THE RELATIONSHIP BETWEEN USD/EUR OFFICIAL EXCHANGE RATES AND IMPLIED EXCHANGE RATES FROM THE BITCOIN MARKET

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Abstract: *We examine the long- and short-run relationships between USD/EUR official rates and implicit exchange rates, through Bitcoin as a currency vehicle, over the period from March 07, 2016 to November 22, 2019. The results show that the two exchange rates are cointegrated and that the cointegrating vector is not statistically different from the theoretical one that results from the law of one price. In the short-run, the implied rate Granger-causes the official reference rate. Our main conclusion is that Bitcoin USD and EUR prices incorporate fundamental information from the USD/EUR official exchange rate.*

Keywords*: Bitcoin, USD/EUR, Exchange rates, Cointegration, Forecasting.*

1. Introduction

On October 31, 2008 someone, with the pseudonym Satoshi Nakamoto, self-published a paper describing a decentralised open source peer-to-peer (P2P) crypto-currency protocol, which became widely known as Blockchain (Nakamoto, 2008).[1] Based on a public ledger (Blockchain), on January 3, 2009 the Bitcoin network was created. This was the "Big Bang" event of the expanding universe of cryptocurrencies. Before Bitcoin there were other attempts to create decentralised virtual currencies, but they were unsuccessful due to the unsolved problem of double spending, i.e. to the possibility of an individual, conducting an online transaction, to send the same claim to more than one counterpart. The Blockchain resolved the double spending issue without the need for a third trusted intermediary.

The first cryptocurrency online exchanges emerged in 2010, with Mt.Gox claiming the market leadership, holding a market share of more than 80% during the next two years. Later, exchange-trading volumes at Bitstamp, BTC-e and Bitfinex rose, as Mt.Gox's fell down due to several technical incidents and legal issues, which ended in its bankruptcy in

[1] The Blockchain is a disruptive technology that may exist for other purposes than to produce and manage a virtual currency. In fact, by now, computer scientists, software developers, and other experts from various fields of knowledge are working together on applications of Blockchain to Finance, Government, Healthcare, Insurance, Real Estate, Transportation and Retail Distribution, just to name a few. Notably, these advances seem to be quite fruitful in underdeveloped countries, where a leap over several technological generations is occurring at the present times.

February 2014 (Brandvold et al., 2015). Based on the unprecedent success of Bitcoin, other cryptocurrencies were afterwards created at an increasing rate and begun to trade against each other and against fiat currencies in a flourishing industry of online exchanges. At the time of writing (November 2019), according to the CoinMarketCap – probably the most comprehensive site on cryptocurrencies, there are more than 4'800 cryptocurrencies traded around the clock, 24/7, on more than 20'800 online exchanges, worth more than 210 billion USD.

Cryptocurrencies have gained an important place in the international financial landscape, attracting widespread media exposure and general awareness ("What is Bitcoin?" was the most popular Google search question in the United States and United Kingdom in 2018). But the interest on cryptocurrencies has also spread across the financial community. In December 2017, at the peak of an exponential bull price rally of Bitcoin and other cryptocurrencies, the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) begun trading Bitcoin futures. By now, undoubtably one may say that Bitcoin has grown from being an obscure geek's thing to be a new financial asset that attracts the attention of individual and institutional investors, regulators and academics.

Early research on Bitcoin came from the fields of computer sciences, cryptography and law. The focus was on the technical features of the Bitcoin network and security and legal issues. However, in recent years, there has been a prolific production of economics and financial literature on Bitcoin. Most notably, the discussion on if Bitcoin is in fact a currency has been quite animated. Regulators, especially central banks, have been concerned with this issue. For instance, the ECB (2012) argues that if Bitcoin is in fact a currency, then it also depends on trust as fiat money does, but it is not supported by its intrinsic value nor on the belief in a central monetary authority solvency. One of the most cited studies on this issue is Yermack (2015), which points out that the Bitcoin exhibits excess volatility, has no correlation with classical currencies and is not regulated. The view that Bitcoin is a pure speculative asset has gained more supporters among the academic community on the grounds of its high volatility, extreme short-run returns and bubble-like price behaviour (see, for instance, Dwyer, 2015, Cheah and Fry, 2015, and Blau, 2017). This led to the inquiry on the possible relationships with macroeconomic and financial variables. Basically, this stream of literature indicates that Bitcoin prices are uncorrelated with the major classes of financial assets (see, for instance, Baur et al., 2018, and Corbet et al., 2018). Hence the claim that Bitcoin prices are mostly idiosyncratic, as they are mainly driven by public recognition (in the wording of Li and Wang, 2017), measured by social media news, Google searches, Wikipedia views, Tweets, or comments in the Facebook or specialized forums (see, for instance, Kristoufek, 2013, Ciaian et al., 2016, and Kim et al., 2016).

Our research question is somehow different. Although Bitcoin prices may be uncorrelated with other macroeconomic and financial variables, they still incorporate information from other financial variables, most particularly exchange rates of traditional currencies. That is, Bitcoin prices, for instance, in euros and dollars should be linked via the official euro-dollar exchange rate (at least in the long-run), otherwise there will be meaningful triangular arbitrage opportunities. As such, not only the euro-dollar exchange rate may help predicting the implicit euro-dollar exchange rate (where Bitcoin is the currency vehicle), but most importantly the implicit euro-dollar exchange rate may help predicting the official exchange rate. In fact, this idea is not completely new. Pieters (2016) finds that implicit rates from Bitcoin Granger-causes half of official exchange rates under study and claims that Bitcoin can be used as an unofficial exchange rate, which in turn allows the estimation of capital controls at a daily interval.

The reminder of this manuscript is structured as follows. Section 2 presents the data used in this study. Section 3 studies the long-run relationship between USD/EUR reference rate and implicit rates and shows the estimation results of a VECM. Section 4 compares the forecasting ability of several models that consider different data sets and assesses the contribution of the Bitcoin market to predict the USD/EUR reference rate. Section 5 concludes this study.

2. Data and preliminary analysis

Data on USD/EUR reference exchange rates (denoted hereafter as E) were obtained from the European Central Bank (ECB) site. These exchange rates are updated around 15:00 UCT on every working day. They are based on a regular daily concertation procedure between central banks across Europe, which usually takes place at 13:15 UCT. Data on the USD/GBP and EUR/GBP were downloaded from the site of the Bank of England. These indicative exchange rates are concerted between all banks governed by the Bank of England and are updated at 9:30 UCT.

In order to get representative data on the USD/EUR through the Bitcoin market, we begun by examining the Bitcoincharts website (https://bitcoincharts.com/) aiming to find the best Bitcoin online exchange for the purposes of our study. So, we search for exchanges with a significant trading volume and a long time series available for both USD/BTC and EUR/BTC, without any significant gaps (more than 3 consecutive days). A simple inspection of the Bitcoincharts database indicated that the online exchange Kraken would be a good choice, where data on both currencies are available since March 7, 2016. Although intraday trading data is available for Kraken, given the daily periodicity of USD/EUR official exchange rates, we just retain one observation per day: the two-hour volume weighted average prices at 16:00 UCT. Choosing a particular online exchange is obviously not innocuous, as Bitcoin prices are not completely arbitraged away (Pieters and Vivanco, 2017, and Makarov and Schoar, 2019) and hence the price discovery process occurs at different rates mainly depending on the trading volume (Sebastião et al., 2017).

The data were synchronized by taking out days missing in at least one of the time series. Because Bitcoin trades 24/7, the procedure mainly resulted in taking out weekends and several European holidays. So, it is worth noticing that this filter biases the results against the claim that Bitcoin is informative. For instance, for a given Monday the Bitcoin information that is used comes from the previous Friday; however, more recent information (from the previous Sunday) is available. We end up with 939 observations (from March 7, 2016 to November 22, 2019). The two GBP exchange rates are used to compute the USD/EUR implied exchange rate, which uses the British Pound as a currency vehicle, as E_{GBP} = (USD/GBP)/(EUR/GBP). The two exchange rates from Kraken are used to compute the USD/EUR implied exchange rate, which uses Bitcoin as a currency vehicle, as E_{BTC} = (USD/BTC)/(EUR/BTC). Figure 1 shows the paths of E, E_{BTC} and E_{GBP} during the sample period.

Figure 1. Daily USD/BTC reference exchange rates from ECB and implied USD/EUR exchange rates, considering British Pound and Bitcoin as currency vehicles. These implied rates were computed as E_{GBP} = (USD/GBP)/(EUR/GBP) and E_{BTC} = (USD/BTC)/(EUR/BTC). The British Pound rates are the indicative rates from the Bank of England and the Bitcoin rates are the 2-hours volume weighted average exchange rates at 16:00 CET from Kraken. The sample is from March 07, 2016 to November 22, 2019.

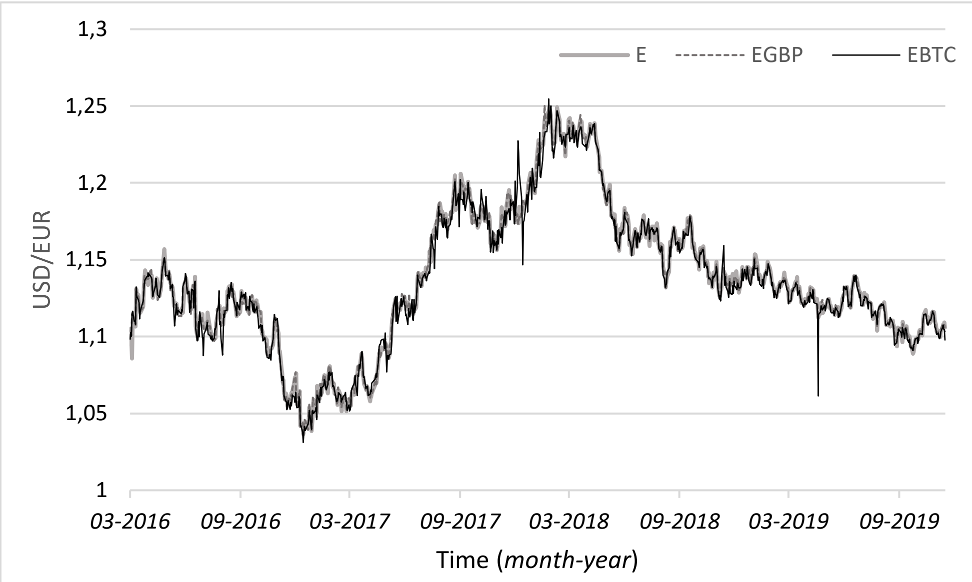

Figure 1 shows that the paths of E and E_{GBP} are indiscernible, whilst E_{BTC} is more jagged and presents some outliers, most probably due to transitory order imbalances at the Kraken exchange. Overall, Figure 1 puts into perspective that most probably the three exchange rates share the same stochastic trend (i.e., are cointegrated).

Table 1 presents the descriptive statistics of the logarithmic rates of change of the exchange rates under examination.

Table 1. Descriptive statistics of the daily logarithmic rates of change

	E	E_{GBP}	E_{BTC}
Mean (%)	0.001	0.001	-0.000
Median (%)	-0.017	0.012	-0.009
Minimum (%)	-2.877	- 2.234	-4.800
Maximum (%)	2.208	2.148	4.877
Standard Deviation (%)	0.466	0.439	0.616
Skewness	0.045	-0.007	0.404
Excess kurtosis	3.413	2.288	9.385
First order autocorrelation	-0.053	0.015	-0.210***
ARCH(1) LM test	1.895	8.533***	176.772***

Source: Data on the USD/EUR reference exchange rate, E, were downloaded from the European Central Bank (ECB) site, data used to compute E_{GBP} were downloaded from the site of the Bank of England, and data used to compute E_{BTC} were obtained from the Bitcoincharts site. Authors' computations in GRETL.
Notes: Significance at the 1%, 5% and 10% levels is denoted by "***", "**" and "*", respectively.

On average, daily exchange rates are not significantly different from zero. The range interval and the standard deviation indicate that E and E_{GBP} are less volatile than E_{BTC}. Also, E and E_{GBP} present mild skewness and excess kurtosis and no significant first order correlation, whilst E_{BTC} is positively skewed, more leptokurtic and has a significant first order correlation of -0.21. The exchange rate E does not present first order ARCH effects, but these effects are highly significant in the E_{BTC} time series.

3. The long run relationships and VECM estimation

The next table shows the results of the unit root and cointegration tests on the logarithm of the exchange rates.

Table 2. Unit root and cointegration tests

Unit root tests						
	Logarithm of E		Logarithm of E_{GBP}		Logarithm of E_{BTC}	
	Level	First difference	Level	First difference	Level	First difference
ADF	-1.861	-32.286***	-1.533	-11.733***	-1.336	-12.042***
KPSS	2.308***	0.155	2.304***	0.155	1.693***	0.139

Johansen cointegration test and cointegration vectors			
No. of CE(s)	Eigenvalue	Trace statistic	p-value
None	0.092	146.670	0.000
At most 1	0.058	57.251	0.000
At most 2	0.002	1.593	0.207

Source: Authors' computations in GRETL.
Notes: The unit root tests were performed with a constant. The number of lags included in the test regressions was chosen according to the AIC criterion. The null hypothesis of the ADF test is the existence of a unit root, while for KPSS under the null the series is stationarity. The Johansen cointegration test was performed with an unrestricted constant and 15 lags (the number of lags was chosen by the AIC criterion). Significance at the 1%, 5% and 10% levels is denoted by "***", "**" and "*", respectively.

The results shown in Table 2 indicate that the three time series are $I(1)$ and that they are cointegrated with rank 2. The two cointegrating vectors are $\beta_1 = [\beta_E \;\; \beta_{E_{GBP}} \, \beta_{E_{BTC}}]' = [1 \;\; 0 \; -1.0059]'$ and $\beta_2 = [\beta_E \;\; \beta_{E_{GBP}} \, \beta_{E_{BTC}}]' = [0 \;\; 1 \; -1.0033]'$. If the three exchanges rates price the same asset, they should be fundamentally equal and the cointegrating vectors should be $[1 \;\; 0 \; -1]'$ and $[0 \;\; 1 \; -1]'$. The likelihood ratio (LR) statistic on the null hypothesis that the cointegrating vectors are the theoretical ones is 2.164, with a p-value of 0.339. So, the test fails to reject the null hypothesis.

The next table presents the estimation results of the VECM with superimposed cointegrating vectors $\beta_1 = [1 \ \ 0 \ -1]$ and $\beta_2 = [0 \ \ 1 \ -1]$.

Table 3. VECM estimation

	E	E_{GBP}	E_{BTC}
Constant	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
α_1	−0.915*** (0.121)	0.097 (0.138)	−0.317* (0.166)
α_2	0.056* (0.032)	0.137*** (0.037)	−0.583*** (0.073)
E(-1)	−0.176* (0.097)	−0.232** (0.109)	0.038 (0.134)
E(-2)	−0.126* (0.076)	−0.186** (0.086)	−0.103 (0.105)
E(-3)	−0.114** (0.050)	−0.159*** (0.058)	−0.089 (0.067)
E_{GBP}(-1)	0.104 (0.109)	0.097 (0.121)	0.433*** (0.160)
E_{GBP}(-2)	−0.012 (0.078)	0.034 (0.092)	0.367*** (0.128)
E_{GBP}(-3)	0.102 (0.067)	0.126* (0.075)	0.333*** (0.094)
E_{BTC} (-1)	0.083*** (0.025)	0.132*** (0.033)	−0.518*** (0.077)
E_{BTC} (-2)	0.081** (0.032)	0.104*** (0.035)	−0.331*** (0.078)
E_{BTC} (-3)	0.057** (0.025)	0.089*** (0.029)	−0.164*** (0.061)
R^2	0.329	0.053	0.322
F- test on lags of E	2.003	2.731**	1.457
F- test on lags of E_{GBP}	2.248*	1.338	4.623***
F- test on lags of E_{BTC}	4.782***	5.016***	4.983***

Source: Authors' computations in GRETL.
Notes: This table shows the estimates and heteroskedasticity-robust standard errors (in parentheses) of the coefficients of the VECM. The long-run adjustment coefficients for the superimposed cointegrating vectors $[1 \ \ 0 \ -1]'$ and $[0 \ \ 1 \ -1]'$ are denoted by α_1 and α_2, respectively. The lag length was chosen by the Bayesian Information Criterion (BIC). The F-test is the test on the null hypothesis that the coefficients of the lags of the variable are all zero. Significance at the 1%, 5% and 10% levels is denoted by "***", "**" and "*", respectively.

The VECM fits well to the data, especially in the cases of E and E_{BTC}, where the R^2 achieve values above 32%, which is impressive given that we are studying financial time series. The reference rate E reacts mostly to the pricing error (long-run relationship) with E_{GBP} but still some adjustment is made for the pricing error with Bitcoin (10% significance). E_{GBP} only reacts to the long-run relationship with E_{BTC}, and this rate only reacts to the long-run relation with E_{GBP}. The main point is that the implicit rate from the Bitcoin market matters in the long-run for all the exchange rates. The short-run dynamics also highlight the importance of E_{BTC}, as the three lags of this rate are always significant at least at the 5% level. This claim is also supported by the F-tests on the E_{BTC} lags, which are significant at the 1% level for the three series. These tests can be interpreted as short-run Granger-causality tests, and hence they imply that E_{BTC} Granger-causes E and E_{GBP} at the 1% significance level.

4. The forecast ability of the Bitcoin market

This section assesses the incremental information of Bitcoin in predicting the USD/EUR reference rate. This analysis is conducted out-of-sample using recursive estimations of restricted VECM models. Firstly, the data is partitioned into two periods: the in-sample period, which includes the observations in 2016 and 2017, and the out-of-sample period, which includes the remaining data (total of 470 obs.). Then a VECM is estimated considering superimposed theoretical cointegrating vectors and a lag length of 3 (as prescribed by the BIC criterion). Finally, the 1-step forecast for the USD/EUR reference (i.e. the forecasts are only obtained from the estimated equation of E) is computed and saved. The procedure is reiterated by withdrawing, at each time, one observation from the out-of-sample period and including it in the in-sample period, until a time series of 470 one-step forecasts is obtained. The procedure is applied to several models that are restricted versions of the VECM that includes the information of the three exchange rates, E, E_{GBP} and E_{BTC}. These models are an AR, which only includes the information on E, two bivariate VECM, that besides the information on E, include the information on E_{GBP} or E_{BTC}, and, finally, the VECM that includes the information on E, E_{GBP} and E_{BTC}. All the VECM consider the theoretical cointegrating vectors. For instance, in the bivariate cases the cointegrating vector is $[1 \quad -1]'$, normalized in order to E. Table 4 shows several forecasting ability metrics of these models.

Table 4. Forecast evaluation statistics

	AR (E)	VECM (E, E_{BTC})	VECM (E, E_{GBP})	VECM (E, E_{GBP}, E_{BTC})
Mean Absolute Error (MAE)	0,317	0,292	0,244	0,254
Root Mean Squared Error (RMSE)	0,405	0,378	0,321	0,334
Theil's U	98,420	86,770	76,512	71,757

Source: Authors' computations in GRETL.
Notes: All values are in percentage. The Theil's U is the ratio of the RMSE of the proposed model to the RMSE of a naïve model which predicts that next value is equal to the present value of the dependent variable. Values less than 100 indicate an improvement relative to the naïve model.

The comparison between the forecast metrics of AR(E) and VECM(E, E_{BTC}) in Table 4 shows clearly that E_{BTC} helps to predict E, but not as much as E_{GBP} (VECM(E, E_{GBP})). However, the difference between the forecast metrics of the two bivariate VECM only marginally favour the E_{GBP}. The VECM(E, E_{GBP}, E_{BTC}), which encompasses the other models, presents mixed results: it is slightly better (worst) than the VECM(E, E_{BTC}) (VECM(E, E_{GBP})) in terms of MAE and RMSE, but it is the best model in terms of Theil's U. The main inference to draw from these results is that Bitcoin is comparable to the British Pound in terms of information on the USD/EUR reference rate.

5. Conclusion

We motivate this study by claiming that USD/EUR implicit exchange rates (considering Bitcoin as a currency vehicle) should be closely related to official USD/EUR exchange rates at least in the long-run. These two exchange rates are fundamentally the same, hence they cannot diverge away boundlessly. This implies that the two exchange rates must share a common stochastic trend. In fact, USD/EUR implicit rates that use other currency vehicles must also be cointegrated with the former rates. Additionally, if this is the case, bidirectional information flows may happen between the official and the implicit USD/EUR exchange rates.

In order to test the aforementioned hypotheses, we gathered data on the USD/EUR from the BCE, USD/GBP and EUR/GBP from the Bank of England and USD/BTC and EUR/BTC from a Bitcoin online exchange (Kraken) for the period from March 07, 2016 to November 22, 2019. The data from the Bank of England and from Kraken were then used to compute the USD/EUR implicit rates through British Pound and Bitcoin, respectively.

The application of a VECM model to the three time series (official rate and the two implicit rates) clearly supports the hypothesis that the exchange rates are cointegrated and quite interestingly that the cointegrating vectors are not statistically different from their theoretical counterparts, which assume that these exchange rates are fundamentally equal, as they price the same asset. In the short-run the implicit rate from Bitcoin Granger-causes the official rate and the implicit rate from British Pound, while causality is also found from the official rate, but most especially from the other implicit rate, to the USD/EUR implicit rate through Bitcoin.

We then proceed by looking at the forecast ability of the implicit rate from Bitcoin on the official rate. The results pointed out that the information from the Bitcoin market helps to predict the official rate, and that this incremental information effect has a similar degree to the one provided by the British Pound.

Given our database and methodology, we cannot defend that Bitcoin market is the best information source to predict the USD/EUR exchange rate, nor can we argue that the information from the Bitcoin market can be used to profit on the Forex market. However, our results clearly support that Bitcoin USD and EUR prices incorporate fundamental information from the USD/EUR official exchange rate.

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