Forecasting Bitcoin Returns: Is there a Role for the U.S. – China Trade War?

Vasilios Plakandaras*°, Elie Bouri** and Rangan Gupta***

*Department of Economics, Democritus University of Thrace, University Campus, Komotini, Greece.

**USEK Business School, Holy Spirit University of Kaslik, Jounieh, Lebanon.

***Department of Economics, University of Pretoria, Pretoria, 0002, South Africa.

Abstract

Previous studies provide evidence that trade related uncertainty tends to predict an increase in Bitcoin returns. In this paper, we extend the related literature by examining whether the information on the U.S. – China trade war can be used to forecast the future path of Bitcoin returns controlling for various explanatory variables. We apply ordinary least square (OLS) regression, support vector regression (SVR), and the least absolute shrinkage and selection operator (LASSO) techniques that stem from the field of machine learning, and find weak evidence of the role of the trade war in forecasting Bitcoin returns. Given that out-of-sample tests are more reliable than in-sample tests, our results tend to suggest that future Bitcoin returns are unaffected by trade related uncertainties, and investors can use Bitcoin as a safe haven in this context.

Key Words: Bitcoin; forecasting; machine learning; U.S. – China trade war.

JEL Classification: C53, G11, G17

° Corresponding author: vplakand@econ.duth.gr, +306944503768, University Campus, Komotini, Greece.

1. Introduction

The most well-known aspect of the "America-first" approach of the Trump administration is the introduction of one of the biggest trade wars in the contemporary history of global trade. To summarize the existing situation from the "war front", the U.S., from 2018 onwards, gradually imposed import tariffs on more than $280 billion worth of U.S. imports. Their main trading partners, such as China, retaliated by adding tariffs on more than $120 billion of U.S. exports.[1] The spillover of the U.S. – China trade war extends to the entire global economy, given that the two opposing parties are in fact the two largest and most important economies in terms of global trade. This situation has spooked investors, who see exchange rates and investments pegged to the U.S. and Chinese economies to be affected, turning to alternative investments such as gold, commodities and cryptocurrencies to hedge economic uncertainty. In this paper, we focus on Bitcoin and examine its ability to act as a hedge in the ongoing U.S. – China trade war. The innovation of our paper originates from the fact that price movements in the Bitcoin market have never been used in the literature in tandem with trade conditions and as an exploratory instrument to detect trade uncertainty.

The line of thinking that the U.S. – China trade war is related to the Bitcoin market is not random, as it is in line with the soaring Bitcoin prices observed recently as the trade war has intensified. Given this, claims have been made by financial practitioners that these two events are not necessarily isolated, but an indication of Bitcoin's hedging ability. In an interview on the 21st of May (2019) in Fortune's "Balancing the Ledger" show, Digital Currency Group founder Mr. Barry Silbert suggested that Bitcoin acts as an asset that is insulated from the uncertainties of the traditional financial system, i.e., there seems to be a "flight to safety" property of Bitcoin, which was also observed, for example, during "Brexit" and "Grexit". And, just like Mr. Silbert, many market watchers have suggested that Bitcoin, at times referred to as "digital gold", has benefited from investors' jitters in the equities and foreign exchange markets which sent stocks and China's currency downward as the trade war heated-up.

[1] The Trump administration has extended the trade war to Canada (which has imposed tariffs on $12.8 billion worth of U.S. goods in return), the EU (which has enforced tariffs on $7.2 billion of U.S. products in return), and Russia (which has also slammed 25-40% additional duties on the import of American products).

The basic characteristic of Bitcoin [2] that differentiates it from many other cryptocurrencies (apart from the fact that it was the first cryptocurrency introduced) is that it has a controlled supply of coins, settled by the creator of the algorithm, so that the number of new Bitcoins introduced in the system declines over time to reach a maximum of 21 million units. From this we can imply that the supply is exogenously determined and that it is deflationary constructed. This characteristic of Bitcoin is discussed heavily in the literature (Yermack, 2013; Böhme et al., 2015), and the consensus is that it represents a serious drawback to it becoming a real currency.

The existing literature has not reached a consensus regarding the determinants of Bitcoin price. Given the exogenous nature of its supply, Bitcoin's price is affected by the demand side according to the number of Bitcoins in circulation, the transaction volume, the hash rate and the mining difficulty (see, among others, Ciaian et al., 2016; Baek and Elbeck, 2014). Other determinants of Bitcoin price are its interconnection with financial markets (Kristoufek, 2015; Bouoiyour and Selmi, 2016; Bouri et al., 2017a), the interest of traders in the Bitcoin market as expressed in Google search trends and Wikipedia articles views (Kristoufek, 2015; Glaser et al., 2014; Panagiotidis et al., 2018), gold and other competing commodities (Bouri et al., 2017a; Panagiotidis et al., 2018), energy prices that are crucial to mining (Bouri et al., 2017b), economic policy uncertainty (Demir et al., 2018; Wang et al., 2018; Panagiotidis et al., 2018, 2019; Cheng and Yen, 2019) and other macroeconomic conditions that shift the interest of investors from government bonds to other assets.

In this study, we examine the ability of Bitcoin to act as a hedge for investors who need to move away from currencies typically monitored and affected by central authorities amidst the U.S. - China trade war. In doing so, we build forecasting models that explore the ability to foresee Bitcoin prices based on their determinants reported in the literature and measures of the political and economic uncertainty imposed by trade tariffs. The examination is conducted within an out-of-sample setting, controlling for the role of various predictors of Bitcoin returns. This represents an extension to previous studies that consider the hedging ability of Bitcoin within an in-sample setting only and use bivariate models (e.g., Bouri et al., 2017a, b; Demir et al., 2018; Corbet et al., 2018;

[2] The most recognizable cryptocurrency is Bitcoin. As of November 2019, its total market capitalization is approximately $164 billion accounting for almost 70% of the total capitalization of cryptocurrencies, while its previous capitalization at the end of 2015 was about $6 billion (https://coinmarketcap.com/).

Wang et al., 2018; Cheng and Yen, 2019; Shahzad et al., 2019; Aysan et al., 2019; Gozgor et al., 2019). Given that the ability of each model to foresee a phenomenon is partially bounded by the forecasting performance of the methodology in hand, we apply ordinary least square (OLS) regression, the state-of-the-art support vector regression (SVR), and the least absolute shrinkage and selection operator (LASSO) techniques that stem from the field of machine learning.

2. Research background

With the imposition of tariffs, the Trump administration hopes to compel China to adjust its economic policies regarding tariffs, limit the alleged theft of U.S. intellectual property by Chinese firms, reverse the transition of manufacturing activities from the U.S. to China and impede the leading role of Chinese firms in high-tech sectors. The Trump administration has threatened to pull the U.S. from the World Trade Organization (WTO) and extend tariffs to additional products, adding hundreds of billions of dollars. Thus, it seems that the trade conflict is bound to escalate and that trade tariffs will be a part of global trade for quite some time.

In a recent paper, a year after the imposition of tariffs, Amiti et al. (2019) find that the full burden of the tariffs fall on domestic consumers, with a reduction in U.S. real income of $1.4 billion per month by the end of 2018, while similar patterns emerge in foreign countries which retaliate against the U.S. with increases in the prices of intermediate and final goods and changes to the supply-chain network of industrial production. Fajgelbaum et al. (2019) find that import tariffs favour sectors that are concentrated in politically competitive counties, while tradable-sector workers in heavily Republican counties are the most negatively affected due to retaliatory tariffs.

Recent history reveals that in tumultuous economic times, many investors use cryptocurrencies to hedge assets that are prone to official control (such as exchange rates or gold reserves). For example, some Chinese investors switched to cryptocurrencies in 2016 when the Chinese national currency, the yuan, was devalued. Other investors turned to Bitcoin during the referendum regarding Brexit (Bouri et al., 2017a).

Cryptocurrencies are digital currencies in which encryption techniques are used to control the units and verify the transfer of funds, functioning independently of a central monetary authority. The basic notion behind a cryptocurrency is the use of a transaction log that is distributed across a network of market participants. This log verifies transactions and the uniqueness of each participant, while it includes mechanisms to reward honest participation, weight the wealth of early adopters, and guard against concentrations of power (Nakamoto, 2008). The quantity of cryptocurrencies that exists is determined by a specific algorithmic process called "mining" (in reference to gold mining). The most intriguing characteristic of a cryptocurrency is its independence of a central monetary authority and legal framework, with the distributed log and the algorithm that sets its existence the sole principles of the market. Cryptocurrencies provide an outlet for wealth accumulation and transfer with no apparent influence from lawyers or regulatory restrictions. The allure, underlying value, and mechanics of cryptocurrencies and decentralized ledgers are pointed out by recent studies (Yermack, 2017; Sockin and Xiong, 2018; Cong et al., 2019).

Many studies consider the hedging property of Bitcoin against financial markets by studying the relationship between Bitcoin returns and the returns of conventional assets (Bouri et al., 2017a, b; Corbet et al., 2018; Shahzad et al., 2019). They find that Bitcoin is decoupled from the global financial system, offering diversification benefits[3]. Other studies focus on the relationship between Bitcoin and uncertainty measures such as global financial stress (Bouri et al., 2018), geopolitical risk (Aysan et al., 2019), or economic policy uncertainty (Demir et al., 2018; Wang et al., 2018), indicating that Bitcoin can hedge uncertainty, or at least is only weakly predicted by uncertainty[4]. However, most studies apply in-sample analysis even though the academic literature (e.g., Campbell, 2008) indicates that the ultimate test of any predictive model (in terms of the econometric methodologies and predictors used) is in its out-of-sample performance. Furthermore, the few studies that consider the hedging property of Bitcoin against uncertainty apply bivariate models, whereas we apply multivariate models, controlling for other predictors. The two papers that considers trade policy uncertainty in respect of Bitcoin are those of Bouri et al. (2019) and Gozgor et al. (2019). While the latter uses wavelet techniques to show that Bitcoin returns and trade policy

[3] Some other studies (e.g., Klein et al., 2018) question the hedging ability of Bitcoin for developed stock markets.

[4] A recent study by Cheng and Yen (2019) considers the economic policy uncertainty of both the U.S. and China and report mixed findings. The economic policy uncertainty of the U.S. has no predictive power over Bitcoin returns, whereas the economic policy uncertainty of China is useful for predicting Bitcoin returns.

uncertainty are positively correlated in general with some exceptions, the former highlights the fact that the (realized) correlation between U.S. equities and Bitcoin returns is negatively impacted by trade uncertainty.

However, to the best of our knowledge, there remains a research gap regarding the price discovery of Bitcoin with trade uncertainty within a model that contains various explanatory variables, based on out-of-sample analyses. This is where we aim to contribute. Methodologically, we apply various techniques, which represents an extension of the work of Panagiotidis et al. (2018, 2019) that applies the LASSO approach only, and disregards the role of the trade uncertainty of the U.S. and China.

3. Data and methodology

3.1 The data

In order to isolate all potential factors that may influence the price determination of Bitcoin, we compile a monthly dataset spanning the period August 2011 to April 2019, comprising financial indices, exchange rates, commodity prices, Bitcoin characteristics and political uncertainty indices. Specifically, we use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) that expresses the market's expectation of one month ahead volatility, the Morgan Stanley Capital International (MSCI) market capitalization weighted stock market index and the MSCI index for China as measures of the financial market, the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) as a benchmark for investment in the commodity market, gold prices given its popularity as a safe-haven, oil prices (Crude Oil West Texas Intermediate) to isolate the linkages with energy prices, the U.S. Dollar Index (USDX) as an index of the value of the United States dollar relative to a basket of foreign currencies, U.S. treasury bond rates with a maturity of 10 years as an alternative safe-haven, Google search hits for Bitcoin, the news-based Global Economic Policy Uncertainty (GEPU) Index of Baker et al. (2016) to isolate global economic and political turmoil,[5] the respective news-based trade uncertainty indices for the U.S. and China derived from Caldara et al.

[5] The GEPU Index is a GDP-weighted average of national EPU indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States.

(2019)[6] and Davis et al. (2019),[7] and Bitcoin specific measures (trading volume of Bitcoin, hash rate etc.). The descriptive statistics of the variables used in training our models are given in Table 1.

Table 1: Descriptive statistics of variables

No	Variable	Abbreviation	Source	Mean	Standard Deviation	Stationarity (according to the ADF test)
1	Bitcoin Price (USD)	Bitcoin	Bitstamp	1,865.36	2,996.86	I(0)
2	Global Morgan Stanley Capital International market capitalization weighted stock market index	MSCI World	DataStream	1,690.18	286.95	I(0)
3	Morgan Stanley Capital International market capitalization weighted stock market index for China	MSCI China	DataStream	66.45	11.56	I(0)
4	Chicago Board Options Exchange Volatility Index	VIX	DataStream	1,341.64	190.09	I(0)
5	Gold prices, Handy & Harman Base $/Troy Oz	Gold	DataStream	3,521.11	1,187.18	I(0)
6	S&P GSCI Commodity Total Return	GSCI	DataStream	89.41	7.96	I(0)
7	U.S. dollar trade index	USDX	DataStream	16.26	5.21	I(0)
8	U.S. benchmark 10-year ds govt. index - clean price index	TB10	DataStream	150.35	5.35	I(0)
9	Trading volume of Bitcoin	Vol	Bitstamp	1,494.78	3,831.87	I(1)
10	Number of Bitcoin transactions excluding	Num	https://www.blockchain.com	9,020.59	7,214.42	I(0)

[6] These authors use automated text searches of the electronic archives of seven newspapers: Boston Globe, Chicago Tribune, Guardian, Los Angeles Times, New York Times, Wall Street Journal, and Washington Post for terms related to trade policy, such as tariff, import duty, import barrier, and anti-dumping. We also conducted our analysis based on the trade uncertainty index of the US developed by Baker et al. (2016), and obtained similar results, which are available upon request from the authors. We report the results based on the index developed by Caldara et al. (2019), as it seems to capture the sharp increases in the trade uncertainty post 2016 relatively better.

[7] These authors use two newspapers from mainland China: the Renmin Daily and the Guangming Daily, and search for terms associated with economy, uncertainty, policy and trade.

	chains longer than 100					
11	Bitcoins in circulation	Supply	https://www.blockchain.com	1,375.45	3,009.65	I(0)
12	Hash rate	Hash		7,871.64	1,524.84	I(0)
13	Crude Oil WTI Cushing U$/barrel prices	Oil	DataStream	71.09	22.87	I(0)
14	Google search index Bitcoin	Google Trends	Google Trends	7.88	13.19	I(1)
15	Global Economic Policy Uncertainty	GEPU	https://www.policyuncertainty.com/	157.06	50.56	I(0)
16	Trade policy uncertainty index for China	TPU_China	https://www.policyuncertainty.com/	180.57	210.61	I(1)
17	Trade policy uncertainty index for the U.S.	TPU_US	https://www2.bc.edu/matteo-iacoviello/tpu.htm	100.47	108.64	I(1)

Note: I(0) is a stationary series, while I(1) denotes a difference stationary process. All tests are performed at the 5% level of significance.

Apart from TB10, all variables are used in their logarithmic form and in levels for the machine learning models, while they are transformed in returns (first- differences) in the econometric models to ensure stationarity.

3.2 Support vector regression

The support vector regression is a direct extension of the classic support vector machine algorithm. This specific machine learning methodology has attracted significant interest in forecasting economic and financial time series (Rubio et al., 2011; Härdle et al., 2009; Öğüt et al., 2012; Khandani et al., 2010; Plakandaras et al., 2015). The algorithm proposed by Vapnik et al. (1992), later extended by Cortes and Vapnik (1995), originates from the field of statistical learning. The basic idea of regression is finding a function that has, at most, a predetermined deviation from the actual data observations. In other words, during the construction of the optimal forecasting model, the error terms do not play any role and are not taken into account as long as they don't violate a predefined threshold ε; only errors higher than ε are penalized. The vectors that define the "error tolerance band" given ε are identified through a minimization procedure, and are called support vectors (SV).

One of the main advantages of SVR in comparison to other machine learning techniques is that it yields a convex minimization problem with a unique global minimum, avoiding local minima. The model is built in two steps: the training and the testing. In the training step, the largest part of the dataset is used for the estimation of the support vectors that define the band. In the testing step, the generalization ability of the model is evaluated by checking the model's performance in the small subset that was left aside during training. Using cross-validation techniques a universal and not sample-specific solution is achieved, avoiding over-fitting the model.

For a training dataset $D = [(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots . (\boldsymbol{x}_n, y_n)], \boldsymbol{x}_i \in \mathbb{R}^m, y_i \in \mathbb{R}, i = 1,2, \ldots . n,$ where $\boldsymbol{x}_i$ is a vector of independent variables and y_i is the dependent variable. The linear regression function takes the form $y = f(\boldsymbol{x}) = \boldsymbol{w}^T\boldsymbol{x} + b$. This is achieved by solving:

$$\min\left(\frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{\iota=1}^{n}(\zeta_i + \zeta_i^*)\right) \tag{1}$$

$$\text{subject to} \begin{cases} y_i - (\boldsymbol{w}\boldsymbol{x}_i + b) \leq \varepsilon + \zeta_i \\ (\boldsymbol{w}\boldsymbol{x}_i + b) - y_i \leq \varepsilon + \zeta_i^* \\ \zeta_i, \zeta_i^* \geq 0 \end{cases}$$

where ε defines the width of the tolerance band, and ζ_i, ζ_i^* are slack variables controlled through a penalty parameter C (see Figure 1). All the points inside the tolerance band have $\zeta_i, \zeta_i^* = 0$. System (1) describes a convex quadratic optimization problem with linear constraints, and has a unique solution. The first part of the objective function controls the generalization ability of the regression, by imposing the "flatness" of our model controlled through the Euclidean norm $\|\boldsymbol{w}\|$. The second part of the objective function controls the fit of the regression to the training data (by increasing C we penalize with a bigger weight any point outside the tolerance band i.e. with $\zeta_i \geq 0$ or $\zeta_i^* \geq 0$). The key element of the SVR concept is finding the balance between the two parts in the objective function that are controlled by the ε and C parameters.

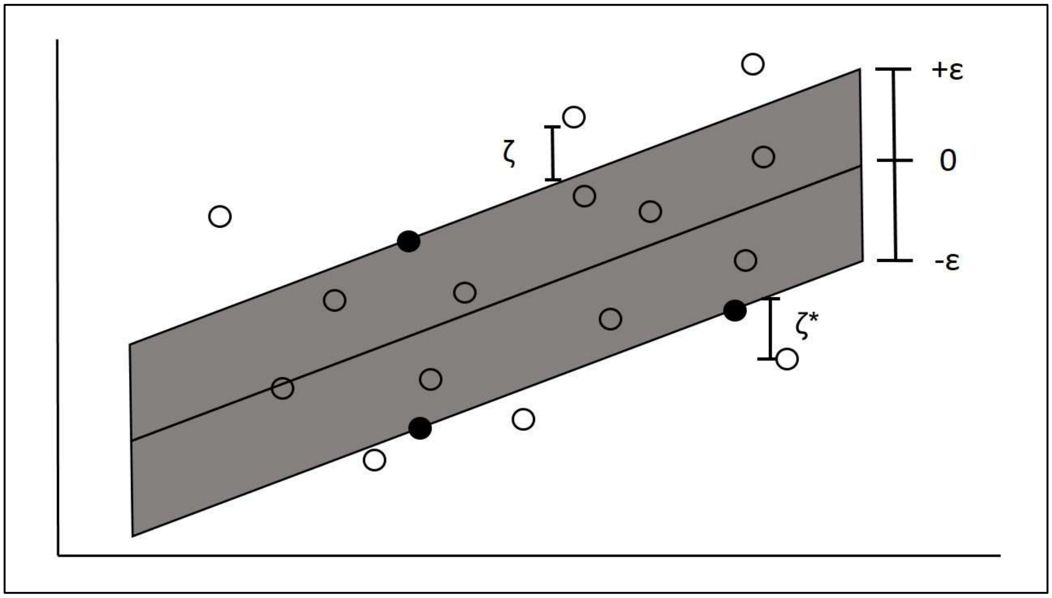

Figure 1: The tolerance band defined by ε. The boundaries of the error tolerance band are defined by the support vectors (SVs) denoted by black filled circles. Forecasted values greater than $|\varepsilon|$ get a penalty equal to ζ that depends on their distance from the tolerance band.

Using the Lagrange multipliers in System (1) the solution is given by:

$$\boldsymbol{w} = \sum_{i=1}^{n}(a_i - a_i^*)\boldsymbol{x}_i \tag{2}$$

and

$$y = \sum_{i=1}^{n}(a_i - a_i^*)\boldsymbol{x}_i^T\boldsymbol{x} \tag{3}$$

with the coefficient α_i, a_i^* = 0 for all non-SVs. Thus, the SVR model is defined solely by its SVs.

The underlying data generating processes of real life phenomena are rarely linear. Thus, deriving linear models to describe them often fails to correctly describe the true data generating process. In order to address this issue, SVR is coupled with kernel functions. The so-called "kernel trick" follows the projection idea while ensuring minimum computational cost: the dataset is mapped in an inner product space, where the projection is performed using only dot products within the original space through "special" kernel functions, instead of computing the mapping of each data point explicitly. When the kernel function is non-linear, the SVR model produced is non-linear as well. In our empirical estimations, we employ two alternative kernels: the linear, and the radial basis function (RBF) kernel, with the latter being purely nonlinear. The mathematical representation of each kernel is:

Linear $$K_1(\boldsymbol{x}_1, \boldsymbol{x}_2) = \boldsymbol{x}_1^T \boldsymbol{x}_2 \tag{4}$$

RBF $$K_2(\boldsymbol{x}_1, \boldsymbol{x}_2) = e^{-\gamma \|x_1 - x_2\|^2} \tag{5}$$

with γ representing a kernel parameter.

3.3 Least absolute shrinkage and selection operator

The least absolute shrinkage and selection operator (LASSO) is a regularization and variable selection methodology proposed by Tibshirani (1996) that has been extensively used in the forecasting literature (for a survey of LASSO applications the interested reader is referred to Bai and Ng (2008)). When using the typical OLS linear regression model:

$$\boldsymbol{y} = \boldsymbol{X\beta} \tag{6}$$

$$\text{with } \boldsymbol{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_i \end{pmatrix}, \boldsymbol{X} = \begin{pmatrix} \boldsymbol{1}^{\boldsymbol{T}} \\ \boldsymbol{x}_{\boldsymbol{1}}^{\boldsymbol{T}} \\ \boldsymbol{x}_{\boldsymbol{2}}^{\boldsymbol{T}} \\ \vdots \\ \boldsymbol{x}_{\boldsymbol{p}}^{\boldsymbol{T}} \end{pmatrix} = \begin{pmatrix} 1 & \cdots & 1 \\ x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ip} \end{pmatrix} \text{ and } \boldsymbol{\beta} = \left(\beta_0, \beta_1, \beta_2, \ldots, \beta_p\right)^T$$

one tries to estimate the values of the vector of the coefficients $\boldsymbol{\beta}$ based on the minimized residual squared error, and $\boldsymbol{X}$ is the matrix of the independent variables. LASSO applies one more restriction to the model, attempting not only to minimize the squared error of the residuals, but also to eliminate uninformative regressors through weighting. In order to find the optimal solution to the trade-off between parsimony and high forecasting accuracy, LASSO minimizes the following:

$$\min_{\beta_o, \boldsymbol{\beta}} \left[\frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{T}} \boldsymbol{\beta}\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j|\right] \tag{7}$$

where $\boldsymbol{x}_{\boldsymbol{i}}$ is a vector *and* λ is a regularization parameter. The imposition of the regularization parameter λ defines the parsimony of the model, with the number of nonzero elements in the coefficients' vector decreasing as λ increases. The optimization problem can be solved with any quadratic programming optimization method.

4. Empirical findings

The motivation of our analysis is to use the usual determinants of Bitcoin in order to forecast future Bitcoin prices, taking into account the economic and trade uncertainty introduced to the model by the U.S. – China trade war. Our approach starts by training a simple autoregressive (AR) model with one lag; using past values of Bitcoin to forecast future values. Then we introduce the financial indices, the commodity index, oil prices, the U.S. exchange rate index, gold prices, the specifics of the Bitcoin market, Google hits and the global uncertainty index (as a proxy for global uncertainty not attributed to the trade war) to the AR(1)[8] model in order to forecast Bitcoin prices. We code this group of variables as "determinants". The results of the second model are compared to a third model that is an augmented version of the second, introducing the trade uncertainty indices (TPU_US and TPU_China). The forecasting ability of the second and third models is compared in order to observe whether the trade war actually influences the underlying Bitcoin price determination mechanism. This is performed in rolling windows of 52 observations, with the first out-of-sample forecast starting at March 2018, the month of the imposition of the first trade tariffs by the U.S.

In Table 2 we report the relative mean absolute percentage error (MAPE) of the machine learning to the OLS models. We measure $MAPE = 100 * \frac{1}{m}\sum_{i=1}^{m}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$ with m denoting the number of out-of-sample forecasts, y_i the actual prices of Bitcoin and $\hat{y}_i$ the estimated values.

Table 2: Relative mean absolute percentage error

Horizon	AR(1)	AR(1)+Determinants	AR(1)+Determinants+TPU
Panel A: OLS			
1	20.05*	33.09	33.52
3	37.00	53.89	57.48
6	57.64	48.95	48.53
12	83.79	37.73	40.70
18	80.94	40.73	42.08
24	51.31	40.50	42.42
Panel B: LASSO			
1	21.05	27.20	25.33
3	32.48*	40.94	40.03
6	52.34	35.50*	41.93
12	71.65	37.17*	41.37
18	66.03	38.85	35.73*
24	55.40	34.29*	38.81
Panel C: SVR - Linear			
1	20.42	25.86	26.91
3	38.96	40.35	37.87
6	54.83	47.99	48.59
12	82.82	42.13	43.92

[8] The use of a higher lag order does not change our conclusions in terms of forecasting performance.

18	85.61	39.27	38.10
24	65.78	37.94	44.68
Panel D: SVR - RBF			
1	25.17	54.81	56.48
3	42.40	55.03	59.32
6	74.43	58.18	59.27
12	57.79	57.08	67.00
18	64.85	51.53	68.68
24	73.77	46.05	61.33

Note: all values are percentage differences between the MAPE of an OLS model versus a model of another technique. The lowest error per forecasting horizon is denoted by an asterisk.

As we observe in Table 2, the autoregressive AR-OLS model exhibits the lowest forecasting error at the 1-month ahead forecasting horizon, while at the 3-month ahead horizon the most accurate model is the AR-LASSO model. The regularization parameter λ in this case has the function of imposing various weights on the constant terms and the past values of Bitcoin prices, respectively. Nevertheless, in longer forecasting horizons, the AR has the lowest forecasting ability and the structural models exhibit a lower forecasting error.

This finding can be explained by the slow diffusion of information paradigm of Hong and Stein (1999). While these authors study assets from various industrial sectors, in our case, the delay in the diffusion of information between commodities, stock markets, exchange rates and Bitcoin seems to exist, since the determinant variables are able to foresee the future price of Bitcoin with a 6 month delay. Over shorter periods, the AR models seem to outperform the determinant set, while over longer periods the forecasting accuracy is significantly improved by adding the information included in the determinant set. From a market efficiency perspective, we could say that in the short run we reject even the weak form of efficiency, given that past values are able to foresee the future price of Bitcoin. Nevertheless, in the long run (above 6 months) the market exhibits a semi-strong form of efficiency, suggesting that publicly available information, in tandem with past values, can forecast future prices. Thus, the Bitcoin market can be manipulated and used as an investing option for profit. This finding is partially in line with previous findings on market efficiency in the Bitcoin market (e.g., Vidal-Tomás and Ibañez, 2018; Nan and Kaizoji, 2019).

Returning to the U.S. – China trade war, Table 2 shows that, in all cases other than the 18-month ahead horizon, the addition of the trade uncertainty indices for the U.S. and

China deteriorates the forecasting ability of the models. This finding suggests that when we control for other parameters, we cannot forecast Bitcoin in out-of-sample forecasting; thus the future path of the Bitcoin market does not seem to be affected by the trade uncertainty between the U.S. and China, which makes Bitcoin an alternative investment option for investors who wish to distance themselves from the trade war uncertainty. This finding, which nicely complements Gozgor et al. (2019), is very interesting, given that almost 70% of all Bitcoin mining is performed in China, suggesting that the Bitcoin market remains unregulated and well-distanced by the more traditional production sectors of the Chinese economy. Our findings are especially important given that most previous studies of Bitcoin that consider uncertainty measures (e.g., Wang et al., 2018; Cheng and Yen, 2019; Aysan et al., 2019; Gozgor et al., 2019) use in-sample forecasting within a bivariate model, while we focus on out-of-sample forecasting; exposing our model to stress, given that we use data that have not been used during the training phase.

5. Conclusion

In this paper we examine our ability to forecast the price of Bitcoin in light of the recent U.S. - China trade war. In doing so we compile a large dataset of variables that are have been found to forecast Bitcoin in the relevant literature and augment this dataset with trade uncertainty indices. Given that the forecasting ability of a model can be attributed to the performance of the selected methodology, we consider alternative methods from the domains of traditional econometrics and machine learning. Our empirical findings suggest that in short-term forecasting the historical information on prices exhibits the highest forecasting accuracy, given the delay in the diffusion of information among variables. At longer forecasting horizons, structural models based on explanatory factors supersede all competitors. Additionally, when we control for other explanatory variables, the trade uncertainty indices do not improve forecasts of the value of Bitcoin. Thus, our results tend to suggest that while there is some in-sample evidence that Bitcoin returns increase in the wake of heightened uncertainty, i.e., it seems to hedge against uncertainties, stronger out-of-sample tests tend to suggest that the future path of Bitcoin cannot be predicted by the information content of the U.S. – China trade war. In other words, Bitcoin seems to be unaffected by the ongoing trade war, and can serve as a safe haven for investors. Future studies could extend the analysis to cover other leading cryptocurrencies.

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