$\boldsymbol{Percentage\ spread}_{i,t} = \alpha + \beta_{1j} \cdot D_{1j} + \beta_{2k} \cdot D_{2k} + \beta_{3l} \cdot D_{3l} + \beta_5 \cdot \ln(vol)_{i,t} + \beta_6 \cdot volatility_{i,t} + \varepsilon_{i,t}$$

30-min block dummies

Bid-ask spreads and trading data is obtained for a certain 30-min time frame (e.g. 00.00 – 00.30, 00.30 – 1.00)

Month dummies

Month effect (Nov 2020 – July 2021)

Exchange dummies

5 local exchanges

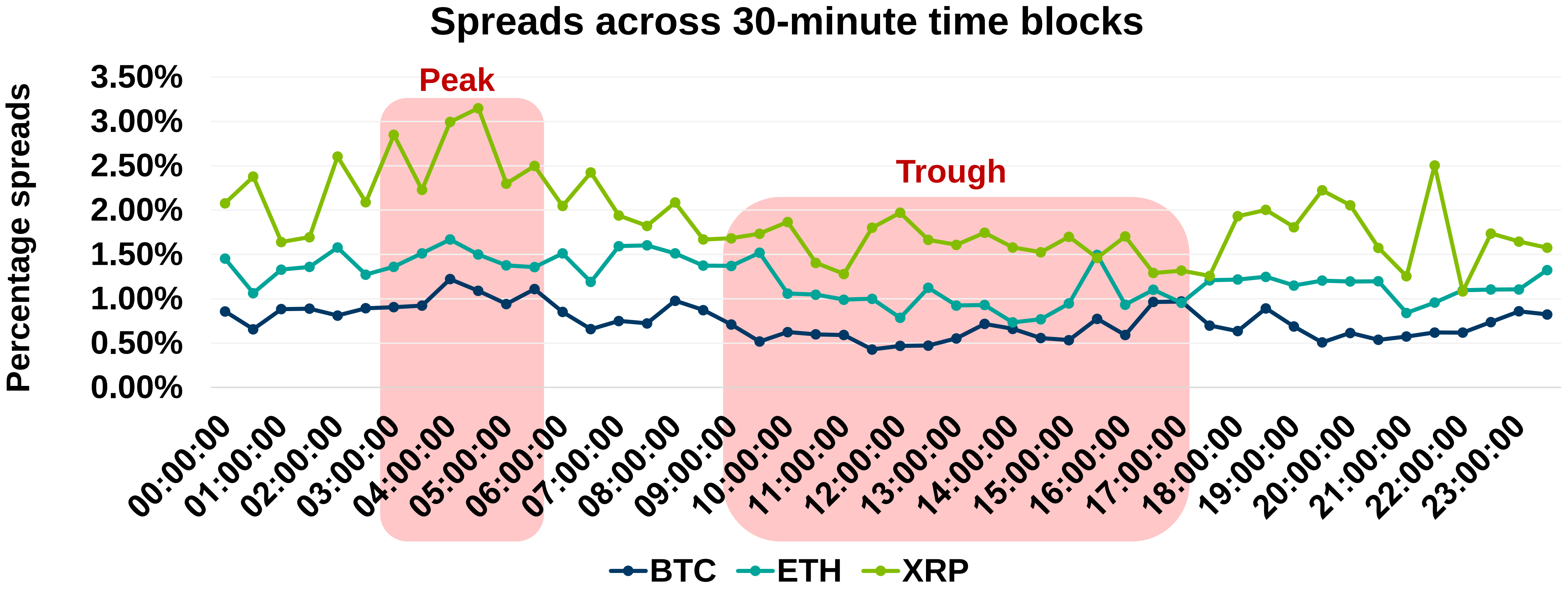
Log transformation of trading

volume per 30-min block

Volatility of each 30-min block

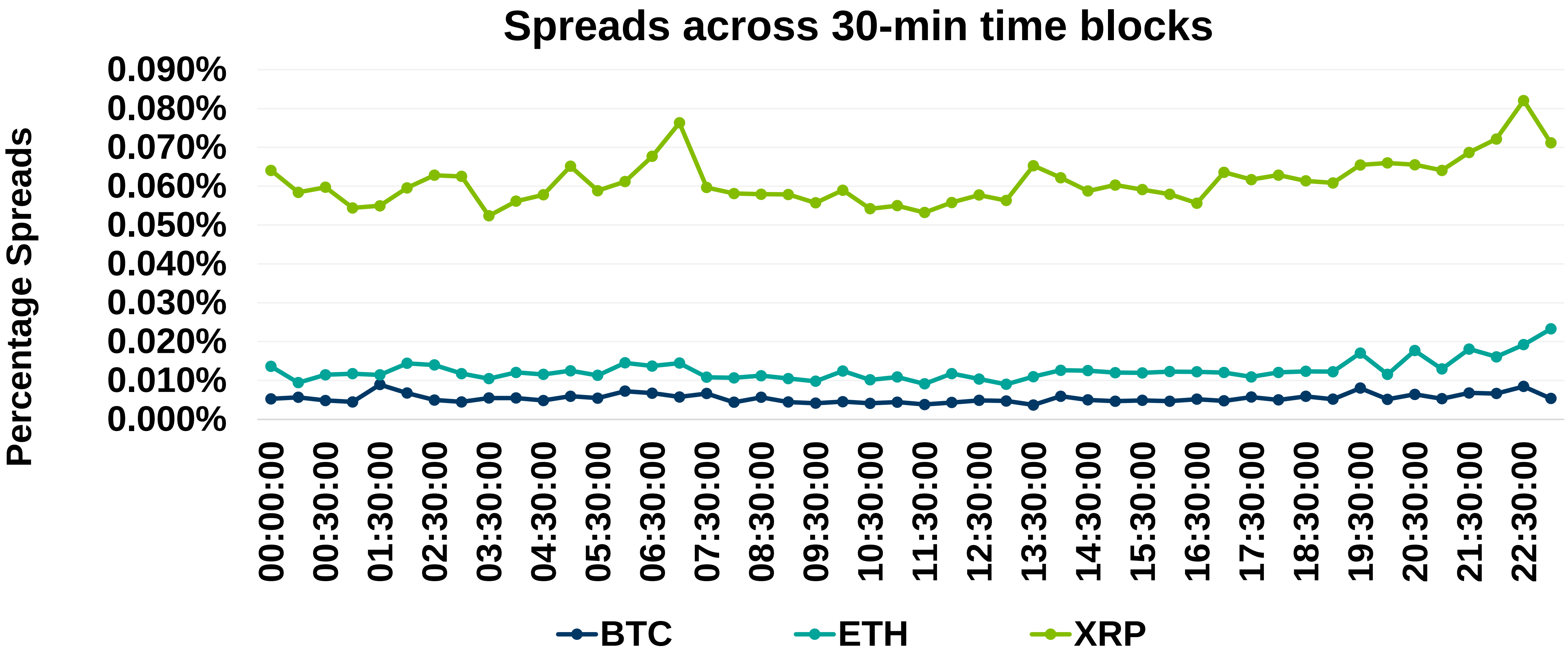
Rogers and Satchell (1991)'s volatility measure

Estimated results of the percentage spreads from the panel data regressions



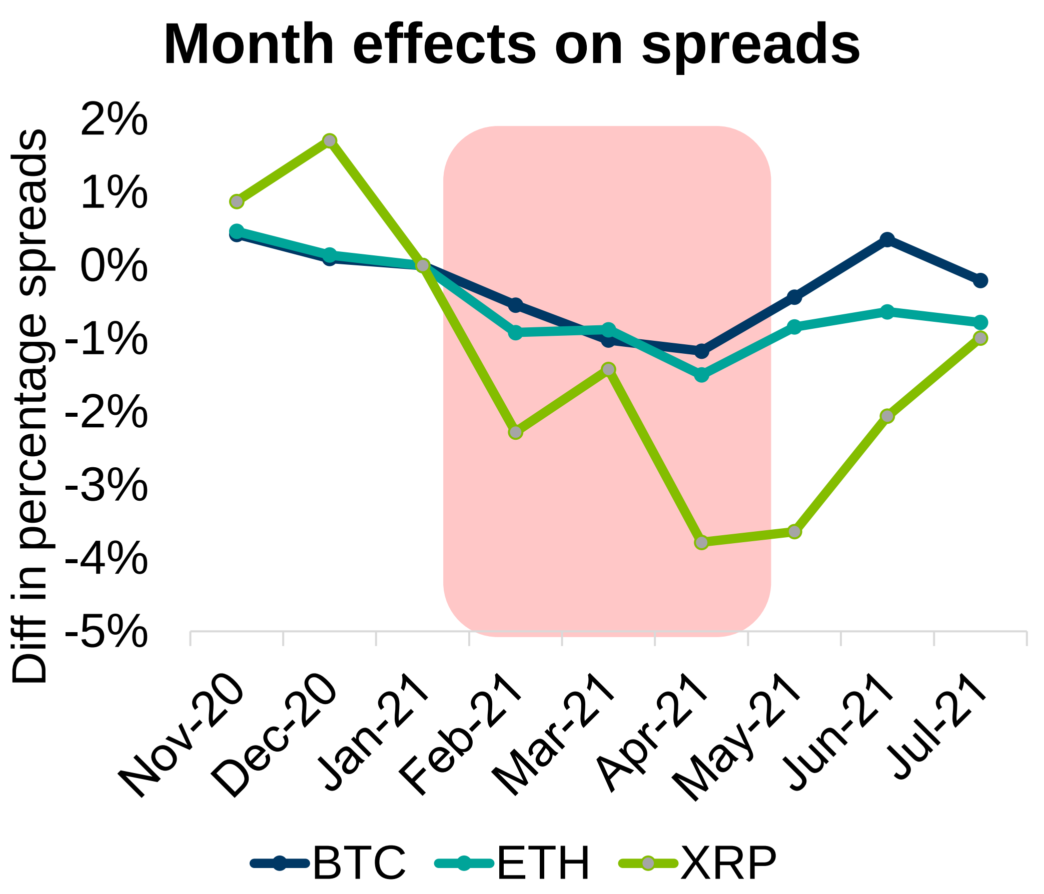
The result is estimated for “Exchange 1”; Month = Jan 2021; volume per 30-min block = 3.5m baht for BTC, 2.4m baht for ETH and 1.6m baht for XRP; volatility per 30-min block = 0.009% for BTC, 0.3% for ETH and 0.097% for XRP.

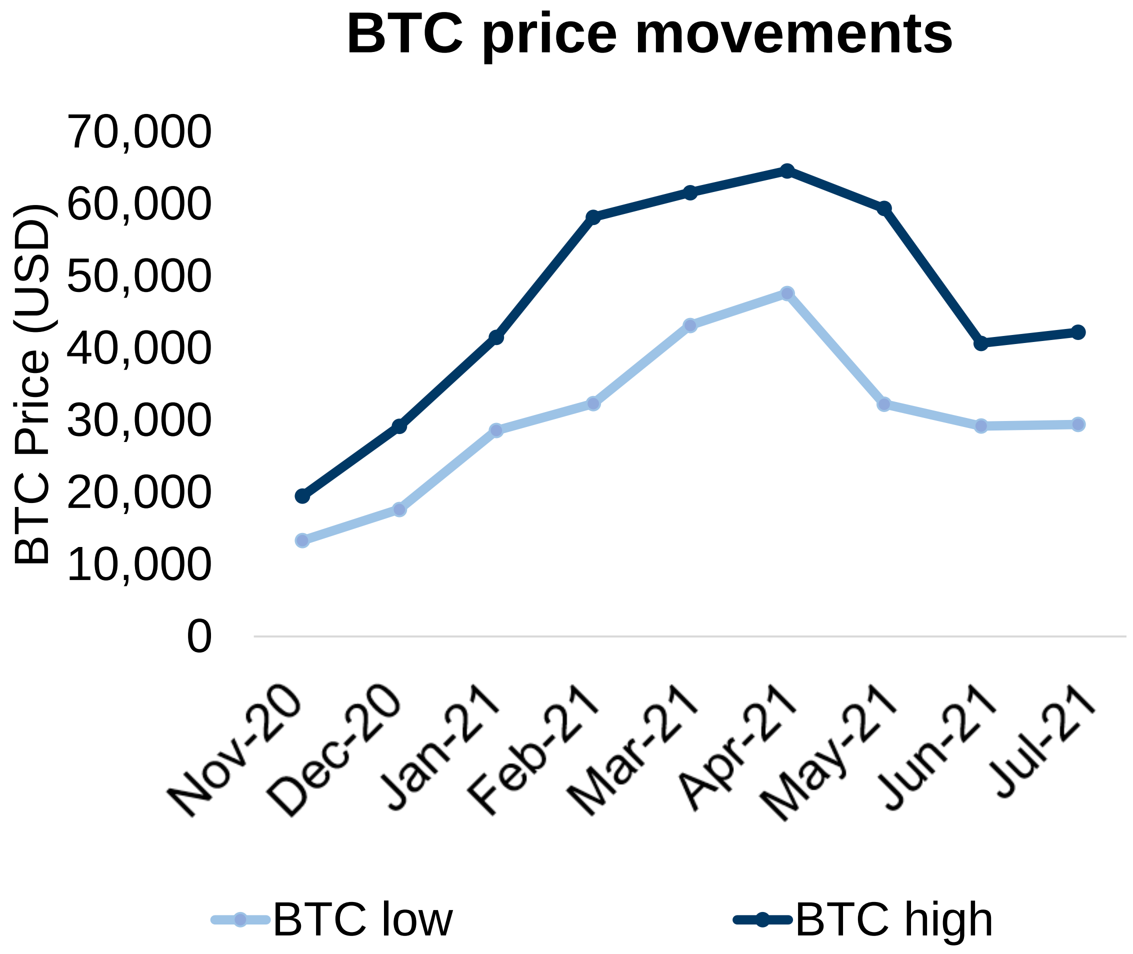
Percentage spreads of Kraken exchange markets



No significant differences of spreads across time

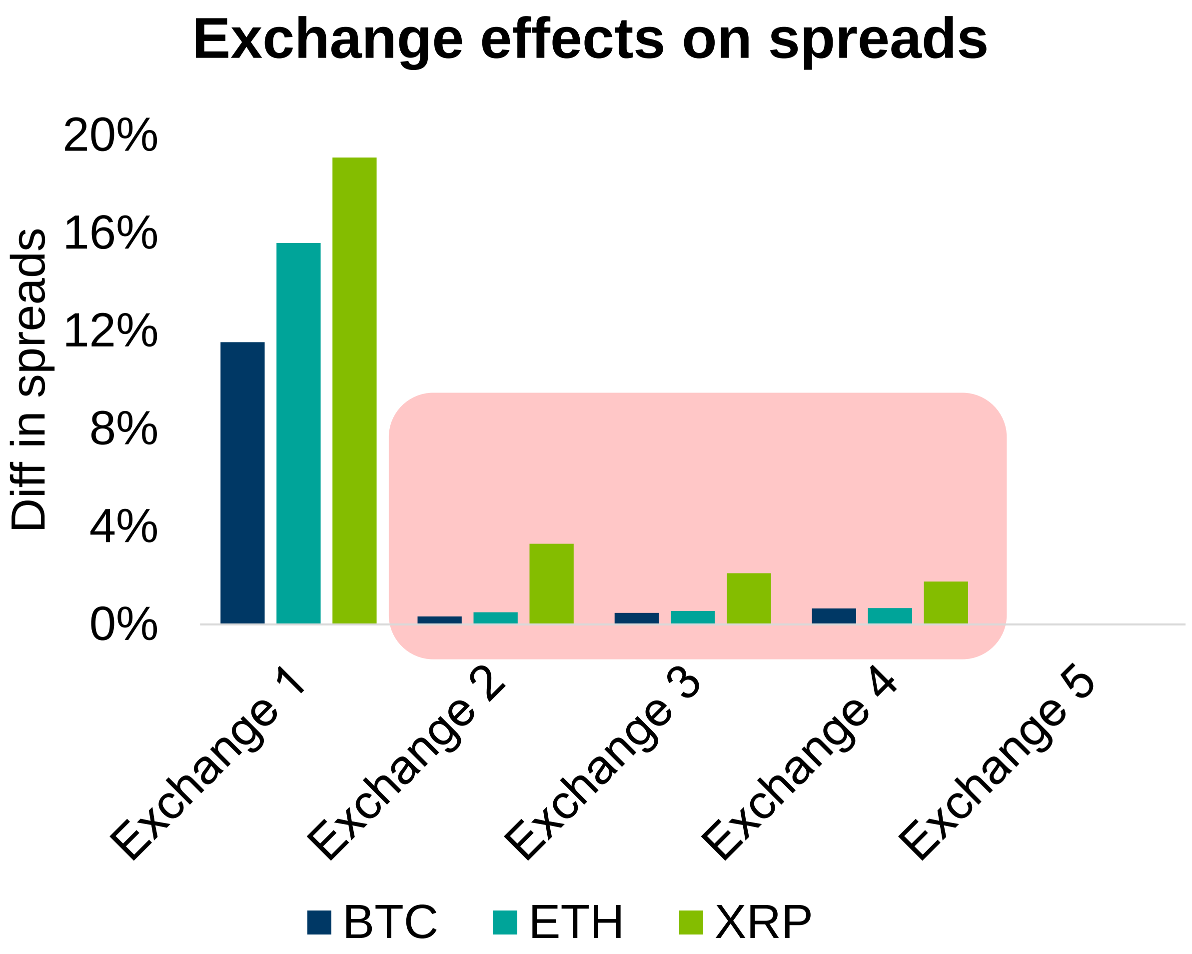
Other effects on percentage spreads of local crypto exchange markets





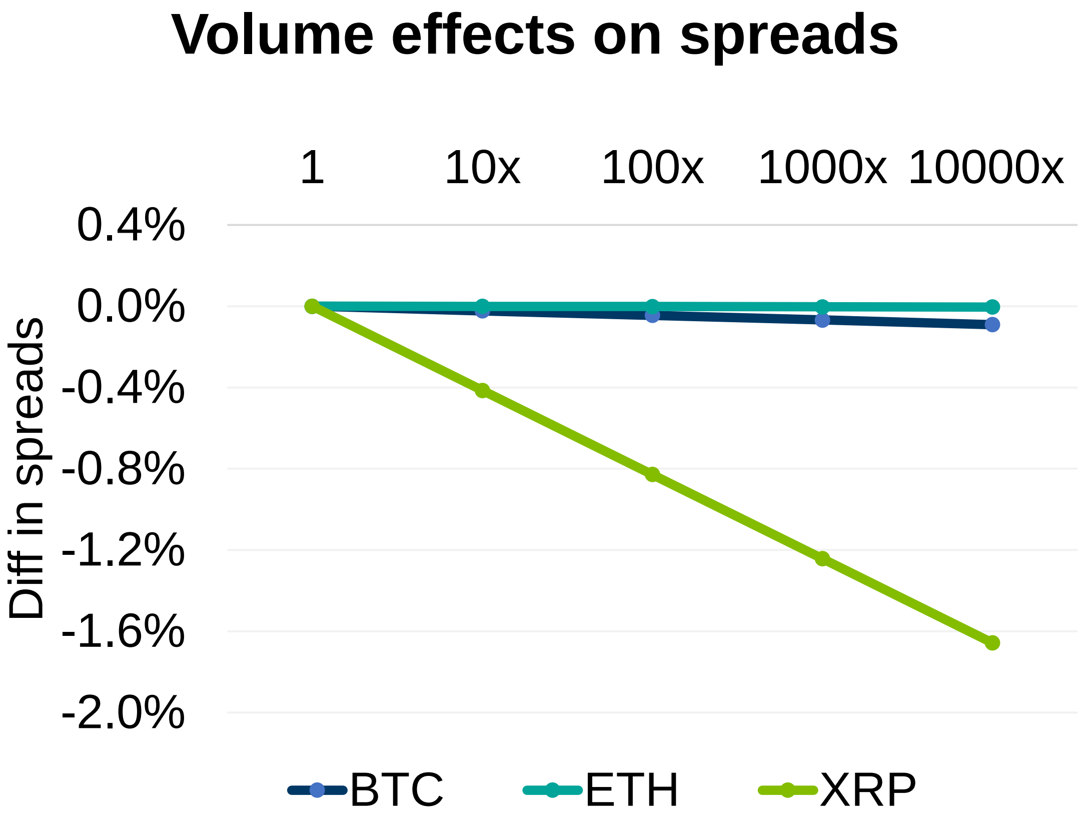
Drop in spreads during Feb-May 2021 may be due to the bull period, not because of increasing volume or trading accounts.

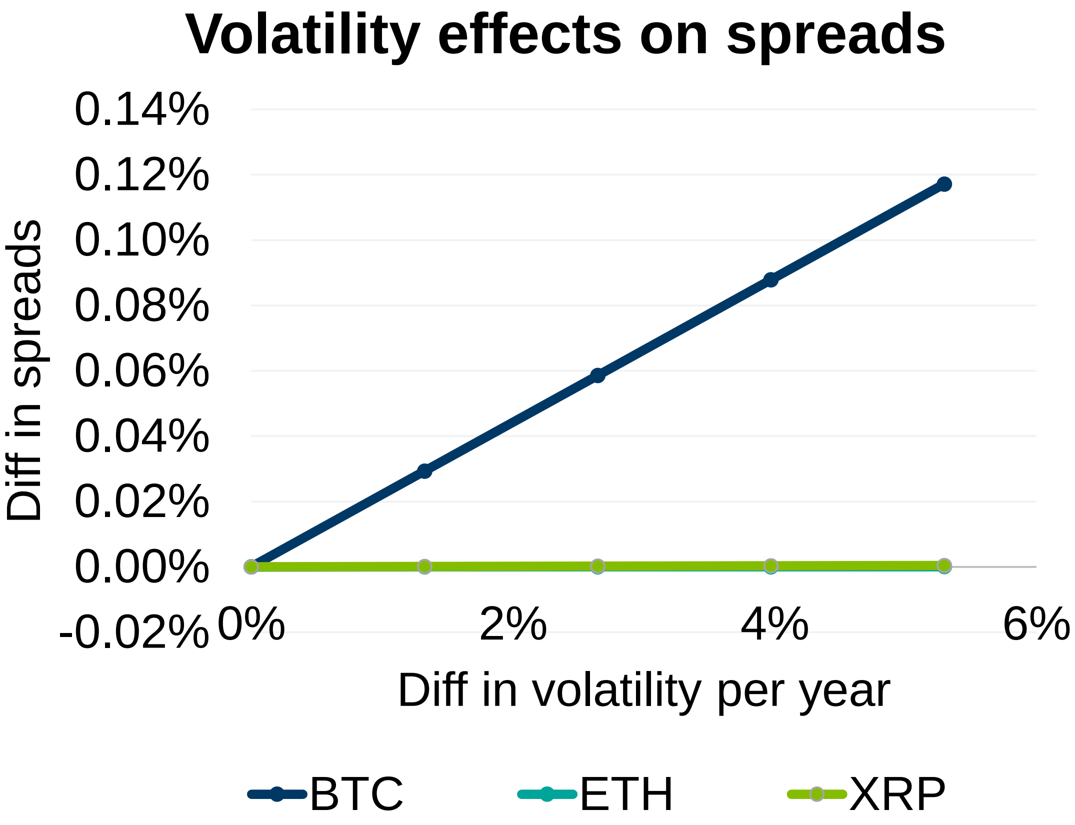
Other effects on percentage spreads of local crypto exchange markets



Exchange	Number of listed coin	Median of trading value per account	Sum of trading value	Individual investor (domestic)	Individual investor (Foreign)
Exchange 1	Low	High	Low	Low	High
Exchange 2	High	Low	High	High	Low
Exchange 3	Low	High	High	High	High
Exchange 4	High	High	Low	Low	Low
Exchange 5	High	Low	High	High	High

Other effects on percentage spreads of local crypto exchange markets





Large trading volume is negatively related to lower spreads only in XRP because the spread of XRP is currently wide.

Higher volatility is positively related to higher spreads only in BTC because the spread of BTC is currently low.

Price discovery analysis with VECM

- **The law of one price suggests that the price of a certain asset should be same across different markets.**
  - Therefore, prices of cryptos in local exchange should move in parallel with the changes in prices in other global markets.
  - The situation that two non-stationary price series will not diverge without bound from each other is called cointegration.
- **This study follows the statistical techniques proposed by Engle and Granger (1997) and Harbrouck (1995)**

$$\Delta P_{L,t} = \alpha \cdot CE_{t-1} + \beta_{L1} \cdot \Delta P_{L,t-1} + \beta_{L2} \cdot \Delta P_{L,t-2} + \beta_{L3} \cdot \Delta P_{L,t-3} + \boxed{\gamma_{L1} \cdot \Delta P_{G,t-1} + \gamma_{L2} \cdot \Delta P_{G,t-2} + \gamma_{L3} \cdot \Delta P_{G,t-3}} + constant$$

$$\Delta P_{G,t} = \alpha \cdot CE_{t-1} + \boxed{\beta_{G1} \cdot \Delta P_{L,t-1} + \beta_{G2} \cdot \Delta P_{L,t-2} + \beta_{G3} \cdot \Delta P_{L,t-3}} + \gamma_{G1} \cdot \Delta P_{G,t-1} + \gamma_{G2} \cdot \Delta P_{G,t-2} + \gamma_{G3} \cdot \Delta P_{G,t-3} + constant$$

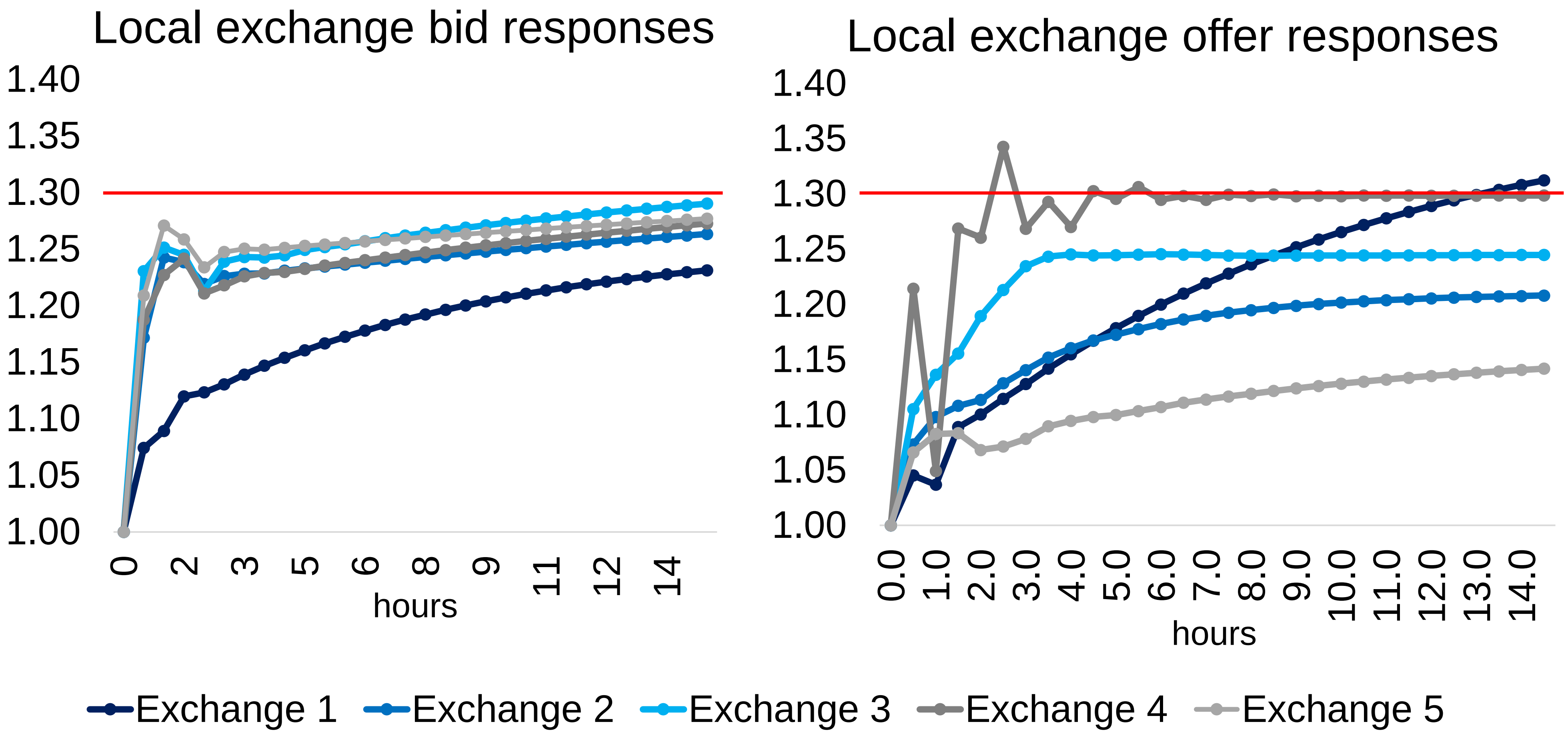
$$CE_{t-1} = P_{L,t-1} + \delta \cdot P_{G,t-1} + constant$$

$P_{L,t}$= price in a local market $P_{G,t}$= price in a global market
CE = Cointegration equation

Examples of VECM results

	Coefficients							
Current different of price	Alpha of the cointegrating term	Lag of the different in price of the local exchange			Lag of the different in price of the Kraken exchange			Constant term
		1	2	3	1	2	3	
Exchange 1								
Local exchange	-0.08119	-0.12435	-0.09696	-0.03052	0.174746	0.03661	0.08866	-0.34834
Std. Err.	0.005211	0.011605	0.011519	0.011322	0.053607	0.053639	0.05359	530.6498
Kraken exchange	0.00102	-0.00056	0.002358	-0.00029	-0.03054	-0.00329	0.009891	-27.7192
Std. Err.	0.001111	0.002475	0.002457	0.002414	0.011432	0.011439	0.011429	113.1647
Exchange 3								
Local exchange	-0.07753	-0.57198	-0.33286	-0.13961	0.683117	0.511625	0.291524	-4.89707
Std. Err.	0.004794	0.009239	0.009642	0.007884	0.015364	0.016377	0.01652	134.2909
Kraken exchange	-0.00504	-0.00343	-0.00442	-0.0067	-0.04285	-0.02109	0.022014	75.40485
Std. Err.	0.002969	0.005722	0.005971	0.004883	0.009515	0.010142	0.010231	83.16813
Exchange 5								
Local exchange	-0.0294	-0.5007	-0.2529	-0.0615	0.6643	0.5665	0.2676	-15.8813
Std. Err.	0.0026	0.0086	0.0084	0.0063	0.0079	0.0096	0.0101	66.7499
Kraken exchange	-0.0070	-0.0143	-0.0120	-0.0030	-0.0413	-0.0152	0.0199	67.0554
Std. Err.	0.0031	0.0103	0.0100	0.0075	0.0094	0.0115	0.0120	79.6880

Price response of local crypto markets after a 30% impulse in the Kraken market



Differences of Bid level between local and global prices

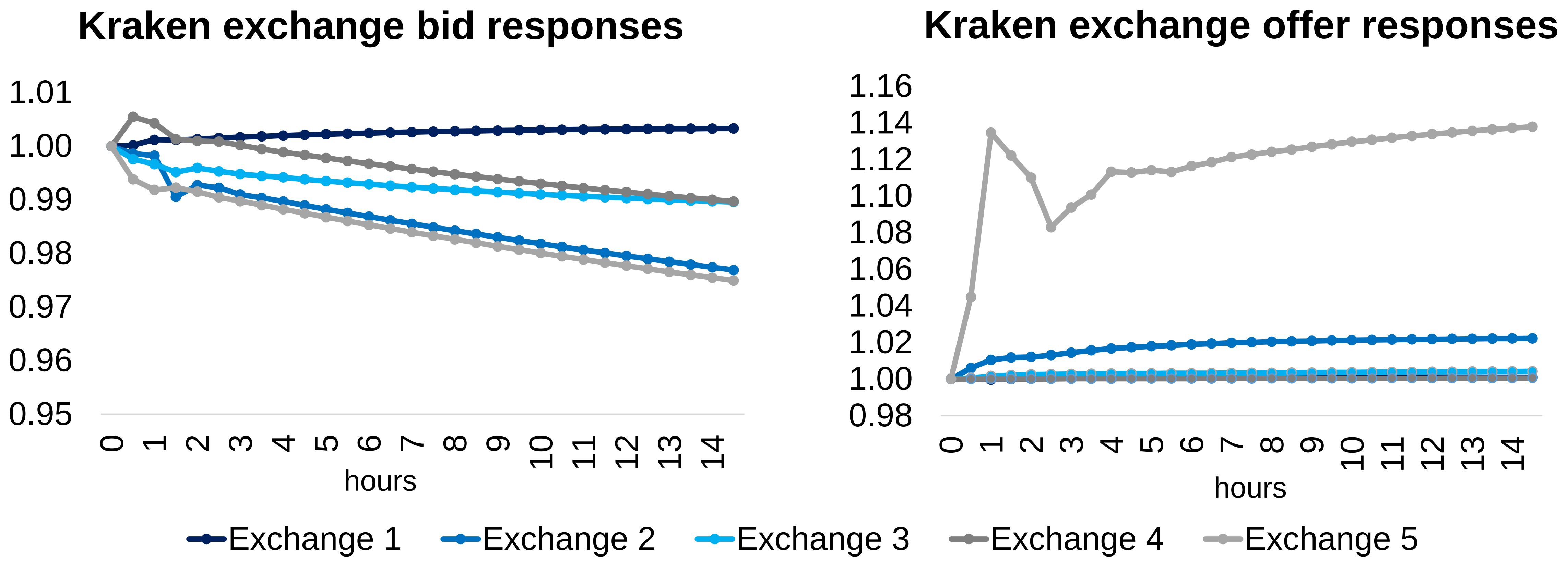
Mean = 0.45%
S.D. = 4.58%

Differences of offer level between local and global prices

Mean = 3.66%
S.D. = 47.09%

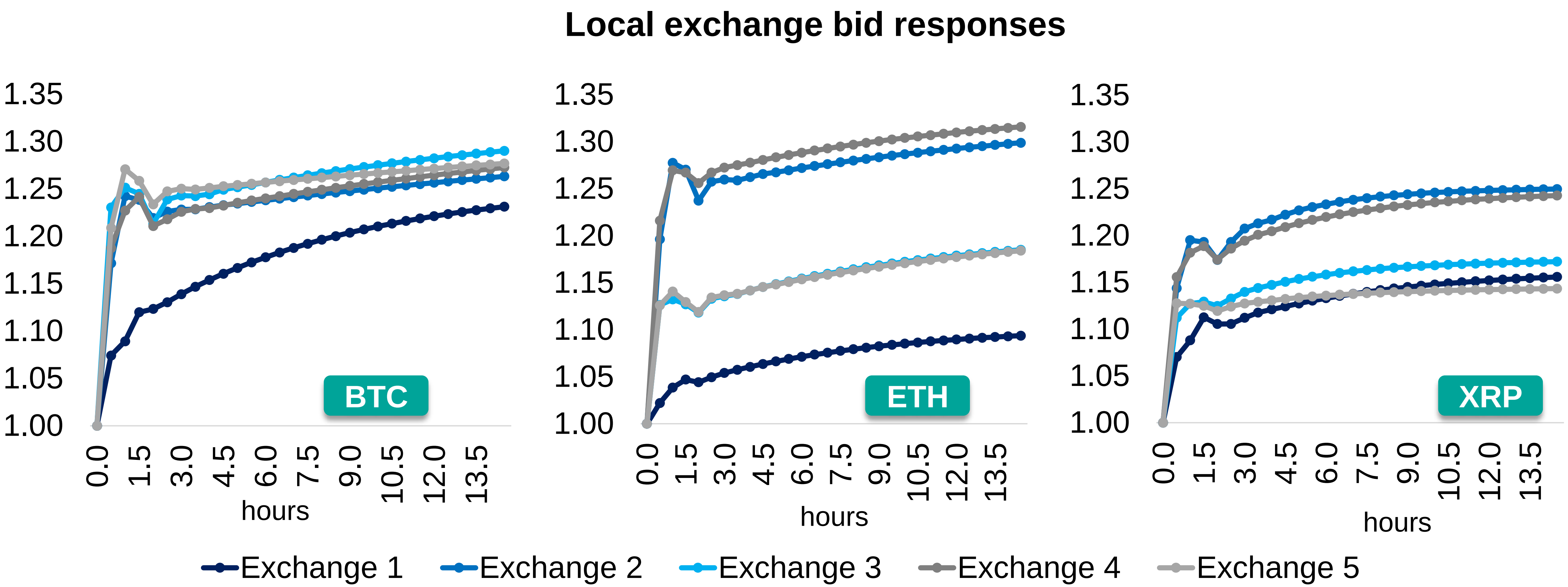
Offer movements appear to exhibit slow response. This may be due to the fact that offer prices in local crypto markets may be at much higher levels compared to the global price at each timeframe.

Price response of the Kraken markets after a 30% impulse in local crypto markets



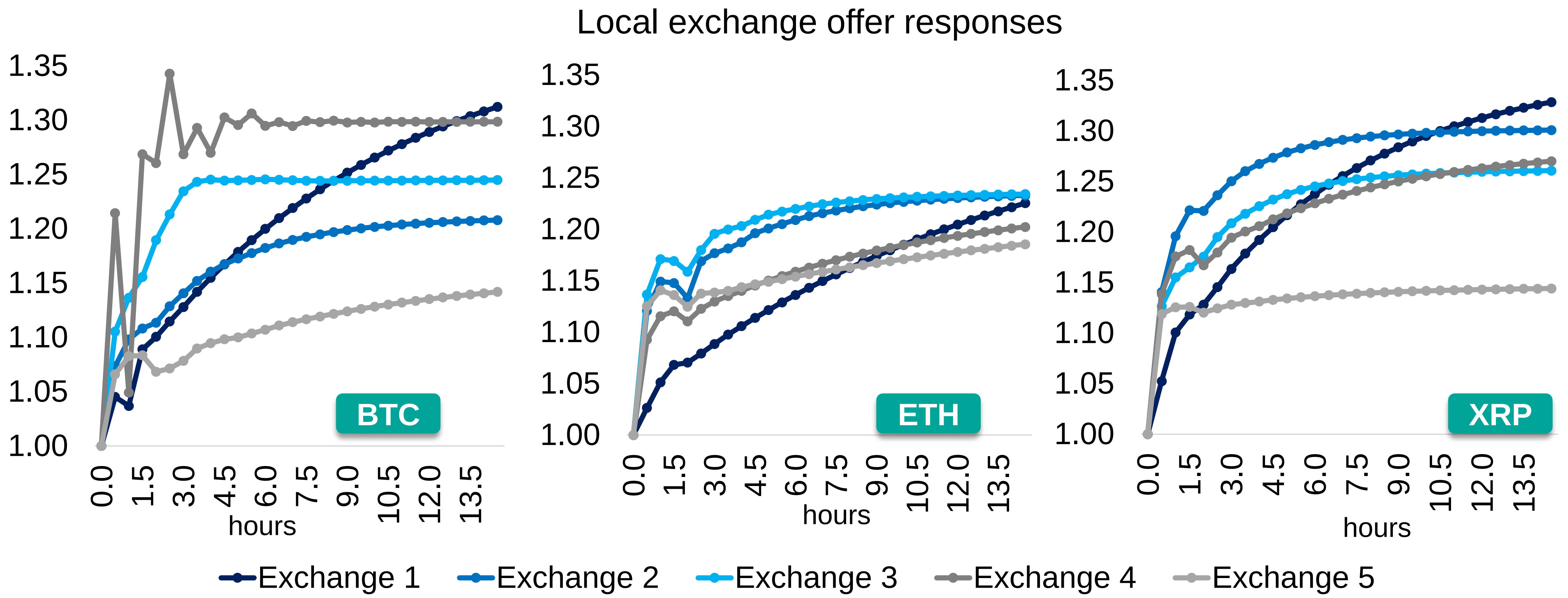
It is not surprising to see that prices in the local crypto markets do not lead the global market. However, the offer movement of one local exchange appears to move prior to the global markets in the correct direction. This may represent the attempt of 'some' investors in the local market to forecast the price movement in the global market and try to prevent the situation of "ขายหมู".

Bid response of local crypto markets after a 30% impulse in the Kraken market for BTC, ETH and XRP



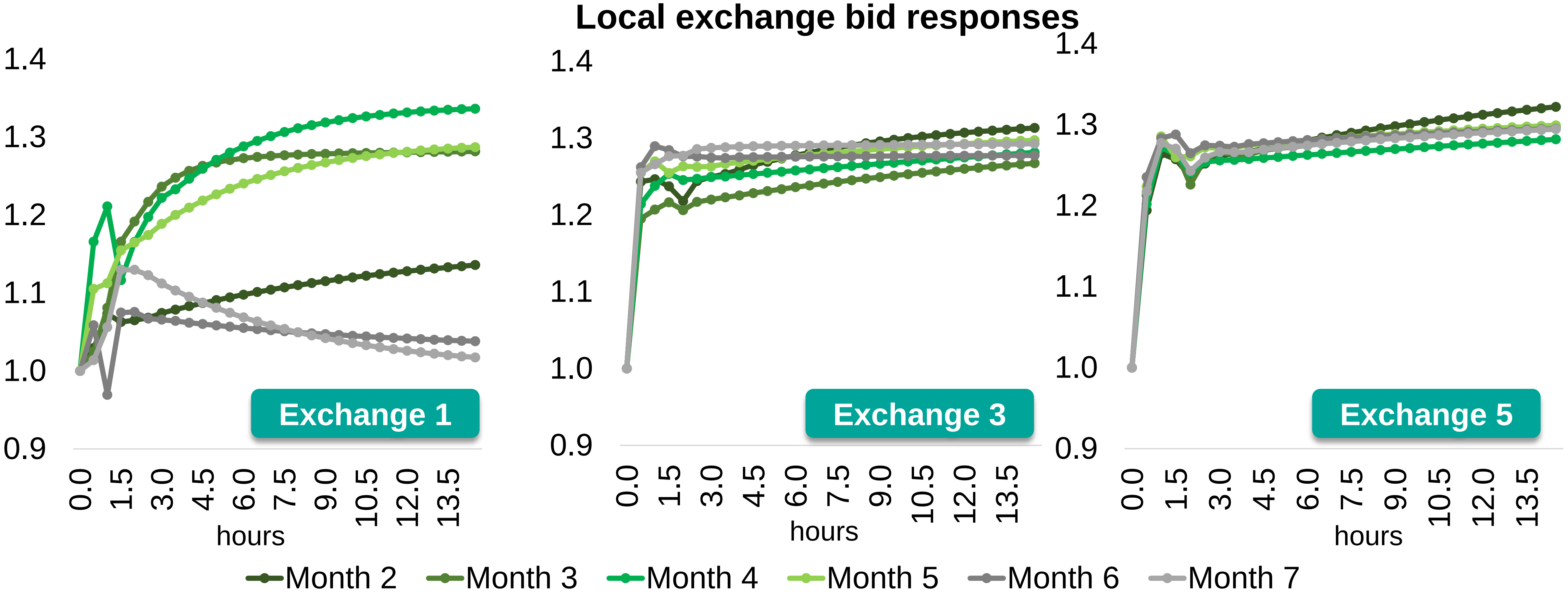
It appears that there is no perfect local exchange markets that exhibit fast price responses for all cryptos. The trading in each market may be concentrated in different cryptos.

Offer response of local crypto markets after a 30% impulse in the Kraken market for BTC, ETH and XRP



Different speeds in price response for different cryptos of a certain local exchange market also exist in the case of offer price movement.

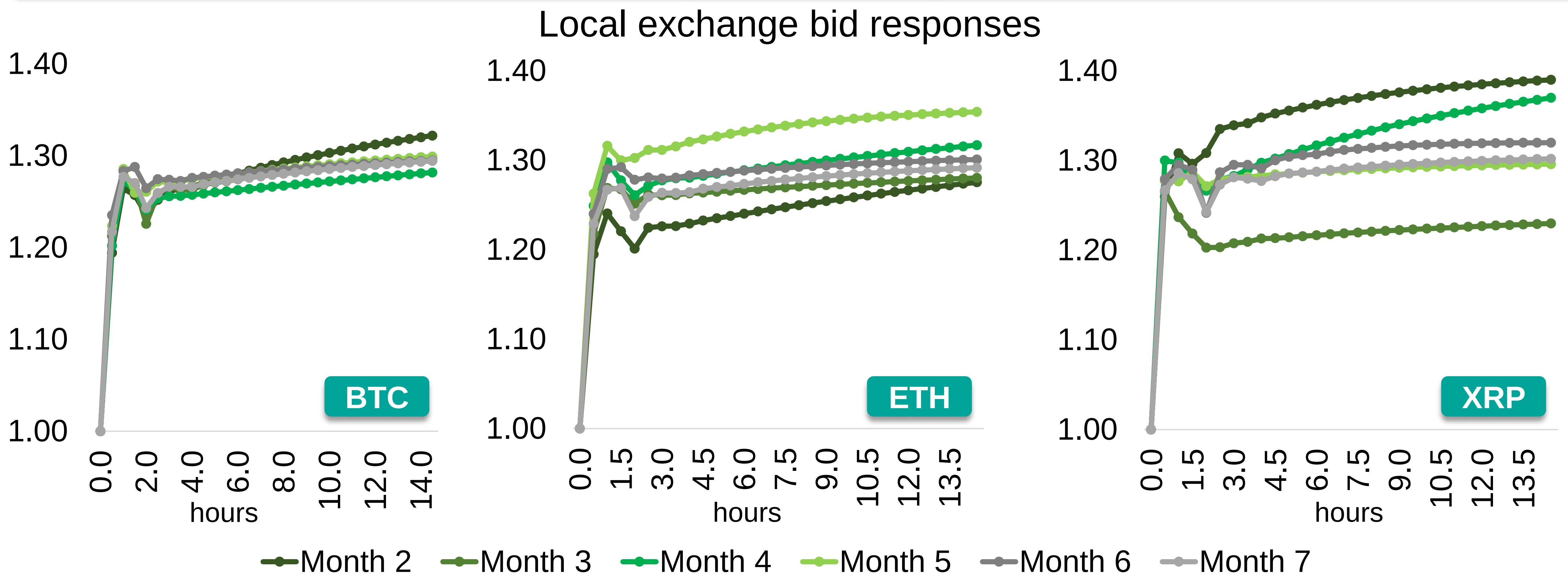
Bid response of local crypto markets after a 30% impulse in the Kraken market for BTC across different time in Exchange 1, 3, and 5



During the bull period (Month 2-4), bid movements in local crypto markets appeared aggressive and can easily move higher than the global price. The price discovery faded away during the bear market (Month 5-7) especially for the exchange with low participations of investors.

Bid response of local crypto markets after a 30% impulse in the Kraken market for BTC, ETH and XRP across different time

Example from Exchange 5



Aggressive move of bid during the bull period also exist across different cryptos.

Key takeaways

- **The analysis on bid-ask spreads**
  - Percentage spreads at around 0.5% - 1.0% (for BTC and ETH) are a bit high if compared with the percentage spreads of SET at around 0.25% or 0.01% for BTC in Kraken.
  - 10.00 – 16.00 is the period where spreads are lowest. This corresponds to the usual trading hours of investors in Thailand.
  - Higher trading volume can reduce spreads only if the spread level is high.
  - Volatility can increase spreads especially for the case when spreads are low.
- **Measurement of price discovery**
  - Price responses of bids are faster than offers which results from the fact that offer levels in local exchange markets tend to be at much higher levels than the level seen in the global market.
  - It takes around 1-2 hours for bids and offers to completely follow the price movement in the global market.
  - Thai investors appear to be quite aggressive in trading especially during the bull market.

It is interesting to investigate further about the trading behavior of Thai investors.

Users: Disposition Effect

Disposition Effect: the tendency to sell winning investments while holding on to losing investments. Shefrin and Statman (1985)

- Documented in many markets, assets and investors. For example:
  - Stocks: Australia (Brown et al., 2006), China (Feng and Seasholes, 2006), Finland (Granblatt and Kelorharju, 2001; Seru et al., 2010)), Israel (Shapira and Veneazia, 2001), Taiwan (Barber et al., 2007), US (Odean, 1998; Dhar and Zhu, 2006; Frazzini, 2006; Ben-David and Hirshleifer, 2012).
  - Digital assets (cryptos): Haryanto et al. (2020), Schatzmann and Haslhofer (2020).

- Potential reasons
  - Prospect theory: Kahneman and Tversky (1979), but not commonly agreed
  - Emotion and regret: Muermann and Volkman (2006)

Digital asset prices have been shown to be driven by behavioral factors.

- Public sentiment from twitter(Kraaijeveld and De Smedt, 2020; Naeem et al., 2020)
- Overreaction to news (Chevapatrakul and Mascia, 2019)
- Small price bias (Aloosh and Ouzan, 2020)
- Herding (Bouri et al., 2019; Kaiser and Stöckl, 2020; Vidal-Tomás et al., 2019)

- But evidence mostly come from aggregate price data. In this study, we use exchange trade book data to directly investigate trading behavior.

Identification of disposition effect requires users to buy AND sell with some frequency, so not all users are included in the study. **Sample: Nov 2020 – July 2021**

Panel A: all accounts

Account size	Num of acc	Share	Av. Size	Median Size
0 - 1,500 baht	190,151	50.0%	496	419
1,500 - 5,000 baht	72,490	19.1%	3,010	2,893
5,000 - 20,000 baht	64,906	17.1%	10,541	9,975
20,000 - 100,000 baht	36,731	9.7%	45,131	39,400
100,000 - 1 milllion baht	14,069	3.7%	272,041	199,500
1 million baht+	1,781	0.5%	4,868,212	1,916,400
Total	380,128	100%		

Account size is classified by maximum capital (at cost) on exchange over entire history.

50% of accounts put in no more than 1,500 baht.

Panel B: accounts with data to analyze disposition effect

Account size	Num of acc	Share	Av. Size	Median Size
0 - 1,500 baht	83,864	41.8%	559	499
1,500 - 5,000 baht	41,321	20.6%	2,967	2,814
5,000 - 20,000 baht	40,971	20.4%	10,461	9,975
20,000 - 100,000 baht	24,233	12.1%	44,242	37,999
100,000 - 1 milllion baht	9,285	4.6%	264,131	191,332
1 million baht+	1,113	0.6%	3,823,937	1,861,914
Total	200,787	100.0%		

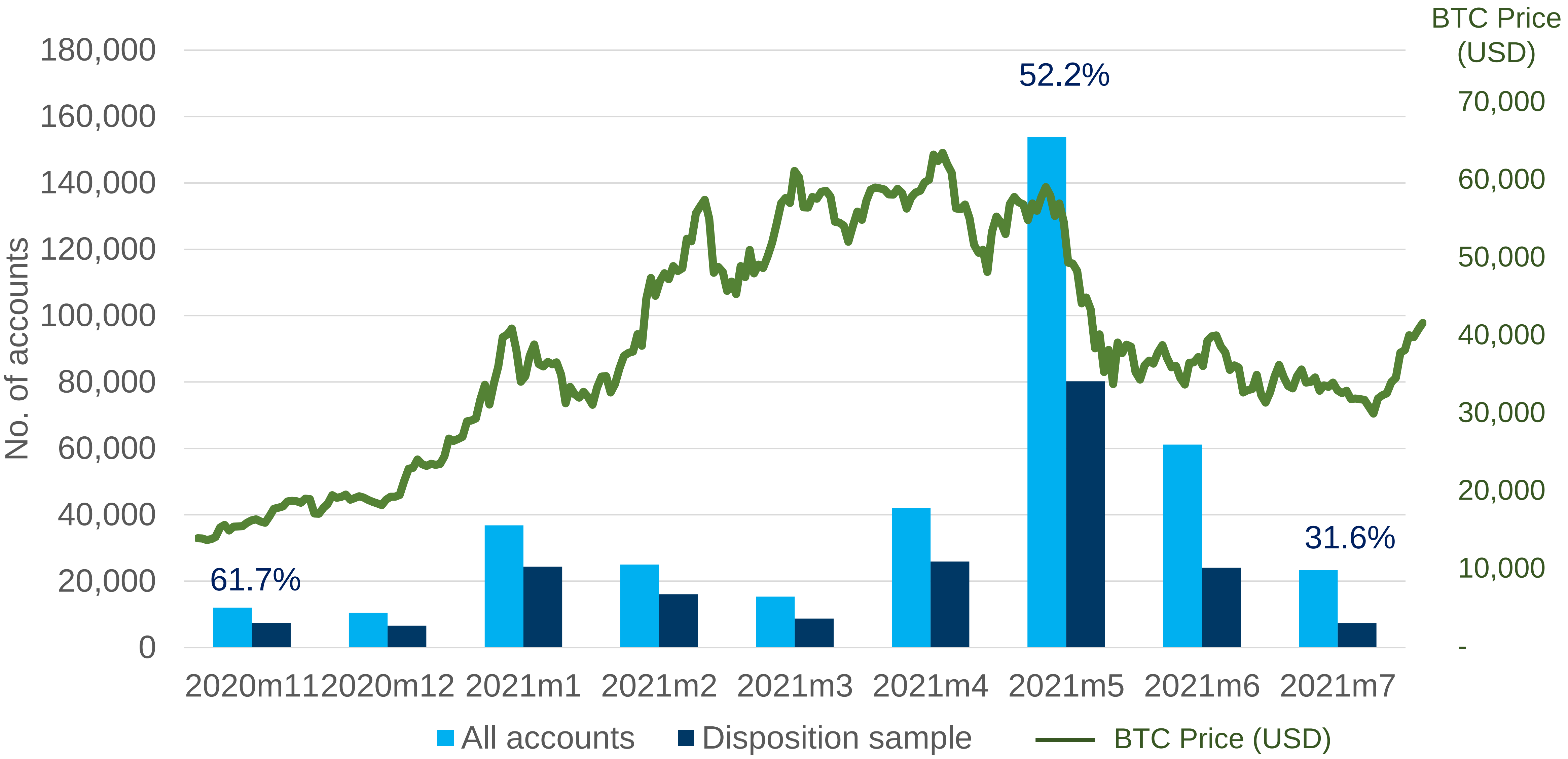
~47% of accounts is excluded.

Experimenters vs long-term holders?

Material differences:

- More trades / day
- Hold more tokens (5 rather than 3)

Accounts that first began trading after April are less active (and hence less likely to be in the disposition sample).



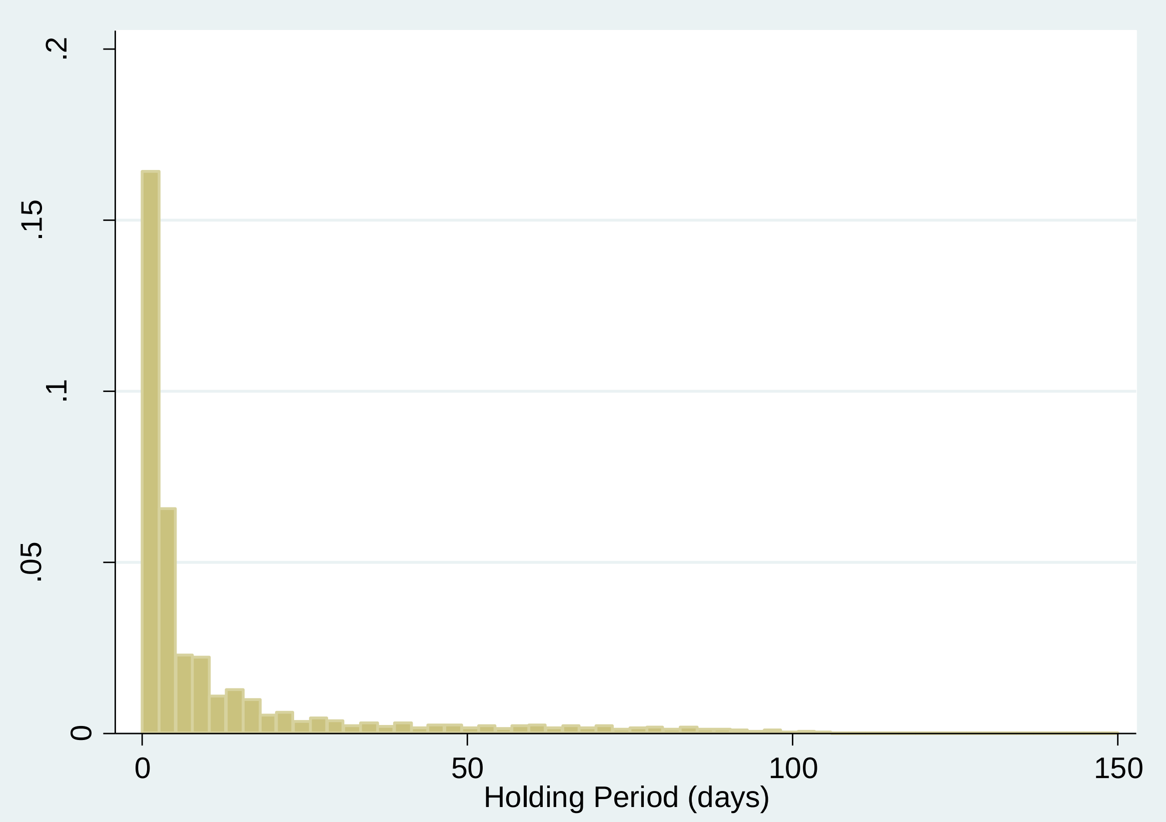
A “round-trip” trade involves opening and closing a position, therefore holding period can be computed.

Note: BTC, ETH, DOGE and XRP only.

Large accounts are less likely to have completed round-trips. Most round-trips are short, but there are users who have very long holding periods as well. The median holding period is ~4 days.

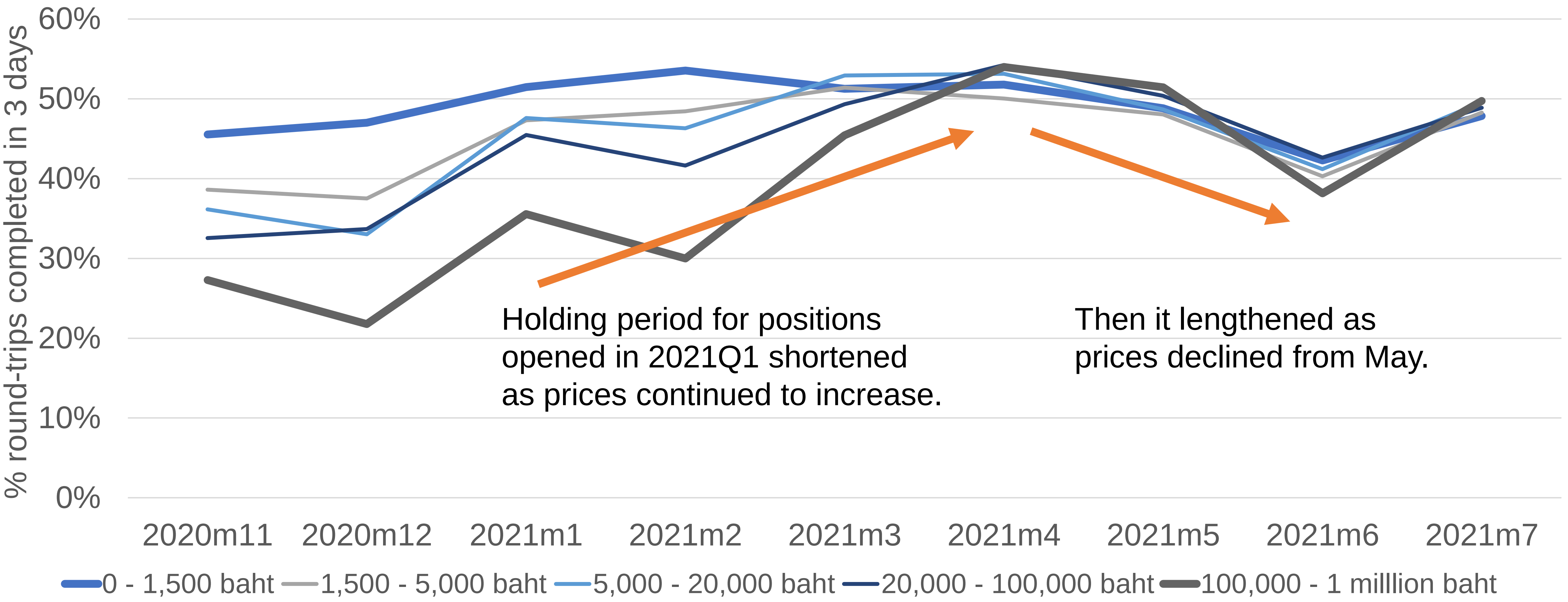
Account size	Num of acc	With RT	Share
0 - 1,500 baht	190,151	93,522	49.2%
1,500 - 5,000 baht	72,490	43,449	59.9%
5,000 - 20,000 baht	64,906	39,438	60.8%
20,000 - 100,000 baht	36,731	21,331	58.1%
100,000 - 1 million baht	14,069	7,183	51.1%
1 million baht+	1,781	570	32.0%
Total	380,128	205,493	54.1%

Account size	Num RT	Share	Av. Num.	Med. HP
0 - 1,500 baht	262,875	40.8%	1.38	4
1,500 - 5,000 baht	139,050	21.6%	1.92	4
5,000 - 20,000 baht	137,575	21.4%	2.12	3
20,000 - 100,000 baht	77,948	12.1%	2.12	3
100,000 - 1 million baht	25,120	3.9%	1.79	3
1 million baht+	1,603	0.2%	0.90	4
Total	644,171	100.0%		



~45% of round-trips are completed within 3 days, and ~30% of round-trips are completed within 1 day.

Graph: within 3 days. Note: BTC, ETH, DOGE and XRP only.



Detecting disposition effect involves examining the relationship between selling decision and P&L of the position at the time of sale.

Recall that disposition effect = capital gains are realized more often than capital losses. There are several approaches. We choose two:

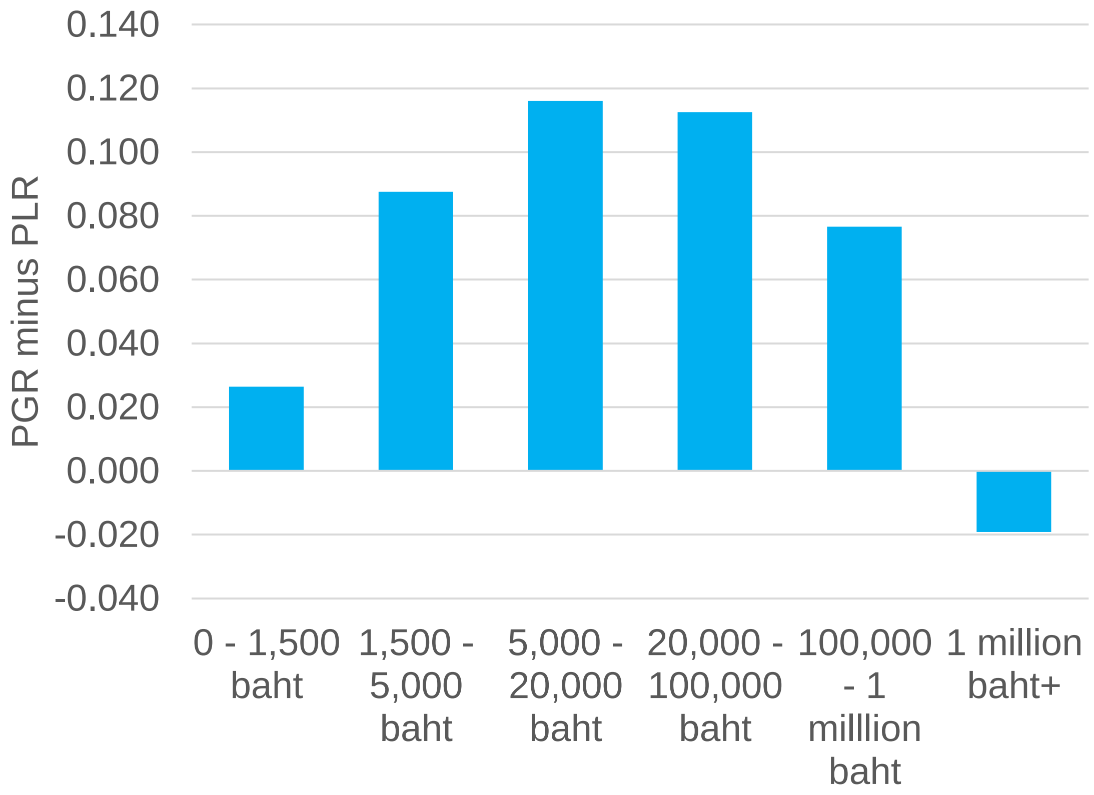
1. Summary of decisions made: Odean (1998)
   - Proportion of realized gain (PGR) = realized gain / (realized + paper gain), and similarly for loss (PLR)
   - → **Disposition effect when PGR > PLR**

2. P&L when a sale transaction is made: Granblatt and Kelorharju (2001), Feng and Seasholes (2006)
   - Probability model of a sale transaction, conditioning on P&L of the asset and controlling for other factors (e.g. general price movements, demographics). Choice: logistic model.
   - → **Disposition effect when P(sale) is lower when there is capital loss.**

Result #1: Disposition effect is weaker for very small (<1,500) and very large (>1m) portfolios.

The level of PGR and PLR depends on portfolio size and proportion of portfolio realized (see Table). If users completely empty their portfolios, then PGR and PLR will either be 0 or 1. These users are excluded from this analysis to prevent bias.

Account size	PGR	PLR	Diff	t-stat
0 - 1,500 baht	0.46	0.43	0.026	14.5
1,500 - 5,000 baht	0.45	0.37	0.088	36.3
5,000 - 20,000 baht	0.43	0.31	0.116	51.3
20,000 - 100,000 baht	0.38	0.26	0.113	41.0
100,000 - 1 milllion baht	0.31	0.24	0.077	18.4
1 million baht+	0.21	0.23	-0.019	-1.8
Total	0.43	0.36	0.073	67.1
Odean (1998)	0.15	0.10	0.050	35.0



Compared to results on US equity in Odean (1998), the magnitude of difference is similar.

Result #2: Disposition effect is greater for users who first began trading in 2020Q2 (less experience)

- May 2021 could be considered the beginning of a bear market. We will define 2021m5 - 2021m7 as bear market.
- Behavior changes in bull/bear markets (Kim and Nofsinger, 2007). Notably, during bear market, volatility tends to be higher.
- Consistent with our result, Cheng et al. (2013) find that traders on TAIFEX exhibit greater disposition effect during bear market.

	Date user first began trading									
Account size	2020m11	2020m12	2021m1	2021m2	2021m3	2021m4	2021m5	2021m6	2021m7	Total
0 - 1,500 baht	-0.01	-0.01	0.01	0.01	0.02	0.02	0.04	0.04	0.04	0.03
1,500 - 5,000 baht	0.04	-0.01	0.05	0.04	0.03	0.07	0.12	0.13	0.11	0.09
5,000 - 20,000 baht	0.03	0.03	0.07	0.07	0.04	0.10	0.17	0.18	0.11	0.12
20,000 - 100,000 baht	0.03	0.00	0.07	0.05	0.02	0.12	0.20	0.20	0.12	0.11
100,000 - 1 milllion baht	0.00	-0.02	0.04	0.04	0.01	0.11	0.21	0.13	0.09	0.08
1 million baht+	-0.05	-0.09	-0.03	-0.03	-0.05	0.02	0.17	0.02	-0.15	-0.02
Total	0.01	0.00	0.04	0.04	0.02	0.08	0.11	0.09	0.06	0.07

Increasing disposition effect
for later cohorts.

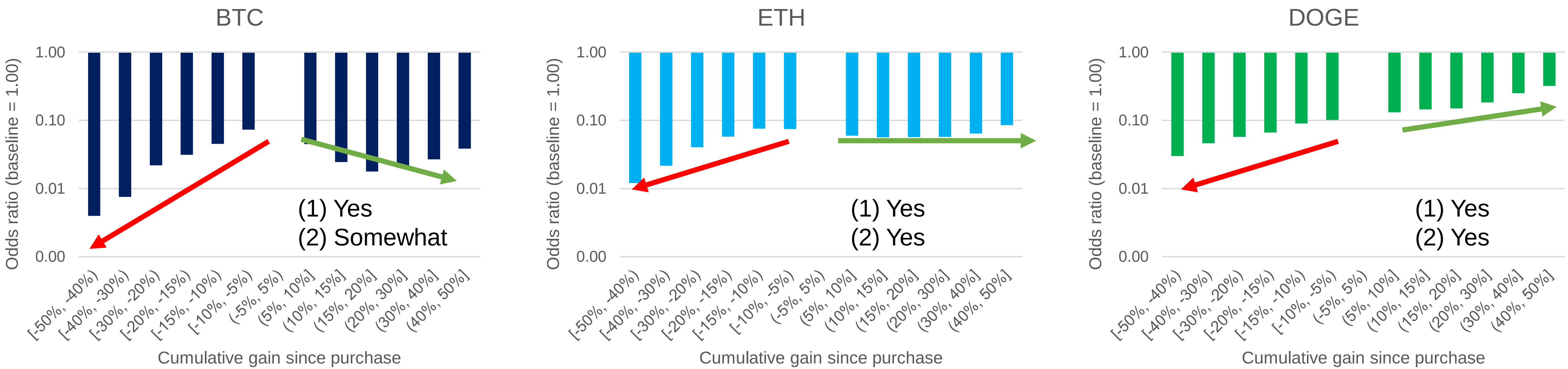
Result #3: Looking at trades during bear market only, users with less experience show greater disposition effect.
Infrequent traders also show lower disposition effect.

	Users who began trading before May						Users who began trading in May and beyond						
Account size	1 (Infreq)	2	3	4	5 (Freq)	All	1 (Infreq)	2	3	4	5 (Freq)	All	Diff
0 - 1,500 baht	-0.02	0.06	-0.02	-0.02	0.00	0.00	-0.02	-0.02	-0.01	0.02	0.05	0.04	0.04
1,500 - 5,000 baht	-0.06	0.07	0.06	0.04	0.07	0.06	-0.08	0.06	0.09	0.12	0.13	0.12	0.06
5,000 - 20,000 baht	0.01	0.10	0.06	0.11	0.08	0.09	0.05	0.13	0.18	0.18	0.16	0.17	0.09
20,000 - 100,000 baht	0.02	0.05	0.12	0.11	0.08	0.10	0.05	0.14	0.21	0.22	0.18	0.20	0.10
100,000 - 1 milllion baht	0.08	0.07	0.07	0.07	0.08	0.08	0.07	0.25	0.25	0.20	0.16	0.19	0.12
1 million baht+	0.01	0.01	0.05	0.02	0.02	0.02	0.07	-0.04	0.19	0.09	0.14	0.12	0.10
Total	0.02	0.07	0.07	0.06	0.05	0.06	0.04	0.11	0.11	0.11	0.10	0.10	0.04

- On average, users who began trading in and after May show greater disposition effect. The difference is increasing in account size.
- **Very small accounts do not exhibit much disposition effect across cohorts and over time.**
- Disposition effect is observably lower for users who trade less frequently (separated into 5 groups based on cohort / account size), but not for frequent users.
- Odean (1997) and Barber and Odean (2000, 2001) document that frequent traders (often interpreted as overconfident) tend to underperform. We do not investigate trading performance in this study.

Result #4: Controlling for price movements and volatility, all tokens exhibit disposition effect. For Dogecoin, the pattern is the clearest of the three.

Reading the graphs: longer bar (odds ratio < 1) = less likely to sell. If no effect, the bars should be flat (all ~1.00). **We can detect from (1) long bars for losses (to the left) and short bars for gains (to the right), and/or (2) asymmetry left and right.**



Note: log scale (non-linear effect). In this analysis, we use logistic model and report exp(coefficient).

- Different tokens serve different purposes with potentially different user base, which is reflected in user behavior.

Key takeaways

- Disposition effect is a common behavioral phenomenon observed in many asset classes, including digital assets.
- Degree of disposition effect can vary depending on:
  - Portfolio size: large = lower disposition
  - Experience: high = lower disposition
  - Market conditions: bull market = lower disposition
  - Frequency of trading: infrequent = lower disposition
- The “middle” groups (5,000 – 100,000 baht range, ~1/3 of the market) exhibit the greatest disposition effect.

Conclusions

Bid-ask spread and price discovery

- Spread is an indirect trading cost which varies by exchange.
- Spread and price discovery are aspects that could be attractive to traders and marketable by exchanges.

Disposition effect

- Human psychology affects financial decision-making, but experience diminishes this behavioral bias.
- Similar to other asset classes, professional and robo-advisors can play a role in overcoming this bias.