Price discovery over time: an application to the Bitcoin market

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Abstract: The cryptocurrency market is leading the process of new money and investors. Although it exists since 2007, it has been picking up as from 2017. The price discovery literature modeling methodology are growing and spread its application. One dimension of this growing is at continuous-time framing direction. The hypothesis that component share, which allows us to identify the leading market in the price discovery process, is susceptible for a time-varying approach already been tested by conventional assets and its future derivatives that are negotiated at regular stockmarkets. For cryptocurrency specifically, such hypothesis isnt been tested yet. Using microstructure data from four Bitcoins exchanges at minute level, we be able to test the time dependency hypothesis, and implement a kernel-based estimator to compute daily estimates for continuous-time price discovery. After that we break the dataset in three different time zones, and we sustained the same empirical results. Our findings are a new framework for CS estimation, specially for Bitcoin application.

Keywords: price-discovery, component-share, time-varying, bitcoin

JEL: G14, C14, C18

Resumo: O mercado de cryptomoedas lidera o processo de novos investimentos e investidores. Apesar de existir desde 2007, a partir de 2017 teve uma rápida expansão. A literatura sobre Price Discovery é crescente e amplia suas aplicações. Uma das dimensões de crescimento é a análise em tempo contínuo. A hipótese de que o component share, que permite identificar o processo

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de liderança sobre price discovery, é suscetível a uma abordagem do tipo time-varying, e esta já foi testada para ativos convencionais e seus derivativos, que são negociados em bolsas por todo o mundo. Para cryptomoedas, especificamente, tal hipótese ainda não foi testada. Usando os dados de microestrutura de quatro exchanges de bitcoins no nível minuto a minuto, foi possível implementar uma estimação com base no estimador de mínimos quadrados em Kernels para computar as estimativas diárias aplicadas ao price discovery. Depois dividiu-se o banco de dados em três diferentes zonas de tempo, e ainda assim, os resultados empíricos para a modelagem do CS se manteve. As estimativas e aplicações do estudo são uma nova aplicação em CS e sua estimação, especialmente para o mercado de cryptomoedas e bitcoins.

Keywords: price-discovery, component-share, time-varying, bitcoin

1 Introduction

In this article, we will promote a study applied to the time-varying in cryptocurrency. As we will discuss above, the parameters associated with price formation are also associated with a cut in time, so we will undertake a statistical test that corroborates or refutes the hypothesis of temporal dependence on the parameters associated with Component Share (CS) concerning the Price Discovery (PD) process (see, among others, Brandvold, Molnar, Vagstad and Valstad, 2015; Urquhart, 2016; Brauneis and Mestel, 2018; Baur and Dimpfl, 2019; Makarov and Schoar, 2019). In a market, in particular, still growing and with low maturity, the parameters might be even more time-dependent than the parameters associated with better-established markets such as the stock market.

Over the stock market, the same methodology was tested by Fernandes and Scherrer (2018) and Fruet Dias, Fernandes and Scherrer (2020), which gives evidence to our research on Price Discovery under time-varying. Specifically in this article we will focus on the PD process and analyze the CS of this process based on (De Jong, 2002 ;Putniņš, 2013), also we will estimate using the temporal dependency hypothesis using a Giraitis, Kapetanios and Yates (2013) kernel least squares estimator (KLS), in order to address this estimate appropriately. Some articles used this hypothesis to test volatility Bohte and Rossini (2019) show the estimation by TV using an bayesian model. Durham using an quantile regressor for describe volatility, with an Dynamic M-GARCH approach.

The cryptocurrency market allows people who are still outside the traditional market, whether it be financial or banking. At the same time, large technology companies offering non-centralized information services and data records can use cryptocurrencies as a money transfer tool, without using the traditional financial system. There are numerous initiatives from companies like Facebook, Google, and Twitter that intend to use cryptos or similar system to allow the transfer of money between its users. This point might guarantee the expansion of demand in the cryptocurrency market. Thus, we understand that studying the PD over CS is necessary to support the correct academic debate on digital financial assets Härdle, Harvey and Reule (2020)..

The regulation of cryptocurrency markets can promote security, stability, and credibility for this market. However, otherwise coming can expel a large number of traders who are looking for precisely this characteristic of non-regulation. The stock market is opposed to the crypto market, because of the considerable legal regulatory framework that mediates the negotiation process. Thus, our methodology that analyzes the CS on temporal dependence may provide theoretical subsidies for this discussion of reduction or increase regulation of the markets. Thus, we promote the theoretical subsidy for TD discussion and analysis of the efficiency of the cryptocurrency markets. This includes all the factors that depend and may vary over time. For that, we will use a model based on the vector error correction, as the methodology that allows decomposing both CS and IS.

The current analysis depends of the fact of the same asset is negotiated at different exchange - that are homogeneous. This predicate is sensitive for applications over the stock markets, because any asset and its ETF or mini-contract or future-contract is not in essence the same. However, the degree of homogeneity of the same cryptocurrency traded in different exchanges is substantially higher, which allows us to guarantee more robust results.

Our analysis is composed of a collection of high-frequency trading data from 4 bitcoin exchanges, between April and October 2018, a period in which there was a total variation in prices of 100%, and there is a price difference between exchanges arrived at 10%. Thus, we intend to answer which is the leading exchange in the price formation process, taking into account the minute-by-minute data to subsidize this answer, and we estimated the KLS that provides the daily curve of this process.

Our results demonstrate a time dependence, through the rejection of the (Elliott and Müller, 2006a), a behavior of the CS over time for each exchange that demonstrated a pattern that depends on the volume traded, costs and fees, security and price. As already tested for the stock market, the test for Bitcoin demonstrated the importance of analyzing the coefficients from their time dynamics and dependence.

The remainder of this paper is organized as follows. Section 2 describes the finance literature of price discovery, and the modelling of our methodology. Section 3 describes the price informativeness at cryptocurrency market of Bitcoins, and describes its exchanges and how exchanges working as a third-party intermediary, which allow the same asset (Bitcoin) be negotiated at singular price at every exchange, and every transaction been registered. Section 4 presents our data set and all exchange price details over the 6 months period. Section 5 discusses the results of our estimations and we offer some concluding remarks in Section 6.

2 Finance Price Discovery Theory

In this section, we discuss the continuous-time model for price discovery, proposed by (Fruet Dias, Fernandes and Scherrer, 2020) and our application at cryptocurrency market.

The VECM framework is the base of the IS proposed by Hasbrouck and the CS proposed by Chu et al.(1999) and others. The IS Its simple the decomposition of variance of the efficient price innovation equation. If and only if the price series represent the same asset. Usually, its used the spot and futures contracts to do such decomposition. In our essay, we can use the same asset (bitcoin) that is trade at differents exchanges and the same nominal value (US$). The CS its the ratio between $\alpha_\perp$ and $\beta_\perp$, which are the two components of the $I(1)$ parts of the price discovery. Assuming this equation for the prices of the finance assets.

$$\mathrm{d}P_t = \Pi P_t \,\mathrm{d}t + C\,\mathrm{d}W_t, \qquad \text{with} \quad P_0 = p_0, \tag{1}$$

The solution to (1) is a homogenous Gaussian Markov process given by

$$P_t = \exp(t\Pi)\left[P_0 + \int_0^t \exp(-u\Pi) C\,\mathrm{d}W_u\right], \tag{2}$$

Using the same structure of Fruet Dias et al. (2020) We assume prices are observed regularly and equidistantly over the unit interval $[0, 1]$ that characterizes, say, one trading day (calendar-time sampling, as discussed in Hansen and Lunde, 2006). Denote each interval in $[0, 1]$ as $[t_{i-1}, t_i]$, where

$i = 1, 2, \ldots, n$ and n is the total number of intervals such that $0 = t_0 < t_1 < \ldots < t_n = 1$. The length of each interval is $\delta = t_i - t_{i-1} = 1/n$ in $[0, 1]$. For instance, the usual trading day in the U.S. market lasts for 6.5 hours (23,400 seconds), and thus, sampling one observation per minute yields $n = 390$ intraday observations, with $\delta = 1/390$. Denoting by $\exp(A)$ the matrix exponential of a $k \times k$ matrix A such that $\exp(A) = \sum_{\ell=0}^{\infty} \frac{1}{\ell!} A^{\ell}$, the exact discretization of (1) at interval length δ reads

$$\Delta P_{t_i} = \Pi_\delta P_{t_{i-1}} + \varepsilon_{t_i}, \tag{3}$$

where $\Pi_\delta = \alpha_\delta \beta'$ and $\alpha_\delta = \alpha(\beta'\alpha)^{-1} [\exp(\delta\beta'\alpha) - I_r]$, with I_r denoting a r-dimensional identity matrix, and P_{t_i} is a $k \times 1$ vector of log-prices observed at discrete time. The innovation ε_{t_i} is iid Gaussian with zero mean and covariance matrix given by $\Sigma_\delta = \int_0^\delta \exp(u\Pi)\Sigma \exp(u\Pi')\, du$.

Kessler and Rahbek (2004) provide the conditions under which the mapping given $\theta = (\Pi, \Sigma) \overset{\psi}{\mapsto} \psi(\theta) = (\Pi_\delta, \Sigma_\delta)$ is unique, θ is identifiable, and the space spanned by the columns of α is equal to the one spanned by the columns of α_δ. Specifically, if all eigenvalues of Π are real and no elementary divisor of Π occurs more than once, Proposition 1 in Kessler and Rahbek (2004) shows that the mapping ψ is injective and θ is identifiable. It is important to note that temporal aggregation preserves the cointegration rank, i.e., $\operatorname{rank} \Pi_\delta = \operatorname{rank} \Pi$, and that the definition of (co)integration for OU processes in continuous time is consistent with the definition in discrete time (Kessler and Rahbek, 2004). This means that one may conduct inference about rank and cointegrating space using discrete-time procedures and then interpret the results in the continuous-time setting.

2.1 Component share

The component share relies on the orthogonal complement of α_δ, namely, $\alpha_{\delta,\perp}$ such that $\alpha'_{\delta,\perp}\alpha_\delta = 0$ (see, among others, Booth, So and Tseh, 1999; Chu, Hsieh and Tse, 1999; Harris, McInish and Wood, 2002; Hansen and Lunde, 2006). Because $\alpha_{\delta,\perp}$ is not unique, one typically imposes $\alpha_{\delta,\perp,1} + \alpha_{\delta,\perp,2} = 1$. While α_δ corresponds to the stationary direction of the process in (3), $\alpha_{\delta,\perp}$ relates to the nonstationary direction. This makes $\alpha_{\delta,\perp}$ a natural quantity to assess how the efficient price relates to each market innovation. The market with the highest $\alpha_{\delta,\perp}$ has the least need of adjustment towards the latent efficient price and hence it is the one that leads the price discovery process.

Using the normalization $\alpha_{\delta,\perp,1} + \alpha_{\delta,\perp,2} = 1$, it follows from the exact discretization of the reduced-rank OU process in (3) that

$$\alpha_{\delta,\perp} = \left(\frac{\alpha_{\delta,2}}{\alpha_{\delta,2} - \alpha_{\delta,1}}, -\frac{\alpha_{\delta,1}}{\alpha_{\delta,2} - \alpha_{\delta,1}} \right)' = \left(\frac{\alpha_2}{\alpha_2 - \alpha_1}, -\frac{\alpha_1}{\alpha_2 - \alpha_1} \right)', \tag{4}$$

given that $(\beta'\alpha)^{-1}[\exp(\delta\beta'\alpha) - I_r]$ cancels out for appearing in both numerators and denominators. It is now clear that $\alpha_{\delta,\perp}$ is invariant to the sampling frequency in that $\alpha_{\delta,\perp} = \alpha_\perp$ for any $0 < \delta < 1$. This means that identification and inference of the continuous-time price discovery measure arises directly from estimating $\alpha_{\delta,\perp}$ at any sampling frequency. From an empirical perspective, (4) allows for us to learn about the continuous-time price discovery mechanism even if using data at a lower frequency (and hence less prone to market microstructure noise).

2.2 Information share

The is Hasbrouck's (1995) information share (see, among others, Baillie, Booth, Tse and Zabotina, 2002; de Jong, 2002b; Grammig, Melvin and Schlag, 2005; Yan and Zivot, 2010). In short, the IS measure gives the share of each market contribution to the total variance of the efficient price ($IS_{\delta,1} + IS_{\delta,2} = 1$). Using the exact discretization of (1), the IS measure of a given market $m \in \{1, 2\}$ for $0 < \delta < 1$ is

$$IS_{\delta,m} = \frac{[\xi_\delta C_\delta]_m^2}{\xi_\delta \Sigma_\delta \xi_\delta'}, \tag{5}$$

where $\Sigma_\delta = C_\delta C_\delta' = \int_0^\delta \exp(u\Pi)\Sigma\exp(u\Pi')\,\mathrm{d}u$, ξ_δ is the common row of Ξ_δ in (**??**) that follows from $\beta_\perp = (1, 1)'$, and $[.]_m$ denotes the mth element of a vector. Using the fact that $\alpha_{\delta,\perp,m} = \alpha_{\perp,m}$ for any $0 < \delta < 1$, the average IS measure in a given market $m \in \{1, 2\}$ for $0 < \delta < 1$ then reads

$$\overline{IS}_{\delta,m} = \frac{1}{2}\left(\frac{[\xi_\delta C_\delta]_m^2}{\xi_\delta \Sigma_\delta \xi_\delta'} + \frac{\left[\xi_\delta \bar{C}_\delta\right]_m^2}{\xi_\delta \Sigma_\delta \xi_\delta'} \right) = \begin{cases} \frac{(\alpha_{\perp,1}\sigma_{\delta,1} + \alpha_{\perp,2}\sigma_{\delta,2}\rho_\delta)^2 + \alpha_{\perp,1}^2\sigma_{\delta,1}^2(1-\rho_\delta^2)}{2\left(\alpha_{\perp,1}^2\sigma_{\delta,1}^2 + \alpha_{\perp,2}^2\sigma_{\delta,2}^2 + 2\alpha_{\perp,1}\alpha_{\perp,2}\sigma_{\delta,1}\sigma_{\delta,2}\rho_\delta\right)}, & \text{if } m = 1, \\ \\ \frac{(\alpha_{\perp,2}\sigma_{\delta,2} + \alpha_{\perp,1}\sigma_{\delta,1}\rho_\delta)^2 + \alpha_{\perp,2}^2\sigma_{\delta,2}^2(1-\rho_\delta^2)}{2\left(\alpha_{\perp,1}^2\sigma_{\delta,1}^2 + \alpha_{\perp,2}^2\sigma_{\delta,2}^2 + 2\alpha_{\perp,1}\alpha_{\perp,2}\sigma_{\delta,1}\sigma_{\delta,2}\rho_\delta\right)}, & \text{if } m = 2. \end{cases} \tag{6}$$

As opposed to the component share, $\overline{IS}_{\delta,m}$ is not invariant to the sampling frequency because the market-specific variances and correlation across markets in (6) depend on δ. In particular, the contemporaneous correlation absorbs most of the lead-lag patterns as δ increases because both markets have now sufficient time to impound the news. In fact, exact discretization yields $|\rho_\delta| \to 1$ as $\delta \to 1$, and thus, $\lim_{\delta\to 1} \overline{IS}_{\delta,1} = \lim_{\delta\to 1} \overline{IS}_{\delta,2} = 1/2$.

Besides, there is an important and unique issue of the bitcoin market. There are endless possibilities for new exchanges to enter. The formation process of each one, as we will see in session 3, takes place in a decentralized way. So, instead of having contracts and mini-contracts traded on a single exchange, we will have the same asset - identical - but traded on multiple platforms, where price detachment informs exactly issues of cost, liquidity, and security of the exchange system. Such characteristics also differ between exchanges, but they could never be compared since, in any exchange, there is precisely the same asset.

Therefore, the methodology had to be able to decompose the $\alpha_{\delta,\perp}$ in multiples markets and finite samples. This means that a fair comparison of IS measures must take into consideration not only the sampling frequency but also the contemporaneous correlation across markets in continuous time. However, this is not straightforward. Teasing out the continuous-time covariance matrix from estimates of $\Sigma_\delta = \int_0^\delta \exp(u\Pi)\Sigma\exp(u\Pi')\,\mathrm{d}u$ tends to produce poor results in finite samples, typically resulting in negative semi-definite estimates of Σ for prices sampled at frequencies lower than 10 seconds. Moreover, markets are currently very fast and interconnected given the rise of high-frequency trading and statistical arbitrage across and within markets (see, among others, Menkveld, 2014, 2016; O'Hara, 2015), implying higher contemporaneous correlation across markets even at the very high frequency and, in turn, IS measures that converge to 1/2.

3 Price informativeness of Crypto Market

In this section, we describe the cryptocurrency Bitcoin. Formation, intermediaries and participants.

3.1 Cryptocurrencies

Since 2008, after the white paper from "Satoshi Nakamoto", that describe a form of stack digital time-stamp information, and using an cryptography protection in order to maintain the information public but non re-writable. Such mechanism allow trustfully and reliable transfer of money between peers without a third party, such as a Bank, in order to maintain the register of such transaction.

The name cryptocurrency cames from the cryptography security technology that protects the old information, and doesnt allow anyone, instead of the key-holder, to write an transfer of that key to another. None of those technologies are new, but the use to maintain an finance book system, in order to provide security and fastness is quite revolutionary. Adding, also, an algorithm that allow the users of the system discovery new keys, this actions is named as: "mine a block"[2]. The mechanism behind such cryptography was describe by Penard and van Werkhoven (2008) and Lamberger and Mendel (2011).

The literature illustrate 3 majors aspects of cryptomarket that drives the demand: fast, safety and anonymity. The anonymity is positive correlated with tax avoidance and criminal activity. Luther and White (2014). The supply side of this market is based on the above already described algorithm, and there is a 21 millions upper-bound limit for units of Bitcoin. Until June of 2020 is already been mined 18,413,350 (87.6% of total) is already been mined. There also some competitive cryptocurrencies that enlarge the market, and even Bitcoin be the biggest and most know, other cryptos and ICO (initial coin offering) process can provide more and more agents and traders to this market Catalini and Gans (2018).

3.2 Exchanges and Historical Information

Acting as the most crucial third-party intermediary at Bitcoin market, exchanges prevail as a gateway for Bitcoin traders. The users had a preference for size or volume, fewer fees and better services Bhaskar and Chuen (2015). At the same time, when Bitcoin acceptance rises, the demand for exchange might decrease, and the numbers of those deal only Bitcoin also.

The differences between exchanges are based on three aspects: i. origin country, ii. currencies that are accepted, iii. fees (transactional, deposit, and withdrawal). We choose Binance, Bitfinex, Bitflyer, and Bitstamp.

The first one (Binance) had originated in China in July 2017. Only one year of working puts the Binance as leader crypto exchange worldwide. Binance trading more than 100 cryptocurrencies, and accepted fiat currencies of most countries in the world. Before China's govern prohibition of crypto trading, the company moved his HQ to Japan in September in the same year. Nowadays (2020) Binance had more than five times the trade dominance of the second one, bitFlyer.

Bitflyer history begins in 2014, with Yuzo Kano, a former Goldman Sachs trader. Hosted in Tokyo, and further spread at São Francisco and Luxembourg. Bitflyer is the number one exchange in Japan, and Bitcoin represents 94% of all volume of crypto's trading.

[2]The algorithm name is SHA-256

Bitifnex is the more old exchange present in our list. Founded in December 2012, start only trading Bitcoin and further added more cryptocurrencies to its portfolio. Its HQ is in Hong Kong, and now had representation in more than 50 countries. Its portfolio of cryptocurrencies had Ethereium, Litecoin, Ripple, and more.

The last one is the Bitstamp, which is the only based outside Asia. Its HQ is in London. The exchange also uses the European Union's Single Euro Payments Area, a mechanism for transferring money between European bank accounts. This could be a facilitator in order to enlarge it's operational and volume in Europe. However, the cryptocurrency market has a large demand for operations under the radar of fiscal authorities. So, this advantage apparently doesn't put the exchange as a leader even in European soil.

3.3 Tranding Bitcoin with Exchanges

As a third party of bitcoin trading, the exchanges working as a regular stock exchange operate. Using the same system, but with much less regulamentation. For a foreign investor citizen trades in NY exchange, it is necessary to open an account at a local brokerage, and an investment account at a local or national bank, to move their investment.

So, the local and the regulatory framework of each country isn't a concern in Bitcoin investors. They can operate using Paypal, credit card, electronic transfer, and every exchange had several lists of fiat currency that they accepted. So we expected that the Timezone and location of the traders don't interfere at the time-varying coefficient of the price-discovery process. The process of choose and specific exchange involves fees, size, and liquidity. We provide a description of our dataset.

4 Data

Our data set consists of 4 exchanges, gathering by API on a minute level and calculate the midquote as the average of the best bid and best ask (Hautsch, Scheuch, e Voigt 2018). The data was collected from April until October. The price difference between highest and lowest was higher than 45%. All four exchanges showed the same pattern, but we persuit describe what is most relevant to price-discovery process. In the 4.1 we describe the dataset and its descriptive statistics.

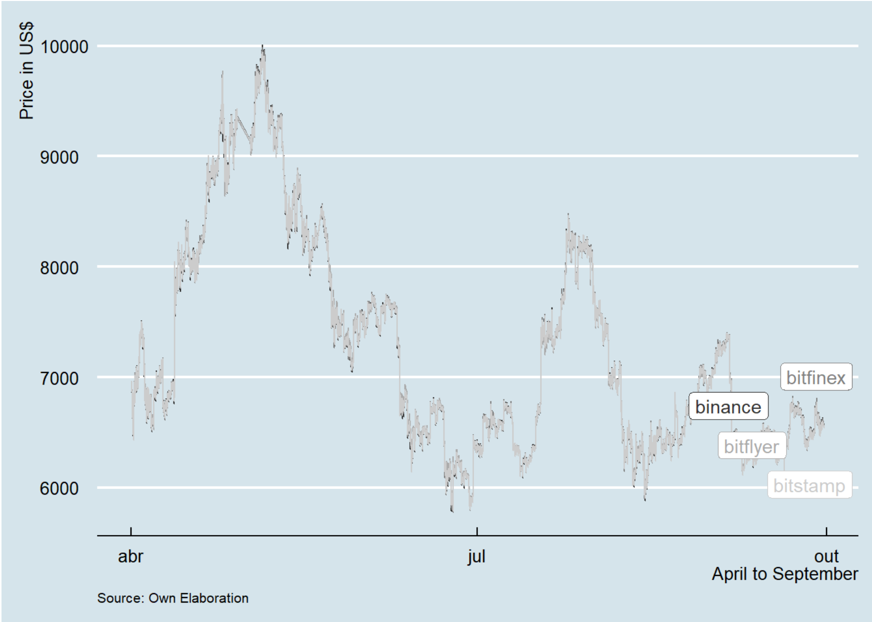

Figure 1: Price of Bitcoin in Selected Exchanges(US$)

4.1 Descriptive Statistics

1 Represents our disposable data-set. With quasi-linearity, we choose this 4 exchanges in order to perform our KLS based estimator. With 95% of all trading in China, is not a surprise that on the big 4 exchange, three of them are located in Asia and only the fourth place is located outside. In the same hand, the volume and the fee cost of trade are negative correlated, and for this, the average price in the less costly exchange is slightly higher.

Table 1: Descriptive Statistics

	Exchange	Count	Bid	Ask	Price	sd	fee	location
1	binance	63423	7226.84	7229.27	7228.05	943.86	0.1	Asia
2	bitfinex	63281	7229.16	7229.39	7229.27	944.34	0.2	Asia
3	bitflyer	63245	7220.31	7235.22	7227.77	935.44	0.15	Asia
4	bitstamp	63037	7222.32	7226.69	7224.50	941.81	0.25	Europa

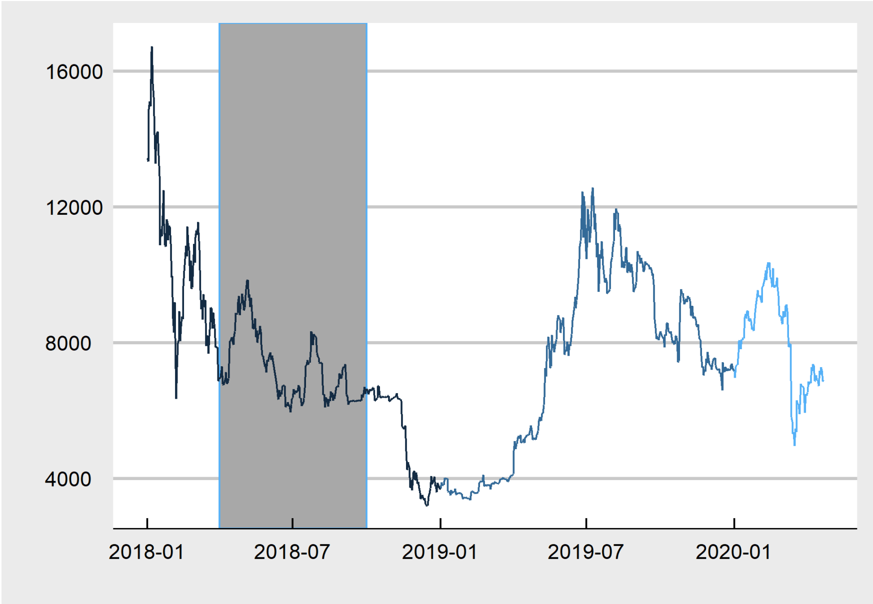

Figure 2: Price of Bitcoin 2018-2020(US$)

The graph 2 allow us understand the size of disposable when compares only 2 years window. Of course, we can promote a continuous methodology for implement the results of time-varying estimator. However, we show that price formation process, specifically the CS can be a good indicator for the price formation leader exchange. Moreover, even with great volatility, and $I(1)$ series, we can provide some valid and uptodate information.

5 Time variation in the continuous-time component shares

There is seemingly a consensus in the literature that the price discovery processes change over time, with many studies running daily VECM specifications to address this issue (see, among others, Hasbrouck, 2003; Chakravarty, Gulen and Mayhew, 2004; Hansen and Lunde, 2006; Mizrach and Neely, 2008). Additionally, empirical evidence suggests that the price discovery changes with some highly persistent market indicators such as trading volume and volatility. For instance, Figuerola-Ferretti and Gonzalo (2010) posit an equilibrium model of commodity spot and future prices in which the speed-of-adjustment parameters of a discrete-time VECM depend on the relative number of market participants. As a result, they establish a direct link between component shares and market activity indicators, such as relative volume or trade intensity.

We start with a formal test of whether component shares change over time. In particular, we employ Elliott and Müller's (2006b) test for the null hypothesis of constant speed-of-adjustment parameters against the alternative hypothesis that they display persistent variation in time. In the context of one asset trading at two markets, time-varying speed-of-adjustment parameters automatically imply that the CS measures also change over time. The Elliott-Müller test is convenient because it accommodates well enough the sort of variation we describe in Section 2.

The price discovery process change over time, and factors such as trading volume, volatility, market participants, are responsible, according to the literature finance, to promote this possible change. Furthermore, these factors varying with time. So, the won price discovery process can be time-varying. So, to explore such a possibility, we implement the Elliott-Müller test.

Table 2: Elliot-Müller test

Exchange	Statistic	Critic Value	Decision
Binance	-54.0122	-19.8400	Rej. H0
Bitfinex	-116.9970	-19.8400	Rej. H0
Bitflyer	-141.4942	-19.8400	Rej. H0
Bitstamp	-513.1238	-19.8400	Rej. H0

Table 2 provides that for all exchanges we had the same decision. Reject the null hypothesis of absence of time-varying. This With those results, was implemented the continuous-time CS estimator.

5.1 Daily evolution of the continuous-time CS measures

Table 3: Today's Data

Exchange	Vol. (US$ B.)	Perc
Coinbase	428	52,4%
Kraken	76	9,3%
Bitstamp	55	6,7%
Bitfinex	51	6,2%
Bitflyer	40	4,9%
Others	167	20,5%

Table 3 presents the descriptive statistics of todays biggets exchanges. A fast looking is sufficient to answer what is the leader exchange in price-discovery process. In another hand, in such volatile market as bitcoin is, all this information can change a lot in just a short period of time. So, in this table we looking for 2020-04-21 data. And we can compares this information with our results, that use 2018, April to September data.

Figure 3 exhibits the daily component share estimates for the four exchanges selected. Plot the estimates of the daily component shares in continuous time and their respective 95% confidence intervals for each exchange. Figure 3 shows us the daily time-dependency component share, which represents each exchange has more or less relevance. The European one keeps its importance over time, with quit stable 20% of CS of the crypto (bitcoin). In order hand, the Binance improves its importance. If we take time, this exchange in September 2017, launch the Binance Coin, that represents 1.19% of all cryptocurrency markets. Over bitcoin market, this one has more than four times the value of the second exchange Coinbase.[3]. The Bitstamp come in fourth place, and Bitfinex in fifth, followed by Bitfinex. If we sum all fives one, the volume is less than the first one. Our estimations capture this.

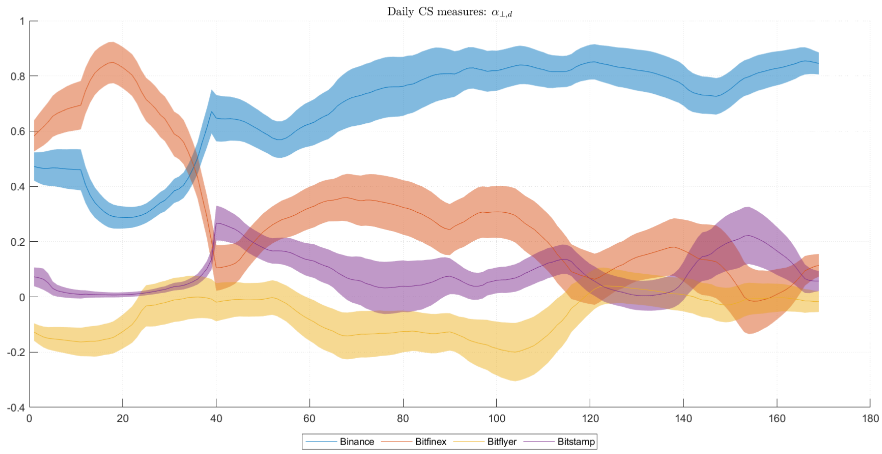

Figure 3: Results of CS in Time-Varying estimator

Our estimate captures the time dependence of the leading Exchange on all possible variant conditions. Thus, issues such as volume, momentum, volatility, and global and regional economic growth affect the CS trend and the orthogonal decomposition for the different exchanges. Also, there may be time variations between exchanges in terms of reliability, costs and fees, risks, and issues of confidentiality and data protection that affect the trend of the PD process.

[3]This data was collected a https://www.bitcointradevolume.com/ access at 2020-04-21

5.2 Time-Varying under Different Time Zones

In this section, we estimate the continuous-time CS measures a set of bitcoin exchanges, adopting time zone breaks, using high-frequency data from April to October 2018. This breaks for time zone had the objective to test the hypothesis of there is some liquidity or geographic characteristic correlated with the continuous-time CS measures. We estimate the continuous-time CS measures by KLS.

5.3 Data

We promoted three breaks into our data set. The timestamps had to lie in one of three sets, Asia time zone: 20:00:00 to 03:00:00, EURO time zone: 04:00 to 11:30, and EUA time zone: 09:00:00 to 16:00:00. The intuit is to test the geography and time dependence for our estimations. Bitcoin markets tend to have less geography (and regulation) dependence than usual stock-markets, for factors that we discuss at section 3.3.

Therefore, we open the possibility of three different patterns for the component-share time-varying. We expected previously that this pattern didnt diverge from the previous, because the time zone is an intrinsically regional variable. And, exchanges and trading bitcoins arent subject to local regulation or locals aspects. So, there is no theoretical evidence that allows us to conclude that some exchange because of HQ location had to be more important than another.

5.4 Results of TV under different Time Zones

As we can see, there is a great methodology question about the ranges of CS estimated by KLS. As long as, theoretically, there is possible to decompose the CS into n-1 vectors orthonormal. However, the computational cost of such task will be huge. Alt ought, our estimations for I.Cs day by day respect such boundary of [0,1] for each orthogonal vector.

As we describe in 3.3, trading with Bitcoin exchange is not correlated of local regulation, size of markets, and local economic activity. Although, an exchange could choose establish itself at a remote place in order to promote some economy in terms of operational costs, for example. On the other hand, every trader can use those four exchanges as a tool to intermediate their negotiation, even he or she is living in the opposite global position.

Our estimates indicate what is the leading exchange in the price-formation and innovative process. We find that there is a non-negligible change between CS by exchanges. The pattern of our estimates indicates that Binance emerges as a leader of CS estimated by time-varying after 60 days of the beginning of data series. After the 60th day, Binance remains as the leader exchange in terms of CS.

Suppose we adopt the conventional approach for CS estimation, all these movements and changes between exchanges will be lost or negligible. The same empirical results were found by (Fruet Dias et al., 2020) for stock markets. Our findings are entirely new, especially for the Bitcoin market.

The results indicate a very similar decomposition between each cut in time, however, with variation in the sample period. Peremptorily indicating the need to adopt the methodology of estimating the CS is time-varying. Also, part of the movement reflects the increased importance of a specific Exchange over the others. It is indicating that there are characteristics linked to the markets that also reflect the CS issue and that in traditional asset markets, it would not be possible to be decomposed. Bearing in mind that in all traditional exchanges, there is no precisely the same asset, with precisely the same characteristics, negotiated in parallel, in a decentralized manner, and potentially by different selling and buyers agents as we had in cryptos exchanges.

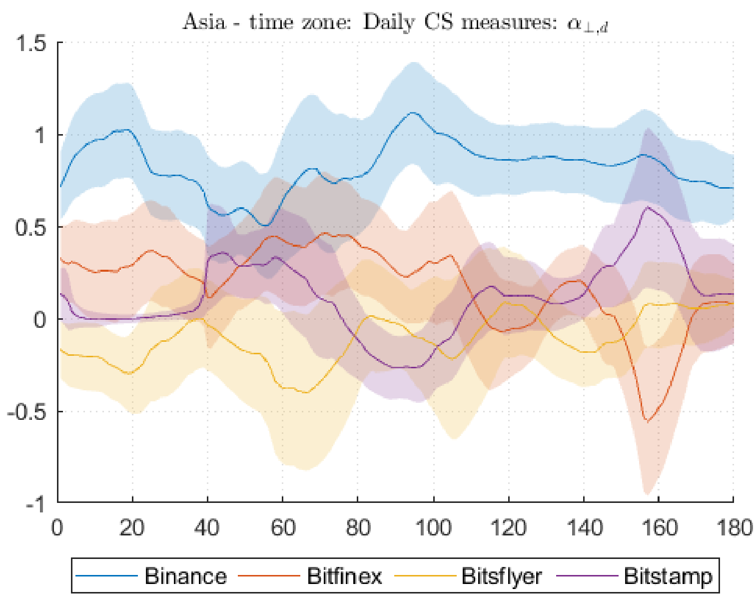

Figure 4: Results of CS in Time-Varying estimator: Asia Time Zone

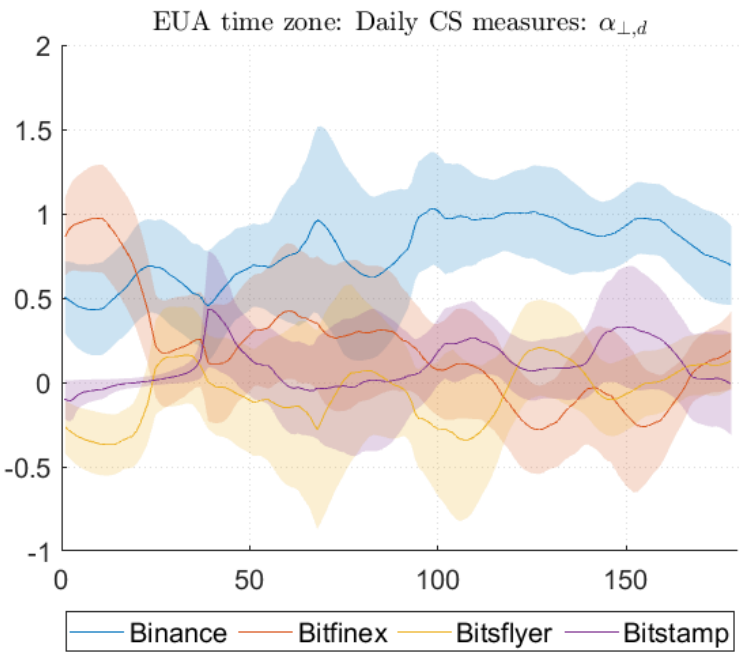

Figure 5: Results of CS in Time-Varying estimator: EUA Time Zone

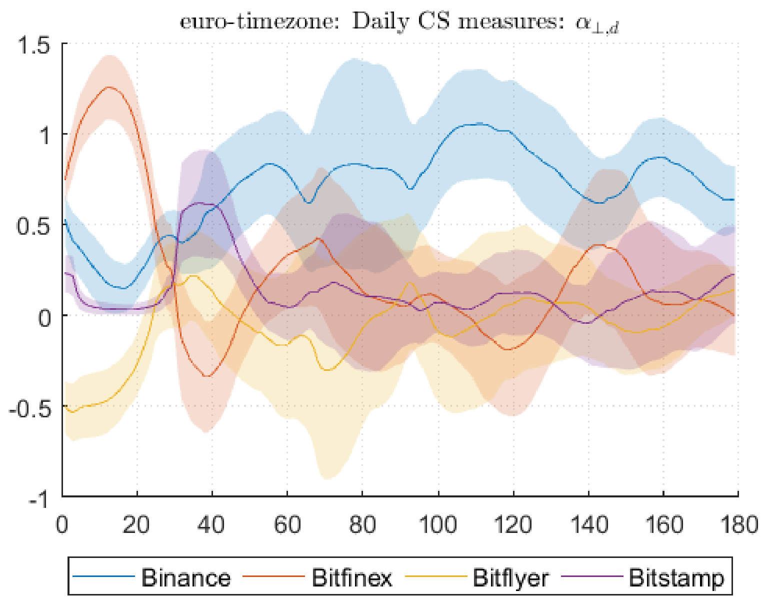

Figure 6: Results of CS in Time-Varying estimator: EUA Time Zone

6 Conclusion

This paper using a time-varying approach for price-discovery in continuous time for estimating the component-share. Using the KLS estimator applied at bitcoin market. We first show that the component share measure of price discovery is invariant to the discretization frequency, allowing us to make inference on the continuous-time price discovery mechanism from discrete sampled prices. This is in contrast with Hasbrouck's (1995) information share, which depends on the contemporaneous correlation across markets, which naturally increases in magnitude as the sampling frequency decreases.

We then make use of Giraitis, Kapetanios and Yates's (2013) KLS method to estimate daily component shares. By exploiting the inter-dependence across days, the KLS approach yields more efficient estimates than we would otherwise obtain by treating the daily variation in the VECM parameters as independent over time.

Empirically, we take 17 bitcoins exchanges, using for exchanges to apply your method. Only four of them provided good informational to allow us estimate the VECM vector. We find statistical evidence that the component shares indeed change over time for virtually every exchange in our sample. Our estimates indicate that market leadership alternates over time, and we have capture this phenomena that are possibly linked to volume and fee of trade.

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