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The Link between Bitcoin Price Changes and the Exchange Rates in European Countries with Non-Euro Currencies

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Abstract: This paper contributes to the literature dedicated to the interlinkages between cryptocurrencies and currencies by investigating whether Bitcoin price movements affect the exchange rates of a sample of nine European countries with non-euro currencies. By resorting to the novel unconditional quantile regression, we show that there is a statistically significant link between Bitcoin price movements and changes in nominal exchange rates. In normal market conditions, an increase in the price of Bitcoin can be associated with an appreciation of the currencies from our sample, while during the COVID-19 pandemic, the relationship inversed. In addition, we find heterogeneities in this relationship, depending on the level of change in the nominal exchange rate. The results emphasize the relevance of Bitcoin price movements to the conduct of monetary policy through the exchange rate channel and that investors in cryptocurrencies and various financial assets denominated in the currencies from our sample can benefit from diversification by including both types of assets in their portfolios.

Keywords: exchange rate; European countries; quantile regression; bitcoin

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1. Introduction

The creation of Bitcoin at the end of the 2000s represented an innovation that had significant effects on global financial markets and economies. With a market capitalization of around 300 billion USD at the end of 2022—down from a maximum of around 1.3 trillion USD during 2021—Bitcoin was the driver for the creation of a vast cryptocurrencies market with a market capitalization of around 800 billion USD at the end of 2022—this was down from a maximum of around 3 trillion USD during 2021. Currently, the market capitalization of Bitcoin represents around 40% of the total market capitalization of cryptocurrencies and is the dominant force in the market.

With an increase in market capitalization, cryptocurrencies in general, and Bitcoin in particular, have become more and more popular among investors. On the one hand, it allowed for a larger diversification of portfolios; on the other hand, investors explored the possibility that Bitcoin could act as a hedge for various assets in their portfolios.

In recent years many papers (Kliber et al. 2019; Kristjanpoller and Bouri 2019, among others) have investigated whether cryptocurrencies exhibit short-term safe-haven, hedge or diversifier features for stock, bond or forex markets. The general consensus is that cryptocurrencies are fulfilling a diversifier role for investments represented by sustainable stock market indices, a safe-haven role for the bond markets and a mixed role for a selection of representative stock market indices or currencies. Furthermore, during episodes with an increasing number of daily COVID-19 cases or deaths, the statistical relationship between both cryptocurrencies and main financial markets determinants weakens (Gil-Alana et al. 2020).

In addition, the increase in the popularity of Bitcoin among investors' portfolios, along with the increase in market capitalization, made Bitcoin susceptible to influence the overall economic activity. Mishkin (2001) pointed out that asset prices and the exchange rate affect GDP, and, as monetary policy can affect both asset prices and the exchange rate, these channels must be taken into consideration when making monetary policy decisions. Thus, asset prices impact the net worth of households and firms, influencing spending and investment decisions and the ability to borrow. The exchange rate affects overall economic activity through its effects on net exports and the balance sheets of economic agents.

In this context, Bitcoin price movements could influence economic activity through the balance sheet channel. An increase in the price of Bitcoin leads to a higher net worth, which stimulates consumption through the wealth effect. Moreover, a higher net worth leads to fewer adverse selection and moral hazard problems, promoting lending, which further supports investments and consumption. As the evolution of Bitcoin can influence overall economic activity, it can also have an impact on monetary policy decisions. Another possible way in which Bitcoin can influence overall economic activity is through the exchange rate channel. If Bitcoin has an influence on the exchange rate, this will influence the relative price of domestic goods, compared to foreign goods, and also the net worth of economic agents with foreign exchange-denominated loans. These effects have the potential to be more pronounced in more open economies and in ones with a larger share of foreign currency-denominated loans. If such a link between Bitcoin and the exchange rate is present, it could also trigger a response from central banks when monetary policy decisions are being made.

Against this background, economic policymakers should be interested in the possible links between the evolution of Bitcoin and the evolution of currencies. This would also be of interest to investors who are trying to diversify their portfolios of assets denominated in various currencies and Bitcoin. Moreover, the response of the exchange rate could be asymmetric, depending on the change in the exchange rate—appreciation or depreciation.

The main objective of this paper is to investigate the link between the change in the price of Bitcoin and the exchange rates in nine European countries with non-euro currencies—Bulgaria, Croatia, Czechia, Hungary, Norway, Poland, Romania, Sweden and Switzerland—after controlling for other factors which affect the exchange rate. The second objective of this paper is to investigate possible heterogeneities in the response of the exchange rate to its determinants by using the novel unconditional quantile regression proposed by Firpo et al. (2009). Unlike linear approaches such as OLS or GMM, which might provide an incomplete picture when investigating the link between the exchange rate and Bitcoin returns, the unconditional quantile regression can draw inferences regarding observations that rank above or below the exchange rate conditional means. Since it does not have any specific hypotheses about the distribution of error terms, its sensitivity to outliers is less significant in comparison to the mean regression, so quantile regressions can provide more accurate and robust regression results.

Using monthly data gathered during the period of 2017m01–2022m12 and the novel unconditional quantile regression, the contribution of this paper to the literature in the field is twofold: first, it identifies the link between Bitcoin and the exchange rates in nine European countries with non-euro currencies; second, it shows the heterogeneities between changes in the price of Bitcoin and other relevant determinants of the exchange rate, depending on the level of change in the exchange rate. Therefore, this paper adds to the relatively scarce literature investigating the link between cryptocurrencies and nominal exchange rates. Moreover, to our knowledge, the investigation of possible heterogeneities through the use of quantile regressions has not previously been performed. The results are of interest to both policymakers in charge of the formulation of monetary policies and investors trying to diversify their portfolios.

The rest of the paper is organized as follows: Section 2 provides a literature review, Section 3 provides a description of the materials and methods used in this research, Section 4 presents the results and provides a discussion of the results, including implications for policymakers, while the Section 5 formulates the conclusions.

2. Literature Review

2.1. Determinants of the Exchange Rate

The topics of exchange rate evolution and the factors that influence its short- and long-term behavior are among the most popular issues in international finance and economics. Dornbusch (1976) and Meese and Rogoff (1983) were the pioneers of this approach, which is based on exchange rate adjustments (sticky prices) and rational expectations. Lane (1999) used both theoretical and empirical approaches to investigate the long-term exchange rate equilibrium by using data sets from 1974 to 1992 from 107 countries. The estimates showed that the inflation rate is the most powerful driver for the nominal exchange rate in the long run. Furthermore, openness, growth and international trade were also found to exhibit statistically significant impacts on exchange rate dynamics.

Morana (2009) indicates that the relationship between macroeconomic volatility and the exchange rate exists, but only in the long run. Furthermore, since the exchange rate is an important determinant of aggregate demand, there should be bidirectional causality. Clostermann and Schnatz (2000) take an empirical approach the evolution of the real euro-dollar exchange rate. Constructing a synthetic euro–dollar exchange rate over a period from 1975 to 1998 and applying cointegration techniques, four factors were identified as fundamental determinants of the real euro–dollar exchange rate: the international real interest rate differential, relative prices in traded and non-traded goods sectors, the price of oil and relative fiscal position. A single-equation ECM model outperformed multivariate models and seems to be the most suitable to analyze and forecast the behavior of the euro–dollar exchange rate in the medium term.

Moving forward, Dua and Sen (2006) investigated the link between the real exchange rate and macroeconomic factors, such as the level of capital flow volatility, fiscal policy and monetary policy from 1993 to 2004. The estimates revealed that all variables were cointegrated to the real exchange rate. Furthermore, Kia (2013) developed a framework of the real exchange rate and its drivers in a small open economy that was based on Canadian currency, finding similar results. Along the same line of argument, AbuDalu et al. (2014) investigated the relationship between the real effective exchange rate and macroeconomic factors. Their covariate list contains money supply, inflation rate, domestic interest rate, foreign interest rate and the terms of trade in ASEAN-5 countries. Furthermore, Qamruzzaman et al. (2021) used a sample of South ASEAN countries between 1980 and 2017 to investigate the Abruzzian impact of foreign direct investment and financial innovations on the volatility of the exchange rate. According to them, foreign direct investments inflow and financial innovation exhibit a positive and statistically significant influence on exchange rate volatility, but only in the long run.

2.2. Cryptocurrencies and Financial Markets

The link between the exchange rate and financial assets has been studied comprehensively by academics and practitioners. For example, Aggarwal (1981) reveals that stock prices from the USA and the exchange rate are positively correlated. Soenen and Hennigar (1988) found a strong negative link between U.S. stock indexes and a several-currency-weighted value of the USD. In addition, Bodart and Reding (1999) report a marked linkage between the patterns of volatilities on the bond market and the foreign exchange market. More recently, Hofmann et al. (2020) showed that in emerging market economies, currency appreciation goes hand in hand with compressed sovereign bond spreads, even for local currency sovereign bonds.

Cryptocurrencies have quickly captivated investors who are seeking new international monetary alternatives, as well as traders and hedgers who are searching for better investment opportunities. Glaser et al. (2014) concluded that Bitcoin should be considered a speculative financial asset, rather than a currency or even an alternative to fiat money. Wu and Pandey (2014) investigated how Bitcoin increases the yield of an investment portfolio, generating income. Briere et al. (2015) obtained identical results, demonstrating how crypto investments can lead to great benefits for diversified portfolios with exposure to a wide variety of industries; these benefits are enough to protect the portfolios against high volatility, due to having a high level of profitability and a low degree of correlation with traditional assets.

Baek and Elbeck (2015) examined the volatility of the S&P 500 stock market index and Bitcoin, concluding that Bitcoin is 26 times more volatile than the S&P 500. Another study was conducted by Atik et al. (2015), who analyzed the relationship between the exchange rate and Bitcoin in the case of Turkey during 2009–2015. In their analysis, they took into account most trading values around the world to discover the influence of Bitcoin over other exchange rates. They also studied the long-term cointegration relationship between exchange rates and Bitcoin. Dyhrberg et al. (2018) used the asymmetric GARCH model in order to determine whether Bitcoin can act as a safe-haven tool or a hedging asset against price drivers. According to the author, in the short run and similarly to gold, Bitcoin presents the same hedging features against stocks in the FTSE and USD currencies. Baur et al. (2018) demonstrated that Bitcoin, compared to other currencies including the US dollar and even gold, has different characteristics of volatility and profitability. This hypothesis contradicts the conclusions supported by Dyhrberg et al. (2018), with empirical evidence presented by the authors to prove the dissimilarities. Furthermore, Wang et al. (2022) indicate that Bitcoin prices affect money supply and share dynamic inter-shock with CPI, EPU and money supply.

Goodell and Goutte (2021) used wavelet analysis on daily data of world deaths caused by COVID-19 and the daily prices of Bitcoin during the pandemic. Their findings show that the price of Bitcoin has increased due to COVID-19. Most studies on COVID-19 have demonstrated the ongoing cost of the pandemic. Analyzing the impact that the pandemic period had on the economy, including on the financial markets, Goodell and Goutte demonstrate the co-movement of the price of Bitcoin with the levels of deaths caused by COVID-19, given the fact that amidst the pandemic, the prices of cryptocurrencies (especially Bitcoin) grew. Furthermore, Kumar et al. (2022) showed a structural change in the connectedness evolving among several cryptocurrencies in 2020, as the market restructured in reaction to the unprecedented monetary injections that were used as a counter to the COVID-19-induced economic standstill.

Iqbal et al. (2021) also conducted a research study to examine the safe-haven and hedge properties of traditional currencies for cryptocurrencies. They chose to study Bitcoin, Ripple, Ethereum and Litecoin using the framework developed by Baur and McDermott (2010). They examined the safe-haven role of these major cryptocurrencies against reverse explosiveness in their prices. They concluded that the official currency of Japan—yen—represents the most consistent hedger, seconded by the British pound and the Chinese yuan, which have a safe haven role for Bitcoin.

The amazing success of Bitcoin made global financial institutions understand the importance of decentralized currencies. However, only a small strand of the literature was devoted to investigating the link between cryptocurrency markets and foreign exchange markets; furthermore, the existing studies highlight an incomplete image regarding the dependency structure between them. More to the point, Palazzi et al. (2021) investigated whether Bitcoin has a nonlinear relationship with six other currencies. They use the nonparametric causality test proposed by Diks and Panchenko and employed a multivariate filtering approach using BEKK-GARCH residuals on daily log-returns. They documented a direct impact of the euro on Bitcoin. Furthermore, in the post-break sample, there was only an effect from CHY to Bitcoin.

Kristjanpoller and Bouri (2019) examined long-range cross-correlations, as well as the asymmetric multifractality between the Swiss franc, the euro, the British pound, the yen, and the Australian dollar and the main cryptocurrencies. The results bring to light significant asymmetric characteristics from the cross-correlation, and these are persistent and multifractal in most cases. Ji et al. (2018) and Bouri et al. (2022) suggest that the integration between Bitcoin and other financial assets is a continuous process that varies over time, but there are also shifts and changes in their dynamics.

In addition, BenSaïda (2023) investigated the connectedness between Bitcoin and fiat currencies using two different samples: the developed G7 and the emerging BRICS. By using the regular (R)-vine copula and comparing it with two benchmark models, the multivariate t copula and the dynamic conditional correlation (DCC) GARCH model, the author showed that the cross-market linkages ware powerful during Bitcoin crashes and also reached significant levels during the 2021 and 2022 pandemic crises. Such an evolution may suggest the end of the market isolation of virtual currency. Finally, Zhu et al. (2017) demonstrate the interdependencies between Bitcoin's price and euro–dollar exchange rates with a significant impact, both in the short and long-term, by using a VECM approach. Stock markets and oil prices can also affect the value of Bitcoin in the long term, according to van Wijk (2013).

3. Materials and Methods

In this paper, we use monthly data to investigate the impact of Bitcoin returns on the percentage change in the exchange rate. Our sample relies on nine European countries with non-euro currencies (Bulgaria, Croatia, Czechia, Hungary, Norway, Poland, Romania, Sweden and Switzerland) during the period of 2017m01–2022m12. We chose the year 2017 as start point for our sample, as, since that point, the market capitalization of Bitcoin increased rapidly and became more susceptible to have a relevant impact on the balance sheets of economic agents and on other asset classes. A detailed description of the variables included in the baseline specification is presented in Table 1.

Table 1. Data description.

Variable	Description	Source
Exchange rate (ER)	The number of units of local currency that can be exchanged for one EUR. An increase (decrease) means a depreciation (appreciation) of the local currency. We consider the monthly percentage change in the baseline model.	Refinitiv
Business confidence (BC)	The business survey indicator provides information on the amount of optimism or pessimism that business managers feel about the prospects of their companies, based upon opinion surveys on developments in production, orders and stocks of finished goods and the general economic situation of the company. It can be used to monitor output growth and anticipate turning points in economic activity. We consider the monthly percentage change in the baseline model.	The global economy
Inflation differential (IF_DIFF)	The difference between the inflation rate in the country *i* in a month *t* and the one reported in the same month across the eurozone.	The global economy; Our own calculations
Interest rate differential (IR_DIFF)	The difference between consumer credit interest rate in the country *i* in a month *t* and the average one reported in the same month across the eurozone.	The global economy; Our own calculations
Covid-19 cases (COVID-19)	The number of new confirmed COVID-19 cases. We consider the monthly percentage change in the baseline model.	The global economy
Bitcoin return (BITCOIN)	The monthly percentage change in the price of Bitcoin.	CoinMarketCap

To avoid any misleading results caused by multicollinearity issues, we summarize the correlation matrix of the dependent variables in Table 2.

Table 2. Correlation matrix.

Variables	BC	IF_DIFF	IR_DIFF	COVID-19	BITCOIN
BC	100.00%				
IF_DIFF	5.83%	100.00%			
IR_DIFF	−2.74%	14.51%	100.00%		
COVID-19	5.30%	6.19%	4.93%	100.00%	
BITCOIN	−6.38%	−4.21%	−6.08%	−4.02%	100.00%

The results reported in Table 2 suggest that the correlation coefficients are lower than 50% in absolute values, so it is unlikely that the estimates were affected by multicollinearity issues. However, we ran a robustness check, which is described in the Results section, and report the variance influence factor (VIF) coefficients for a linear model.

Another issue that might affect the consistency of the estimates is the presence of non-stationary data in the baseline specification. To investigate this aspect, we present the results of two stationarity tests for panel data in Table 3, namely the LLC test proposed by Levin-Lin-Chu and the IPS test described by Im-Pesaran-Shin.

Table 3. Panel unit root test (all specifications include an intercept).

Variables	LLC Test		IPS Test	
	Trend	No Trend	Trend	No Trend
ER	−10.7882 (0.0000)	−9.7155 (0.0000)	−9.8823 (0.0000)	−10.8372 (0.0000)
BC	−12.6860 (0.0000)	−16.4352 (0.0000)	−13.5242 (0.0000)	−12.3116 (0.0000)
IF_DIFF	−11.8929 (0.0000)	−6.6137 (0.0000)	−11.7150 (0.0000)	−11.3744 (0.0000)
IR_DIFF	−9.6998 (0.0000)	−2.3965 (0.0083)	−10.2235 (0.0000)	−5.2917 (0.0000)
COVID-19	−11.3311 (0.0000)	−11.7114 (0.0000)	−10.5662 (0.0000)	−11.0339 (0.0000)
BITCOIN	−5.2130 (0.0000)	−5.3537 (0.0000)	−7.0933 (0.0000)	−7.7419 (0.0000)

Note: The null hypothesis is the presence of a unit root; *p*-values are reported in parentheses.

As evident in Table 3, the null hypothesis describing the presence of a unit root is rejected at the 1% level for all of the situations. This implies that it is very unlikely to run spurious regressions that will bias the conclusions regarding the real impact of Bitcoin on the exchange rates of European countries with non-euro currencies.

Econometric Approach

As mentioned in the Introduction section, the goal of this paper is to study to what extent the Bitcoin price evolution is influencing the level of the exchange rate against the euro for a panel containing nine European countries with non-euro currencies. The baseline specification has the following structure:

$$ER_{i,t} = \alpha_i + \beta_1 ER_{i,t-1} + \beta_2 CV_{i,t} + \beta_3 BITCOIN_{i,t} + \varepsilon_{i,t}. \quad (1)$$

In Equation (1), $i = \overline{1, N}$ and $t = \overline{1, T}$ are countries and months, respectively; $ER_{i,t}$ is the percentage change in the exchange rate for country I in month t; $ER_{i,t-1}$ is the percentage change in the exchange rate for country i in month $t-1$; $CV_{i,t}$ is a matrix of control macroeconomic variables; and $BITCOIN_{i,t}$ is a matrix of variables that contain the Bitcoin and its different interactions. Finally, $\varepsilon_{i,t}$ represents the error term.

To solve the potential endogeneity issues when estimating Equation (1), the econometric literature proposes some techniques, such as a panel GMM of the system GMM. However, in some situations, linear approaches can produce misleading results, especially when the distribution of the dependent variable is asymmetric. To overcome this issue, Koenker and Bassett (1978) proposed the conditional quantile regression, which has the capacity to draw inferences on the data that rank above or below the conditional mean of the percentage change in the exchange rate. For any level τ across the conditional distribution of ER, denoted by y, and given the set of explanatory variables denoted by x, the conditional quantile, $Q_y(\tau|x)$, shows $inf\{k : C(k|x) \geq \tau\}$, where $C(*|x)$ represents the conditional distribution function. To assess the impact of a certain factor or event at a certain level throughout the distribution of ER, the most common approach is the conditional quantile regression (CQR) for panel data developed by Koenker (2004):

$$Q_{y_{i,t}}(\tau|x_{i,t}) = \alpha_i + x_{i,t}^T \beta^{CQR}(\tau). \tag{2}$$

In Equation (2), $y_{i,t}$ is the dependent variable; $x_{i,t}$ is the set of covariates, including Bitcoin-related factors; $\beta^{CQR}(\tau)$ is the common slope; and α_i is a location-shift parameter. To account for the unobserved country heterogeneity, Koenker (2004) treats the fixed effects of the panel as nuisance factors. The relevance of this approach resides by the inclusion of a penalty term in the minimization algorithms:

$$\min_{(\alpha,\beta)} \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{i=1}^{N} w_k \rho_{\tau_k} \left(y_{i,t} - \alpha_i - x_{i,t}^T \beta(\tau_k) \right) + \lambda \sum_{i}^{N} |\alpha_i|. \tag{3}$$

In Equation (3), K represents the indices of the quantiles, ρ_{τ_k} is the quantile loss-function, while w_k is the relative weight associated with the kth quantile. The penalty term λ is included to diminish the individual fixed effects to zero. Moreover, when λ approaches zero, the model converges to a standard fixed effects specification.

Even though the conditional quantile regression (CQR) is a powerful method when studying variables with asymmetric distributions, it renders coefficients which fail to reflect the impact of these covariates across quantiles poorly. Firpo et al. (2009) proposed the unconditional quantile regression (UQR) by computing a recentred influence function (RIF), designed without any reference to covariates, which is subsequently regressed on the explanatories:

$$IF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right) = \lim_{\varepsilon \to 0} \left(\frac{v\left[(1-\varepsilon)F_{y_{i,t}} + \varepsilon G_{y_{i,t}}\right] - v\left(F_{y_{i,t}}\right)}{\varepsilon} \right) \tag{4}$$

In Equation (4), $0 \leq \varepsilon \leq 1$, $F_{y_{i,t}}$ represents the cumulative distribution function of $y_{i,t}$, $G_{y_{i,t}}$ denotes the distribution that puts mass at the value $y_{i,t}$ and $v\left(F_{y_{i,t}}\right)$ is the value of the considered statistic. The RIF is an estimator of ν with a probability distribution of F at point $y_{i,t}$ and is computed by adding this statistic to its IF:

$$RIF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right) = v\left(F_{y_{i,t}}\right) + IF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right) \tag{5}$$

In Equation (5), the expected value of the RIF is $v\left(F_y\right)$, if the expected value of the $IF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right)$ is zero. If we select the τth quantile as the statistic of interest and estimate the density functions based on kernel density techniques, the RIF, given q_τ, is specified as follows:

$$RIF\left(y_{i,t}; q_\tau; F_{y_{i,t}}\right) = q_\tau + IF\left(y_{i,t}; q_\tau; F_{y_{i,t}}\right) = q_\tau + \frac{\tau - \mathbb{I}\{y_{i,t} \leq q_\tau\}}{f_{y_{i,t}}(q_\tau)}. \tag{6}$$

In Equation (6), q_τ is the τth quantile of the unconditional distribution of the percentage change of the exchange rate, $f_{y_{i,t}}(q_\tau)$ express the probability density function of $y_{i,t}$

conditioned by the τth quantile base and $\mathbb{I}\{y_{i,t} \leq q_\tau\}$ is an indicator function showing whether $y_{i,t}$ is below the τth quantile. Thus, the *UQR* estimator is presented in Equation (7):

$$RIF(y_{i,t}; q_\tau; F_{y_{i,t}}) = x_{i,t}^T \beta^{UQR}(\tau). \tag{7}$$

In this paper, we use *UQR* as the baseline specification for panel data, as developed by Borgen (2016), which accounts for country- and time-fixed effects.

4. Results and Discussion

We present the *UQR* estimates in Table 4. Conventionally, five representative quantities from the probability distribution of the percentage change in the exchange rate (Q10, Q25, Q50, Q75 and Q90) were considered. In line with Borgen (2016), we used a Gaussian kernel for the coefficients, while the SEs were bootstrapped with 200 replications. For example, around the 10th quantile, which is the extreme lower quantile, we had situations in which the national currencies strongly appreciated against the euro. On the other hand, the 90th quantile, which is the extreme upper quantile, illustrates our method of dealing with situations in which national currencies strongly depreciated against the euro.

Table 4. UQR estimates (p-value in parentheses).

Variables	Q10	Q25	Q50	Q75	Q90
ER (−1)	0.2564 (0.0000)	0.3241 (0.0000)	0.2657 (0.0000)	0.3049 (0.0000)	0.1514 (0.1611)
BC	−0.0857 (0.0000)	−0.0680 (0.0000)	−0.0702 (0.0028)	−0.0788 (0.2015)	−0.0823 (0.0872)
IF_DIFF	−0.0088 (0.0001)	−0.0063 (0.0038)	−0.0022 (0.0806)	−0.0024 (0.1574)	−0.0013 (0.6825)
IR_DIFF	0.0011 (0.1389)	0.0008 (0.2632)	0.0008 (0.1560)	0.0001 (0.9288)	−0.0001 (0.9576)
COVID-19 cases	0.0026 (0.3846)	0.0031 (0.0807)	−0.0004 (0.7680)	−0.0016 (0.1492)	0.0016 (0.2957)
BITCOIN	−0.0094 (0.1343)	−0.0106 (0.0429)	−0.0072 (0.0981)	−0.0147 (0.0061)	−0.0163 (0.0175)
BITCOIN × COVID-19 dummy	0.0063 (0.4025)	0.0120 (0.2289)	0.0253 (0.0005)	0.0293 (0.0152)	0.0327 (0.0381)
Intercept	−0.0235 (0.0000)	−0.0112 (0.0000)	−0.0007 (0.5646)	0.0119 (0.0000)	0.0251 (0.0000)
Observations	648	648	648	648	648
R-squared	0.1587	0.1290	0.0899	0.0800	0.0796

Appendix A illustrates that the JB test rejected the null hypothesis, which suggests that we have a normal distribution that describes the percentage change in the exchange rate. The Kurtosis coefficients show that an asymmetric distribution characterizes the exchange rate dynamic. Against this background, the quantile regression approach can provide some interesting insights regarding the asymmetric response of the percentage change in exchange rates to different covariates, especially Bitcoin returns.

To investigate the potential endogeneity in the baseline model that was caused by reverse causality, we performed the Dumitrescu and Hurlin (2012) causality test and provide the results in Appendix B. As it demonstrates, there was a unidirectional causality, namely, from Bitcoin to exchange rate dynamics, in a panel-data approach. In this way, we provide an additional argument, relative to the survey of the literature, regarding the specification of the model in a quantile regression framework. Furthermore, the potential endogeneity caused by reverse causality is very unlikely to appear.

First, our results show a very persistent impact of the exchange rate up to the 75th quantile. This reflects that past evolutions of the exchange rate matter a great deal for the current evolution; therefore, a trend in the evolution of the currency is difficult to reverse.

Second, improved business confidence led to the appreciation of the national currencies from our sample for all quantiles, with the impact being somewhat higher across the higher quantiles, when the national currencies were depreciating against the euro. This result is in line with the literature and with economic intuition. The estimates showed limited heterogeneities for this variable, suggesting that the link with the exchange rate does not depend too greatly on the evolution of the nominal exchange rate.

Third, a higher inflation differential led to an appreciation of the exchange rate up to the 50th quantile, when national currencies were appreciating against the euro. Such an evolution could be explained by the rapidly rising productivity in many countries from our sample, which exhibited a catch-up effect towards the euro area.

Fourth, we did not find significant estimates relating the interest rate differential to the exchange rate dynamic. This result does not confirm previous findings in the literature (Ismailov and Rossi 2018).

Fifth, we did not find a significant link between the intensity of the COVID-19 pandemic, measured through the number of cases, and the nominal exchange rate.

Sixth, in normal market conditions, we report a negative relationship between Bitcoin returns and the evolution of the currencies from our sample from the 25th quantile onwards. Thus, a positive return of Bitcoin was associated with nominal exchange rate appreciation. There was also some heterogeneity in the results, with the impact being stronger when the exchange rate was depreciating and less strong when the national currency was experiencing appreciation. Interestingly, this relationship was reversed during the COVID-19 pandemic, with the coefficients being statistically significant from the 50th quantile onwards. These results suggest that Bitcoin movements are also relevant for monetary policy through the exchange rate channel. Thus, central banks should take the evolution of Bitcoin into consideration when making monetary policy decisions. In addition, from the perspective of investors of financial markets, investments in Bitcoin and in the various assets denominated in the currencies from our sample do not seem to exhibit hedging characteristics.

The reported findings complement the growing literature investigating the link between exchange rate markets and cryptocurrency markets. More to the point, in line with Kristjanpoller and Bouri (2019), our study reveals the existence of significant asymmetric characteristics relating the two markets, arising from the usage of several non-linear approaches. Unlike Palazzi et al. (2021), who show a direct impact of the euro on Bitcoin, our study reveals that this relationship is bidirectional, especially during normal exchange market conditions. Like BenSaïda (2023), Ji et al. (2018) and Bouri et al. (2022), our study reveals that the interlinkages between the cryptocurrencies market and the forex market are following different patterns over time, especially during times of financial or pandemic turmoil. Finally, similarly to Zhu et al. (2017), we demonstrate that the interdependencies between Bitcoin returns and the exchange rates of EU currencies are powerful, in both the short- and the long-term.

In summary, our results provide additional evidence regarding the impact of Bitcoin returns on the nominal exchange rate. More specifically, we performed an analysis of EU countries with non-EUR currencies, which was eluded by the previous research on this topic. Furthermore, we used the novel quantile regression as the baseline specification, which is a novel approach that extends the findings reported in the literature using linear methods such as GMM or Panel OLS. Unlike other papers, such as BenSaïda (2023), Ji et al. (2018) and Bouri et al. (2022), we also provide implications for policy making, which might help policymakers to better adjust their interventions in currency markets, considering that the majority of the countries from the selected sample are candidates to adopt the EUR as their national currency.

5. Conclusions

This paper has investigated whether Bitcoin returns affect the evolution of the national currency for nine non-euro European countries, and it has also considered the existence of heterogeneities in this relationship, depending on changes in the national currencies. A number of control variables were used for the evolution of the national currencies—business confidence, inflation differential, interest rate differential—but the number of COVID-19 cases was also examined in order to account for the pandemic. Our results showed that in normal market conditions, an increase in the price of Bitcoin leads to an appreciation of the currencies from our sample, while during the COVID-19 pandemic, that relationship inversed. In addition, heterogeneities were present in the relationship, depending on the changes in nominal exchange rates. The main implication of our study is that Bitcoin fluctuations have the potential to influence the conduct of monetary policy through the exchange rate channel. Another implication is that investors in cryptocurrencies and in various financial assets denominated in the currencies from our sample can benefit from diversification by including both types of assets in their portfolios. The limitations of our study are the choice of the currencies in our sample, as other currency pairs could behave differently, and the sole consideration of Bitcoin among cryptocurrencies. Investigations of the link between other currency pairs from other parts of the world and Bitcoin or other cryptocurrencies constitute directions for future research.

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Appendix A

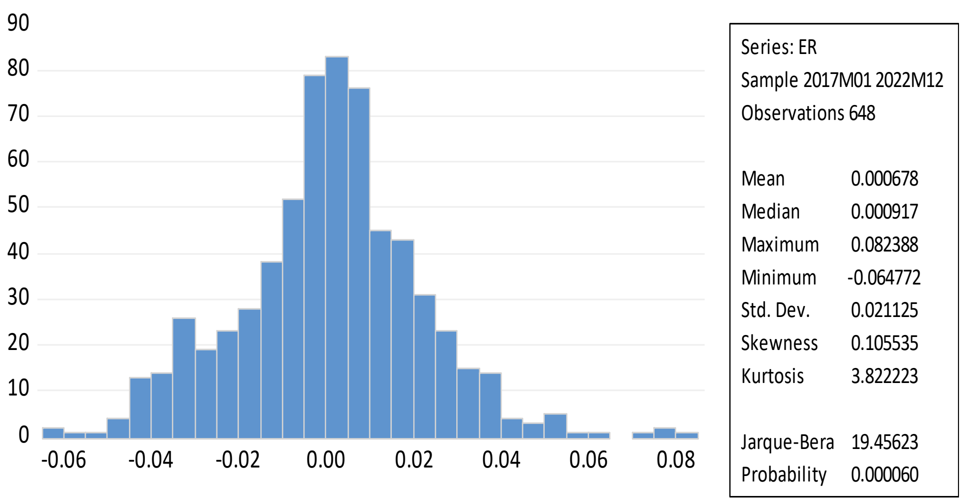

Figure A1. Histogram of the exchange rate change. Descriptive statistics.

Appendix B

Table A1. Dumitrescu and Hurlin (2012) causality test.

Null Hypothesis	Prob.
Exchange rate does not homogeneously cause Bitcoin	0.9947
Bitcoin does not homogeneously cause exchange rate	0.0000

Source: own estimations.

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