Implications of cryptocurrencies for the monetary systems: The case of Bitcoins in Turkey

Advanced Macroeconomics Final Project

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Abstract: Cryptocurrencies have become a phenomenon that concerns many monetary authorities around the world, with Bitcoin (BTC) being the main driver of this market. Initially seen in a disinterested way, several countries discouraged the use of Bitcoins in the latest years because of its inappropriate influence on the monetary systems. This analysis is focused on Turkey, whose central bank banned cryptocurrencies for purchases in April 2021, considering them as a possible irreparable damage and a transaction risk. To understand the rationale for this decision, we develop a conceptual link between BTC and Turkey's monetary aggregates (inflation, real exchange rate, and money velocity) by applying a GARCH modelling technique. We find evidence that BTC price and volatility have a negative effect on inflation growth.

Keywords: Bitcoin • cryptocurrencies • GARCH • inflation • monetary aggregates • monetary policy

© Master in Data Science and Economics.

1. Introduction

Money has been used in almost all the transactions that underlie economic activity, but the ways payments are made has changed dramatically in recent decades. Although the usage of digital currencies is currently very low in terms of volume of transactions, their increasing adoption is a cause for concern because they can potentially influence the monetary systems in the long run. One popular type of digital currency, whose popularity and use has rapidly increased in the last years, are cryptocurrencies. They were defined as *"a digital asset designed to work as a medium of exchange using cryptography to secure the transactions and to control the creation of additional units of the currency"* [2]. We focus our analysis on Bitcoin, the first and the most popular cryptocurrency in the world.

1.1. Bitcoin pros and cons

Bitcoin is a pure peer-to-peer version of electronic cash and allows payments between two parties without going through a financial institution, usually needed to prevent double spending problems and to ensure trust in

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the transactions. This problem is overcome by using a new technology based on the cryptographic proof of the transactions: the block-chain. It consists of a set of hashes and associated blocks chained among them, each of them containing a set of transactions which track the history of the electronic money and needs a proof-of-work to be created. The network is based on trust between nodes and it is usually insured by them working and building on the last block of the longest found chain, recognising in this way the reliability of all the previous blocks and related transactions. By convention, the first transaction in a block is a special one with which a new coin is launched, owned by its creator and there is a steady increase of coins entering in the process along the time. If the cost of electricity and time needed to mine Bitcoins does not exceed the gain provided by creating a new block, the possible gain could encourage the nodes to stay honest with the network.

Limiting access to information to the parties, the privacy is guaranteed by the bank in the traditional model. The need to announce all the transactions publicly does not allow this structure: here, privacy is protected by anonymous keys without information about who is making the transaction. Moreover, the network is consistently insured by the attacks of hackers which would change the chain to fraud the network. In fact, this would cost a potential hacker a huge amount of electricity and time to manipulate a chain constructed by honest nodes, as mathematically and computationally shown by Nakamoto (2009) [18].

However, there would also be drawbacks in a hypothetical world where all the money available to spend in the market were Bitcoins: central banks would lose their power over the economy and they could not stabilise it using traditional tools because nobody would have control over the money. Inspired by this scenario, nowadays countries and their monetary authorities are worried by the spread of cryptocurrencies and new rules aimed to regulate or ban them have been introduced.

1.2. Bitcoin experiences around the world

"Neither subject to any regulation and supervision mechanisms nor a central regulatory authority" and *"Payment service providers will not be able to develop business models in a way that crypto assets are used directly or indirectly in the provision of payment services and electronic money issuance"* [23] were cited by Turkish central bank as the reasons and threats which caused the ban of cryptocurrencies in April 2021. Starting from an inflation rate of 16% in the last month, this news caused the decrease of Bitcoin price by almost 5%. Previously, other countries had prevented the use of *cryptos* as medium of exchange.

In Indonesia, several efforts were carried out by the central bank and national Police to prevent the spread of virtual currencies in January 2018, as reported on *The Jakarta post* [13]. Given the high number of tourist spots as Bali, a virtual and unsupervised money would have been useful for illegal transactions, often stemming from criminal roots. Moreover, the ban was due to the unregulated influence which *cryptos* carried out on monetary aggregates of the country, destabilising payment systems and currencies, as analysed in Narayana et al. (2019) [19].

In China, cryptocurrencies trading has been declared illegal since 2019 in order to curb money laundering, but a few forms of online trading were still allowed. For this reason and to protect the spread of the digital Yuan coined by the central bank, Chinese regulators imposed a further stop to the crypto trades in May 2021, causing a backlash on Bitcoin price of about -5%.

However, a different approach was taken by El Salvador, whose government announced on June 5, 2021 at the *Bitcoin 2021 Conference* the introduction of Bitcoin as legal tender, *"designing a country for the future"* [21]. Doing so, Bitcoin would help Salvadoran immigrants living in the US to avoid remittances' taxes, include the 70% of the population which does not have a bank account and protect the local economy from extraordinary measures carried out by the FED, which create inflation and harm the national economy.

Interest in Bitcoin was also expressed by big companies, especially from Tesla, which has been on the mainstream of this topic. Through its announcements of allowing payments with Bitcoin, first this firm pulled up the price of the currency and then it caused its shrink reconsidering its position toward it [5]. Moreover, the argument became more salient in the first half of June 2021 with the message sent by the global hacker group called "Anonymous" to Tesla's CEO, Elon Musk, charging him to play an immoral game with his announcements on Bitcoin without respecting the investing purposes of the low-income population.

From this brief description, what seems clear is that countries are worried about how cryptocurrencies affect their monetary systems and what they can do to drive their evolution. Recently, several studies were made on these topics: *"Inflation and Bitcoin"* (Blau et al., 2021) [4] found a significant Granger-causality relation between changes in Bitcoin and forward inflation rate, and *"Cryptocurrencies and Cagan's Model of Hyperinflation" (Jermann, 2020)* [14] explained Bitcoin price changes as a function of its supply and transaction volume.

The paper is developed in the following way: Section 2 states the aim of the study, Section 3 describes the methodology and the data employed, Section 4 goes on with empirical results and Section 5 discusses the main conclusions.

2. Aim of the study

The aim of the project is to study the implications of cryptocurrencies for Turkey's monetary system, trying to understand the reasons why the central bank of Turkey banned cryptocurrencies in April 2021. By the development of several GARCH models, we analyse the link between Bitcoin price and volatility and the key monetary aggregates (inflation, real exchange rate, and money velocity) in Turkey, based on a previous work of Narayana et al. (2019) [19] about the monetary system of Indonesia. We conclude our study with a brief discussion about the macroeconomic implications of the use of Bitcoins in a generalised way.

3. Theoretical framework and data description

This section discusses the background theory, where we establish the conceptual link between Bitcoin price and monetary aggregates, and describes the data we employ to carry out our analysis.

3.1. Motivating theory

Here, we provide a brief discussion of the theories that motivate modelling the three monetary aggregates: inflation, real exchange rate, and velocity of money.

Firstly, we develop a model to examine the link between Turkish Lira inflation and Bitcoin price based on the New Keynesian Phillips Curve (NKPC) framework, where inflation is a function of: (1) marginal cost of production, via import prices relative to domestic prices and oil prices; (2) lags of inflation, to allow for the formation of inflation through expectations built by backward looking agents; (3) leads of inflation to allow for forward looking agents; and also (4) unemployment rate.

Then, we run a model on the real exchange rate for the Turkish Lira with the US dollar. This model includes the real interest rate differential between the US and Turkey, inspired by the uncovered real interest rate parity; and productivity differentials, explained in the Balassa-Samuelson model.

Finally, we model the velocity of money that, under the framework of the quantity theory, states that the circulation of money (MV) depends on its demand covering all transactions in an economy (PY) and is represented by MV = PY, where M is the nominal money supply defined as M1, or M2; V is velocity; P is prices; and Y is the real GDP. The increased usage of Bitcoins, a financial innovation that could be seen as a substitute for money in terms of its role as a store of value, is predicted to be negatively associated with V.

All the models presented above are augmented with both Bitcoin price and volatility.

3.2. Data description

We collected Bitcoin closing price data along with several macroeconomic indicators related to Turkey: difference of the logarithm of industrial production of the US and Turkey (DY), real exchange rate, computed as the number of foreign currency units per home currency unit (RER), inflation rate (INF), consumer price index (CPI), import price index for goods (MP), unemployment rate (UM), West Texas Intermediate oil price (OP), velocity of money with respect to the aggregates M1 and M2 (V1 and V2) and gross domestic product (GDP). The final dataset spans the period between October 2014 and May 2021, where the bottleneck is represented by Bitcoin price. This latter was collected with both monthly and quarterly data, the latter to be used with the other quarterly variables in the models, V1 and V2. The complete definition of the variables are shown in the Table 1, while Table 2 reports all the main descriptive statistics: sample period, mean, maximum, minimum, standard deviation (SD), skewness, kurtosis, and the p-value of the Augmented Dickey Fuller test (ADF).

Table 2 gives us several pieces of information to highlight the structure of the data, especially in the last three columns. ADF columns present our tests to detect unit roots or stationarity, extremely important to understand in which way our variables should be included in the econometric model, using them in levels or in differences. The tests have been run with the following specifications: constant model adopted, and Bayes

Table 1. Data definition and sources

Variable	Definition	Calculation	Source
Inflation model			
Bitcoin	It captures closing price of Bitcoin		Yahoo finance
INF	Inflation rate	Year-on-year percentage change in the consumer price index (CPI, of all items) Turkey	World Bank
MP	Import Price Index		OECD
UM	Unemployment rate for Turkey		OECD
OP	Crude Oil Prices: West Texas		OECD
Exchange Rate model			
RER	Real exchange rate, expressed as the number of foreign currency units per home currency unit		Nominal exchange rate (Turkish Lira): Central Bank of Turkey; US and Turkey CPI: FRED; RER is calculated by the author.
RIR1	Difference between United States and Turkish 1-month Interbank Rate	$RIR_{i,t} = Nominal\, interbank\, rate_{i,t} - \; inflation\, rate_{i,t}$, where i is the US or Turkey $RIR1_t = RIR_{Turkey,t} - RIR_{US,t}$	Nominal interest rates: FRED; US and Turkey CPI: FRED; RIR1 is calculated by the author.
DY	Difference of the logarithm of industrial production (IP) of the US and Turkey	$LOG(IP_{Turkey}) - LOG(IP_{US})$	US and Turkey IP: OECD; DY is calculated by the author.
Velocity of money model			
V1 and V2	Velocity of M1 and M2	$V = PY/M$ *where M is M1 and M2*	FRED
RGDP	Real GDP	$RGDP = GDP/CPI$	FRED
IR_1	One-month Inter-bank rate		FRED

This table describes each variable, its calculation (where applicable) and its source used in estimating the inflation model, exchange rate model, and the money velocity model.

Table 2. Descriptive statistics of data

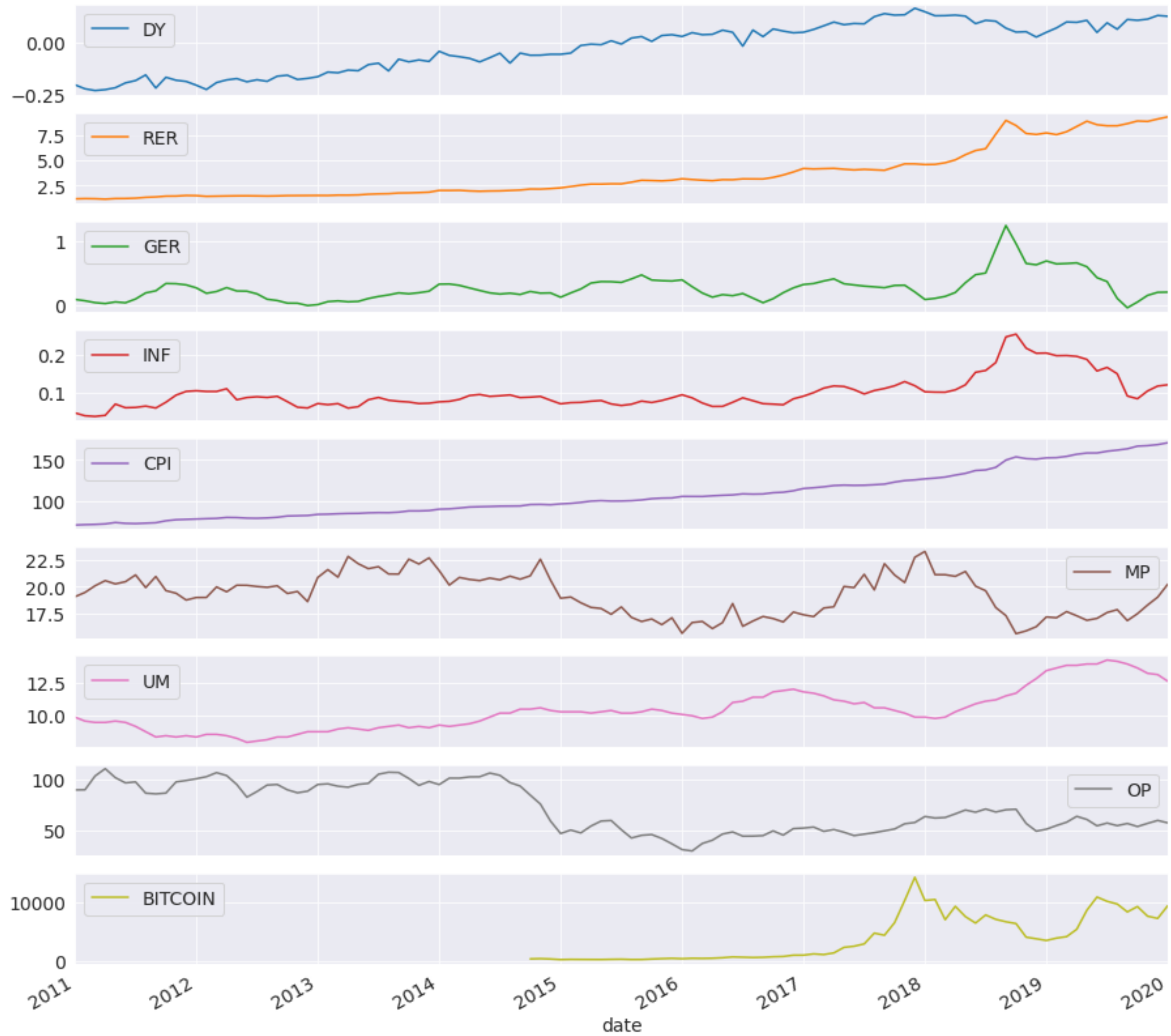
Var	Sample period	Mean	Maximum	Minimum	SD	Skewness	Kurtosis	ADF
DY	1970:01- 2021:05	-0.52	0.29	-1.11	0.33	0.80	-0.61	0.97
RER	1970:01- 2021:05	2.49	14.81	0.03	3.20	2.07	3.60	1.00
INF	1970:01- 2021:05	0.36	1.25	0.03	0.29	0.78	-0.38	0.14
CPI	1970:01- 2021:05	33.36	204.27	0.00	48.82	1.50	1.49	1.00
MP	1970:01- 2021:05	18.17	23.25	9.99	2.94	-0.83	0.29	0.24
UM	1970:01- 2021:05	10.53	14.30	8.00	1.64	0.71	-0.59	0.14
OP	1970:01- 2021:05	36.21	133.93	3.31	27.50	1.15	0.58	0.09
BITCOIN	2014:10- 2021:05	7705.19	58918.83	217.46	11539.43	2.95	9.56	0.00*
IR1TY	1970:01- 2021:05	36.32	430.86	4.14	43.27	4.12	27.49	0.00
RIR1	1970:01- 2021:05	33.54	425.07	3.97	41.89	4.41	30.56	0.00
V1	1998:Q1- 2020:Q3	1318.22	3437.10	343.75	818.18	0.91	-0.52	0.01
V2	1998:Q1- 2020:Q3	315.05	890.47	123.06	188.14	0.96	-0.33	0.23
GDP	1998:Q1- 2020:Q3	291401.97	475901.28	168979.84	95180.54	0.36	-1.20	0.99

Summary statistics of descriptive data, ADF columns report the associated p-values.

Information Criteria (BIC) used to select the number of lags. According to the results reported in the table, all the variables, except for BITCOIN and V1, have a p-value greater than 0.05, therefore all these variables should be modelled in differences. It seemed reasonable to us to detect more in depth the result about Bitcoin: running the test with Akaike Information Criteria (AIC), we found that the series is not stationary, the same result is reported by the KPSS test. Therefore, we decided to model Bitcoin price in differences, although our contrasting results are aligned with a broad discussion on the topic, whether Bitcoin and other cryptocurrencies are destined to become a widespread medium of exchange or they will disappear. We tested also for further unit roots, but we concluded to reject the null hypothesis and that the first difference transformation of the variables are unit root stationary processes. For this reason, our regression model is composed of variables only modelled in levels or first differences.

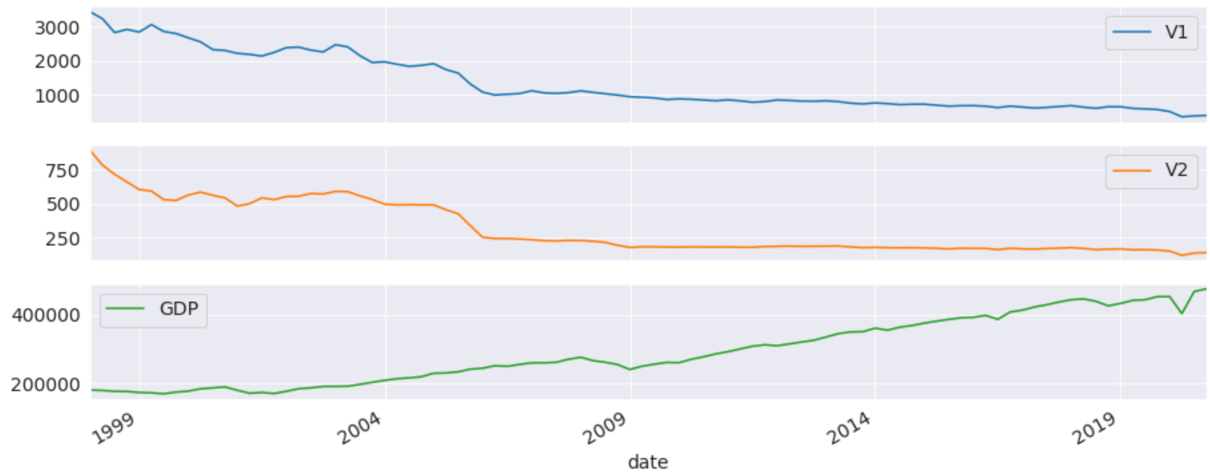
Skewness represents the asymmetry of the distribution, where negative values correspond to larger left hand-side tail and positive values to right hand-side tail, while Kurtosis produces heaviness of the distribution tails. These measures are noteworthy since levels of both these moments significantly different from 0 are indicators of non-normality in the distribution of the data, and this could imply the presence of heteroskedasticity.

Figure 1. **A time-series plot of monthly data**



Starting from these hints, and according to the type of modelling selected by the ADF tests, we decided

Figure 2. **A time-series plot of quarterly data**



to fit the optimal ARIMA models for our monetary indicators and the Bitcoin price using a time series analysis approach. This imply plotting the autocorrelation and partial autocorrelation functions, as well as computing the Bayes Information Criterion to select the optimal number of lags. After that, we tested whether the residuals were conditionally heteroskedastic through the Engle's test for Autoregressive Conditional Heteroskedasticity (ARCH). Considering the null hypothesis of no ARCH, this also-called Lagrange Multiplier test consists of a F-test, where p-values lower than 0.05 implies to reject the null and to consider the hypothesis of heteroskedasticity in the series. The results we obtained running the analysis for each of our variables are pretty similar: monthly BITCOIN differences take a F-statistic = 25,92 and p-value = 0.00, INF differences take a F-statistic = 9.52 and p-value = 0.00, RER differences take value F-statistic = 3.19 and p-value 0.00, while V1 and V2 differences have F-statistic = 3.90 and F-statistic = 2.96, respectively, with p-values equal to 0.00. Overall, we can state that heteroskedasticity is a feature of our series.

Those are the proofs that we need a GARCH modelling framework to test the validity of our hypothesis that Bitcoin affects the key monetary aggregates in Turkey.

4. Empirical framework and main results

We proved that there is a need of taking into account the different variance along the time of the series. The GARCH framework represents an ideal model in this regard, which is composed of two equations: one conditional mean equation and one conditional variance equation. They are simultaneously estimated and allows us to consider volatility of the previous periods.

This section has two objectives: the first is to establish the empirical framework on which we move and the second is to test the hypothesis that Bitcoin price affects monetary indicators in Turkey.

4.1. Empirical framework

The ideal framework to test whether Bitcoin affects Turkey's monetary system, taking into account the data heteroskedasticity, is a GARCH model. Therefore, the mean equation has the following representation:

$$MI_t = a_0 + \rho BITCOIN_t + \pi X_t + \epsilon_t$$

Here, MI is one of the monetary indicators (namely, INF, RER and MV) and $BITCOIN$ is the first difference of the Bitcoin price or it GARCH variance. Finally, X_t represents a vector of control variables. When MI is MV, X_t includes GDP and 1-month interest rate; When MI is INF, the controls are leads and lags of inflation, output gap or unemployment rate, import price, and oil price; and when MI is RER, we use real interest rate differential, productivity differential, and oil price as controls. In this setup, ϵ_t, follows the first-order GARCH model (GARCH (1, 1)), written as:

$$\epsilon_t = \eta_t \sqrt{h_t}, \quad {\sigma_t}^2 = x + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Here, ${\sigma_t}^2$ is the conditional variance in this period, x the weighted long run average variance, ϵ_{t-1}^2 the squared residual return in the previous period (ARCH term) and σ_{t-1}^2 the variance in the previous period (GARCH term). The parameters $x > 0$, $\alpha \geq 0$, $\beta \geq 0$, and η_t is a sequence of independently and identically distributed random variables with zero mean and unit variance. We assume errors behave normally and use the maximum likelihood to estimate the parameters. The key statistic in a GARCH model is the sum of α and β, which gives us a parameter of persistence that tells how fast large volatilities decay after a shock.

We check whether the explanatory variables (X) have an effect on the monetary indicators (MI), by adding the control variables to the conditional mean equation of each MI GARCH model.

4.2. Main results

Firstly, we perform a set of models for each monetary aggregate (inflation, real exchange rate, and money velocity) including only their conventional determinants (Models 1), that is, without Bitcoin related variables. Then, we augment all these three theoretical models with the Bitcoin price (Models 2) and its volatility (Models 3).[1]

4.2.1. Inflation models

In the case of inflation (INF), several alternative empirical models were performed for the purpose of comparison and robustness. The Model 1 results, reported in Table A1 in Appendix, include as regressors in

[1] *The empirical analysis was performed using Python as data analysis language, the complete notebook with the results can be accessed here.*

Table 3. **Inflation model augmented with Bitcoin price (Model 2).**

Dep. Variable:	INF_d	**R-squared:**	-441716.796
Mean Model:	AR-X	**Adj. R-squared:**	-481872.959
Vol Model:	GARCH	**Log-Likelihood:**	-1944.09
Distribution:	Normal	**AIC:**	3908.18
Method:	Maximum Likelihood	**BIC:**	3931.08
		No. Observations:	73
Date:	Sat, Jun 26 2021	**Df Residuals:**	66

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
Const	9.3271e-03	0.923	1.010e-02	0.992	[-1.801, 1.819]
INF_d[1]	0.3770	1076.955	3.501e-04	1.000	[-2.110e+03,2.111e+03]
INF_d[2]	-0.2599	144.979	-1.793e-03	0.999	[-2.844e+02,2.839e+02]
UM_d	3.5089e-03	14.612	2.401e-04	1.000	[-28.635, 28.642]
MP_d	-8.2113e-03	1.329	-6.180e-03	0.995	[-2.612, 2.596]
OP_d	2.2537e-03	0.146	1.543e-02	0.988	[-0.284, 0.289]
BITCOIN_d	-5.0888e-03	5.495e-04	-9.260	2.042e-20	[-6.166e-03,-4.012e-03]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	1.7500e-05	6.767e-04	2.586e-02	0.979	[-1.309e-03,1.344e-03]
alpha[1]	0.2000	4.214	4.746e-02	0.962	[-8.060, 8.460]
beta[1]	0.7000	13.542	5.169e-02	0.959	[-25.842, 27.242]

the conditional mean equation: (1) first and second lag of inflation (INF) to capture inflation expectations by backward looking economic agents; (2) first lead of inflation to capture inflation expectations of forward looking economic agents; and (3) marginal cost defined as unemployment (UM), oil prices (OP) and import prices (MP). All these variables appear in first difference form. The second panel provides results from the variance equation. In summary, INF lags and lead, and OP are statistically significative at 99% of confidence, with their theoretical correct signs. In the variance equation, the GARCH term is significative at 99% (0.6986) so that the volatility of inflation in the previous period does influence current volatility of inflation. It is also important to note that because $\beta + \alpha < 1$, the persistence condition is met.

In Table 3, we see that the introduction of Bitcoin price (Model 2) affects the relationship that the traditional NKPC factors had with inflation in Turkey. In fact, only MP is significative at 99%, with a expected positive effect, while Bitcoin price has a statistically significative and small negative effect on inflation, at 99% of confidence.

Finally, we also find that volatility of Bitcoin price (Model 3) has a negative statistically significant effect on Turkey's inflation rate, at 99% of confidence, while the lag 1 of inflation is the only variable among the conventional determinants that is significative at 99% of confidence. In the variance equation, both ARCH (α) and GARCH (β) terms are statistically significative and their sum is less than one. The results are reported in Table 4.

Table 4. **Inflation model augmented with Bitcoin volatility (Model 3).**

Dep. Variable:	INF_d	**R-squared:**	-11.114
Mean Model:	AR-X	**Adj. R-squared:**	-12.232
Vol Model:	GARCH	**Log-Likelihood:**	149.048
Distribution:	Normal	**AIC:**	-278.096
Method:	Maximum Likelihood	**BIC:**	-255.329
		No. Observations:	72
Date:	Tue, Jun 22 2021	**Df Residuals:**	65

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
Const	9.9147e-03	2.501e-03	3.964	7.382e-05	[5.012e-03,1.482e-02]
INF_d[1]	0.3793	0.216	1.754	7.939e-02	[-4.448e-02, 0.803]
INF_d[2]	-0.2646	0.239	-1.106	0.269	[-0.733, 0.204]
UM_d	1.3099e-03	1.003e-02	0.131	0.896	[-1.835e-02,2.097e-02]
MP_d	1.0938e-03	2.222e-03	0.492	0.622	[-3.260e-03,5.448e-03]
OP_d	1.7675e-04	3.739e-04	0.473	0.636	[-5.560e-04,9.095e-04]
BITCOIN_var	-3.2515e-05	4.549e-06	-7.148	8.816e-13	[-4.143e-05,-2.360e-05]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	1.7606e-05	3.785e-11	4.652e+05	0.000	[1.761e-05,1.761e-05]
alpha[1]	0.2000	4.561e-02	4.385	1.160e-05	[0.111, 0.289]
beta[1]	0.7000	0.114	6.136	8.476e-10	[0.476, 0.924]

4.2.2. Real exchange rate models

The real exchange rate (RER) models were performed fitting an ARMA(1,2) for the mean equation. The results are reported in Appendix. The Model 1, includes as determinants the difference in the short-term real interest rate between Turkey and the US (RIR1), oil prices (OP), and the difference in log of industrial production between Turkey and the US (DY). Besides the ARMA terms, the only regressor statistically significant is RIR1, at 95% of confidence, with a positive sign. In the variance equation, GARCH (β) is statistically significative, at 99% of confidence, as shown in Table A2.

The traditional relation between RER and RIR1 is unaffected when Bitcoin price is introduced in the model (Model 2), whose effect on RER is not statistically significative, at 99% of confidence (see Table A3). Moreover, Bitcoin volatility has no statistically significant effect on RER, at 99% of confidence, as shown in Table A4 in Appendix. However, the inclusion of Bitcoin price and volatility in the determinants model makes significative the effect of DY on RER, with a negative sign, at 95% of confidence. Hence, an increase in the difference in log of industrial production with the US leads to an depreciation of the RER in Turkey.

4.2.3. Velocity of money models

Finally, we examine models relating to the velocity of money, using data on a quarterly basis. The models were performed fitting an ARMA(1,2), in the case of V1, and an AR(1), for the V2 mean equation. The outcome of the models are presented in Appendix.

Two proxies are used as money velocity (which is the dependent variable), namely, V1 and V2, where $V = RGDP/M$ and M is either M1 or M2. The independent variables are first difference of real GDP (GDP), and the inter-bank one-month rate (IR_1). We found that GDP is a statistically significant positive determinant of the velocity of money, across the two definitions of velocity (see Table A5 and Table A8), which is a finding supported by the theory. The introduction of Bitcoin price (Model 2), not statistically significant at 99% of confidence, did not affect the importance of GDP determining velocity. However, we find also that by the inclusion of Bitcoin volatility (Model 3), GDP keeps only significant in the M2 velocity model (see Table A10) but not in the M1 model (see Table A7).

5. Conclusions

Despite not playing an important role as money in society, cryptocurrencies could be a threat to the stability of the national economies in the long run. The main potential risks that may develop over time are related to financial and monetary stability.

Financial stability could be put at risk due to the high volatility of the prices of cryptos, that could lead to a price crash. Although its impact would be limited to the direct holders of the this type of currencies, the negative effects could be expanded if, for example, an important financial institution were to have a significant unhedged exposure to Bitcoins. A price crash would have also a great impact on the overall economy if cryptos were used with financial instruments such as derivatives contracts.

Among the risks to monetary stability, in the extreme scenario were everybody conduct their everyday transactions entirely with an alternative currency, the monetary authority's ability to influence price-setting and real activity would be highly damaged.

According to the most recent macroeconomic theory [1], social welfare would be lower in a hypothetical economy based on a current digital currency compared with another based on a fiat money system. As most cryptocurrencies were developed with the idea that total supply is not unlimited, this could contribute to deflation in the prices of goods and services. The inability of the money supply to vary in response to demand would cause volatility in prices and real activity. It is known that when the prices of goods and services are falling, households have an incentive to postpone their spending plans, increasing deflationary pressures and discouraging investment plans. Therefore, aggregate demand is predicted to fall and the unemployment rate to be higher.

Employing a range of models for monetary aggregates, we found that Bitcoin price has a negative effect con Turkish Lira's inflation. This deflationary pressure is due to the fact that cryptocurrencies have been used as substitutes of fiat money, gaining space in those markets where it was accepted as a medium of exchange. Since the growth of Bitcoin price is positively correlated with its transaction volume [14], a possible explanation could be that the use of Bitcoins reduced the amount of money in circulation, appreciating the value of the Turkish Lira.

We also found that Bitcoin volatility negatively affects inflation. This is surely a threat to the economy, specially from a wise-political point of view. Given the results of our study, and since Bitcoin price and its volatility are driven by transaction volume that is decided and moved by private agents, big firms and investors would potentially be able to make and impact on inflation in Turkey by deciding to allow more or less payments with Bitcoins. This perspective is not very auspicious because it is well known that private agents and, in general, human beings are selfish and they should not affect the capacity of the monetary authority in a country.

In summary, a variety of potential risks to financial stability could emerge if a digital currency reaches systemic status as a payment system, most of which could be addressed through some kind of regulation. There is a wide range of measures that can be taken, as the strategy of the central bank of Turkey of banning cryptos, or the trial to stabilise cryptocurrencies as the FED is doing with the so-called Tether. In particular, the radical solution adopted by the monetary authority of Turkey, whose influence over monetary policy is threatened, can be understood based on the flourish cryptocurrency speculation due to the economic context of the country, with a rising inflation, lowering demand for its debt, and a high unemployment rate.

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Appendix A

Table A1. Inflation model without Bitcoin price (Model 1).

Dep. Variable:	INF_d	**R-squared:**	0.195
Mean Model:	AR-X	**Adj. R-squared:**	0.122
Vol Model:	GARCH	**Log-Likelihood:**	226.658
Distribution:	Normal	**AIC:**	-433.317
Method:	Maximum Likelihood	**BIC:**	-410.276
		No. Observations:	74
Date:	Sat, Jun 26 2021	**Df Residuals:**	67

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
Const	7.5719e-04	9.465e-04	0.800	0.424	[-1.098e-03,2.612e-03]
INF_d[1]	0.2582	5.100e+05	5.062e-07	1.000	[-9.997e+05,9.997e+05]
UM_d	1.4103e-03	3.889e-03	0.363	0.717	[-6.212e-03,9.033e-03]
MP_d	-6.3699e-04	1.048e-03	-0.608	0.543	[-2.692e-03,1.418e-03]
OP_d	3.7982e-04	1.553e-04	2.446	1.443e-02	[7.552e-05,6.841e-04]
INF_d_1	0.2582	5.086e+05	5.077e-07	1.000	[-9.967e+05,9.967e+05]
INF_d_2	-0.2970	0.133	-2.232	2.558e-02	[-0.558,-3.625e-02]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	1.7843e-05	1.730e-11	1.031e+06	0.000	[1.784e-05,1.784e-05]
alpha[1]	0.2003	9.320e-02	2.149	3.165e-02	[1.759e-02, 0.383]
beta[1]	0.6998	9.099e-02	7.691	1.462e-14	[0.521, 0.878]

Table A2. **Real Exchange rate model without Bitcoin price (Model 1).**

Dep. Variable:	RER_d	**No. Observations:**	75
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-5.140
Date:	Sat, 26 Jun 2021	**AIC**	26.279
Time:	14:09:39	**BIC**	44.819
Sample:	11-01-2014	**HQIC**	33.682
	- 01-01-2021		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	0.1314	0.078	1.680	0.093	-0.022	0.285
DY_d	0.0297	0.583	0.051	0.959	-1.112	1.172
RIR1_d	0.1511	0.032	4.673	0.000	0.088	0.215
OP_d	-0.0043	0.007	-0.600	0.549	-0.018	0.010
ar.L1	-0.5071	0.206	-2.466	0.014	-0.910	-0.104
ma.L1	1.4147	0.143	9.889	0.000	1.134	1.695
ma.L2	0.7424	0.125	5.932	0.000	0.497	0.988
sigma2	0.0656	0.011	6.121	0.000	0.045	0.087

Ljung-Box (L1) (Q):	0.67	**Jarque-Bera (JB):**	44.90
Prob(Q):	0.41	**Prob(JB):**	0.00
Heteroskedasticity (H):	7.97	**Skew:**	0.24
Prob(H) (two-sided):	0.00	**Kurtosis:**	6.76

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
mu	-0.0251	1.721e-02	-1.460	0.144	[-5.886e-02,8.615e-03]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	4.8536e-03	7.022e-03	0.691	0.489	[-8.909e-03,1.862e-02]
alpha[1]	0.3954	0.350	1.131	0.258	[-0.290, 1.081]
beta[1]	0.6046	0.306	1.975	4.824e-02	[4.671e-03, 1.205]

Table A3. **Real Exchange rate model augmented with Bitcoin price (Model 2).**

Dep. Variable:	RER_d	**No. Observations:**	75
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-12.042
Date:	Sat, 26 Jun 2021	**AIC**	42.084
Time:	14:09:41	**BIC**	62.941
Sample:	11-01-2014	**HQIC**	50.412
	- 01-01-2021		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	0.1512	0.071	2.136	0.033	0.012	0.290
DY_d	-1.7275	0.776	-2.226	0.026	-3.249	-0.206
RIR1_d	0.1153	0.041	2.790	0.005	0.034	0.196
OP_d	0.0043	0.009	0.499	0.618	-0.013	0.021
BITCOIN_d	-1.412e-05	2.05e-05	-0.690	0.490	-5.42e-05	2.6e-05
ar.L1	0.1351	1.962	0.069	0.945	-3.711	3.981
ma.L1	0.4760	1.978	0.241	0.810	-3.401	4.353
ma.L2	-0.1635	1.290	-0.127	0.899	-2.691	2.364
sigma2	0.0854	0.016	5.206	0.000	0.053	0.118

Ljung-Box (L1) (Q):	0.34	**Jarque-Bera (JB):**	29.47
Prob(Q):	0.56	**Prob(JB):**	0.00
Heteroskedasticity (H):	10.28	**Skew:**	0.24
Prob(H) (two-sided):	0.00	**Kurtosis:**	6.03

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
mu	-0.0460	2.211e-02	-2.080	3.755e-02	[-8.932e-02,-2.649e-03]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	9.6540e-03	8.191e-03	1.179	0.239	[-6.400e-03,2.571e-02]
alpha[1]	0.6249	0.478	1.308	0.191	[-0.312, 1.561]
beta[1]	0.3751	0.287	1.307	0.191	[-0.188, 0.938]

Table A4. Real Exchange rate model augmented with Bitcoin volatility (Model 3).

Dep. Variable:	RER_d	**No. Observations:**	74
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-12.290
Date:	Sat, 26 Jun 2021	**AIC**	42.580
Time:	14:09:44	**BIC**	63.316
Sample:	12-01-2014 - 01-01-2021	**HQIC**	50.852

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	0.1455	0.124	1.176	0.240	-0.097	0.388
DY_d	-1.6450	0.694	-2.371	0.018	-3.005	-0.285
RIR1_d	0.1108	0.045	2.462	0.014	0.023	0.199
OP_d	0.0032	0.009	0.366	0.714	-0.014	0.020
BITCOIN_var	-1.886e-05	5.89e-05	-0.320	0.749	-0.000	9.66e-05
ar.L1	0.1679	1.955	0.086	0.932	-3.663	3.999
ma.L1	0.4424	1.948	0.227	0.820	-3.375	4.260
ma.L2	-0.1856	1.259	-0.147	0.883	-2.653	2.281
sigma2	0.0866	0.016	5.452	0.000	0.055	0.118

Ljung-Box (L1) (Q):	0.21	**Jarque-Bera (JB):**	30.67
Prob(Q):	0.65	**Prob(JB):**	0.00
Heteroskedasticity (H):	10.42	**Skew:**	0.29
Prob(H) (two-sided):	0.00	**Kurtosis:**	6.10

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
mu	-0.0381	2.008e-02	-1.898	5.768e-02	[-7.747e-02,1.242e-03]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	7.5473e-03	4.356e-03	1.733	8.315e-02	[-9.899e-04,1.608e-02]
alpha[1]	0.6452	0.380	1.699	8.941e-02	[-9.930e-02, 1.390]
beta[1]	0.3548	0.204	1.741	8.172e-02	[-4.467e-02, 0.754]

Table A5. **Velocity of M1 model without Bitcoin price (Model 1).**

Dep. Variable:	V1_d	**No. Observations:**	20
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-95.175
Date:	Sat, 26 Jun 2021	**AIC**	204.349
Time:	14:09:44	**BIC**	211.320
Sample:	0 - 20	**HQIC**	205.710

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	-20.8327	16.632	-1.253	0.210	-53.430	11.765
GDP_d	0.0015	0.001	2.238	0.025	0.000	0.003
IR1_d	4.0047	4.043	0.991	0.322	-3.919	11.928
ar.L1	0.2716	1.477	0.184	0.854	-2.623	3.166
ma.L1	0.2005	1.725	0.116	0.907	-3.180	3.581
ma.L2	-0.6530	1.317	-0.496	0.620	-3.234	1.928
sigma2	1052.8324	863.596	1.219	0.223	-639.784	2745.449

Ljung-Box (L1) (Q):	0.02	**Jarque-Bera (JB):**	0.40
Prob(Q):	0.88	**Prob(JB):**	0.82
Heteroskedasticity (H):	2.13	**Skew:**	-0.12
Prob(H) (two-sided):	0.34	**Kurtosis:**	2.36

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
mu	2.4141	18.518	0.130	0.896	[-33.880, 38.709]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	70.2756	1216.388	5.777e-02	0.954	[-2.314e+03,2.454e+03]
alpha[1]	0.0000	1.218	0.000	1.000	[-2.386, 2.386]
beta[1]	0.9205	1.566	0.588	0.557	[-2.149, 3.990]

Table A6. **Velocity of M1 model augmented with Bitcoin price (Model 2).**

Dep. Variable:	V1_d	**No. Observations:**	20
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-93.424
Date:	Sat, 26 Jun 2021	**AIC**	202.848
Time:	14:09:45	**BIC**	210.814
Sample:	0 - 20	**HQIC**	204.403

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	-19.4112	16.508	-1.176	0.240	-51.765	12.943
GDP_d	0.0014	0.001	2.395	0.017	0.000	0.003
IR1_d	4.7626	4.140	1.150	0.250	-3.352	12.877
BITCOIN_d	-0.0011	0.002	-0.581	0.561	-0.005	0.003
ar.L1	0.3985	0.598	0.666	0.505	-0.774	1.571
ma.L1	0.0298	1.934	0.015	0.988	-3.761	3.821
ma.L2	-0.8481	1.124	-0.754	0.451	-3.051	1.355
sigma2	813.6964	901.421	0.903	0.367	-953.056	2580.449

Ljung-Box (L1) (Q):	0.05	**Jarque-Bera (JB):**	0.13
Prob(Q):	0.82	**Prob(JB):**	0.94
Heteroskedasticity (H):	1.45	**Skew:**	0.00
Prob(H) (two-sided):	0.63	**Kurtosis:**	2.60

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
mu	5.0241	8.821	0.570	0.569	[-12.265, 22.313]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	174.1007	1381.096	0.126	0.900	[-2.533e+03,2.881e+03]
alpha[1]	5.7763e-15	0.650	8.888e-15	1.000	[-1.274, 1.274]
beta[1]	0.7192	2.014	0.357	0.721	[-3.229, 4.667]

Table A7. Velocity of M1 model augmented with Bitcoin volatility (Model 3).

Dep. Variable:	V1_d	**No. Observations:**	17
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-76.644
Date:	Sat, 26 Jun 2021	**AIC**	169.287
Time:	14:09:45	**BIC**	175.953
Sample:	0	**HQIC**	169.950
	- 17		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	37.1808	91.276	0.407	0.684	-141.718	216.079
GDP_d	0.0013	0.001	1.168	0.243	-0.001	0.003
IR1_d	2.3913	3.736	0.640	0.522	-4.931	9.714
BITCOIN_var	-0.0093	0.017	-0.533	0.594	-0.043	0.025
ar.L1	-0.0009	0.856	-0.001	0.999	-1.679	1.677
ma.L1	-0.0209	3.489	-0.006	0.995	-6.860	6.818
ma.L2	-0.8604	1.458	-0.590	0.555	-3.719	1.998
sigma2	552.0065	705.156	0.783	0.434	-830.075	1934.088

Ljung-Box (L1) (Q):	0.05	**Jarque-Bera (JB):**	0.90
Prob(Q):	0.82	**Prob(JB):**	0.64
Heteroskedasticity (H):	1.27	**Skew:**	0.56
Prob(H) (two-sided):	0.78	**Kurtosis:**	3.19

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
mu	-1.7478	5.291	-0.330	0.741	[-12.117, 8.622]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	219.3709	450.111	0.487	0.626	[-6.628e+02,1.102e+03]
alpha[1]	0.0000	7.393e-02	0.000	1.000	[-0.145, 0.145]
beta[1]	0.5203	1.136	0.458	0.647	[-1.705, 2.746]

Table A8. Velocity of M2 model without Bitcoin price (Model 1).

Dep. Variable:	V2_d	**R-squared:**	0.742
Mean Model:	AR-X	**Adj. R-squared:**	0.690
Vol Model:	GARCH	**Log-Likelihood:**	-56.5725
Distribution:	Normal	**AIC:**	127.145
Method:	Maximum Likelihood	**BIC:**	133.756
		No. Observations:	19
Date:	Sat, Jun 26 2021	**Df Residuals:**	15

	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
Const	-3.3496	1.265	-2.648	8.100e-03	[-5.829, -0.870]
V2_d[1]	0.0618	0.205	0.302	0.763	[-0.340, 0.464]
GDP_d	4.0253e-04	8.328e-05	4.833	1.343e-06	[2.393e-04,5.658e-04]
IR1_d	0.3947	0.671	0.588	0.556	[-0.920, 1.709]
	coef	**std err**	**t**	**P> |t|**	**95.0% Conf. Int.**
omega	6.7818	18.477	0.367	0.714	[-29.433, 42.997]
alpha[1]	1.0000e-02	0.301	3.327e-02	0.973	[-0.579, 0.599]
beta[1]	0.6900	0.724	0.953	0.341	[-0.729, 2.109]

Table A9. **Velocity of M2 model augmented with Bitcoin price (Model 2).**

Dep. Variable:	V2_d	**R-squared:**	0.756
Mean Model:	AR-X	**Adj. R-squared:**	0.687
Vol Model:	GARCH	**Log-Likelihood:**	-56.0415
Distribution:	Normal	**AIC:**	128.083
Method:	Maximum Likelihood	**BIC:**	135.639
		No. Observations:	19
Date:	Sat, Jun 26 2021	**Df Residuals:**	14

	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**
Const	-2.9522	1.559	-1.894	5.823e-02	[-6.007, 0.103]
V2_d[1]	0.1175	0.283	0.416	0.678	[-0.436, 0.671]
GDP_d	4.1449e-04	7.258e-05	5.711	1.123e-08	[2.722e-04,5.567e-04]
IR1_d	0.5213	1.939	0.269	0.788	[-3.279, 4.321]
BITCOIN_d	-2.5065e-04	2.493e-04	-1.005	0.315	[-7.393e-04,2.380e-04]
	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**
omega	10.6658	534.572	1.995e-02	0.984	[-1.037e+03,1.058e+03]
alpha[1]	1.0000e-02	3.129	3.196e-03	0.997	[-6.123, 6.143]
beta[1]	0.4900	24.029	2.039e-02	0.984	[-46.606, 47.586]

Table A10. **Velocity of M2 model augmented with Bitcoin volatility (Model 3).**

Dep. Variable:	V2_d	**R-squared:**	0.411
Mean Model:	AR-X	**Adj. R-squared:**	0.197
Vol Model:	GARCH	**Log-Likelihood:**	-44.2791
Distribution:	Normal	**AIC:**	104.558
Method:	Maximum Likelihood	**BIC:**	110.739
		No. Observations:	16
Date:	Sat, Jun 26 2021	**Df Residuals:**	11

	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**
Const	3.4458	5.243	0.657	0.511	[-6.831, 13.723]
V2_d[1]	-0.4251	0.278	-1.531	0.126	[-0.970, 0.119]
GDP_d	4.1644e-04	9.058e-05	4.598	4.274e-06	[2.389e-04,5.940e-04]
IR1_d	0.2934	0.386	0.760	0.447	[-0.463, 1.050]
BITCOIN_var	-1.3449e-03	1.090e-03	-1.233	0.217	[-3.482e-03,7.922e-04]
	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**
omega	5.2470	3.658	1.434	0.152	[-1.923, 12.417]
alpha[1]	0.5906	0.404	1.462	0.144	[-0.201, 1.382]
beta[1]	0.1399	0.212	0.660	0.510	[-0.276, 0.555]