

DISCUSSION PAPER SERIES

IZA DP No. 14323

**New Moneys under the New Normal?
Bitcoin and Gold Interdependence during
COVID Times**

Pablo Agnese
Jonathan Thoss

APRIL 2021

DISCUSSION PAPER SERIES

IZA DP No. 14323

New Moneys under the New Normal? Bitcoin and Gold Interdependence during COVID Times

Pablo Agnese

UIC Barcelona and IZA

Jonathan Thoss

Luxembourg Stock Exchange and ESADE Business School

APRIL 2021

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

New Moneys under the New Normal? Bitcoin and Gold Interdependence during COVID Times

Bitcoin in particular and so-called cryptocurrencies in general have shaken up the financial world and seem to be claiming an increasing size of the market share. These new virtual assets present investors with significant opportunities, but also with significant risks. This paper analyzes the connection between one such crypto, bitcoin, and other traditional assets (e.g. metals) in times of financial turbulence. Our impulse-response function and variance decomposition analyses indicate that, as of late, bitcoin has become increasingly interdependent with gold, and seems just as suitable to hedge against market uncertainty—we believe this is a very timely conclusion given the pervasive uncertainty that dominates post-pandemic life.

JEL Classification: G15, G12, G11

Keywords: bitcoin, gold, COVID-19, impulse response

Corresponding author:

Pablo Agnese

UIC Barcelona

Inmaculada 22

08017 Barcelona

Spain

Germany

E-mail: pagnese@uic.es

1 A world of uncertainty and covid

The new normal is with us and quite likely to stay for a long time. It is thus timely to reevaluate the relationship between bitcoin (BTC) and other assets such as gold and silver, which are traditionally considered as old forms of money and, hence, safe havens against uncertainty. This relationship has been studied in the literature with varying results, going from a strong linkage (Dyhrberg, 2016a, 2016b; Kang et al., 2019; or Panagiotidis et al., 2018) to a mild (or no) connection (Bouri et al., 2017a, 2017b; Cheah & Fry, 2015; Corbet et al., 2018; Dwyer, 2015; or Klein et al., 2018). We wonder how the previous evidence stands under the light of the new normal paradigm employing conventional impulse response and variance decomposition analyses.

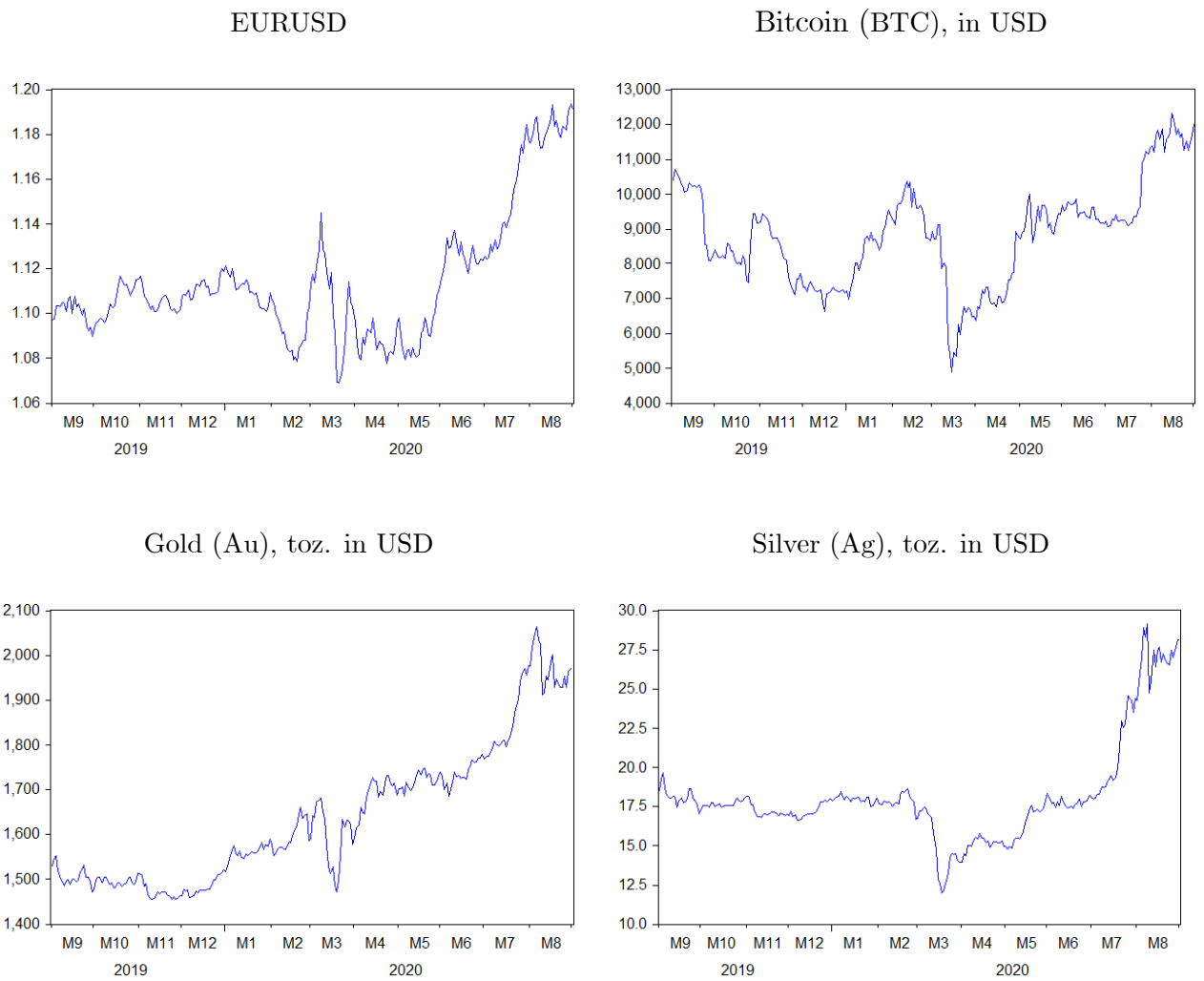
Figure 1 shows the recent post-covid-19 trends in the EURUSD exchange rate, along with the prices of BTC, gold, and silver. The data seem to point to a substantial depreciation of the USD against these assets, starting in March 2020 right after the pandemic outbreak. Increased worldwide uncertainty might well be a major driver behind the undermining of the USD as the de facto world currency. However, we might also wonder whether the covid-19 has been the triggering event that points to other fundamental problems with the USD, such as the exploding behavior of the debt and the ever-increasing rate at which money is printed.

Intrinsic value has been, from time immemorial, what people identified precious metals with. This has been the case of gold and, to a lesser degree, silver. It is thus no surprise to see both assets faring respectably well in times of financial turbulence and uncertainty. The purpose of our exercise below is to see to what extent Bitcoin is mimicking the role precious metals are known for, being a reliable store of value. This reliability is due to history, whereas the intrinsic value of bitcoin is found in the yet-to-be-understood technology, the Blockchain, which, arguably, can become money and payment system *all at once*.

Table 1 shows the leap in the amount of gold reserves in countries that are arguably poised to be the economic powerhouse in the forthcoming years. This is most significantly the case of China, the largest US trading partner, and the second foreign holder of US debt after Japan. Given the context, the Chinese government has every reason to diversify in gold, but also in Bitcoin—China is now the second holder in the world after the Grayscale Bitcoin Trust and the first among countries, claiming 1% of all the BTC in circulation (the US is the second with a third of that number).

The remainder of the paper is structured as follows. Section 2 introduces our analytical framework; Section 3 discusses our results; and Section 4 concludes.

Figure 1: Competing moneys?



Source: Bloomberg (2020).

Table 1: Gold reserves, last 10 years

#	Country	Population	Reserves 2009 (toz.)	Reserves 2019 (toz.)	Reserves change (%)	Reserves p.c. (g.)	btc share (%)
1	United States	327,167,434	8,133	8,133	0	25.01	0.33
2	Germany	82,927,922	3,407	3,370	-1	40.75	
3	Italy	60,431,283	2,452	2,452	0	40.50	
4	France	66,987,244	2,435	2,436	0	36.30	
5	Russia	144,478,050	649	2,113	226	14.62	
6	China	1,392,730,000	1,054	1,853	76	1.34	0.93
7	Switzerland	8,516,543	1,040	1,040	0	123.06	
8	Japan	126,529,100	765	765	0	6.04	
9	Netherlands	17,231,017	612	612	0	35.75	
10	India	1,352,617,328	558	600	8	0.45	

Source: bullionvault.com (2020) and own elaboration.

2 Analytical framework

The economics and fundamentals of cryptos are still unclear. The pervading lack of strong theoretical underpinnings in this field makes for a conservative approach where we refrain from establishing a clear-cut cause and effect relationship among the variables under study. Rather, we rely on Vector autoregressive (VAR) modeling as it yields a very flexible framework for forecasting and interpreting the interdependencies among variables, both pre and post-covid-19 (see also Panagiotidis et al., 2019).

A major criticism of VAR modeling is its a-theoretical nature and, in general, the lack of an underlying structural system descriptive of the real relationships among the variables in the model.¹ On the other hand, VARs provide a very intuitive framework to see how a shock in one variable is transmitted to all other endogenous variables through the model’s dynamic structure, what is known as impulse response functions (IRFs)—this is particularly suitable when the underlying structural model is unknown (Sims, 1980). Three analysis are typically carried out after estimation, Granger causality tests,² IRFs, and variance decomposition analysis, which is what we set out to do in the following section.

We estimate a reduced-form VAR model to analyze the interdependencies among

¹We refrain from structural VAR (SVAR) analysis for the reason mentioned in the previous paragraph.

²Let us remember that causality here does not strictly mean that changes in one variable cause changes in another variable, but rather, that the predictive power of a simple AR model will be increased if we were to include additional variables—strictly speaking, we should be talking about ‘within-sample’ predictability and not causality.

a few money-related variables as done in the literature (see, for instance, Corbet et al., 2018), namely, the bitcoin price, the gold price, the silver price, the EURUSD exchange rate, the SP500 index, and the Dow Jones index. We perform the analysis for a sample of 713 daily observations, drawn from the Bloomberg database, and spanning from February 2018 to November 2020. We also work with a ‘covid-19 subsample’ of 154 daily observations, which zooms into the period that starts with the pandemic outbreak in March 2020, and covers the first wave of the pandemic up to the end of September 2020. The model is of the form:

$$y_t = v + A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t \quad t \in \mathbb{Z}$$

where y_t is a vector of endogenous variables of dimension k , v is a vector of intercepts, A_1, \dots, A_p are the coefficient matrices with p the VAR order, and u_t is a white noise vector of innovations (with nonsingular covariance matrix Σ_u) that may be contemporaneously correlated with each other,³ but are uncorrelated with their own lagged values and also with all of the right-hand side variables.

The orders of the estimated VARs are determined by the more conventional Akaike criterion (AIC), which seems to be the usual choice in large samples with monthly or daily frequencies. They turn out to be $p = 9$ for the full sample ($n = 713$) and $p = 1$ for the covid-19 subsample ($n = 154$).⁴

Notice too that all the variables are transformed into growth rates by taking the first differences of the logarithms of the (daily) closing prices and indices in our dataset. By transforming our data into stationary series we satisfy the stability condition of the VARs, as all the roots of the characteristic polynomial lie outside the unit circle (see Appendix)—thus precluding the use of more complex cointegration techniques.

3 Dynamic behavior

3.1 Granger causality

We carry out pairwise Granger causality tests for each equation in the VAR above. Table 2 displays the joint significance of each of the other lagged endogenous variables

³In order to interpret IRFs it is customary to apply a transformation to the innovations so that they become uncorrelated.

⁴Even when the AIC is not a consistent criterion, Lütkepohl (2006) shows that it will asymptotically choose the correct order almost with probability one when the VAR has a large dimension—typically when $k \geq 5$, as is our case. Moreover, he runs a few simulations and shows that although it may not estimate the orders correctly (with a small k), the AIC produces superior forecasts both in small and large samples when compared to other criteria such as HQ and SC. Given that our yardstick is forecasting (and not consistency), we make use of the AIC over the alternatives. In addition, the order suggested by the FPE (also by Akaike) coincides with the AIC.

(rows), including the joint overall significance (last row), in each equation of the model (columns). As shown there, BTC and gold seem to have a two-way ‘causal’ relationship (instantaneous causality), with BTC-to-gold being the stronger one. BTC also seems to Granger-cause both fiat money (EURUSD) and, to some extent, the Dow Jones and silver. The evidence also suggests fiat money coming before the changes in SP500 and the Dow.

The EURUSD rate can be seen as a proxy variable for the US monetary policy and, by extension, the world’s monetary policy.⁵ US monetary policy is, arguably, behind the recent asset and housing inflation (see Bordo & Landon-Lane, 2013; and Calvo, 2013, for instance) and also behind the skyrocketing trend of US debt.⁶

Table 2: Pairwise Granger causality tests

<i>lags</i>	Equation in VAR					
	BTC	Au	Ag	EURUSD	SP500	DOW
BTC	-	***	*	***		*
Au	*	-			**	**
Ag		***	-			*
EURUSD	*			-	**	**
SP500		**	*	*	-	
DOW		**	**	*		-
All	**	***	***	***	***	***

Note: χ^2 Wald test is not passed or passed at 1 (***) , 5 (**), and 10% (*) significance.

3.2 IRF analysis

Our figures below offer our selected IRFs from the estimated VAR model above. A shock to the $i - th$ variable is transmitted to all the endogenous variables through the dynamic structure of the VAR. In particular, the IRFs trace the effect of a one-time shock to one innovation on the current and future values of those endogenous variables. While the number of IRFs is large⁷ only a few are noteworthy—our focus is thus placed on the gold-BTC relationship for what it might mean for the future of money.

Further, given that the innovations u_t in the VAR model are usually contemporaneously correlated, they can be seen as having a common component which cannot be associated with a specific variable. As done in the literature, we apply the Cholesky transformation to orthogonalize the impulses (Sims, 1980)—or formally $\epsilon_t = P u_t \sim (0, D)$, where D is a diagonal covariance matrix—thus imposing an ordering of the variables in

⁵The USD as the de facto world currency makes up for roughly 60–65% of international trade transactions.

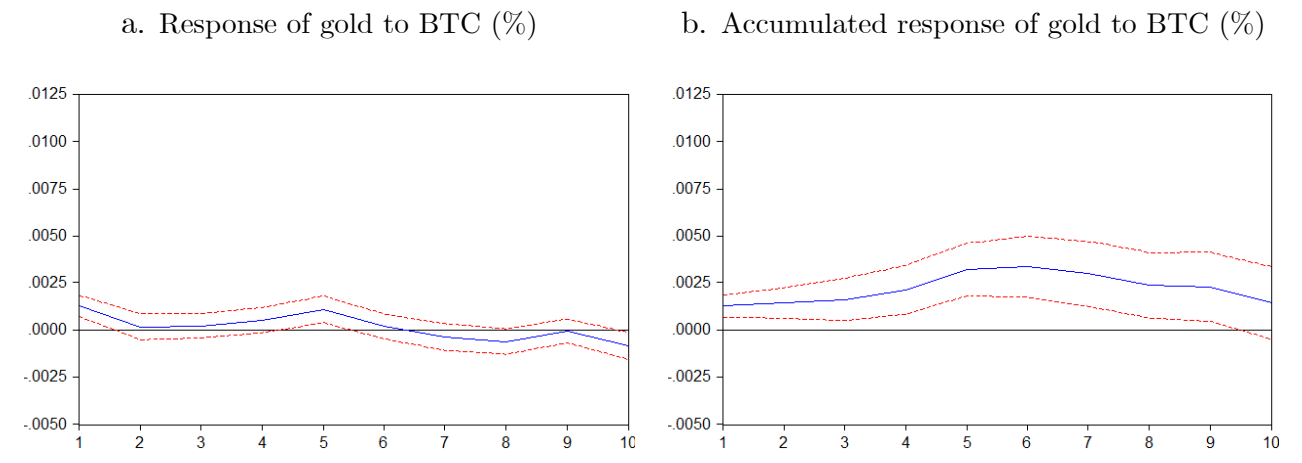
⁶By April 2021, the Fed’s balance sheet has grown to about USD 7.7 trillion in US securities.

⁷A total of 36 as we have 6 variables (=6x6).

the VAR model which will assign the effects of any common component to the variable that comes first. For our analysis this will be the EURUSD rate, as monetary policy seems to have been a driving force of much speculation in the past few decades.⁸

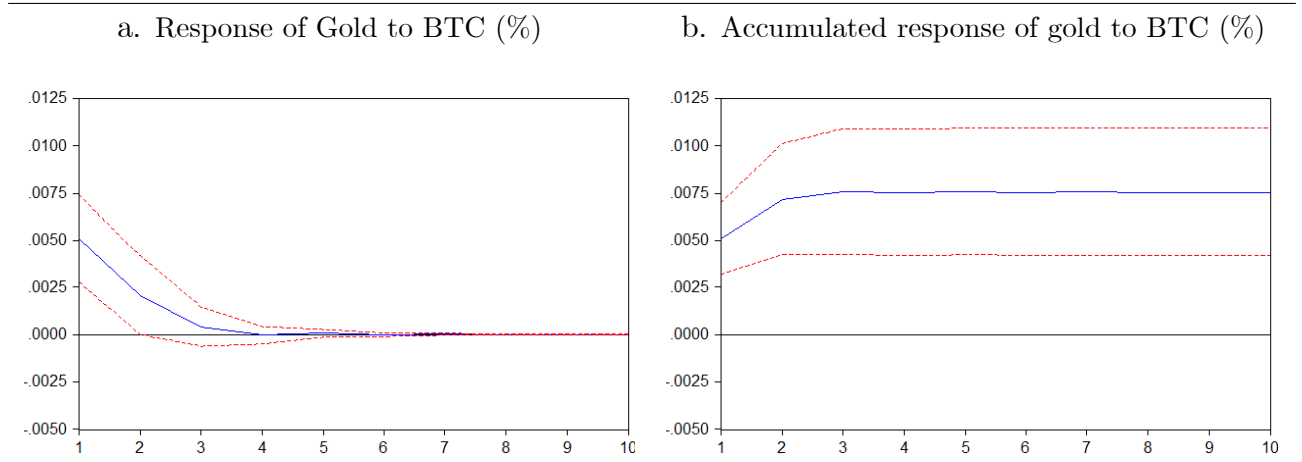
Figure 2a shows a very mild reaction of gold to shocks in the BTC equation—cumulatively, this is never above the quarter of a percentage point for the whole sample (Figure 2b), which goes from February 2018 to November 2020. However, for the covid-19 subsample, March 2020 to September 2020, the reaction of gold to a bitcoin shock is significant and instantaneous, yet fades away completely after the third day (Figure 3a). The accumulated response has however more than tripled (Figure 3b).⁹

Figure 2: Response (days) to Cholesky one s.d. innovations ± 2 s.e., full sample



Note: Monte Carlo response s.e. (100 repetitions).

Figure 3: Response (days) to Cholesky one s.d. innovations ± 2 s.e., ‘first wave’



Note: Monte Carlo response s.e. (100 repetitions).

⁸There seems however to be no critical difference were we to choose a different ordering of the variables.

⁹Contrariwise, the response of BTC to gold was virtually nonexistent.

3.3 Variance decomposition

While IRFs trace the effects of an unanticipated shock to one endogenous variable in the whole VAR system, variance decomposition breaks down the variation in one endogenous variable into the different component shocks to the VAR. Hence, it provides information on the relative weight of each random innovation in affecting the variables in the VAR. In short, the values in Tables 3 and 4 can be seen as the r^2 values of each variable in different time horizons of shocks. Notice that each row adds up to 100%.

Tables 3 (full sample) and 4 (covid-19 subsample) show the forecast error of gold (Au) at the given forecast horizon. The variation in the current and future values of the innovations to each variable are the contributing factors to the forecast error displayed in the tables, with the columns to the right representing the percentage of the forecast variance due to each innovation.

As with the IRFs above, we base our variance decomposition on the Cholesky transformation, which can yield different results when altering the ordering of the variables. It is worth noting the significant ‘jump’ in the weight of BTC as a driver of gold in the ‘first-wave’ covid-19 subsample.¹⁰ We interpret this as BTC and gold coming together in times of financial uncertainty, with BTC taking a leading role.

Table 3: Variance decomposition of gold (10 days), full sample

	Forecast error	BTC	Au	Ag	EURUSD	SP00	Dow
1	0.008402	2.21	83.22	0.00	14.56	0.00	0.00
2	0.008425	2.23	82.76	0.00	14.65	0.03	0.33
3	0.008461	2.27	82.10	0.30	14.58	0.42	0.33
4	0.008538	2.58	80.62	0.64	14.54	0.41	1.20
5	0.008730	3.99	77.34	1.86	14.26	0.53	2.01
6	0.008849	3.92	76.36	2.30	13.91	1.19	2.31
7	0.008949	4.02	75.01	2.64	13.81	2.06	2.46
8	0.008996	4.46	74.69	2.67	13.66	2.07	2.43
9	0.009049	4.42	74.05	2.66	13.54	2.63	2.69
10	0.009180	5.18	72.66	3.59	13.27	2.68	2.62

Note: as with IRFs above, EURUSD includes ‘common’ shocks (Cholesky ordering).

¹⁰In contrast, the weight of gold in the forecast error of BTC (not shown) is less than 1% both for the whole sample and the covid subsample.

Table 4: Variance decomposition of gold (10 days), ‘first wave’

	Forecast error	BTC	Au	Ag	EURUSD	SP00	Dow
1	0.013397	14.41	75.57	0.00	10.02	0.00	0.00
2	0.013718	16.02	72.10	0.14	10.05	0.66	1.02
3	0.013729	16.08	72.00	0.14	10.04	0.68	1.06
4	0.013730	16.08	71.99	0.14	10.03	0.69	1.06
5	0.013730	16.08	71.99	0.14	10.03	0.69	1.06
6	0.013730	16.08	71.99	0.14	10.03	0.69	1.06
7	0.013730	16.08	71.99	0.14	10.03	0.69	1.06
8	0.013730	16.08	71.99	0.14	10.03	0.69	1.06
9	0.013730	16.08	71.99	0.14	10.03	0.69	1.06
10	0.013730	16.08	71.99	0.14	10.03	0.69	1.06

Note: as with IRFs above, EURUSD includes ‘common’ shocks (Cholesky ordering).

4 Final remarks

Our IRF and variance decomposition analyses show how bitcoin has become increasingly interdependent with gold, while taking a leading role that seems to place it and, by extension, other cryptos, in a suitable position to hedge against market uncertainty in post-pandemic life. Future research should focus more on the similarities between cryptos and precious metals as it will throw more light on what seems to have become a money race. We hold that cryptos at large, and bitcoin in particular, have come to challenge the financial status quo, not only by introducing much needed competition, but also by exposing its long-lived weaknesses.

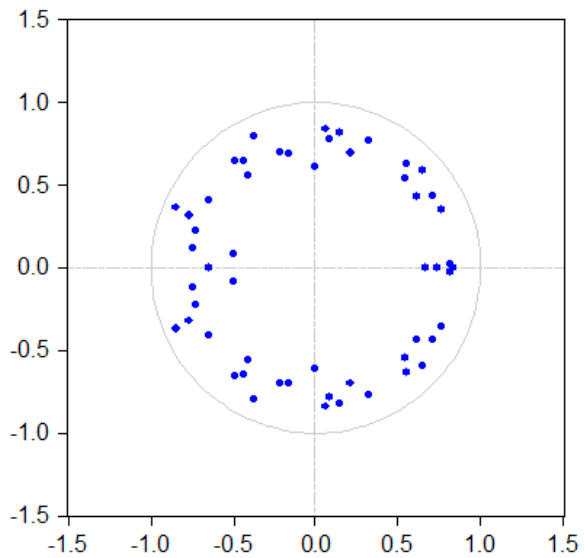
References

- [1] Bordo, Michael D., & Landon-Lane, John, 2013. Does expansionary monetary policy cause asset price pooms: Some Historical and Empirical Evidence. *Journal Economica Chilena (The Chilean Economy)*, *Central Bank of Chile* 16 (2), 4–52.
- [2] Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D., 2017a. Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters* 23, Supplement C, 87–95.
- [3] Bouri, E., Molnar, P., Azzi, G., Roubaud, D., & Hagfors, L. I., 2017b. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters* 20, 192–198.

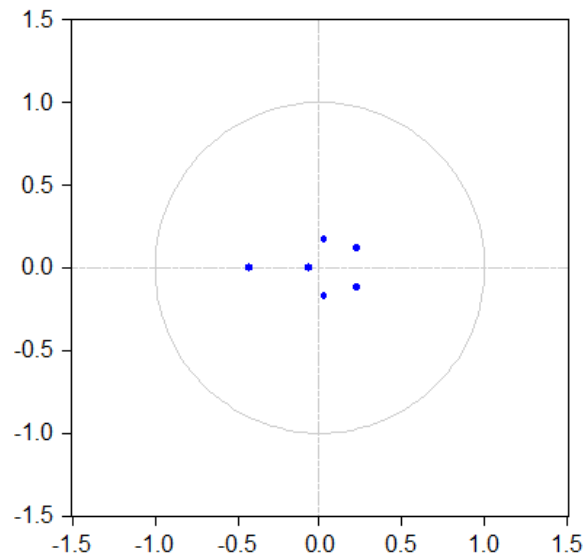
- [4] Calvo, Guillermo, 2013. Puzzling over the anatomy of crises: Liquidity and the veil of finance. *Bank of Japan IMES Discussion Paper* 13-E-09.
- [5] Cheah, E-T & Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters* 130, 32–36.
- [6] Corbet, S., Meegan, A., Larkin, C., Lucey, B. & Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters* 165, 28–34.
- [7] Dyrhberg, A. H., 2016a. Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters* 16, 85–92.
- [8] Dyrhberg, A. H., 2016b. Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters* 16, 139–144.
- [9] Kang, S.H., Yoon, S-M, Bekiros, S., & Uddin, G., 2019. Bitcoin as hedge or safe Haven: Evidence from stock, currency, bond and derivatives markets. *Computational Economics* 56, 529–545.
- [10] Klein T., Thu H. P., & Walther, T., 2018. Bitcoin is not the New gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis* 59, 105–116.
- [11] Lütkepohl, Helmut, 2006. New introduction to multiple time series analysis. Springer-Verlag, Berlin, Heidelberg.
- [12] Panagiotidis, T., Stengos, T., & Vravosinos, O., 2018. On the determinants of bitcoin returns: A LASSO approach. *Finance Research Letters* 27, 235–240.
- [13] Panagiotidis, T., Stengos, T., & Vravosinos, O., 2019. The effects of markets, uncertainty and search intensity on bitcoin returns. *International Review of Financial Analysis* 63, 220–242.
- [14] Sims, Christopher A., 1980. Macroeconomics and reality. *Econometrica* 48, 1–48.

Appendix: Inverse Roots of AR Characteristic Polynomials

a. Full sample ($p = 9$)



b. Covid-19 subsample ($p = 1$)



Note: No roots outside the unit circle (stability condition).