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Informational Content of Exchange Flows in Cryptocurrency Markets

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Abstract

How predictable are the prices and liquidities of cryptocurrencies listed at different exchanges? We analyze price, trading volume, and in-and-out flows of Bitcoin and Ethereum at multiple crypto-exchanges using cross-sectional analysis. We examine the intraday data at hourly intervals from January 1st, 2018 to September 30th, 2019. The results show that returns, trading volumes, and net flows in different crypto-exchanges predict each other significantly. In particular, the movement in big exchanges presents a disproportionately large predictive impact on the movement in other markets. Therefore, inefficiencies are prevalent in crypto-markets, and the cross-sectional analysis for exchanges is essential for traders in the market.

Keywords : Bitcoin, Ethereum, crypto-exchange, cryptocurrency, fund flows.

1. Introduction

Cryptocurrency exchanges play a vital role in the development of the blockchain industry. They allow investors to trade, buy, or sell cryptocurrencies instantly. Most importantly, they built a whole new industry in the spirit of decentralization, the core idea of blockchain technology. This empowerment of individuals, which urged centralized entities such as exchanges, shifted their focus toward decentralization of custody, and hence the birth of multiple crypto-exchanges. In other words, the cryptocurrency market has several non-integrated exchanges that are independently owned and exist in parallel across countries. This implies that

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we cannot rule out the effect between exchanges which can increase the role of arbitragers who can trade across the different exchanges. Extending previous literature, we examine the relationship between cryptocurrencies trading in various exchanges.

The primary focus of this paper is to analyze the relationship between return, volume, and net flows of cryptocurrencies across exchanges. Earlier works in finance demonstrate that the fund flows reflect information about markets' fundamental prospects, and thereby can aid in predicting future returns of local equity markets(Froot et al., 2001). This implies that our paper can contribute to the exploration of the informational role of the net flow in the cryptocurrency market. To the best of our knowledge, this is the first study that examines the relationship between the returns and the net flows between crypto-exchanges. In order to analyze this, we use returns, trading volumes, and in-and-out-flows of Bitcoin and Ethereum in nine crypto-exchanges (Binance, Bitfinex, Bitmex, Bitstamp, Bittrex, Huobi, Kraken, Kucoin, and Poloniex) at one hour intervals, from January 1, 2018, to September 30, 2019.

We find that returns, trading volume, and net flow exhibit strong predictability of each other. Especially, the results from the Granger-causality test between return and net flow, and between return and volume show that the two exchanges of Binance and Huobi, which are ranked as the most traded and most widely used crypto-exchanges in the world, have a large impact on the entire market.

The remainder of this paper proceeds as follows. Section 2 reviews the literature on the predictability of the cryptocurrency market. Sections 3 discusses the empirical analysis, and Section 4 concludes the paper.

2. Literature Review

Previous literatures have attempted to analyze the characteristics of cryptocurrencies(Choi et al., 2018; Kang, 2019). Especially, some studies focus on the causal-relation between Bitcoin return, volatility and traded volume. Balcilar et al.(2017) find that volume can predict returns, but not volatility, at some quantiles using non-parametric causality in quantile tests. Zhang et al.(2018) also find the nonlinear dependencies and cross-correlations in return and volume. Bianchi, Dickerson(2019) show that the interaction between lagged volume and past returns has significant predicting power for the future return of Bitcoin and Ethereum. Bouri et al.(2019) also suggest that trading volume carries useful information to predict extreme negative and positive returns of seven cryptocurrencies including Bitcoin and Ethereum. El Alaoui et al.(2019) find the existence of price-volume multifractal cross-correlations of Bitcoin which implies that Bitcoin volume may help predict the underlying dynamics of Bitcoin price changes. Some studies attempt to analyze the relationship between return and transaction activity in Bitcoin market. Koutmos(2018) show the bidirectional linkages between Bitcoin returns and transaction activity. Especially, they find that the contribution of return shocks to transaction activity is larger in magnitude on the third day following the shock.

Also, there are some papers that analyze the relationship between crypto-exchanges. Less popular Bitcoin exchanges are more likely to be shut down or suffer a security breach than popular ones due to the 'Bitcoin-exchange risk' (Moore, Christin, 2013). Makarov, Schoar(2020) find that there exist large arbitrage opportunities across exchanges with low bid-ask spreads. Even the influence on the web are vary across the crypto-markets (Park, Park, 2018). Borri, Shakhnov(2019) analyze the cross-section relationship of cryptocurrencies and state that investors are exposed to risk factors such as aggregate liquidity, momentum, and counterparty risks of Bitcoin. Lim, Kim(2018) show no clear price spillover between the four crypto-markets, while volatility spillover were exists in the market.

However, there is no prior literature investigating the effect of net flows between crypto-exchanges on return while it is important with respect to the informational effect. While there is no related work in the cryptocurrency market, we can extend the literature to traditional markets. Earlier works in finance have two basic theories regarding the relationship between net flows and the return(Swanson, Lin, 2003). First, past returns affect flows due to feedback trading or momentum trading. Second, flows affect the returns due to the information contribution on returns(Ali, Pope, 1995; Edelen, Warner, 2001). Brennan, Cao(1997) argue that flows incorporate new information and propose a model that shows that portfolio flows are a linear function of local equity returns. Froot et al.(2001) find that cross-border fund flows reflect information about markets' fundamental prospects, and thereby can aid in predicting future returns of local equity markets. Our paper mainly focuses on the second perspective. Would such phenomenon extend to the cryptomarkets? In addressing these issues, this paper highlights the relationship between the net flows and the return between crypto-exchanges to examine the informational content of exchange flows.

Cryptomarkets offer an ideal empirical setting to analyze the information flow across markets. We exploit the unique characteristics of cryptomarkets in which cryptocurrency traders tend to use the information from all possible exchanges in order to optimize its profits. Would this practice imply the lead-lag predictability analysis across exchanges? We address this practical issue and contribute to the literature about information and trading flows in financial markets.

3. Empirical analysis

To analyze the relationship between cryptocurrencies listed in various exchanges, we use price, trading volumes, and in-and-out-flow of Bitcoin and Ethereum in nine crypto-exchanges at one hour intervals, from January 1, 2018, to September 30, 2019. We collect data from nine exchanges: Binance, Bitfinex, Bitmex, Bitstamp, Bittrex, Huobi, Kraken, Kucoin, and Poloniex. Considering the large volatile price of cryptocurrencies even at daily intervals, we analyze log returns at an hourly frequency. The data is publically available at

TokenAnalyst(https://tokenanalyst.io), the popular cryptocurrency-related data vendors. Among nine exchanges, we only use the exchanges which offer hourly data. For example, since Huobi provides hourly data of Bitcoin but not of Ethereum, we only consider the Huobi exchange for Bitcoin analysis. If parts of the hourly price data are missing due to no transactions, the most recent price data is used. We also test with the data covering up the missing hourly price data using the linear interpolation methods and the results are similar (unreported). The total number of observations is 15,288.

Table 1. Summary statistics

			Mean	Standard deviation	Min	Median	Max	Jarque-Bera	ADF unit-root tests
Bitcoin	RET	EX1	0.000	0.009	-0.094	0.000	0.109	189,676***	-25.448***
		EX2	0.000	0.009	-0.096	0.000	0.113	192,444***	-25.267***
		EX4	0.000	0.009	-0.092	0.000	0.112	184,636***	-25.489***
		EX5	0.000	0.009	-0.096	0.000	0.116	189,245***	-19.510***
		EX6	0.000	0.008	-0.099	0.000	0.108	237,179***	-25.275***
		EX7	0.000	0.009	-0.093	0.000	0.113	192,187***	-19.344***
		EX8	0.000	0.010	-0.155	0.000	0.107	273,450***	-20.145***
		EX9	0.000	0.009	-0.092	0.000	0.102	148,378***	-19.347***
	VOL	EX1	1497.80	1081.84	0.000	1200.59	7095.24	21,397***	-9.695***
		EX2	941.33	1105.30	0.000	533.89	7119.61	32,949***	-8.652***
		EX3	6126.59	6288.37	0.000	5008.98	32353.97	3,934***	-4.885***
		EX5	55.75	83.28	0.000	22.15	562.34	58,065***	-5.469***
		EX8	39.45	97.48	0.000	8.07	551.11	70,771***	-5.226***
		EX9	57.47	81.63	0.000	25.33	554.18	56,540***	-6.270***
	NET	EX1	41.21	522.97	-29880.46	30.18	22427.51	859,980,168***	-19.470***
		EX2	6.97	695.88	-15767.86	5.30	14692.65	4,926,941***	-23.717***
		EX3	12.41	485.79	-9458.76	46.99	18051.21	24,413,660***	-22.433***
		EX4	27.20	312.49	-4427.06	10.52	5335.01	783,988***	-65.232***
		EX5	-6.84	151.07	-3171.90	-4.20	2688.91	1,376,886***	-19.512***
		EX6	17.58	242.29	-3147.20	12.99	7013.62	3,349,206***	-17.669***
		EX7	2.06	200.74	-2290.54	-2.16	5076.62	3,414,023***	-59.636***
		EX9	-1.92	271.01	-7652.20	-4.56	11649.46	172,651,303***	-25.585***
Ethereum	RET	EX1	0.000	0.012	-0.141	0.000	0.149	202,380***	-23.922***
		EX2	0.000	0.011	-0.139	0.000	0.141	194,551***	-25.012***
		EX5	0.000	0.011	-0.138	0.000	0.166	217,113***	-24.130***
		EX7	0.000	0.011	-0.136	0.000	0.142	213,971***	-24.160***
		EX8	0.000	0.012	-0.142	0.000	0.145	185,063***	-18.762***
		EX9	0.000	0.012	-0.142	0.000	0.139	162,006***	-24.971***
	VOL	EX1	11834.67	11102.23	0.000	8185.80	71453.69	25,998***	-7.849***
		EX2	8470.28	9692.19	0.000	5203.59	66927.14	49,551***	-9.763***
		EX5	229.34	323.84	0.000	109.57	2236.11	64,363***	-9.151***
		EX8	760.69	2230.43	0.000	81.20	14141.45	93,693***	-4.516***
		EX9	326.53	451.22	0.000	156.12	2985.14	55,306***	-9.345***
	NET	EX1	119.53	3292.75	-38982.99	26.39	48589.57	279,215***	-18.823***
		EX2	48.55	13053.13	-840022.59	-3.22	492152.87	1,893,711,660***	-19.021***
		EX5	18.79	2149.63	-159936.66	-5.22	56750.65	3,502,003,688***	-44.237***
		EX7	-25.98	3060.78	-137162.86	-69.33	92842.41	108,782,067***	-21.307***
		EX8	4.46	351.18	-5526.59	4.55	6428.98	1,755,045***	-23.171***
		EX9	-90.22	1763.30	-65904.58	-12.02	62489.85	132,927,438***	-16.414***

Notes: The symbols *, **, and *** denote the rejection of the null hypothesis at the 10%, 5%, and 1% significance levels.

Table 1 describes the summary statistics and the unit-root tests of all data series. 'RET', 'VOL', and 'NET' denotes the hourly log return, trading volume, and net flow respectively. The net flow is measured as inflow minus outflow of cryptocurrencies. The abbreviations of 'EX1' to 'EX9' denotes each nine crypto-exchange: Binance, Bitfinex, Bitmex, Bitstamp, Bittrex, Huobi, Kraken, Kucoin, and Poloniex.

The results from Table 1 show that the descriptive statistics of cryptocurrencies are vary across exchanges while cryptocurrencies are homogeneous assets regardless where they are trades. The standard deviation of Bitcoin return is lower in Huobi (EX6) with 0.008 and higher in Kucoin (EX8) with 0.009. Also, this shows the substantial variations exist regarding the size and volatility of trading volumes across crypto-exchanges. Both the average and standard deviation of trading volume were highest in Bitmex (EX3) and lowest in Kucoin (EX8). With regards to net flow of Bitcoin, we can also find the large variations in net flows in each crypto-exchange. For example, Binance (EX1) has the largest net flow with 41.21 and Bittrex (EX5) has the lowest net flow with －6.84.

In addition, Table 1 indicate that the distributions of all returns are asymmetric and leptokurtic, thus rejecting the normality identified in the Jarque-Bera test. Also, the results with the Augmented Dickey-Fuller (1997) unit-root test indicate that all return, trading volume, and net flow series are stationary.

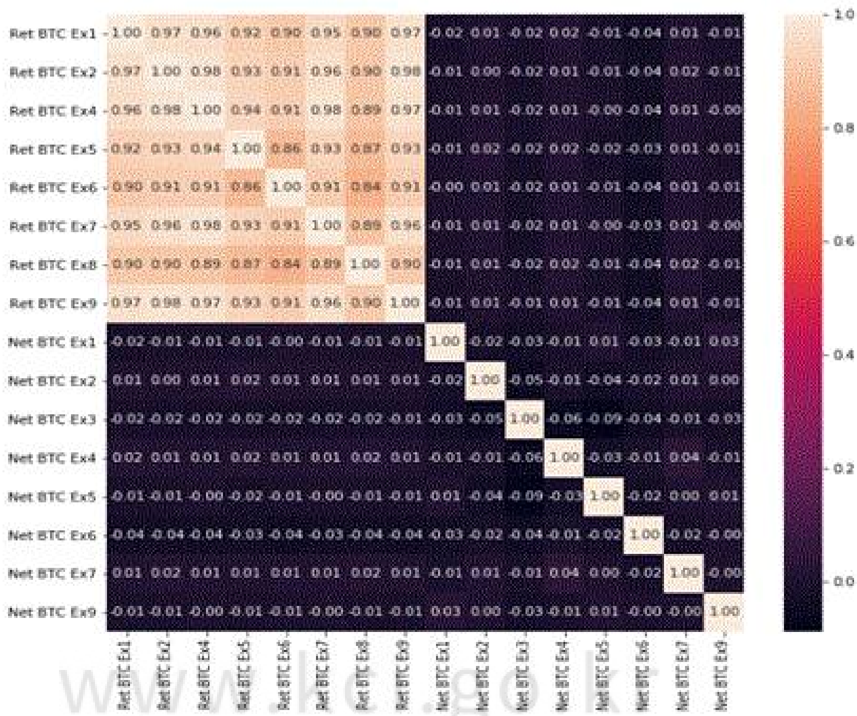

Figure 1. Correlation heatmap between return and net flow of Bitcoin among crypto-exchanges

Figure 1 describes the correlation between net flow and return of Bitcoins. The correlation of each variable over the exchanges was generally positive. Especially in the case of returns, in which the correlation among all exchanges was close to one. This implies that the returns in different currencies have a strong positive relationship.

Table 2 reports the results from VAR between return and net flow of Bitcoin among the crypto-exchanges, with the lagged variables up to three lags. The results from Panel A show that the most past one-hour returns (L1.RET) of each exchange are significantly related to the return of other exchanges. Also the past one-hour net flow(L1.NET) from Binance (EX1), Bitfinex (EX2), and Huobi (EX6) are significantly related to the returns of all crypto-exchanges. Panel B also show that the most past one-hour returns (L1.RET) of each exchange are significantly related to the net flow of most other exchanges. Also, not only the past net-flow affect the net-flow of that exchange, it affect other exchanges. For example, the past one-hour net flow from Binance (EX1), Bitfinex (EX2), and Huobi (EX6) are significantly related to net flow of other exchanges. Moreover, lagged one net flow from some of the other exchanges affected the return of other exchanges. Overall, the results from VAR show that the net flow and return among exchanges have strong predictability of each other.

Table 3 and Table 4 shows the t-statistics of the Granger-causality test used to investigate the causal relationship among the exchanges. We checked the lagged variables up to three lags. This tests the null hypothesis that the variables in the vertical axis do not Granger-cause the variables in the horizontal axis.

Table 3 shows the results from the Granger-causality test used to investigate the causal relationship between return and net flow of Bitcoin among the exchanges. The dependent variables are return of Bitcoin, which we test the past returns and net flow as the source of causations in Panel A from Table 3. The results indicate that the net flow of Binance (EX1) caused the returns of all other exchanges. Also, the net flow of Huobi (EX6) affected the returns of Binance (EX1), Bitstamp (EX4), and Bittrex (EX5). In Panel B, the returns from all exchanges except Kucoin (EX8) affected the net flow of Bittrex (EX5). Moreover, returns from different exchanges affected the net flow of Binance (EX1), Bitfinex (EX2), and Huobi (EX6). In Particular, returns from Huobi (EX6) and Kraken (EX7) affected Binance (EX1), Bitfinex (EX2), Bittrex (EX5), and Huobi (EX6) in common. Moreover, we found that net flow from Bitfinex (EX2) affected the largest number of exchanges including Binance (EX1), Bitmex (EX3), Bittrex (EX5), Huobi (EX6), and Kraken (EX7). In addition, the results show that the net flow of certain exchanges affected each of the other exchanges. The exchanges of Binance (EX1) and Huobi (EX6) granger-caused price movement in the other exchanges. As these two exchanges are ranked as the most traded and most widely used crypto-exchanges in the world. This broadly imply that the price and net-flow movements in big exchanges has large predictive impact on the entire crypto-exchanges.

Table 2. Vector autoregression between return and net-flow of Bitcoin among exchanges(Continued)

Panel A. Model 1: Dependent variable is return

		RET							
		EX1	EX2	EX4	EX5	EX6	EX7	EX8	EX9
L1.RET	EX1	-0.304***	0.071*	0.069*	0.06	-0.022	0.061	0.178***	0.139***
	EX2	0.215***	-0.225***	0.150***	0.201***	0.144***	0.145***	0.174***	0.248***
	EX4	0.018	0.065	-0.368***	0.061	0.046	0.117**	0.05	0.053
	EX5	-0.035	-0.042*	-0.018	-0.258***	-0.051**	-0.028	-0.009	-0.046*
	EX6	-0.051**	-0.045*	-0.047**	-0.050**	-0.088***	-0.069***	-0.171***	-0.031
	EX7	0.036	0.062	0.136***	0.019	-0.001	-0.282***	0.042	0.036
	EX8	-0.034*	-0.026	-0.029	-0.061***	-0.02	-0.027	-0.423***	-0.016
	EX9	0.115**	0.106**	0.088*	-0.014	-0.04	0.06	0.146***	-0.417***
L2.RET	EX1	-0.350***	-0.097**	-0.102**	-0.131***	-0.033	-0.117***	-0.06	-0.052
	EX2	0.192***	-0.022	0.156***	0.136**	0.092*	0.159***	0.181***	0.215***
	EX4	0.087	0.008	-0.212***	0.039	0	0.07	-0.015	0.032
	EX5	-0.013	-0.014	-0.004	-0.074***	-0.011	0.005	-0.012	-0.015
	EX6	0.105***	0.096***	0.099***	0.129***	-0.048**	0.115***	0.115***	0.109***
	EX7	-0.048	0.025	0.071	-0.013	0.023	-0.203***	0.051	0.002
	EX8	-0.008	-0.001	0	-0.023	-0.008	-0.008	-0.258***	0.007
	EX9	-0.009	-0.037	-0.045	-0.105*	-0.054	-0.056	-0.046	-0.341***
L3.RET	EX1	-0.03	0.033	0.027	0.034	-0.016	0.06	0.071*	0.062
	EX2	0.052	-0.007	0.086*	0.062	0.038	0.090*	0.054	0.092*
	EX4	-0.06	-0.079	-0.176***	-0.088*	-0.02	-0.074	-0.067	-0.067
	EX5	0.018	0.035	0.036	-0.007	0.017	0.041	0.042	0.03
	EX6	0.051**	0.006	-0.002	0.037	-0.022	0.004	0.060**	0.029
	EX7	0.075*	0.088**	0.102**	0.063	0.064	-0.017	0.089*	0.075*
	EX8	-0.047**	-0.036*	-0.037*	-0.049***	-0.017	-0.055***	-0.228***	-0.018
	EX9	-0.054	-0.028	-0.023	-0.04	-0.033	-0.033	-0.006	-0.191***
L1.NET	EX1	-0.000**	-0.000**	-0.000*	-0.000**	0	-0.000*	-0.000*	-0.000**
	EX2	-0.000*	-0.000**	-0.000**	-0.000*	0	-0.000**	0	-0.000*
	EX3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EX4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EX5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EX6	0.000	0.000	-0.000*	-0.000**	-0.000*	-0.000*	0.000	0.000
	EX7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EX9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L2.NET	Ex1	-0.000***	-0.000*	-0.000*	-0.000**	-0.000*	0.000	-0.000***	-0.000*
	Ex2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Ex3	-0.000*	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000
	Ex4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Ex5	-0.000***	-0.000**	-0.000*	-0.000**	0.000	-0.000**	-0.000**	-0.000**
	Ex6	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000	0.000*
	Ex7	0.000	0.000	0.000	0.000	0.000**	0.000	0.000	0.000
	Ex9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L3.NET	Ex1	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	Ex2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Ex3	0.000	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
	Ex4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Ex5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Ex6	-0.000*	-0.000*	-0.000*	0.000	-0.000*	-0.000**	-0.000**	0.000
	Ex7	0.000**	0.000**	0.000*	0.000	0.000*	0.000	0.000**	0.000*
	Ex9	0.000***	0.000**	0.000**	0.000**	0.000	0.000**	0.000**	0.000**

Panel B. Model 2: Dependent variable is net flow

		NET							
		EX1	EX2	EX3	EX4	EX5	EX6	EX7	EX9
L1.RET	EX1	4673.588**	-5402.109*	-1225.499	-2241.911*	4732.847***	2886.834***	695.08	3.636
	EX2	-5533.658*	25221.193***	9469.775***	3401.198*	-2047.616**	-2112.832	2275.015**	-29.246
	EX4	3125.63	-8821.908**	-3630.076	2190.531	-1249.535	-3768.406***	-382.491	-3187.654**
	EX5	-3185.395**	-3570.666*	269.608	-498.305	1888.544***	-702.716	-246.659	799.853
	EX6	-2866.973**	5431.592***	-911.766	1375.074*	-2068.465***	594.392	-380.708	-2848.462***
	EX7	997.916	-8630.753***	-587.612	-1956.636	174.259	-2414.749**	138.66	3421.953***
	EX8	2833.908**	-1734.028	-161.961	-1212.895*	115.854	711.913	-235.466	-450.765
	EX9	1632.643	-1581.338	-5037.003*	-826.991	-367.954	4148.136***	-2287.126**	2919.727*
L2.RET	EX1	5284.727**	-5655.196*	211.581	273.772	3411.860***	950.056	222.994	163.949
	EX2	-12424.681***	20394.188***	10905.959***	1039.26	-2758.237***	-2745.320*	1782.647	-2526.351
	EX4	2067.286	-9171.357**	-5776.589*	1261.378	-1331.159	-4060.145***	190.602	-2083.879
	EX5	14.048	-4159.905**	1247.756	-627.799	1527.068***	393.903	-812.463	-835.091
	EX6	-2794.137**	2412.18	937.863	182.155	-343.993	1677.050***	530.05	-2788.198***
	EX7	-8188.166***	-4266.023	-2006.074	16.158	3032.886***	-1310.608	845.326	1494.205
	EX8	6718.130***	-2624.273*	-260.402	161.323	269.583	953.194*	-190.862	797.561
	EX9	9502.360***	3092.907	-7068.552**	-1438.28	-2939.834***	3419.965**	-2551.427**	6008.942***
L3.RET	EX1	3607.842	2529.326	-1559.758	-9042.000***	704.204	665.326	762.883	-1311.954
	EX2	-11314.398***	8624.973**	9315.005***	1414.105	-267.612	-933.08	237.302	455.968
	EX4	6368.334**	-5139.657	-841.277	3002.078*	2906.039***	-3828.021***	21.9	-2756.475*
	EX5	-1222.6	-3641.506*	-1057.29	-201.62	-373.556	410.096	35.347	-101.163
	EX6	-916.829	2171.855	-839.014	2250.830***	-620.024	-93.656	1099.764**	330.513
	EX7	-2343.456	3781.019	-390.472	-3459.964**	-143.226	2395.010**	-965.743	1119.956
	EX8	1744.85	-2135.29	152.541	1011.562	-267.742	-861.224*	375.77	428.481
	EX9	3891.879	-6409.575	-5273.649*	5593.702***	-2008.000**	2286.743*	-1611.496	2344.1
L1.NET	EX1	0.031***	0.003	0.006	0.004	-0.008***	0.000	0.004	-0.002
	EX2	0.016***	-0.058***	0.000	0.003	-0.004**	-0.008***	0.008***	0.004
	EX3	-0.004	-0.007	0.060***	0.007	0.005*	0.002	0.002	0.006
	EX4	-0.008	0.045**	0.002	-0.021**	0.000	0.006	0.019***	-0.011
	EX5	-0.045	0.027	0.018	-0.009	0.122***	-0.007	0.010	0.042***
	EX6	-0.004	0.002	0.015	-0.038***	0.000	0.129***	0.007	-0.019**
	EX7	0.033	0.053*	0.048**	0.013	-0.001	-0.004	0.015*	0.002
	EX9	0.019	-0.001	-0.004	-0.003	0.008*	-0.009	-0.003	-0.035***
L2.NET	Ex1	0.027***	-0.005	-0.012	0.004	-0.003	-0.001	0.006*	0.003
	Ex2	-0.003	0.005	0.016***	0.000	-0.003	0.000	0.001	0.006*
	Ex3	0.007	-0.002	0.003	0.006	0.006**	0.007*	0.007**	0.002
	Ex4	0.025*	0.008	0.016	-0.035***	0.002	-0.006	0.004	-0.001
	Ex5	-0.01	-0.011	0.021	-0.020	0.060***	-0.021	-0.023**	-0.002
	Ex6	0.005	-0.021	0.003	-0.007	-0.004	0.055***	-0.017**	0.008
	Ex7	0.036*	0.021	-0.033*	0.006	-0.002	-0.009	0.015*	-0.006
	Ex9	0.01	0.01	-0.003	0.012	0.010**	0.014*	0.002	0.004
L3.NET	Ex1	0.019**	-0.012	0.014*	-0.005	0.001	-0.003	-0.002	0.003
	Ex2	-0.009	0.032***	-0.007	0.004	-0.006***	-0.002	0.002	0.002
	Ex3	-0.016*	0.016	-0.006	-0.007	0.002	0.003	0.007**	-0.004
	Ex4	-0.028**	0.004	0.001	-0.011	-0.006*	-0.002	0.015***	-0.009
	Ex5	0.001	-0.036	-0.038	-0.044**	0.032***	0.007	-0.004	0.009
	Ex6	0.019	0.015	0.067***	0.008	-0.006	0.056***	-0.001	0.010
	Ex7	0.009	0.027	0.055***	-0.013	0.011*	-0.014	0.001	-0.005
	Ex9	-0.015	-0.005	0.010	-0.001	0.002	-0.004	0.003	-0.010

Notes: *p-value<0.1, **p-value<0.05, ***p-value<0.01

Table 3. Granger causality tests with returns and net flow among crypto-exchanges

Panel A. Model 1: Dependent variable is return

		RET							
		EX1	EX2	EX4	EX5	EX6	EX7	EX8	EX9
RET	EX1	-	5.704***	5.810***	7.737***	0.294	7.637***	10.698***	8.233***
	EX2	7.243***	-	4.202***	5.518***	3.266**	4.129***	4.742***	9.780***
	EX4	2.012	1.637	-	2.053	0.441	3.312**	0.93	1.327
	EX5	0.894	1.829	0.955	-	1.906	1.368	1.066	1.812
	EX6	10.488***	7.430***	7.918***	13.259***	-	11.654***	27.366***	8.925***
	EX7	2.426*	1.868	4.405***	1.014	0.922	-	1.341	1.321
	EX8	2.760**	1.867	2.124*	4.809***	0.653	3.302**	-	0.756
	EX9	2.649**	2.544*	2.022	1.315	0.455	1.425	3.851***	-
NET	EX1	11.131***	5.812***	6.709***	7.459***	4.926***	6.129***	7.385***	6.755***
	EX2	1.415	2.432*	1.75	1.245	0.974	2.006	0.758	1.717
	EX3	2.077	2.012	1.817	1.26	1.181	1.65	1.658	1.815
	EX4	0.571	0.57	0.291	0.375	0.664	0.457	0.811	0.873
	EX5	4.708***	1.661	1.295	2.512*	0.743	1.983	2.148*	1.885
	EX6	2.805**	2.501*	3.071**	2.872**	3.037**	3.379**	1.74	2.255*
	EX7	1.796	1.832	1.694	1.424	2.899**	1.392	2.558*	1.674
	EX9	2.659**	1.746	1.736	1.569	0.441	1.526	1.591	2.270*

Panel B. Model 2: Dependent variable is net flow

		NET							
		EX1	EX2	EX3	EX4	EX5	EX6	EX7	EX9
RET	EX1	2.440*	2.675**	0.355	18.415***	21.431***	2.659**	0.414	0.549
	EX2	7.313***	15.957***	7.630***	1.365	4.089***	1.474	1.581	1.212
	EX4	1.652	2.240*	1.42	1.196	7.327***	4.478***	0.067	1.956
	EX5	1.939	2.833**	0.61	0.228	10.451***	0.692	0.725	0.985
	EX6	2.924**	3.805***	0.509	3.231**	10.332***	2.807**	2.186*	11.010***
	EX7	4.193***	3.567**	0.237	2.498*	7.080***	4.300***	0.881	2.391*
	EX8	11.358***	1.361	0.042	2.320*	0.711	3.406**	0.543	1.195
	EX9	3.164**	1.877	2.432*	5.200***	4.310***	3.669**	2.012	4.379***
NET	EX1	-	0.484	2.128*	0.789	5.149***	0.296	1.965	0.442
	EX2	3.066**	-	3.413**	0.57	6.217***	2.963**	3.810***	1.581
	EX3	1.276	0.743	-	1.658	3.548**	1.268	3.124**	0.852
	EX4	2.682**	2.103*	0.575	-	1.029	0.762	7.147***	1.36
	EX5	0.91	0.471	0.948	3.190**	-	1.074	1.653	2.827**
	EX6	0.463	0.366	6.214***	4.798***	0.851	-	2.372*	1.889
	EX7	1.916	1.756	5.544***	0.771	1.246	1.093	-	0.182
	EX9	0.937	0.106	0.184	0.614	2.713**	1.952	0.179	-

Notes: This table reports the t-statistics and its significance of Granger-causality tests. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

In addition, we test the causality of Bitcoin returns in various exchanges in Panel A of Table 4. They show that the trading volume of Binance (EX1) significantly caused the returns of all other exchanges (Row 9), while the volume of other exchanges did not significantly cause the returns of any other exchanges (Row 10 to 14). This implies that only the volume of Binance (EX1) affected the return of other exchanges. Moreover, the return of Binance (EX1), Bitfinex (EX2), and Huobi (EX6), which had a relatively higher trading volume than others, caused almost all of the returns of the other exchanges. However, the return of Bitstamp (EX4), Bittrex (EX5), Kraken (EX7), Kucoin (EX8), and Poloniex (EX9), which had relatively low trading volumed, caused only a few returns of the other exchanges. This suggests that the exchange which had a higher trading volume affected the return of the other exchanges.

Panel B of Table 4 show the results from the causality of trading volume, from which we can find that the volume from Bitfinex (EX2) and Bitmex (EX3) significantly affected the volume of the other exchanges, except Kucoin (EX8). On the other hand, the volume from Binance (EX1) significantly affected Bitfinex (EX2), Bitmex (EX3), and Kucoin (EX8). Moreover, the result shows that the volume form Kucoin (EX8) and Poloniex (EX9) also affected the volume of Binance (EX1), Bitfinex (EX2), and also Bittrex (EX5). In unreported tests with Ethereum, the results are similar and our results are robust with sub-sample period of 2018 and 2019.

Table 4. Granger causality tests with returns and trading volumes among crypto-exchanges

Panel A. Model 1: Dependent variable is return

		RET							
		EX1	EX2	EX4	EX5	EX6	EX7	EX8	EX9
RET	EX1	-	5.623***	5.608***	7.788***	0.376	7.390***	10.702***	8.166***
	EX2	6.932***	-	4.056***	5.393***	3.267**	4.193***	4.426***	9.674***
	EX4	2.093*	1.752	-	2.103*	0.503	3.306**	1.083	1.372
	EX5	0.863	1.907	1.049	-	2.026	1.455	1.166	1.821
	EX6	11.030***	7.436***	7.837***	13.417***	-	11.723***	27.926***	9.288***
	EX7	2.634**	1.86	4.169***	1.074	1.047	-	1.333	1.421
	EX8	3.151**	2.012	2.289*	5.214***	0.782	3.455**	-	0.928
	EX9	3.061**	2.739**	2.168*	1.154	0.364	1.573	4.043***	-
VOL	EX1	4.149***	4.154***	4.095***	4.070***	3.511**	3.350**	5.827***	3.534**
	EX2	1.628	1.305	1.175	1.159	0.72	1.817	1.36	1.218
	EX3	0.245	0.31	0.072	0.068	0.247	0.114	0.454	0.049
	EX5	1.064	1.3	0.701	0.84	1.636	0.894	1.48	1.03
	EX8	1.124	1.4	1.503	1.701	1.183	1.343	1.564	1.816
	EX9	0.865	0.285	0.631	0.703	0.912	0.47	1.293	0.932

Panel B. Model 2: Dependent variable is trading volume

		VOL					
		EX1	EX2	EX3	EX5	EX8	EX9
RET	EX1	1.033	4.237***	0.394	8.057***	1.434	5.742***
	EX2	0.845	0.738	1.135	6.425***	0.225	3.733**
	EX4	0.873	0.216	3.381**	4.637***	0.348	0.82
	EX5	1.602	2.410*	3.145**	1.078	0.147	0.755
	EX6	1.833	20.595***	1.684	7.235***	0.464	6.083***
	EX7	0.666	4.787***	0.71	2.201*	0.288	0.325
	EX8	2.893**	0.997	0.474	6.013***	0.269	14.849***
	EX9	0.731	0.77	0.937	7.024***	1.198	12.614***
VOL	EX1	-	31.819***	12.976***	0.972	5.036***	2.433*
	EX2	24.662***	-	11.595***	49.649***	2.021	39.257***
	EX3	46.274***	14.486***	-	109.923***	0.477	16.339***
	EX5	1.449	34.424***	2.009	-	0.313	88.127***
	EX8	19.783***	18.944***	0.314	6.793***	-	0.544
	EX9	10.618***	42.372***	1.601	117.489***	0.702	-

Notes: This table reports the t-statistics and its significance of Granger-causality tests. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4. Conclusion

The fund flow is also referred to as 'Smart Money,' as it will inject or release the net asset value of funds and eventually impact the price of the assets being dealt. Hence, asset managers are actively following the global fund flow data and trends in order to anticipate the relevant tendency of the rise or fall of the asset prices that they trade upon. We extend this intuition into crypto-markets. We analyzed the trading flows in crypto-exchanges in which identical assets were simultaneously traded in multiple locations, the unique experimental setting to analyze the dynamics, as well as the effect of trading flows on asset pricing. We applied the empirical design for traditional financial assets to cryptocurrencies to map the flow activities into in-and-out flows at diverse crypto-exchanges. Hence, this paper suggests whether cryptocurrency in-and-out flows in crypto-exchanges can be used to anticipate the relevant price movement trends in the cryptocurrencies.

We analyzed the lead-lag relationship of the hourly price and liquidity movement of cryptocurrencies listed in nine crypto-exchanges. We found that returns, trading volume, and net flow exhibit strong predictability of each other. Our results using the trading volume and the returns are consistent with the previous literature (Balcilar et al., 2017; Bianchi, Dickerson, 2019). Considering there is no prior literature analyzing the effect of net flows between crypto-exchanges, the main takeaway of this paper is the Granger-causality results between return and net flow among the crypto-exchanges. The results show that the price and liquidity movements in big exchanges present a disproportionately large predictive impact to the movement in entire markets. The exchanges of Binance and Huobi granger-caused price movement in the other exchanges. As these two exchanges are ranked as the most traded and most widely used crypto-exchanges in the world, this can be a comparable benchmark to the traditional financial system's fund flow scheme. This results imply that, in order to build models to predict returns and liquidity, one needs to take into account price and trading flows across exchanges. The cross-sectional analysis for exchanges should be essential for any investor and trader in crypto-markets. However, while our analysis shows predictability in price and liquidity, its results do not automatically imply profitable trading opportunities. Transaction costs will overwhelm predictability in naive models. Therefore, sophisticated modeling would be required in order to design practical trading algorithms. Future studies can address such issues.

The limitations of this paper are as follows. First of all, the length of data and the frequency of the candle data that we were able to obtain was limited. If dataset with longer history and lower frequencies than hourly data were able to be acquired, more thorough statistical analysis would have been able to be conducted. Second, not all of the exchanges involved in the data analysis ranked within the top ten trading volume or number of users in the world. Going forward, involving data sets for top-tier Korean and Japanese local crypto-exchanges, which will be included in the top ten trading volume and number of users, would present further insights. Third, as we were only able to conduct analysis on two cryptocurrencies that show the largest market capitalization, it is indeed important to obtain dataset for other cryptocurrencies for future studies. Last, it would be valuable to obtain the orderbook snapshots that can be mapped to the traded data. Then, we would analyze how the bid-ask spread discrepancy widens or narrows as we directly link net flow to the change in liquidity levels, which would be highly comparable to the traditional finance fund flow concept.

Digital assets and related technologies experienced tremendous growth and gained much importance over the past few years. On account of the innovation in digital payment systems derived from blockchain technologies, there has been an increasing demand in secured and decentralized digital payments. Unlike the explosive growth of technology and infrastructure, cryptocurrency still remains a highly volatile and risky asset due to the lack of regulations and accounting standards, as compared to the traditional financial asset classes. That being said, many who are involved in trading cryptocurrency tend to maximize their profits via investment strategies that leverage unorthodox dataset and trading schemes solely focused in cryptocurrency and blockchain technology fundamentals. We believe the largest contribution of this paper is to present a cornerstone for future research on cryptocurrency trading markets by reviewing cryptocurrency fundamentals with trade-related dataset from various crypto-exchanges.

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