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Demand elasticities of Bitcoin and Ethereum

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ABSTRACT

In this paper we analyze dynamic demand elasticity for Bitcoin and Ethereum in terms of price, transaction fees, and energy usage. We find that while both BTC and ETH have significantly positive price elasticities, transaction fee elasticity is negative and positive for BTC and ETH respectively, indicating differences in potential uses for these cryptocurrencies.

1. Introduction

In this paper, we derive robust estimates of demand elasticity along three dimensions, i.e., price, transaction fees and energy, for the two main proof-of-work cryptocurrencies — Bitcoin and Ethereum.[1] Elasticity of financial assets is a central element in asset pricing theory (Atanasov and Merrick, 2011) as it helps predict movements in asset demand following changes in key parameters.

Cryptocurrency markets have been associated with speculation and bubble behavior (Baur et al., 2018; Yarovaya et al., 2021; Jalan et al., 2022) and prior studies have established the link between cryptocurrency volumes and factors such as prices, energy costs and transaction fees among others. Despite the bi-directional causalities that exist between cryptocurrency prices and volumes, most papers in this area treat demand as endogenous (e.g., Yarovaya and Zięba, 2022). Benetton and Compiani (2021), hereafter BC (2021), simulate the impact of investor belief on cryptocurrency prices and volumes and find that the price elasticity of Bitcoin, Ethereum and Ripple range between −36 and −57%.

An increasing transaction fee, an important consideration in the blockchain, serves as a reward to miners in a limited-coin supply setting (Lavi et al., 2017) and as the block rewards fall in size, the importance of transaction fees will increase. Recent spikes in mining fees have led to the speculation that regular users might even abandon this technology (Basu et al., 2019) as it becomes too costly. Using a structural approach to model user and miner behavior, (Ilk et al., 2021) document a negatively sloping demand curve for transaction fees and crypto volume relationship with a fee elasticity quite small in comparison to critical goods such as gasoline and eggs. They attribute this to the 'niche' and hard-to-substitute nature of the Bitcoin.

The huge energy footprint of cryptocurrencies such as Bitcoin and Ethereum, built on the PoW protocol has raised doubts on their sustainability (De Vries, 2018). Simulation results by BC (2021) suggest a drop in Bitcoin and Ethereum prices by about 12% if investors were to become more aware of the limitations of the PoW framework. Ripple, a non-PoW currency, is expected to rise by about 6% in the same case.

In this study, we drive robust estimates of price, transaction fee and energy elasticities of demand (volumes) for BTC and ETH by using well-established Local Projections, hereafter LPs (Jordà, 2005). LPs have been shown to be more robust to misspecification of impulse response functions (IRFs) than standard autoregressive inference (Montiel-Olea and Plagborg-Møller, 2021). We use four different measures of volumes — total volume, exchange inflow and outflow volume, and inter-exchange volume while also controlling for investor sentiment using up and down-market days. The choice of four different volume types is dictated by the difference in investor sentiments and trading objectives they capture. Specifically, while total volume represents the quantity of coins successfully transferred on-chain, inflows show the movement of coins to exchange wallets from wallets outside the exchange, for a fee, indicating increased selling pressure. Outflows demonstrate coin movement following purchases, potentially for storage. This could imply a future scarcity of the crypto (potentially indicating bullish sentiments). Inter-exchange volumes could represent arbitrage strategies as investors move

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[1] Ethereum is migrating to proof-of-stake but at the time of writing, is still a proof-of-work cryptocurrency.

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their cryptocurrency holdings across exchanges to benefit from mispricing therein.

This study, the first of its kind for cryptocurrencies, contributes to the stream of literature on the factors affecting demand for cryptocurrencies, adding to predictability of this asset class. Our results indicate positive price elasticities for both BTC and ETH, negative and positive fee elasticities for BTC and ETH, respectively and mixed results for energy elasticity. Our results are useful to investors and policy makers in facilitating a better understanding of what drives crypto demand.

2. Data and models

Our dataset comprises daily close prices (in USD), volumes, total transaction fees (source: glassnode.com) and Energy Consumption Indexes (estimated TWh of electricity, source: digiconomist.net) for BTC and ETH over the period 11/09/2018 –09/05/2022.[2] Total transaction fee reflects the total transaction fees paid to miners.[3] We use 4 different volumes: total (total amount of coins successfully transferred on-chain), exchange inflow (total amount of coins transferred to exchange addresses), exchange outflow (total amount of coins transferred from exchange addresses), and inter-exchange (total amount of coins transferred between exchanges). In line with common practice, the data is log-difference transformed to improve estimation, allowing for more homogeneous variances throughout the sample (Lütkepohl and Xu, 2012).

We use LPs, a robust alternative approach to vector autoregression models. The latter have been criticized for shortcomings such as imposed dynamics on the system, the curse of dimensionality, and difficulty in application to nonlinearities (Auerbach and Gorodnichenko, 2013). Plagborg-Møller Wolf (2019) document that LPs and VAR approaches yield similar IRFs if lag structures are unrestricted, implying that estimates differ at longer horizons. LP estimators can be considered to be nonparametric estimators of IRF (Angrist et al., 2018; Stock and Watson, 2018).

Elasticity is estimated in the following manner (following a one-time factor shock):

$$E = \frac{\%\Delta in\ cryptocurrency\ volumes}{\%\Delta \text{ in factors}} = \frac{Cumulative\ response\ of\ volume}{Cumulative\ response\ of\ factor}, \tag{1}$$

where factors considered are cryptocurrency prices, transaction fees and energy consumption. Cumulative responses are derived by calculating cumulative IRFs withing the LP framework and are estimated for a 30-day period following shocks in prices, transaction fees and energy consumption, respectively.

The regression for each forecast horizon is defined as follows:

$$y_{t+h} = \alpha^h + B_1^h y_{t-1} + \cdots + B_p^h y_{t-p} + u_{t+h}^h, h = 0, 1, \ldots, H-1 \tag{2}$$

where α^h is a vector of constants, B_1^h is the slope matrix capturing the response of y_{t-1} to a reduced form shock in t (Kilian and Kim, 2011), B_p^h are parameter matrices for lag p, h is forecast horizon, u_{t+h}^h are autocorrelated and/or heteroscedastic disturbances estimated in Newey and West (1987) way. The set of Eq. (2) composes LPs.

Structural impulse responses are presented as:

$$\widehat{IR}(t, h, d_i) = \hat{B}_1^h d_i, \tag{3}$$

where $d_i = B_0^{-1}$.

[2] The data period is constrained by data availability.

[3] Block rewards are not included in our analysis since they represent fixed rewards over 210,000 blocks.

We estimate responses in a non-linear fashion:

$$Regime\ 1\,(R1) : y_{t-1} \cdot (1 - F(z_{t-1})) \tag{4}$$

$$Regime\ 2\,(R2) : y_{t-1} \cdot (F(z_{t-1})) \tag{5}$$

where $F(z_t) = \frac{e^{(-\gamma z_t)}}{(1+e^{(-\gamma z_t)})'}$ var $(z_t) = 1$, $E(z_t) = 0$, z_t is a standardized variable, and γ is provided externally. The two regimes are up(R1)/down(R2) days in the cryptocurrency market (positive/negative return), to capture bullish/bearish sentiment. For instance, if z_t corresponds to a change in return at time t, an increase in z_t would cause a decrease in $F(z_t)$. To differentiate between the two regimes, the endogenous variables y_{t-p} are multiplied with the values of $F(z_t)$ at $t-1$. Thus, Eq. (2) is extended to derive the respective coefficients given two regimes:

$$\begin{aligned} y_{t+h} = \alpha^h &+ B_{1,R1}^h y_{t-1} \cdot (1 - F(z_{t-1})) \\ &+ \cdots + B_{p,R1}^h y_{t-1} \cdot (1 - F(z_{t-1})) + B_{1,R2}^h y_{t-1} \cdot (F(z_{t-1})) + \cdots \\ &+ B_{p,R2}^h y_{t-1} \cdot (F(z_{t-1})) + u_{t+h}^h, h = 0, 1, \ldots, H-1 \end{aligned} \tag{6}$$

The respective responses are transformed into cumulative sums and plugged into Eq. (1). AICc is used for a lag selection.

3. Results and discussion

Results for prices, energy and transaction fees are presented below. Here, R1 refers to up regimes and R2, to down regimes. All results are statistically significant at 95% confidence bands (see Tables 1 and 2).

Our elasticity estimates indicate that on average, upward shocks in prices have a positive effect on BTC and ETH transaction volumes. This seems to suggest that both crypto assets defy the law of demand which stipulates a negative relationship between price and demand. This effect is stronger for BTC, while for ETH, it remains dependent on the market day.

Given that elasticity of inflow volumes represents the sensitivity of moving coins to exchange wallets from wallets outside exchanges, we can interpret it as increased selling pressure due to upward shocks in the selected factors. On average, for BTC and ETH, a positive shock in price causes an increase in accumulated selling pressure with variation for up/down market days. For the BTC, an interesting phenomenon is observed. Even when price elasticity for the BTC remains generally positive, for the three-day window, we observe a negative price elasticity for down-market days for all four volume types used. This could be interpreted as the immediate transmission of negative sentiments for the three-day period. In terms of transaction fee, on average, the accumulated transaction fee elasticity remains negative for BTC and positive for ETH, indicating negative and positive selling pressure for BTC and ETH, respectively. Rising energy costs, in general cause a negative selling pressure for BTC and a positive one for ETH.

Elasticity of outflows demonstrate moving coins after purchases, implying potentially bullish sentiments. Naturally, a positive price shock in BTC and ETH results in increased outflow. Fee elasticity of outflow (bullish sentiments) is negative for BTC and positive for ETH, indicating the differences in the transaction fee mechanisms of the selected cryptos. Also, Bitcoin transaction fees are more often lower compared to that for Ethereum, given that ETH is also used for deploying transactionally intensive decentralized applications. The use of BTC, however, remains largely restricted to transfer of value. Energy outflow elasticity is similar for both BTC and ETH, i.e., positive on up market days and negative on down market days. This result highlights the importance of market conditions in the analysis of the effects of energy costs on investment behavior in crypto assets.

Table 1
BTC-elasticity.

Average elasticity	Regime	3-day	1-week	2-week	3-week	1-month
			Volume type			
			Total			
Price	R1	3490.74	1544.97	1022.43	716.35	861.58
	R2	−139.14	4771.87	2326.63	1558.31	1150.36
Fee	R1	−0.55	−1.08	−0.57	−0.49	−0.29
	R2	−0.33	−0.50	−0.35	−0.50	−0.24
Energy	R1	−164.36	−82.23	−427.00	170.64	171.55
	R2	−42.39	−27.36	−37.13	−35.46	−51.54
			Inflow			
Price	R1	270.48	95.53	−27.27	−11.43	18.30
	R2	−154.49	121.71	126.52	108.54	103.26
Fee	R1	−0.10	−0.35	−0.33	−0.40	−0.38
	R2	0.06	0.04	−0.11	−0.23	−0.24
Energy	R1	8.76	4.58	2.96	−1.74	−9.63
	R2	−79.59	−32.54	−22.03	−21.26	−23.71
			Outflow			
Price	R1	445.12	175.96	204.95	137.51	106.22
	R2	−66.42	−44.34	44.18	56.31	68.57
Fee	R1	0.07	−0.12	−0.20	−0.43	−0.39
	R2	0.15	0.14	−0.12	−0.23	−0.17
Energy	R1	4460.10	1790.91	889.00	571.20	247.61
	R2	346.54	79.12	−255.62	−164.21	−106.91
			Inter-exchange			
Price	R1	122.34	−80.94	846.62	582.24	451.09
	R2	−22.47	−376.30	29.05	65.50	88.40
Fee	R1	−0.10	−0.53	−0.52	−0.66	−0.64
	R2	0.16	0.00	−0.22	−0.34	−0.32
Energy	R1	−1896.99	−1528.95	−714.02	−342.09	−227.93
	R2	−24.96	55.90	360.93	186.58	105.39

Table 2
ETH-elasticity.

Average elasticity	Regime	3day	1-week	2-week	3-week	1-month
			Volume type			
			Total			
Price	R1	115.57	73.27	−170.91	−123.96	−312.22
	R2	117.61	171.84	184.50	249.39	257.27
Fee	R1	0.41	6.10	3.67	2.59	2.04
	R2	0.21	0.17	0.97	0.76	0.54
Energy	R1	−4307.77	−2013.38	−955.74	−605.61	−404.89
	R2	1603.69	436.54	157.77	79.25	30.05
			Inflow			
Price	R1	117.61	171.84	184.50	249.39	257.27
	R2	85.94	174.87	157.98	134.00	133.11
Fee	R1	0.21	0.17	0.97	0.76	0.54
	R2	0.60	0.65	1.71	1.60	1.60
Energy	R1	1603.69	436.54	157.77	79.25	30.05
	R2	484.17	439.75	153.77	76.95	38.86
			Outflow			
Price	R1	839.27	258.88	130.07	90.17	55.20
	R2	−59.97	−212.80	−45.55	21.53	87.40
Fee	R1	0.23	0.34	0.51	0.28	0.62
	R2	1.53	−0.59	−0.45	−1.61	0.40
Energy	R1	430.21	407.19	269.86	194.43	146.39
	R2	−650.28	−551.36	−325.38	−252.20	−197.22
			Inter-exchange			
Price	R1	323.05	219.55	8115.63	5646.55	4058.10
	R2	−177.59	196.14	1157.73	466.14	144.07
Fee	R1	1.95	0.34	−1.15	104.67	67.60
	R2	0.54	−0.07	1.20	1.47	1.37
Energy	R1	258.99	1.63	−458.55	−972.66	−746.50
	R2	1709.87	116296.01	57999.70	38601.82	27045.80

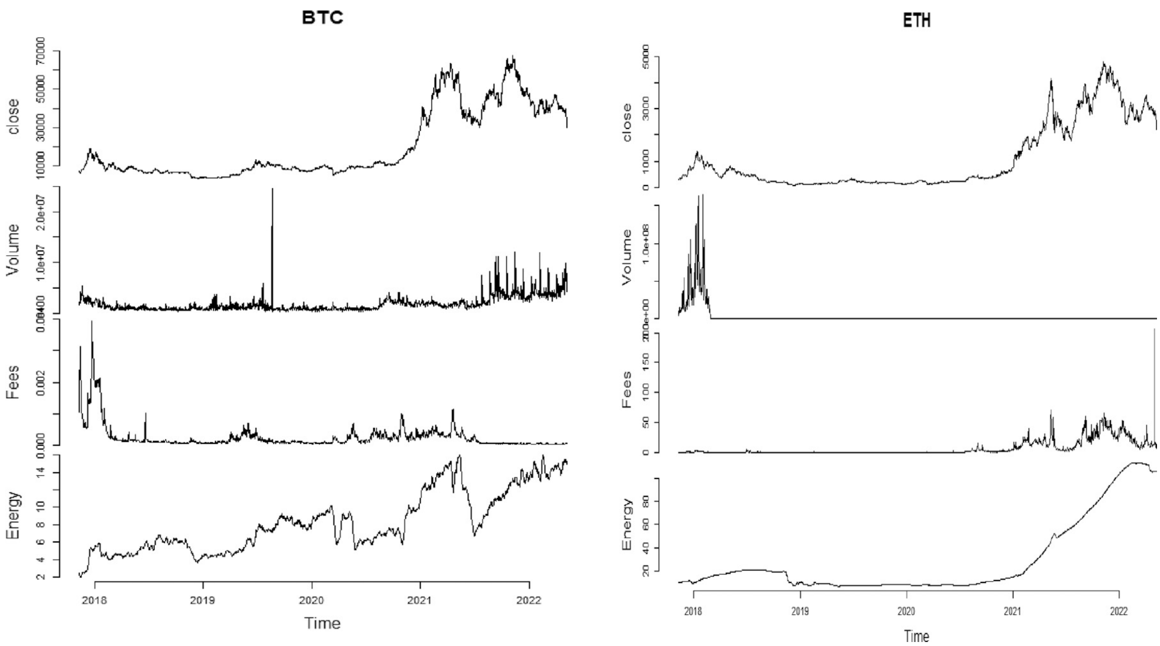

Fig. 1. Close prices, volumes, fees and energy consumption of bitcoin.

Elasticity of inter-exchange volumes can be explained by arbitrage strategies as investors move their cryptocurrency holdings across exchanges to benefit from mispricing. The price and energy elasticities of inter-exchange demand are similar for both BTC and ETH in terms of sign. For instance, while it is positive to price shocks for the selected cryptos, it is generally negative on up-market days and positive for down-market days for energy shocks in both BTC and ETH. This might indicate that positive shocks to energy cost on down-market days incentivizes traders to search more intensively for alternative arbitrage strategies, while on up-market days, the need for arbitrage remains largely unaffected by changes in energy costs. The fee elasticity results for inter-exchange demand for BTC and ETH are consistent with those obtained for inflow and outflow volumes used. It remains generally negative for BTC and positive for ETH, regardless of market days and time window.

Overall, one potential explanation of the differences between BTC and ETH in terms of analyzed elasticities lies in differences in technical specifications of the underlying blockchain networks. While BTC transactions are largely monetary and serve as transfers of value, those for ETH encompass smart contracts, self-executing contracts, dApps, etc., thereby serving a broader purpose, more like a utility token. Energy elasticity results are more heterogeneous and sensitive to up/down market days. A potential reason could lie in the mining differences of Ethereum as the required equipment is cheaper and uses less energy while generating higher returns. This could provide more opportunities for small miners who follow daily market trends more closely and may choose to mine accordingly.

4. Conclusion

In this paper, we calculate demand elasticities for BTC and ETH for price, transaction fee and energy. Both cryptocurrencies have positive price elasticities, pointing to a potential deviation from the law of demand. We leave the factors behind the phenomenon, potentially FOMO and investor expectations among others, for future research. Fee elasticity is negative for BTC and positive for ETH. Energy elasticity results remain mixed. Our results contribute to a better understanding of the dynamics of crypto markets in general and crypto demand in particular.

Data availability

The authors do not have permission to share data.

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Appendix

See Fig. 1

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