1 Introduction

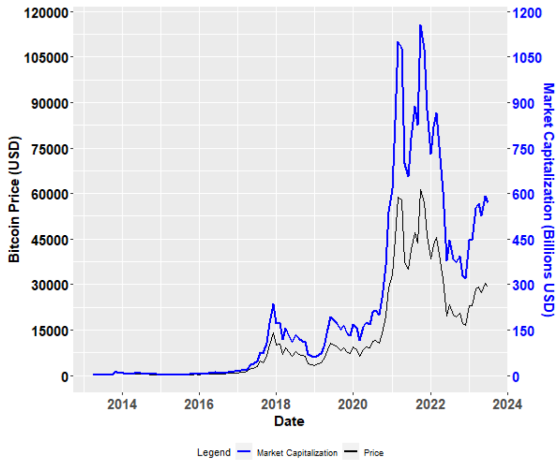
The popularity of cryptocurrencies increased rapidly since the mysterious Nakamoto, 2008 first published his (or her, or their) proposal for a purely peer-to-peer version of electronic cash. Bitcoin's first and leading cryptocurrency, has grown large in the last decade. In figure 1(a), it is possible to visualize the price on the left side (black axis) and on the right side (blue axis) the market capitalization of the Bitcoin. Since its creation, the total return are higher than 6000%. Also, the market capitalization of a single coin achieved a peak of 1.2 trillion US dollars recently. On the right side, figure 1(b) displays the price and market capitalization for the second most popular cryptocurrency Etherium. It is also possible to note the tremendous increase in the value in a short period after 2020 and the large movements and declines in both cryptocurrency valuations. At the same time, the popularity of cryptocurrencies has been growing. Figure 1(c) displays the Google search intensity query achieved its historical peak in 2018 and the second peak in 2021.

Due to this intense increase in the valuation of cryptocurrencies and the high volatility, there is an ongoing debate about the role of cryptocurrencies in the finance world. Our research addresses this question by examining which factors move or correlate with cryptocurrency variables. More specifically, we want to uncover the predictive or trailing relationship of cryptocurrency's return, volatility, and trading volume with returns and volatilities of other markets such as equities, foreign exchanges, commodities and interest rates.

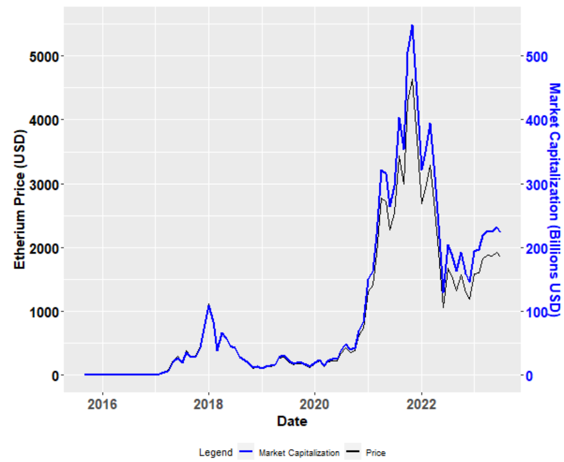
Understanding the factors that move or correlate with cryptocurrencies is still limited. Thus, by exploring this question, we contribute to the literature on how cryptocurrency markets predict or respond to other markets. Moreover, the answer to this question is also related to the literature that explores the diversification role of cryptocurrency, which previously often focused only on Bitcoin.

This paper investigates the leading and trailing between cryptocurrency and other markets using a static VAR and a TVP-VAR. First, we construct a proxy for the cryptocurrency market by creating an index from an initial sample of over 9000 cryptocurrencies. We computed the return, volatility, and trading volume from this index. Further, we proxy the equity market by the representative SPX 500 index, the currency market by the British Pound, the commodity market by the gold, and the interest market as the interest of the USA ten-year treasury bond. For each other market, we computed the return of the index and the volatility estimated by the APARCH model.

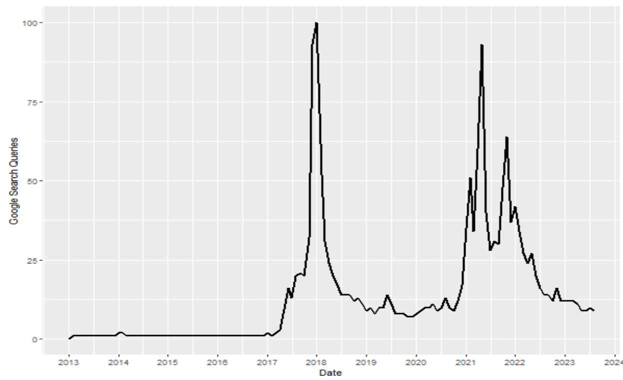
We estimate the static VAR and TVP-VAR models separately for each market, using the cryptocurrency variables, return, and volatility from the other market indexes. Our results indicate that the equities market and commodities have a closer relationship with



((a)) Bitcoin Price and Market Cap.



((b)) Etherium Price and Market Cap



((c)) Google Search

Figure 1: Figure (a) plots the price and market capitalization of Bitcoin. Figure (b) shows the price and market capitalization of the second most popular coin, Etherium. Figure (c) shows the Google search queries associated with the ”cryptocurrency” term.

cryptocurrency than the currency market. For equities, the cryptocurrency return predicts the volatility of the SPX. But also, the volatility (return) of SPX predicts crypto’s return (volatility). Thus, a cross-relationship exists between the return and volatility for both markets. Furthermore, the trading volume of cryptocurrency is highly impacted by the equities variables. Indeed, the IRF response to shock in the return and volatility of the SPX is negative and economically meaningful.

We proxy the currency market using the British Pound, and the results indicate that the return and trading volume of the cryptocurrency have a leading effect on the Pound’s volatility, and the Pound’s return leads to the cryptocurrency return. Our results do not suggest spillover among the variables for both markets. Nevertheless, interestingly, the trading volume predicts the volatility of the Pound, and the IRF shows a negative response to the shock in the former.

Our results for the commodities section indicate that cryptocurrency volatility predicts gold volatility. Moreover, the IRF response to the shock in the first is positive, which is consistent with the spillover volatility of the crypto market to the gold market. Also, the gold variables do not predict the return and volatility of the cryptocurrency index. However, the volatility predicts the cryptocurrency trading volume, and the shock in the first leads to a highly negative response of the former, which is statistically significant for five days.

We also explore the relationship between the government bond market (interest rates) and the cryptocurrency. We reference the ten-year interest rate of the USA for this market. Our results indicate a tight connection between the volatility of the variation of interest rate and the volatility of the cryptocurrency. Both variables granger-cause each other, and the Irfs of the former are positively impacted by a shock in the second. Furthermore, IRFs indicate a negative impact on the trading volume of crypto by interest volatility shock, a pattern similar to that observed in the other markets.

To summarize, our results imply that the equities, commodities, and government bonds sectors are more related to the cryptocurrency market than the currency sector. There exists a cross-relation between the return and volatility of crypto and equities. Also, there is a spillover among the volatility of the commodities and crypto markets. Furthermore, the trading volume of crypto is highly impacted by the volatility of other markets. The IRF shows a statistically significant negative response lasting an average of five days. The paper is structured as follows. Section 2 discusses the related literature and highlights our contribution. Section 3 describes the sources of data and the construction of the cryptocurrency portfolio. Section 4 presents the current developments in data description and model specification. Section 5 will present the results for all markets. Section 6 summarizes this paper.

2 Related Literature

Our paper is connected with two broad strands of finance literature. First, the literature explores the interconnection between financial markets, more precisely, trying to identify which financial asset in one market precedes or is followed by another asset in other markets. The second is the recent and fast-growing literature related to cryptocurrencies.

We aim to contribute to the first literature by exploring the lead-lag relationship between many financial classes, mainly equities, currency, commodities, and interest rates with the cryptocurrency markets. Analyzing the connection between standard asset classes King et al., 1990 explored the dynamic between sixteen national stock market indexes in a factor model with a time-varying matrix of variance-covariance, and their results support the view the global stocks markets are not integrated. Forbes and Rigobon, 2002 examine the effect of the 1997 East Asian crisis and its effects on the broad set of stock market indexes over the globe. Their results indicate no presence of contagion in the market but the presence of interdependence between financial markets. Furthermore, Ehrmann et al., 2011 investigates the international transmission across international markets using variables in equities, bonds, money markets, and exchange rates.

Unlike those papers, we will focus on the lead-lag relationship between variables and other markets and the cryptocurrency index being agnostic about the fundamental underlying structure of economic shocks. However, we estimate a TVP-VAR model that incorporates dynamic structure in the coefficients, allowing for a time-variation in the lead-lag relationship among the variables[1].

The paper most related to ours is Corbet et al., 2018, which explores the interconnection between the three cryptocurrencies, Bitcoin, Ripple, and Lite, with the bond, equity, commodities, and currency markets. Although a similar question, our paper diverges from theirs in many aspects. First, the analysis period starts in 2017 and ends in 2022. This led to a substantial difference between our article and Corbet et al., 2018, since the first boom of cryptocurrency occurred in 2018, which might matter to examine the relationship between cryptocurrency and other markets. Second, we focus on a cryptocurrency index constructed by many cryptocurrencies, which eliminates the idiosyncratic patterns of each cryptocurrency[2]. Third, we relax the assumption of a static lead-lag relationship by exploiting a TVP-VAR.

We also contribute to the literature related to cryptocurrency by showing the market's connection using a cryptocurrency index with other markets. Previously, the literature on cryptocurrency has focused on asset pricing features such as pricing risk, efficiency, and predictability. For example, Li and Wang, 2017 that three-factors market, size, and momentum are able to capture the cross-section of cryptocurrency expected returns. Moreover, Liu and Tsyvinski, 2021 results show that the predictability of cryptocurrency markets is related to the own market and not others markets, and also that cryptocurrencies are more exposed to network than produced factors risk. Related to efficiency, Pieters and Vivanco, 2017 documents a significant difference in Bitcoin prices across 11 different markets which they justify by different regulations in each market. Nevertheless, Brauneis and Mestel, 2018 shows that

[1]Our model also incorporates dynamic in the variance-covariance in the TVP-VAR structure. This approach is different from many articles that explore lead-lag connection using multivariate GARCH models proposed by Engle, 2002, Ding and Engle, 2001, Bollerslev et al., 1994

[2]Indeed, several studies of cryptocurrency show evidence of considerable inefficiency in cryptocurrency markets related to lower liquid in many cryptocurrencies at the time, see Köchling et al., 2019, Zargar and Kumar, 2019, Jiang et al., 2018, Aggarwal, 2019

as the liquid in cryptocurrency increases, it becomes less predictable.

The cryptocurrency markets, due to their high volatility and fast valuation increases, attract the attention of speculators, which can drive the prices away from the "fundamental" value. For example, Baur, Dimpfl, et al., 2018 using transaction data of Bitcoin accounts is used mainly for speculative investment. At the same time, due to considerable price variation, Cheah and Fry, 2015 estimate that the fundamental value of Bitcoin is not statically different from zero. That 48% of the price increase of Bitcoin belongs to the bubble component.

Furthermore, this price increase can attract investors' attention, which can lead to a posterior boost in buying activity, leading to a subsequent increase in prices. This mechanism is found by Kogan et al., 2023 shows that USA retail investors invest in cryptocurrency using a trend-following strategy. However, when these investors invest in other assets, such as gold or equity, they follow a contrarian strategy. In the same context, Weber et al., 2023 provides evidence that investors who are exogenously provided information about the historical price of cryptocurrencies increase their desire to invest in these assets.

3 Data

The interest of this article is to explore the relationship between cryptocurrency and other asset classes. We extracted all the cryptocurrency prices and volume disposable on Yahoo Finance, which spans a set of 9078. We merged this data set with the monthly market capitalization of those cryptocurrencies from the CoinMarket website. We construct a cryptocurrency portfolio using two weighting schemes, equal and value-weighted. However, we screen the cryptocurrency to avoid introducing noise in the portfolio due to crypto's lower liquidity and market capitalization. First, from the 9078, we selected those cryptocurrencies with at least one year between 2013 and 2022 and a market capitalization above $US100$ million in December, arriving at 586 cryptocurrencies. We also eliminate those with extreme noise, those we are not able to match across the two data sets, and with extreme returns, then our final sample contains 494 tickers[3] Furthermore, the portfolio is evaluated each year, and only the cryptocurrency with a market capitalization above $US100$ million in the preceding year enters the portfolio. Also, the portfolio is quarterly rebalanced[4].

Furthermore, the cryptocurrency portfolio spans January 2017 to December 2022. Table 1

[3]Second, we merge the data set of market capitalization and price using the ticker that is the same as yahoo and CoinMarket, we remain with 537. From those, we eliminate eleven tickers with a price equal to 0 and volume positive volume. We also exclude 28 tickers with extreme returns above (below) of the 99.99% quantile (0.0001% quantile). The last screen eliminates tickers that do not contain prices before market capitalization. The final sample of cryptocurrency then contains 494 tickers.

[4]The correlation between the monthly re-balanced portfolio and the quarterly is high

Table 1: This table shows the descriptive summary of the cryptocurrencies that enter the cryptocurrency index. The market capitalization variables are denoted in billions of $US\$$

		Market Capitalization						
Year	# Crypto	Mean	Mean	Min	Max	Pct25	Pct75	Total
2014	1	9.082	9.082	9.082	9.082	9.082	9.082	9.082
2015	2	2.460	0.587	1.524	2.460	3.397	4.333	4.920
2016	2	3.250	0.152	1.701	3.250	4.799	6.348	6.501
2017	5	3.120	0.133	0.213	0.232	0.626	14.396	15.600
2018	34	16.456	0.211	1.126	2.854	7.753	237.467	559.495
2019	33	3.682	0.105	0.249	0.619	1.553	67.476	121.520
2020	61	3.183	0.101	0.161	0.311	0.814	134.571	194.163
2021	129	5.452	0.102	0.158	0.360	0.990	488.213	703.275
2022	148	15.437	0.103	0.728	1.385	4.428	960.900	2284.685

shows a descriptive summary of the market capitalization and the number of cryptocurrencies included in the portfolio by year. Although our sample contains the return before 2017, the screen of market capitalization imposes that our portfolio is concentrated in less than five cryptocurrencies in the year before 2017. Thus, we focus on 2017 to avoid extreme portfolio concentration.

The other asset classes are equity markets, exchange markets, commodities, and government bonds. Our data on these classes comes from Bloomberg and spans January 2017 to December 2022. In the equity market, we focus on the S&P 500 market index (SPX), as well as the Dow Jones Industrial Average (DJI) and NASDAQ Composite (IXIC) for US equities, and the MSCI World equity index (MSCI) as a proxy of international global markets. In the exchange market, we obtained data for the Special Drawing Rights (SDR) index from the International Monetary Fund (IMF) as a proxy index that encompasses a basket of major currencies (the U.S dollar, Euro, Japanese yen, pound sterling, and the Chinese renminbi) and other four most traded currencies, such as the Euro (EUR), Japanese Yen (JPY), Pound Sterling (GBR) and the Chinese Renminbi (CNY), all of them paired with as U.S dollar (USD). We focus on gold and Brent oil prices, for government bond returns for the Euro Zone, Japan, EUA, Great Britain, and China. Moreover, we focus on bonds with ten years of maturity[5]. It is essential to address that all the returns are in daily frequency[6].

[5]We also collected returns of bonds with short maturity, 3 months, 1 year, and 5 years. However, daily series of these bond returns are subject to extreme volatility due to covid shock during the sample and the negative value of yields.

[6]Also, the cryptocurrency has traded on all days of the weak; to synchronize the data set, we opted

Figure 2 displays the cumulative return in the first panel, the return in the second, and the squared return in the third. It is possible to visualize the cumulative return peak in the final of 2021. Furthermore, a highly negative significant return in 2020 is evident in the squared return plot. This is close to the period of the covid. Moreover, the return series indicates some volatility clusters around 2018, the start of 2020, and the middle of 2021.

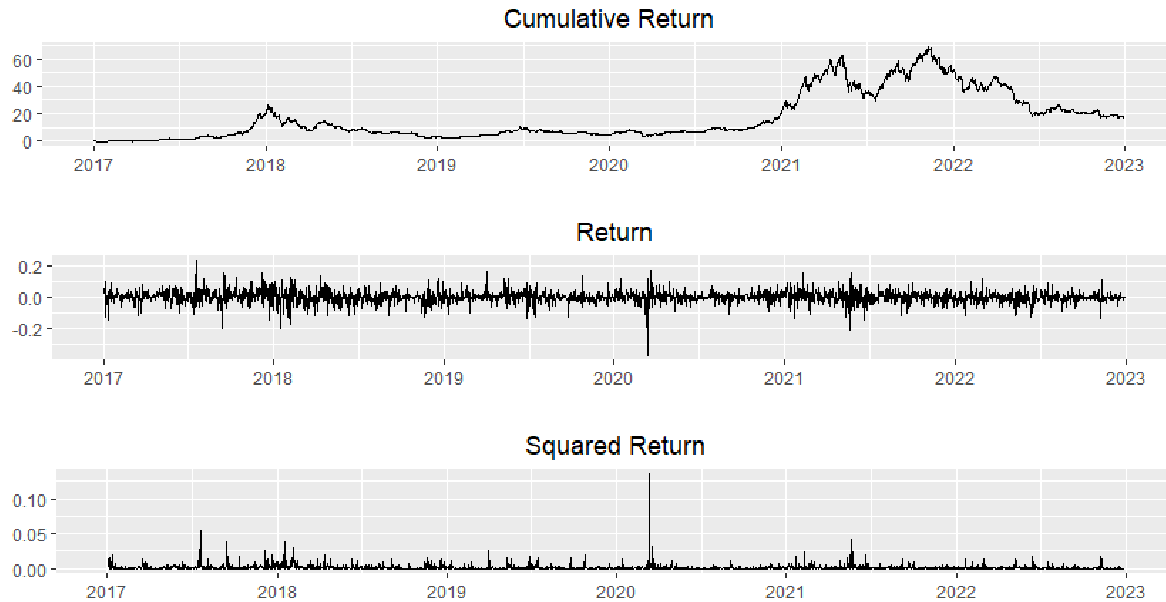


Figure 2: Cryptocurrency index, return, and squared return

4 Empirical Procedure

Time-varying parameter VAR proposed by Primiceri, 2005 has been increasing in popularity since it captures the economy's dynamic by allowing the model's parameters to vary over time. Furthermore, in contrast to static VAR, allowing for variation can enable the model to capture non-linearities often observable in economic and financial variables. We follow the model proposed by Primiceri, 2005, the time-varying parameter VAR is given by equation 1

$$Y_t = C_t + \sum_{j=1}^{K} A_j Y_{t-j} + u_t \tag{1}$$

With Y_t is a $n \times 1$ vector of the observable endogenous variable, C_t is a vector of constant coefficient that varies over time with the exact dimension of Y_t and the A_j are matrix of

to input the price on the weekend for other markets by using a Kalman filter with the intercept and slope varying in time, and then we take the return or variation for each day.

$n \times n$ of time-varying coefficients, $u_t \sim N(0, \Omega_t)$ is heteroscedastic unobservables shocks with the variance and covariance matrix Ω_t with dimension M, we can consider a triangular decomposition of the variance-covariance given by $\Phi_t \Omega \Phi' = \Sigma_t \Sigma_t'$, where Σ_t is a diagonal matrix with elements given by $\sigma_{i,t}$ and Φ_t is a lower-triangular with elements denoted by ϕ_t with diagonal elements equal to 1. The TVP-VAR model can be written in a compact form, such as:

$$y_t = X_t' B_t + \varepsilon_t \tag{2}$$

where $B = vec(([C_t', A_1', ..., A_k']))$ is a $M(1+MK) \times 1$ vector and $X_t' = I_n \otimes [1, y_{t-1}', \ldots, y_{t-k}']$ is a $M \times M(1+MK)$ vector. To incorporate dynamics in the model and uncertainty in the parameters, we assume the they follow a random walk structure given by the equations: 3, 4, 5.

$$B_t = B_{t-1} + \nu_t \tag{3}$$

$$\phi_t = \phi_{t-1} + \zeta \tag{4}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t \tag{5}$$

Where B_t is the tie-varying autoregressive coefficient of the compact form 2, ϕ_t is the stacked coefficient of the triangular matrix Φ_t that capture the dynamic in the correlation of the shocks and σ_t are the diagonal coefficient of the matrix Σ_t that captures dynamics in the shock of the own variable. Furthermore, we assume that all innovations follow a jointly normal distribution with the variance-covariance matrix:

$$V = \text{Var}\left(\begin{bmatrix} \varepsilon_t \\ v_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{6}$$

Where Q, S, and W are positive definite matrices. The diagonal structure of the variance of innovation serves two purposes. First, it implies a lower dimension of the parameters space, which already has a high dimension due to the time-varying matrices. Second, we do not step into the source of correlation among the uncertainty in the innovations, which is not the scope of the article. Further, as it is easy to notice, the standard VAR is nested in the case where the Q, S, W equals a zero-matrix, which turns the coefficients static.

For the dependent variables of the VAR, we included the volatility estimated for each return used in the specification. Once that is a well-stylized fact, the financial series have conditional heteroscedasticity, and volatility is often used to measure risk. Thus, we explore the lead-lags relationship among returns and the dependence of the return and volatility in the same series and cross-series.

To incorporate the main stylized facts about the volatility, we model the volatility process by the Asymmetric Power ARCH (APARCH) model of Ding et al., 1993[7], allowing both leverage and the Taylor effect. To establish the APARCH framework, let $r_t = p_t - p_{t-1}$ be the log return of an asset at time index t. For simplicity, assume that $\{r_t\}$ is either serially uncorrelated or serially correlated with the minor lower order. Then, the returns can be modeled by

$$\begin{aligned} r_t &= \mu_t + a_t, \\ a_t &= \sigma_t \varepsilon_t \end{aligned}$$

where $\mu_t = \mathrm{E}\left(r_t \mid \mathcal{F}_{t-1}\right)$ and $\sigma_t^2 = \mathrm{VAR}\left(r_t \mid \mathcal{F}_{t-1}\right)$ are, respectively, the mean and variance parameters. Since σ^2 is non-observable, we assume that

$$\sigma_t^\delta = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt}\right) + \sum_{j=1}^{q} \alpha_j \left(\left|\varepsilon_{t-j}\right| - \gamma_j \varepsilon_{t-j}\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \tag{7}$$

We select the appropriate order of the Aparch model for each variable by minimizing the Bayesian Information Criteria, spanning all possible combinations of lags of the coefficients p, q up to $2, 2$. To assess the adequacy of the volatility estimated, we check for the presence of heteroscedasticity and autocorrelation in each residual of the estimations for different lags. The descriptive table of the volatilities estimation 10 indicates that the cryptocurrency measures have much higher volatility than all other variables. The diagnostics table 11 indicates a well-specified volatility estimation; the Lung-Box tests for the residual and squared of the residuals are always p-values above 10%, and the Arch tests are often higher than 10%.

Since we deal with multiple time series from different markets, we opted to estimate a TVP-VAR model for each market separately to keep the size of the TVP-VAR relatively short. In all specifications, the order of the variables is the market index's return and volatility, followed by the variables related to cryptocurrency, return, volatility, and standardized trading volume.[8]

Also, we estimated the TVP-VAR using a Bayesian framework. We specify the priors following the same procedure as Primiceri, 2005, and use a part of the sample to estimate a

[7]This model nest some other volatility models such as Standard GARCH Bollerslev, 1986, AVGARCH, Taylor, 1987 and Schwert, 1990, GJR GARCH Glosten et al., 1993, TGARCH Zakoian, 1994, Nonlinear GARCHHiggins and Bera, 1992

[8]The formula constructs the standardized trading volume, $\frac{TV_t - \bar{\mathrm{TV}}}{sd(TV)}$, where the average and the standard deviation of the last 30 trading days. Aalborg et al., 2019 also standardized their trading measure.

static VAR in order to obtain priors for the parameters. We used one year of observation, or 252 observations, to estimate a static VAR.

Moreover, we extended the analysis by exploiting how the variables react to a shock in another variable by examining the IRF function from the TVP-VAR estimation. We used a Cholesk decomposition of the error to disentangle the effects. The order of the decomposition is the same as the TVP-VAR estimation, from the market index to the standardized trading volume of the cryptocurrency index. In this setting, we estimate the IRF of the TVP-VAR and compare it with the IRF of a static VAR, estimated using all samples. This allows us to understand the reaction of the variable's changes over time and compare it with the static prediction using a full sample.

Furthermore, we test the predictive relevance among the variables by testing the granger-causality of each variable separately using the static VAR model. Since TVP-VAR is estimated using a Bayesian framework, the hypothesis test is not defined, which makes it impossible to test the granger-causality as a frequentist estimation. To overcome this issue, we estimate a rolling-window static VAR estimation and test the granger-causality in these estimations. Thus, we can generate a dynamic test of the lead-lag relationship between each pair of variables and between blocks of the variable based on each market. For example, we test if all return and volatility of the equity market granger-cause conjointly the return of the crypto index and if all cryptocurrency variables granger-cause return of the equity market. Thus, we aim to disentangle the granger-causality among markets.

5 Results

5.1 Equities

In this section, we explore the leading-trailing relationship of our cryptocurrency index with the stock market. We use the SPX 500 as a proxy for the stock market since it is the most representative index. Also, other indexes are strongly correlated with the SPX, which makes including the others unnecessary for our purposes. Table 2 shows the VAR estimation for the equities markets. The model includes the returns from the index and estimated volatility, the cryptocurrency index return, its volatility, and the standardized trading volume. The first five columns include the model with a constant coefficient, and the last five include the trend term as robustness.

The first two columns show the estimated coefficients for the SPX variables. For both, the standard trading volume of crypto is statistically significant but close to zero in magnitude. Also, the cryptocurrency return is not economically significant for the return of the SPX. Still, it does matter for the volatility of the SPX since the first lag has a negative impact on the volatility. Moreover, we do not find a statistical effect of the volatility of the cryptocurrency index on the volatility of SPX.

The table results show that SPX variables do not respond strongly to the cryptocurrency index variables. However, the opposite occurs; precisely, there is a negative response to the cryptocurrency index return to the lag of the SPX volatility, and the second lag is still negative but not significant. The volatility of crypto also negatively impacts the return of the SPX, and both lags are statistically significant. Moreover, we do not find a spill-over effect between the volatilities. For the standardized trading volume, we find that the two variables of the SPX have a negative impact on the first lag, which indicates that the volume of the crypto index decreases compared to the last 30 trading due to past SPX variables.

Figure 4 shows the IRF response to Cryptocurrency to SPX variables. Panel a) shows a positive impact of SPX's return on the cryptocurrency returns. Panel b) shows a negative effect of the cryptocurrency returns to an SPX volatility, showing that although the initial impact is not statistically significant, the point estimate is negative and statistically significant for the second days to 8 days after the shock. Panel d) shows a positive effect of the volatility of SPX on the volatility of the cryptocurrency index. Panel e) e f) shows a similar effect of the SPX and volatility SPX in the standardized trading volume of the cryptocurrency index. The negative effect in the short term is highly significant and reverts to shock in the returns and converges to zero for the shock of the volatility.

Figure 5 show the impulse response function from the TVP-VAR estimation. Since this model provides IRFs for each point in time, we examine if the average IRFs over the year are similar across 2020, 2021, and 2022. For almost all the IRFS, the average response is similar over the years, except for the response of volatility and trading volume to a shock in the volatility of SPX. The first case is shown in panel 5(d), the response of cryptocurrency volatility becomes monotonically more negative over the year, but in magnitude, the effect is still closer. In contrast, in the panel 5(f), the response of trading volume is more negative and twice as significant in 2022 than in 2020.

Table 3 shows the granger-causality tests. The column indicates the dependent variables, and the rows indicate the variables being tested, except the last row, which tests a block granger-causality. The first striking pattern is that cryptocurrency variables do not granger-cause SPX return, individually or in the block. However, both the return and the standardized trading volume granger cause the SPX volatility with high statistical significance. On the other way, the volatility (return) of the SPX matters for the return (volatility) of the crypto, and both are rejected with significance lower than 5%. Previously, Aalborg et al., 2019 does not find that variation in the VIX index an important predictable variable for the bitcoin return, volatility, and trading volume, which is in the opposite direction of our results. This difference potentially emerges because we consider an index of the cryptocurrency instead of only Bitcoin and explore the volatility of SPX instead of the variation of VIX. Moreover, Bouri et al., 2018 finds significant predictability of volume on return and volatility for a set of leading cryptocurrencies. Consistent with these results, our standardized trading volume granger-cause a return and volatility for the crypto index.

Moreover, we estimate a static VAR using a 252-day trading day rolling window sample to obtain a time-varying Granger-causality test. We test if all the variables in market j granger-cause the variable of the market i, then in figure 3 display the p-value of the test, and the gray areas denote the periods in which the p-value is lower than 10%. It's possible to notice that SPX return is only granger-cause by crypto variables on the periods that comprehend the COVID shock. Also, the return of the cryptocurrency index displays the same pattern. Furthermore, the volatility of the SPX was granger-caused during 2018, the first cryptocurrency boom, and from 2022 forward. In opposition, neither the cryptocurrency volatility nor the crypto trading volume were caused by SPX variables during 2018.

In summary, the equity market has a higher impact on cryptocurrency than the opposite. The static and time-varying IRFS points to a large response of cryptocurrency's volatility and trading volume to a shock in the SPX volatility. Also, we have evidence that the first response varies over time. At the same time, the second does not. Second, the Granger-causality test shows evidence that only the volatility of SPX is predictable to cryptocurrency variables. However, returns are commonly caused in the Granger sense due to COVID shock. Conversely, volatility and trading volume are more predictable by SPX variables.

Table 2: Regression Table

	SPX	Volatility SPX	Crypto	Volatility Crypto	Standardize TV	SPX	Volatility SPX	Crypto	Volatility Crypto	Standardize TV
SPX_{t-1}	-0.124***	-0.022***	-0.008	-0.026***	-7.281***	-0.124***	-0.022***	-0.008	-0.026***	-7.266***
	(0.022)	(0.003)	(0.093)	(0.007)	(2.021)	(0.022)	(0.003)	(0.093)	(0.007)	(2.019)
Volatility SPX_{t-1}	-0.044	0.341***	-1.038*	0.046	-44.205***	-0.054	0.324***	-0.976*	0.056	-39.564**
	(0.137)	(0.021)	(0.580)	(0.041)	(12.566)	(0.139)	(0.021)	(0.587)	(0.042)	(12.690)
$Crypto_{t-1}$	-0.002	-0.002**	-0.058**	-0.020***	1.277**	-0.002	-0.002**	-0.058**	-0.020***	1.256**
	(0.005)	(0.001)	(0.022)	(0.002)	(0.480)	(0.005)	(0.001)	(0.022)	(0.002)	(0.479)
Volatility $Crypto_{t-1}$	0.042	0.010	-0.169	0.920***	-34.167***	0.043	0.012	-0.176	0.919***	-34.727***
	(0.068)	(0.011)	(0.287)	(0.020)	(6.225)	(0.068)	(0.010)	(0.288)	(0.020)	(6.221)
Standardize TV_{t-1}	0.000*	0.000***	0.001	0.002***	0.563***	0.000*	0.000***	0.001	0.002***	0.560***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.021)	(0.000)	(0.000)	(0.001)	(0.000)	(0.021)
SPX_{t-2}	0.050**	-0.012***	0.069	-0.015**	-3.048	0.049**	-0.013***	0.070	-0.015**	-3.002
	(0.022)	(0.003)	(0.094)	(0.007)	(2.043)	(0.022)	(0.003)	(0.094)	(0.007)	(2.040)
Volatility SPX_{t-2}	-0.516***	0.189***	-0.516	0.026	-3.906	-0.526***	0.172***	-0.456	0.035	0.629
	(0.136)	(0.021)	(0.575)	(0.041)	(12.449)	(0.138)	(0.021)	(0.581)	(0.041)	(12.567)
$Crypto_{t-2}$	0.003	-0.001	0.035	-0.009***	0.952*	0.003	-0.001	0.034	-0.009***	0.930*
	(0.005)	(0.001)	(0.023)	(0.002)	(0.496)	(0.005)	(0.001)	(0.023)	(0.002)	(0.495)
Volatility $Crypto_{t-2}$	-0.036	-0.007	0.338	0.058**	25.425***	-0.034	-0.004	0.328	0.056**	24.694***
	(0.068)	(0.011)	(0.288)	(0.021)	(6.243)	(0.068)	(0.010)	(0.289)	(0.021)	(6.242)
Standardize TV_{t-2}	0.000	0.000*	0.001	-0.001***	0.098***	0.000	0.000	0.001	-0.001***	0.095***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)
Constant	0.001	0.001***	-0.003	0.001***	0.441***	0.001	0.000	-0.001	0.001***	0.568***
	(0.001)	(0.000)	(0.003)	(0.000)	(0.068)	(0.001)	(0.000)	(0.004)	(0.000)	(0.085)
Num.Obs.	2160	2160	2160	2160	2160	2160	2160	2160	2160	2160
R2	0.030	0.253	0.014	0.942	0.412	0.030	0.264	0.014	0.942	0.414
Constant	True	True	True	True	True	True	True	True	True	True
Trend	False	False	False	False	False	True	True	True	True	True

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

This table show the results of the model (1)

Table 3: This table provides the results of the granger-causality test for the equities market. Each column is the outcome variable and in each row, the coefficient associated with that variable is tested. In the last row, the test is in the block, being the block formed by the variables in the market opposite of the outcome variable. Furthermore, the granger-causality uses the linear equation from the VAR(2). The variables being tested are the return and volatility of the SPX 500 index, return, volatility, and the standardized trading volume from the cryptocurrency index.

	SPX		Volatility SPX		Crypto		Volatility Crypto		Standardize TV	
Variable	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
SPX	40.009	0.000	47.984	0.000	0.568	0.753	18.489	0.000	14.093	0.001
Volatility SPX	19.198	0.000	575.532	0.000	6.691	0.035	2.765	0.251	16.608	0.000
Crypto	0.473	0.790	9.224	0.010	9.498	0.009	187.608	0.000	10.251	0.006
Volatility Crypto	0.434	0.805	1.660	0.436	5.806	0.055	33942.499	0.000	52.622	0.000
Standardize TV	3.148	0.207	16.315	0.000	7.099	0.029	684.184	0.000	1271.728	0.000
Others	3.983	0.679	26.166	0.000	7.646	0.105	22.299	0.000	29.361	0.000

Figure 3: This figure displays the Granger-causality test for the static VAR with SPX and cryptocurrency variables using a 252-day rolling window sample. The left axis shows the associated p-value of the test. The outcome variable is on top of each figure, and the predictive variables are all variables from other markets. The gray area denotes the periods in which the p-value is lower than 10%.

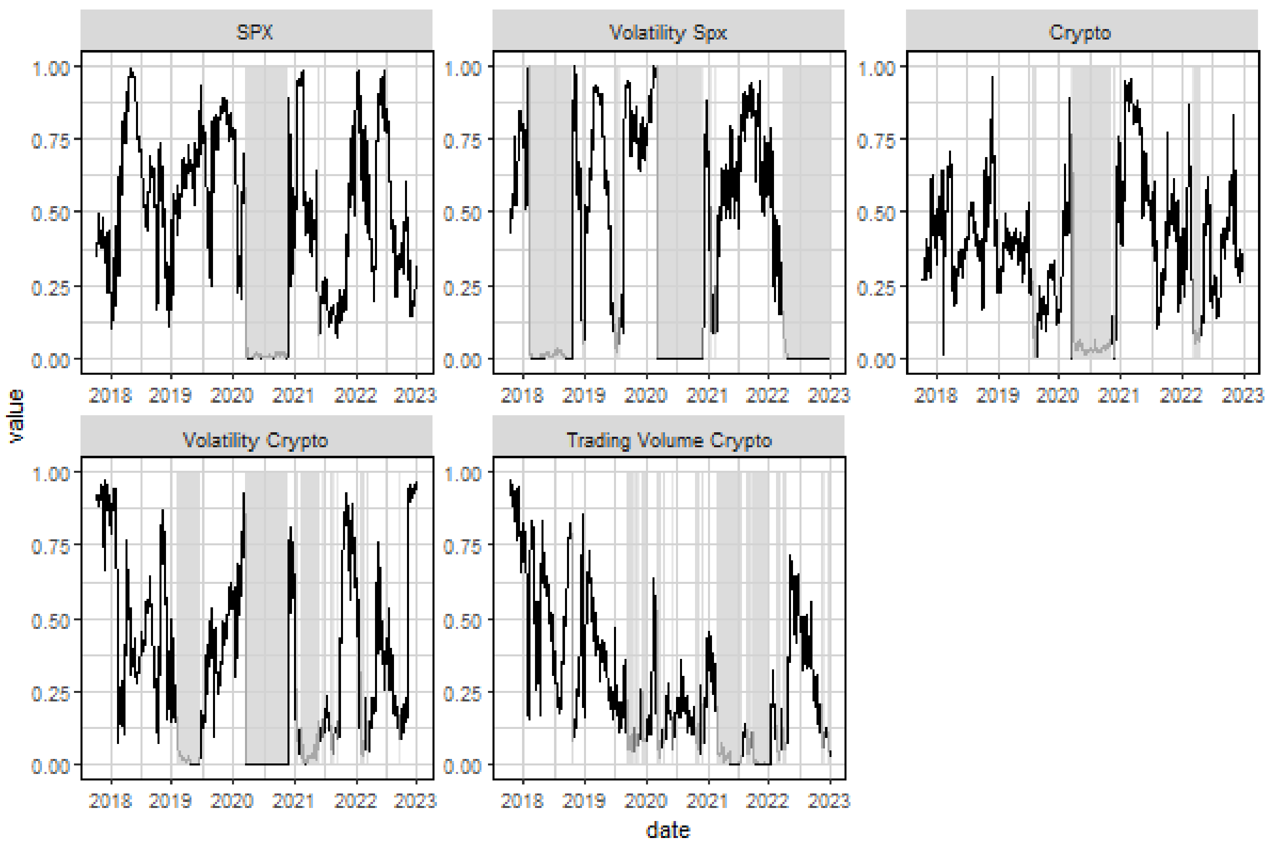
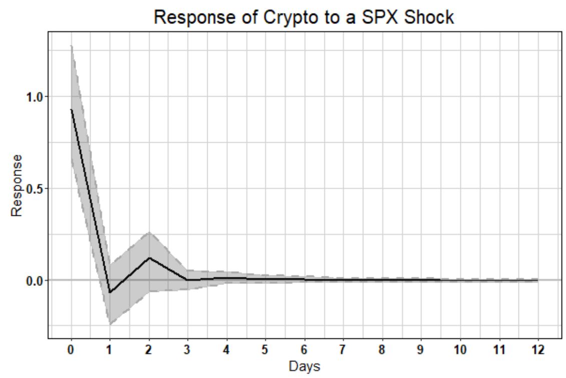
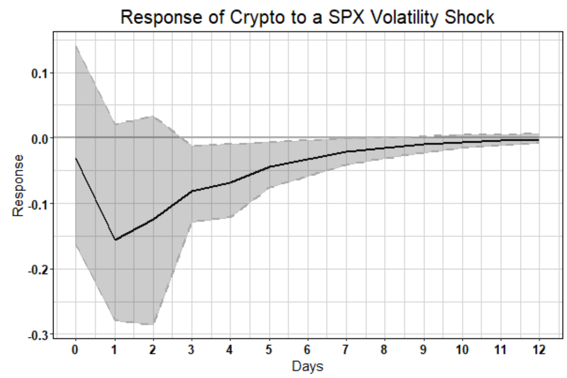


Figure 4: This figure shows the principal IRFs plots from the VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks and identify the errors. The order of the decomposition is the same as of the VAR(2), return and volatility of the SPX 500 index; return, volatility, and trading volume standardized of the cryptocurrency index.

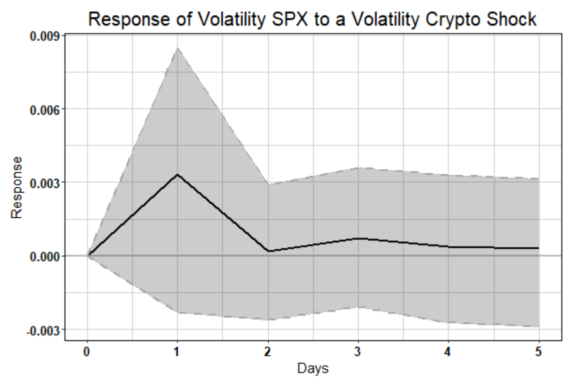
((a)) Figure



((b)) Figure



((c)) Figure



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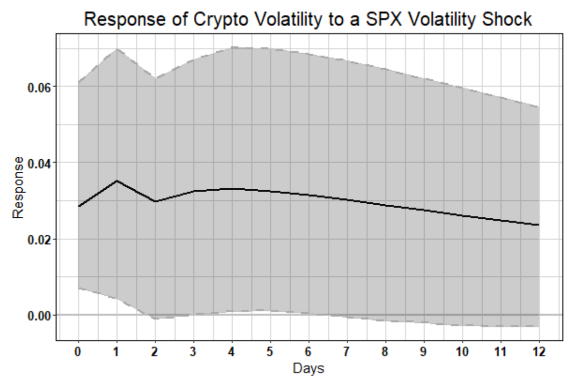
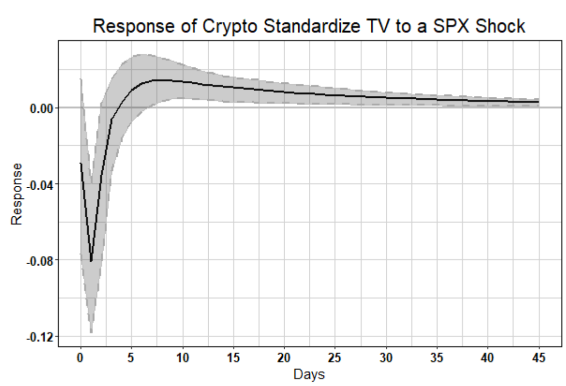


((e)) Figure



((f)) Figure

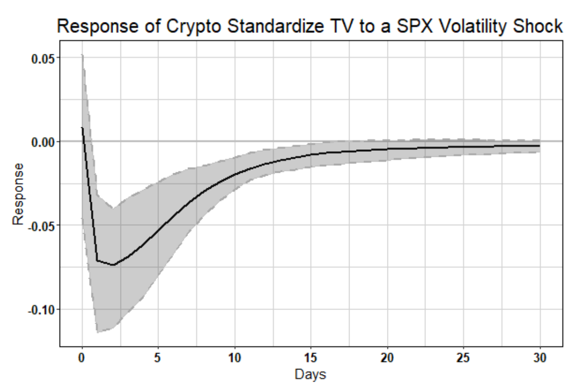
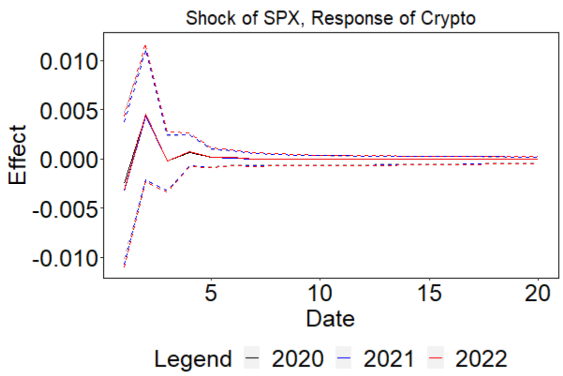
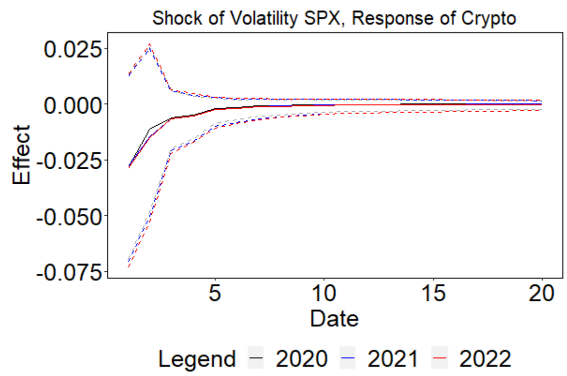


Figure 5: This figure shows the principal IRFs plots from the TVP-VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks and identify the errors. The order of the decomposition is the same as that of the TVP-VAR(2), return, and volatility of the SPX 500 index; return, volatility, and trading volume are standardized of the cryptocurrency index. Which line is the average and the 95% confidence interval for the average distribution over the year from 2020 to 2022.

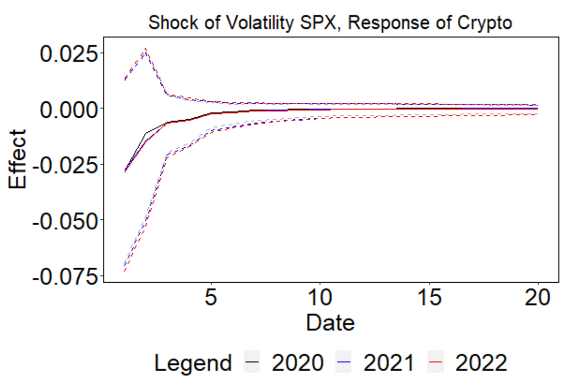
((a)) Figure



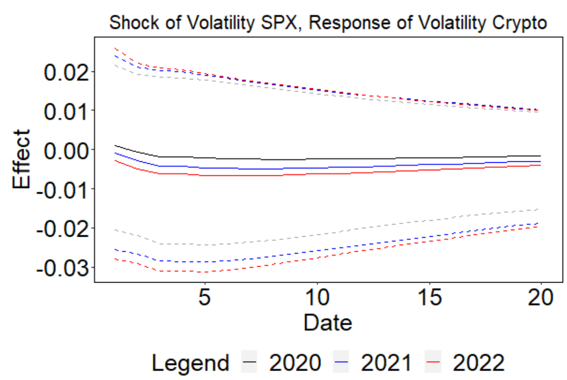
((b)) Figure



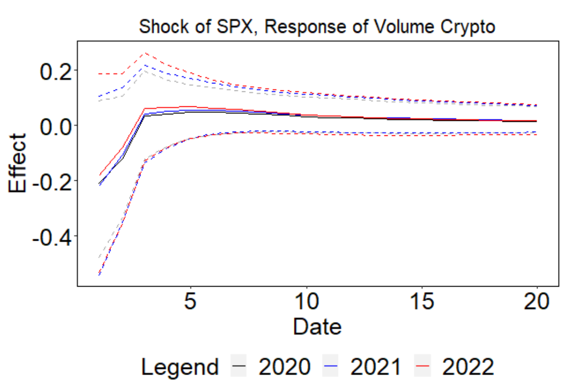
((c)) Figure



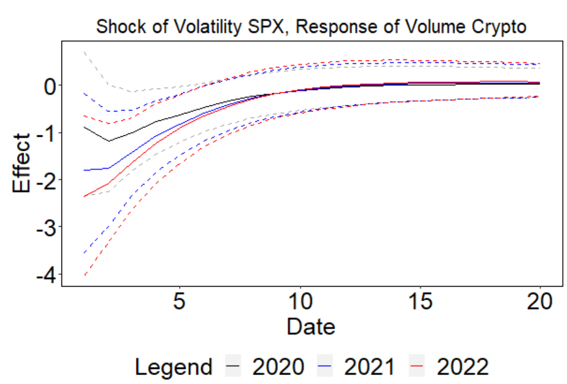
((d)) Figure



((e)) Figure



((f)) Figure



5.2 Currency

Table 4 shows the results from the VAR estimation analyzing the relation between the Cryptocurrency Index and Britsh Pound currency as a reference for the currency market. The first five columns are relative to the VAR specification with only constant, and the last five with constant and trend. Columns 1 and 2 are the return and volatility of the currency variable. These columns indicate that the first lag of cryptocurrency return is statistically significant to return with a positive coefficient, and the second lag is negative for the volatility. Also, the cryptocurrency trading volume matters for the volatility of the British Pound and not for the return. Analyzing the cryptocurrency variables, it is possible to note that the British pound variables do not impact the return. However, the volatility is positively impacted by the volatility, and the standardized trading volume is impacted by the return and volatility of the British Pound, although only the second is statistically different from zero.

In Table 5, we explore the predictive power of the variables using a granger-causality test. The first column indicates that the cryptocurrency variables do not granger-cause the return of the Pound, neither separately nor in conjunct (last row). The same pattern does not hold for the volatility since the cryptocurrency return and standardized trading volume granger-cause volatility of the Pound individually. The pound variables do not granger the return and volatility of the cryptocurrency index. However, the volatility separately granger causes the standardized trading volume. Baur, Dimpfl, et al., 2018 investigates the correlation of Bitcoin and FX dollar in a GARCH specification and does not find any correlation. Corbet et al., 2018 finds that among several markets, the FX market volatility is more correlated with crypto volatility than SPX and bond, for example, which is in accordance with our granger-causality test for the volatility of Briths Pound. Further, Bouri et al., 2017 argues that Bitcoin acts as an intraday hedge against GBP, the granger-causality on the third column and the coefficient from VAR estimation indicates a negative and significant prediction of GBP, which is consistent with the hedging argument.

Moreover, figure 6 shows the granger-causality test using the rolling window VAR estimation. Similar to the analysis using SPX, cryptocurrency and the pound were closely connected during the Covid period. However, the main difference is that the trading volume of cryptocurrency is Caused in more periods by the Bristh Pound variable than SPX variables, and this difference is more related to the period of 2021 forwards.

Figure 7 displays the IRFs from the VAR estimation. A shock positively impacts the cryptocurrency index's return on the pound return, but the impact is quickly dissipated. In contrast, a shock in the pound volatility provokes a negative reaction to the standardized trading volume, remaining at least ten days until it dissipates. Moreover, the volatility of

Table 4: Regression of the Currency Model

	GBP	Volatility GBP	Crypto	Volatility Crypto	Standardize TV	GBP	Volatility GBP	Crypto	Volatility Crypto	Standardize TV
GBP_{t-1}	0.056**	-0.008**	-0.487**	0.005	-0.988	0.056**	-0.008**	-0.492**	0.005	-1.232
	(0.022)	(0.003)	(0.191)	(0.014)	(4.134)	(0.022)	(0.003)	(0.191)	(0.014)	(4.128)
Volatility GBP_{t-1}	-0.013	0.252***	-1.869	0.152*	-159.645***	-0.003	0.247***	-1.754	0.160*	-154.426***
	(0.136)	(0.022)	(1.193)	(0.085)	(25.753)	(0.136)	(0.022)	(1.196)	(0.085)	(25.783)
$Crypto_{t-1}$	0.004*	-0.001	-0.048**	-0.022***	0.939**	0.004*	-0.001	-0.049**	-0.022***	0.904*
	(0.002)	(0.000)	(0.022)	(0.002)	(0.470)	(0.002)	(0.000)	(0.022)	(0.002)	(0.469)
Volatility $Crypto_{t-1}$	-0.007	0.010*	-0.253	0.922***	-35.685***	-0.007	0.010**	-0.259	0.922***	-35.965***
	(0.032)	(0.005)	(0.284)	(0.020)	(6.143)	(0.032)	(0.005)	(0.284)	(0.020)	(6.134)
Standardize TV_{t-1}	0.000	0.000***	0.001	0.002***	0.561***	0.000	0.000***	0.001	0.002***	0.557***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.021)	(0.000)	(0.000)	(0.001)	(0.000)	(0.021)
GBP_{t-2}	0.032	0.009**	0.002	-0.012	-3.502	0.031	0.009**	-0.005	-0.012	-3.784
	(0.022)	(0.003)	(0.192)	(0.014)	(4.136)	(0.022)	(0.003)	(0.192)	(0.014)	(4.131)
Volatility GBP_{t-2}	-0.048	0.031	0.674	-0.006	-13.819	-0.040	0.026	0.772	0.001	-9.371
	(0.136)	(0.022)	(1.192)	(0.085)	(25.741)	(0.136)	(0.022)	(1.194)	(0.085)	(25.752)
$Crypto_{t-2}$	0.001	-0.001**	0.043*	-0.010***	0.926*	0.001	-0.001*	0.043*	-0.010***	0.894*
	(0.003)	(0.000)	(0.023)	(0.002)	(0.487)	(0.003)	(0.000)	(0.023)	(0.002)	(0.487)
Volatility $Crypto_{t-2}$	0.000	-0.010*	0.395	0.058**	26.560***	-0.002	-0.009*	0.373	0.056**	25.568***
	(0.033)	(0.005)	(0.286)	(0.020)	(6.172)	(0.033)	(0.005)	(0.286)	(0.020)	(6.173)
Standardize TV_{t-2}	0.000	0.000	0.001	-0.001***	0.106***	0.000	0.000	0.001	-0.001***	0.103***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)
Constant	0.000	0.000***	-0.003	0.001**	0.510***	0.001	0.000***	0.000	0.001**	0.649***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.070)	(0.000)	(0.000)	(0.004)	(0.000)	(0.086)
Num.Obs.	2159	2159	2159	2159	2159	2159	2159	2159	2159	2159
R2	0.008	0.092	0.015	0.941	0.416	0.008	0.096	0.015	0.941	0.418

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$
This table shows the results of the model (1)

the Pound is positively impacted by the volatility of the cryptocurrency, and interestingly the inverse is not statistically different from zero. Furthermore, the measure of the trading also positively impacts the pound volatility, even lasting for five days until it dissipates and has a great magnitude.

In extension, figure 8 shows the IRFs computed using the TVP-VAR. The panel at the left column does not show significant response differences over time, in contraposition to the right column. Panel 8(c) shows the response of cryptocurrency trading volume to a shock in the volatility of the Pound, as in the static VAR, the effect is highly significant, and its average effect seems to become more negative over the year, although not monotonically. A similar pattern occurs with the response of the volatility of the Pound to a shock in the volatility in cryptocurrency. The response is mainly positive but shifts downwards comparing 2021 to 2022.

Table 5: This table provides the results of the granger-causality test for the currency market. Each column is the outcome variable and in each row, the coefficient associated with that variable is tested. In the last row, the test is in the block, being the block formed by the variables in the market opposite of the outcome variable. Furthermore, the granger-causality uses the linear equation from the VAR(2). The variables being tested are the return and volatility of the libra, return, volatility, and the standardized trading volume from the cryptocurrency index.

	GBP		Volatility GBP		Crypto		Volatility Crypto		Standardize TV	
Variable	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
GBP	9.309	0.010	10.454	0.005	6.492	0.039	0.817	0.665	0.805	0.669
Volatility GBP	0.160	0.923	158.949	0.000	2.485	0.289	3.363	0.186	43.339	0.000
Crypto	3.403	0.182	5.924	0.052	8.946	0.011	228.105	0.000	7.246	0.027
Volatility Crypto	0.730	0.694	3.753	0.153	4.826	0.090	34218.143	0.000	58.985	0.000
Standardize TV	0.995	0.608	21.264	0.000	7.371	0.025	691.170	0.000	1286.500	0.000
Others	4.878	0.560	38.751	0.000	9.018	0.061	4.335	0.363	43.734	0.000

Figure 6: This figure displays the Granger-causality test for the static VAR with British Pound and cryptocurrency variables using a 252-day rolling window sample. The left axis shows the associated p-value of the test. The outcome variable is on top of each figure, and the predictive variables are all variables from other markets. The gray area denotes the periods in which the p-value is lower than 10%.

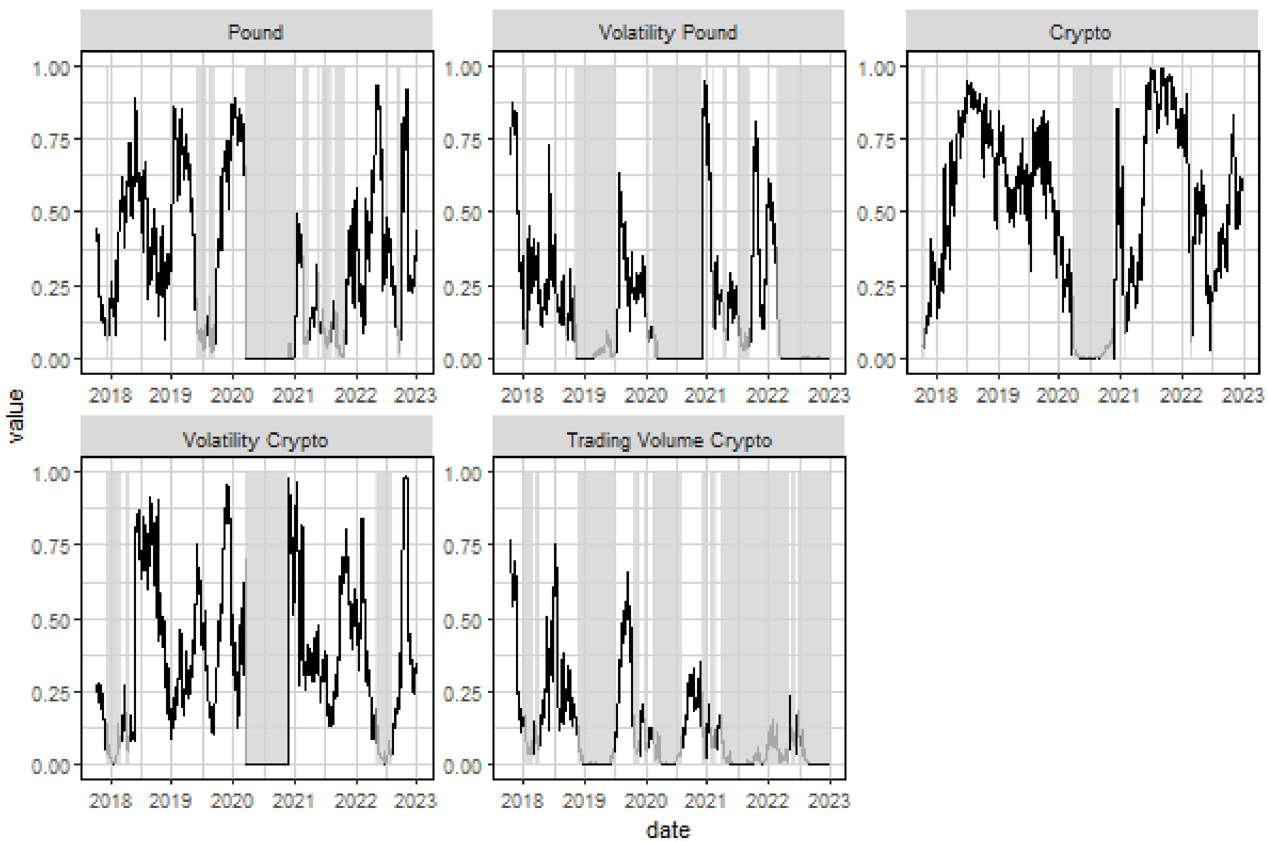
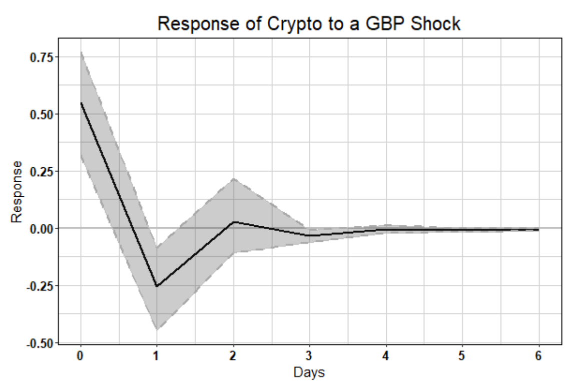


Figure 7: This figure shows the principal IRFs plots from the TVP-VAR(2) estimation. It uses a Cholesky decomposition to decompose. The order of the decomposition is the same as of the VAR(2), return and volatility of the libra index; return, volatility, and trading volume standardized of the cryptocurrency index. Which line is the average and the 95% confidence interval for the average distribution over the year from 2020 to 2022.

((a)) figure



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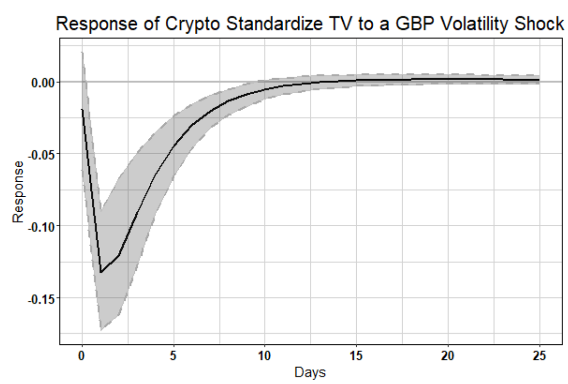

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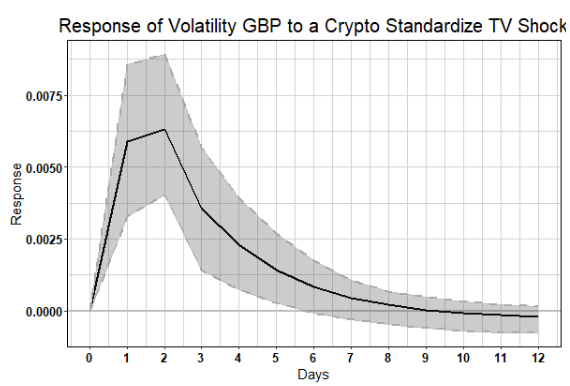

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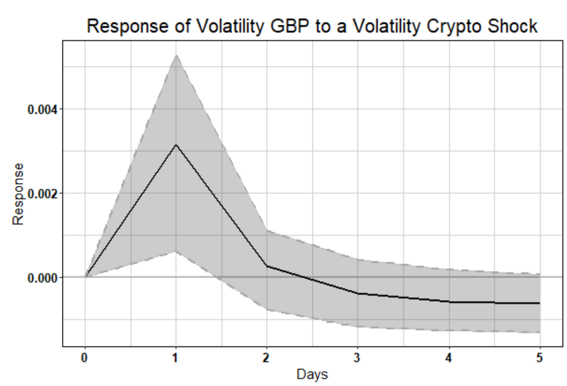
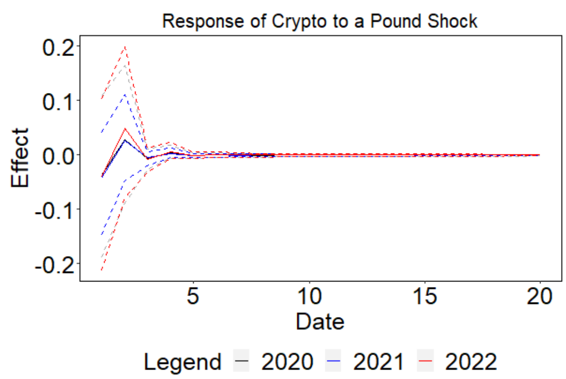


Figure 8: This figure shows the principal IRFs plots from the VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks and identify the errors. The order of the decomposition is the same as of the VAR(2), return and volatility of the libra index; return, volatility, and trading volume standardized of the cryptocurrency index. Which line is the average and the 95% confidence interval for the average distribution over the year from 2020 to 2022.

((a)) figure



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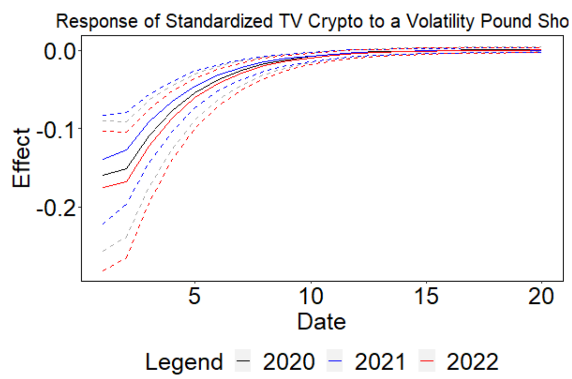

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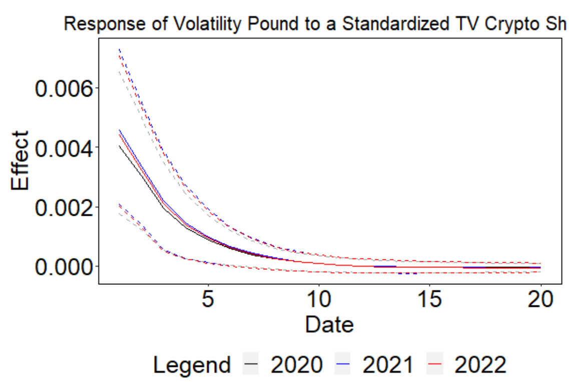

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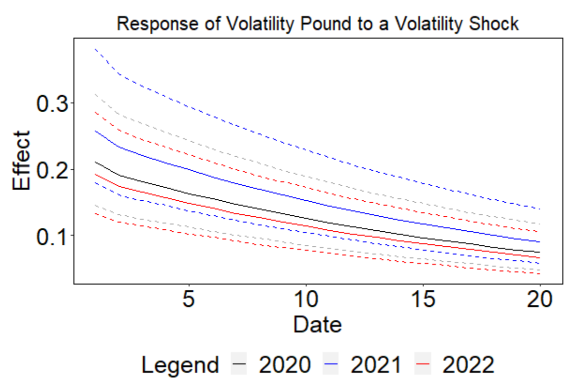


5.3 Commodities

Table 6 shows the result from VAR estimation for the commodities sector. We use gold as a proxy for this sector because cryptocurrency is often created to be a reserve of value similar to gold, and previous studies focused on the relation between the two markets such as Baur, Dimpfl, et al., 2018, Baur, Hong, et al., 2018, Baur and Hoang, 2021, Adebola et al., 2019. The first column displays the gold as a dependent measure, and the returns indicate a time dependency of its own first and second lag, but more interestingly, the first lag of the cryptocurrency has a positive impact on the gold return. However, the opposite does not occur since the cryptocurrency return depends on its first and second lag. Therefore, in return, the direction of the results indicates that cryptocurrency's impact on gold is not the opposite. Analyzing the gold volatility dynamics, it's possible to notice a positive impact of the cryptocurrency volatility and the standardized trading volume on gold. This indicates a spillover effect between the volatilities of both markets, with the cryptocurrency leading the other. Also, the volatility of the crypto index is not statistically related to gold variables. Moreover, the standardized trading volume is negatively (positively) related to the first (second) lag of the volatility of gold, which indicates an alternate impact of gold risk on the trading activity of the cryptocurrency market.

Table 7 shows the granger-causality test of the model of the variables from the VAR model. It is possible to notice in the first column that cryptocurrency returns granger-cause gold return with a p-value lower than 5%, the other variables related to cryptocurrency do not granger cause gold separately, nor all the three variables together showed by the p-value of 34%. Interestingly, the volatility of gold is granger-caused by the volatility of the crypto index and the standardized trading volume, both with p-values lower than 5%, which indicates a closer relation of the volatility of gold with the cryptocurrency market. Analyzing the cryptocurrency together indicates a granger-causality with p-values lower than 1%. The other columns examine if the cryptocurrency is granger-caused by gold variables. The striking evidence is that only the standardized trading volume is granger-caused by the gold variables, more precisely, the volatility of the gold. However, we also reject at 10% that both variables do not granger-caused the measure of trading in the cryptocurrency market. Thus, the evidence is that cryptocurrency variables have a larger predictive power on the gold variables than the opposite. Expect the trading volume of the cryptocurrency to be predicted by the volatility of the gold. The granger-causality for the return variables tests is in general accordance with the results obtained by Adebola et al., 2019 that found little or no evidence of cointegration between gold and cryptocurrency. However, the positive impact of crypto volatility on gold is in accordance with the spillover effect found by Corbet et al., 2018 that finds that gold has higher spillover volatility from Bitcoin than FX, bond, and

SPX 500.

In extension, 12 plots the p-values of the granger-causality test. The cryptocurrency variable causes both variables of the commodity section return and volatility of gold during the COVID shock. At the same time, both the return and volatility of the cryptocurrency index are also caused in the Granger Sense by gold variables. Interestingly, the gold variable does not predict the trading volume for any period. This is different from the analysis with SPX and British Pound.

Figure 10 displays the main IRfs from the model. 11(a) shows the impact of a shock on the gold return and its effect on cryptocurrency return, and 11(b) shows the opposite. Both graphics show almost the same positive pattern. However, in the first, the impact is contemporaneous; in the former, its effect is with one lag. The second row of the graphics examines the volatilities relation. It is striking that gold volatility reacts positively to one shock of crypto volatility, and the effects remain for almost five trading days. However, the inverse effect is not statistically different from zero. The third row displays two interesting results. First, standardized trading volume positively impacts gold volatility and remains positive for at least 20 days after the shock. Second, there is the negative impact of the volatility of gold on the standardized trading volume that lasts almost five days.

The figure 11 gives the dynamic response. Interestingly, the response of volatility and trading volume of the cryptocurrencies to the volatility of gold varies over time but not the response of the return. Also, the positive response to the volatility of cryptocurrency has decreased in 2022 in comparison with 2021 and relative to 2020. The same occurs with the impact on trading volume, which is also below the 2020 response over all periods of the IRFs. At the same time, the volatility of SPX's response to a shock in the volatility of cryptocurrency varies over time. Still, the difference is mainly seen at the medium horizon of days to twenty days.

Table 6: Table VAR Results

	GOLD	Volatility GOLD	Crypto	Volatility Crypto	Standardize TV	GOLD	Volatility GOLD	Crypto	Volatility Crypto	Standardize TV
Gold_{t-1}	-0.040*	0.001	-0.029	0.002	-0.374	-0.040*	0.001	-0.031	0.002	-0.495
	(0.022)	(0.001)	(0.125)	(0.009)	(2.706)	(0.022)	(0.001)	(0.125)	(0.009)	(2.702)
$\text{Volatility Gold}_{t-1}$	0.361	0.963***	-0.409	0.087	-150.251**	0.375	0.960***	-0.223	0.098	-141.546**
	(0.487)	(0.022)	(2.807)	(0.200)	(60.991)	(0.488)	(0.022)	(2.810)	(0.201)	(60.953)
Crypto_{t-1}	0.009**	0.000	-0.055**	-0.022***	0.948**	0.009**	0.000	-0.056**	-0.022***	0.905*
	(0.004)	(0.000)	(0.022)	(0.002)	(0.470)	(0.004)	(0.000)	(0.022)	(0.002)	(0.469)
$\text{Volatility Crypto}_{t-1}$	-0.016	0.006**	-0.271	0.924***	-37.318***	-0.016	0.006**	-0.277	0.924***	-37.625***
	(0.049)	(0.002)	(0.285)	(0.020)	(6.198)	(0.050)	(0.002)	(0.285)	(0.020)	(6.188)
$\text{Standardize TV}_{t-1}$	0.000	0.000**	0.001	0.002***	0.568***	0.000	0.000**	0.001	0.002***	0.564***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.021)	(0.000)	(0.000)	(0.001)	(0.000)	(0.021)
Gold_{t-2}	0.070**	0.000	0.097	-0.002	-1.106	0.070**	0.000	0.093	-0.002	-1.278
	(0.022)	(0.001)	(0.124)	(0.009)	(2.698)	(0.022)	(0.001)	(0.124)	(0.009)	(2.694)
$\text{Volatility Gold}_{t-2}$	-0.264	0.019	0.281	-0.089	131.777**	-0.258	0.018	0.355	-0.085	135.254**
	(0.487)	(0.022)	(2.808)	(0.201)	(61.024)	(0.487)	(0.022)	(2.808)	(0.201)	(60.926)
Crypto_{t-2}	0.002	0.000	0.040*	-0.010***	0.967**	0.002	0.000	0.039*	-0.010***	0.924*
	(0.004)	(0.000)	(0.022)	(0.002)	(0.489)	(0.004)	(0.000)	(0.022)	(0.002)	(0.488)
$\text{Volatility Crypto}_{t-2}$	0.015	-0.005**	0.419	0.056**	28.208***	0.013	-0.005**	0.394	0.055**	27.055***
	(0.050)	(0.002)	(0.287)	(0.020)	(6.227)	(0.050)	(0.002)	(0.287)	(0.021)	(6.228)
$\text{Standardize TV}_{t-2}$	0.000	0.000	0.001	-0.001***	0.094***	0.000	0.000	0.001	-0.001***	0.092***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)
Constant	0.000	0.000**	-0.003	0.001**	0.512***	0.000	0.000*	-0.001	0.001**	0.596***
	(0.001)	(0.000)	(0.005)	(0.000)	(0.104)	(0.001)	(0.000)	(0.005)	(0.000)	(0.107)
Num.Obs.	2160	2160	2160	2160	2160	2160	2160	2160	2160	2160
R2	0.010	0.962	0.011	0.941	0.406	0.010	0.962	0.012	0.941	0.408
Constant	True	True	True	True	True	True	True	True	True	True
Trend	False	False	False	False	False	True	True	True	True	True

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

This table show the results of the model (1)

Table 7: This table provides the results of the granger-causality test for the commodities market. Each column is the outcome variable and in each row, the coefficient associated with that variable is tested. In the last row, the test is in the block, being the block formed by the variables in the market opposite of the outcome variable. Furthermore, the granger-causality uses the linear equation from the VAR(2). The variables being tested are the return and volatility of the gold index, return, volatility, and the standardized trading volume from the cryptocurrency index.

	Gold		Volatility Gold		Crypto		Volatility Crypto		Standardize TV	
Variable	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Gold	14.503	0.001	2.191	0.334	0.682	0.711	0.113	0.945	0.183	0.913
Volatility Gold	1.442	0.486	53678.923	0.000	0.069	0.966	0.198	0.906	7.768	0.021
Crypto	6.119	0.047	0.521	0.771	10.154	0.006	228.919	0.000	7.581	0.023
Volatility Crypto	0.103	0.950	8.646	0.013	5.306	0.070	34177.581	0.000	60.723	0.000
Standardize TV	0.412	0.814	7.192	0.027	7.212	0.027	696.428	0.000	1268.657	0.000
Others	6.748	0.345	19.559	0.003	0.740	0.946	0.303	0.990	8.040	0.090

5.4 Interest Rates

Table 8 displays the results from the VAR estimation for the interest rate. The first five columns indicate the results from the VAR estimation without trend, and the last five with the inclusion of the trend. In the first column, it is possible to visualize that the variation in the 10-year interest rate of the USA is not predicted by any of the variables in VAR, especially the cryptocurrencies. In contrast, column two shows that the volatility of the variation of interest rates depends positively on its lags and the lag of the variation of the interest rate. More interestingly, the cryptocurrency's volatility and standardized trading volume are important predictors of interest rate volatility. The impact of cross-volatility changes of signal, being positive on the first lag and negative on the second, but the trading volume's effect is always positive. Therefore, the evidence is that cryptocurrency variables lead to the volatility of interest rates but show no impact on the interest rate variation. At the same time, the cryptocurrency return only depends on its lags. This pattern does not occur in the volatility and trading volume, which depends on the interest rate volatility. For the first, the second lag of the volatility is positive and statistically significant. The interest rate volatility negatively affects the trading volume, which is significant only in the first lag. Therefore, the VAR estimation indicates a positive leading and lag relationship between the volatilities. Concurrently, the relation between the interest rate volatility and trading volume indicates an inverse relationship. Interest volatility negatively leads to the trading volume, but the trading volume positively leads to the interest rate volatility.

Figure 9: This figure displays the Granger-causality test for the static VAR with Gold and cryptocurrency variables using a 252-day rolling window sample. The left axis shows the associated p-value of the test. The outcome variable is on top of each figure, and the predictive variables are all variables from other markets. The gray area denotes the periods in which the p-value is lower than 10%.

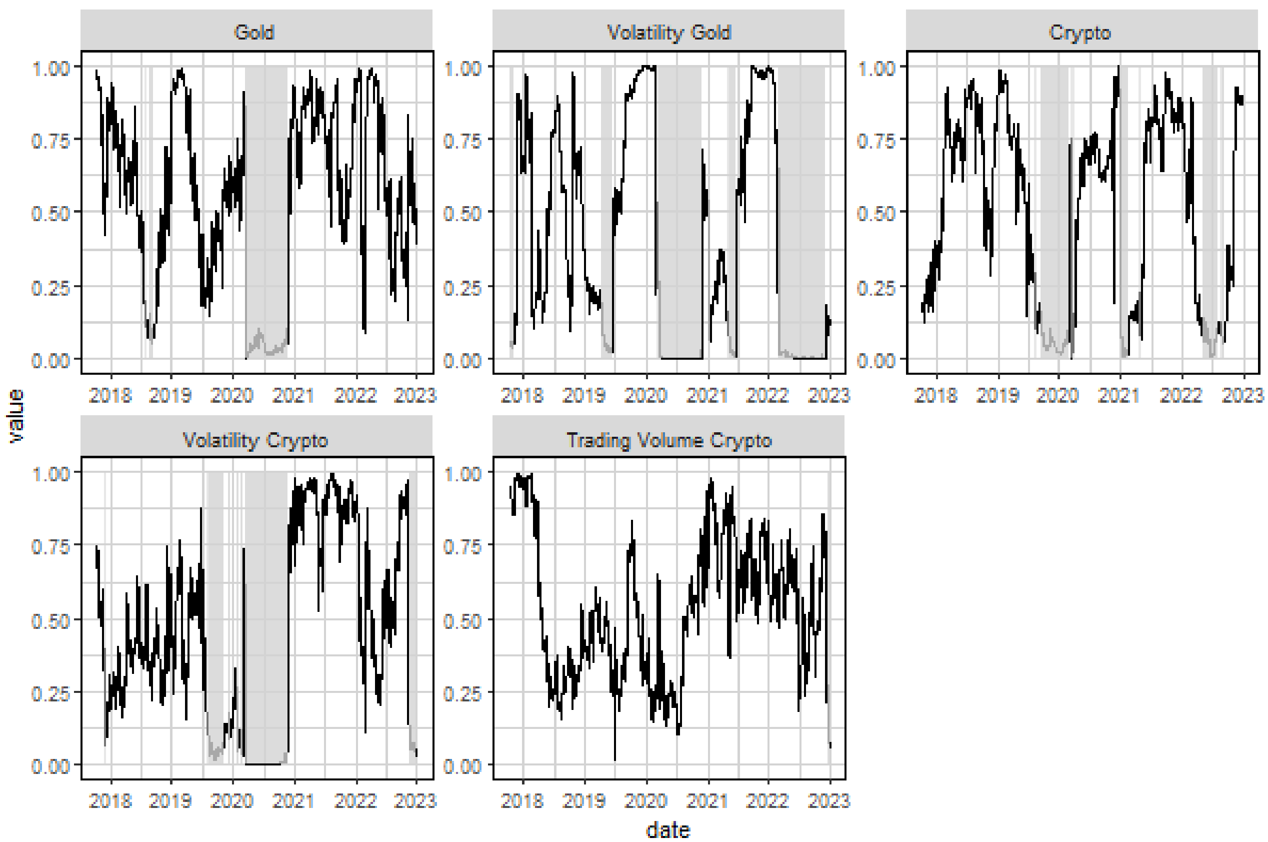
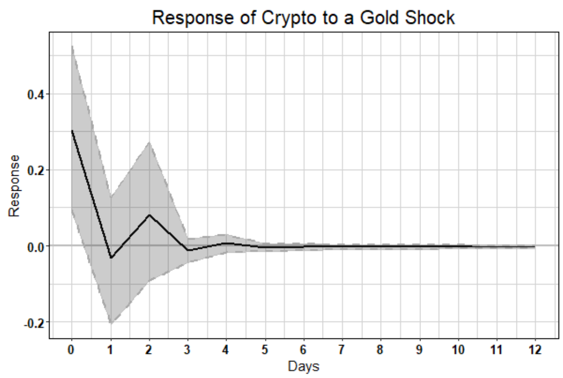
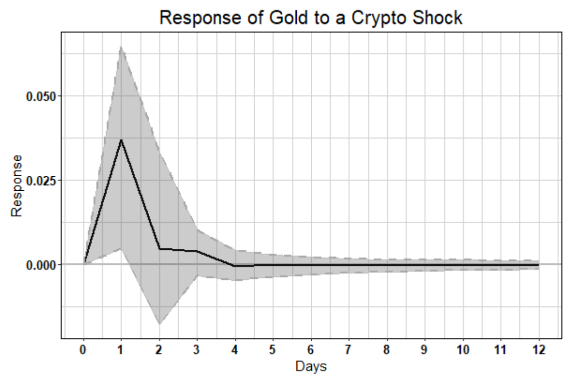


Figure 10: This figure shows the principal IRFs plots from the VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks and identify the errors. The order of the decomposition is the same as of the VAR(2), return and volatility of the libra index; return, volatility, and trading volume standardized of the cryptocurrency index.

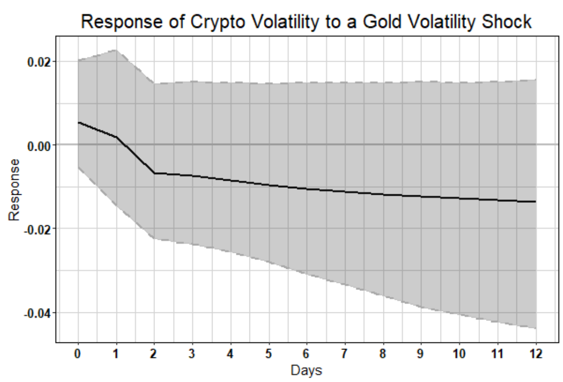
((a)) figure



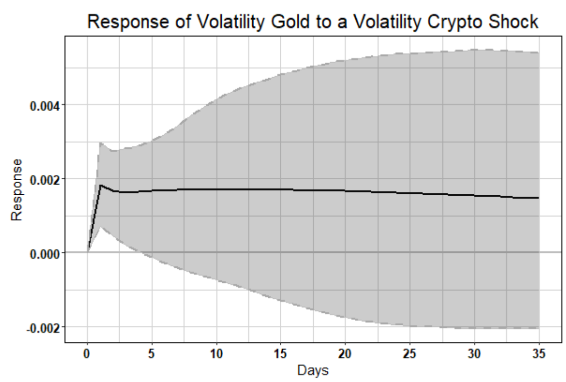
((b)) Figure



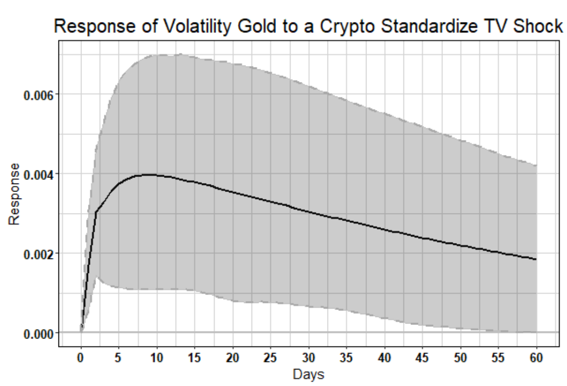
((c)) Figure



((d)) Figure



((e)) Figure



((f)) Figure

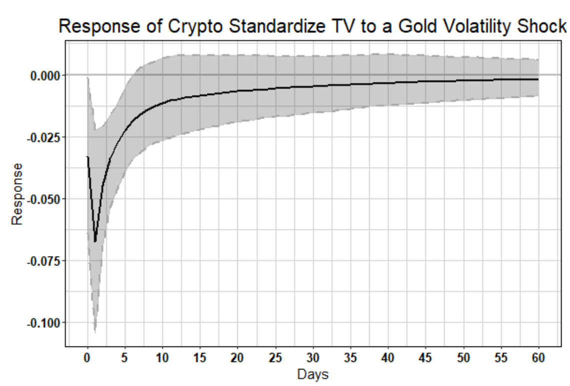
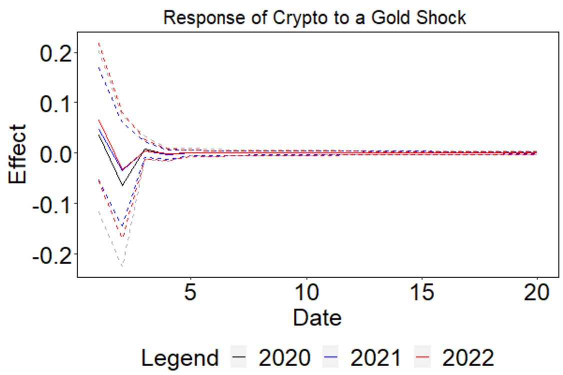
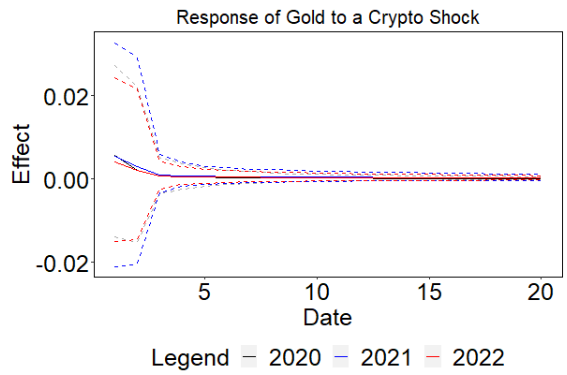


Figure 11: This figure shows the principal IRFs plots from the TVP-VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks and identify the errors. The order of the decomposition is the same as of the VAR(2), return and volatility of the libra index; return, volatility, and trading volume standardized of the cryptocurrency index.

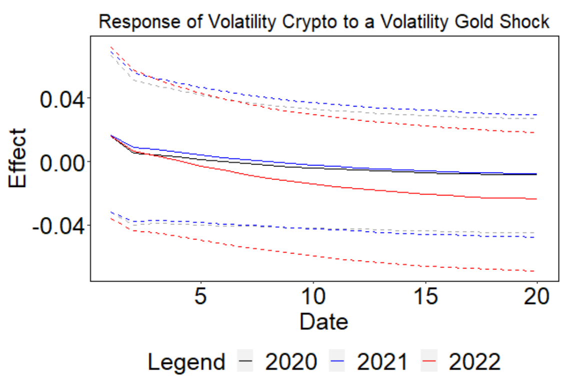
((a)) figure



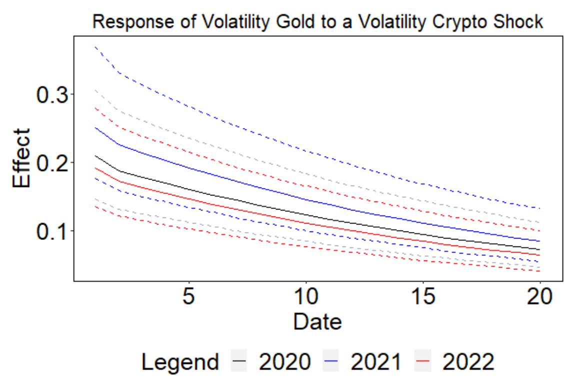
((b)) Figure



((c)) Figure



((d)) Figure



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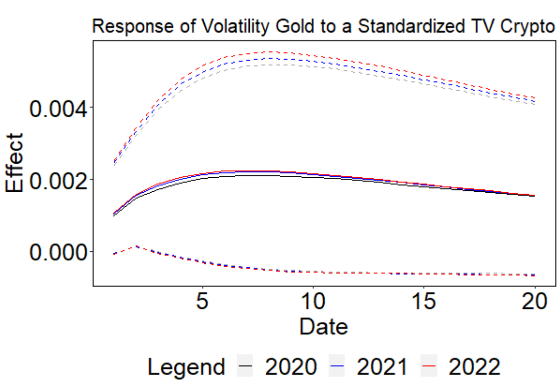


((f)) Figure

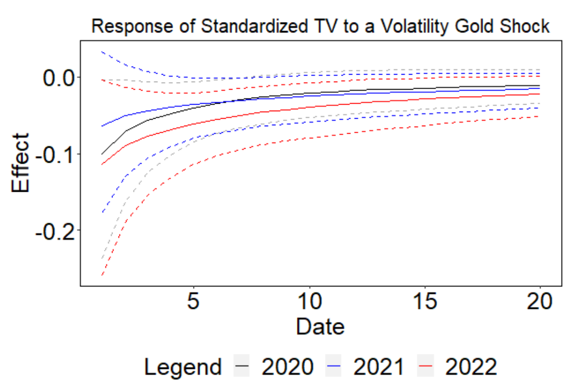


Figure 12: This figure displays the Granger-causality test for the static VAR with USA 10Y interest rate and cryptocurrency variables using a 252-day rolling window sample. The left axis shows the associated p-value of the test. The outcome variable is on top of each figure, and the predictive variables are all variables from other markets. The gray area denotes the periods in which the p-value is lower than 10%.

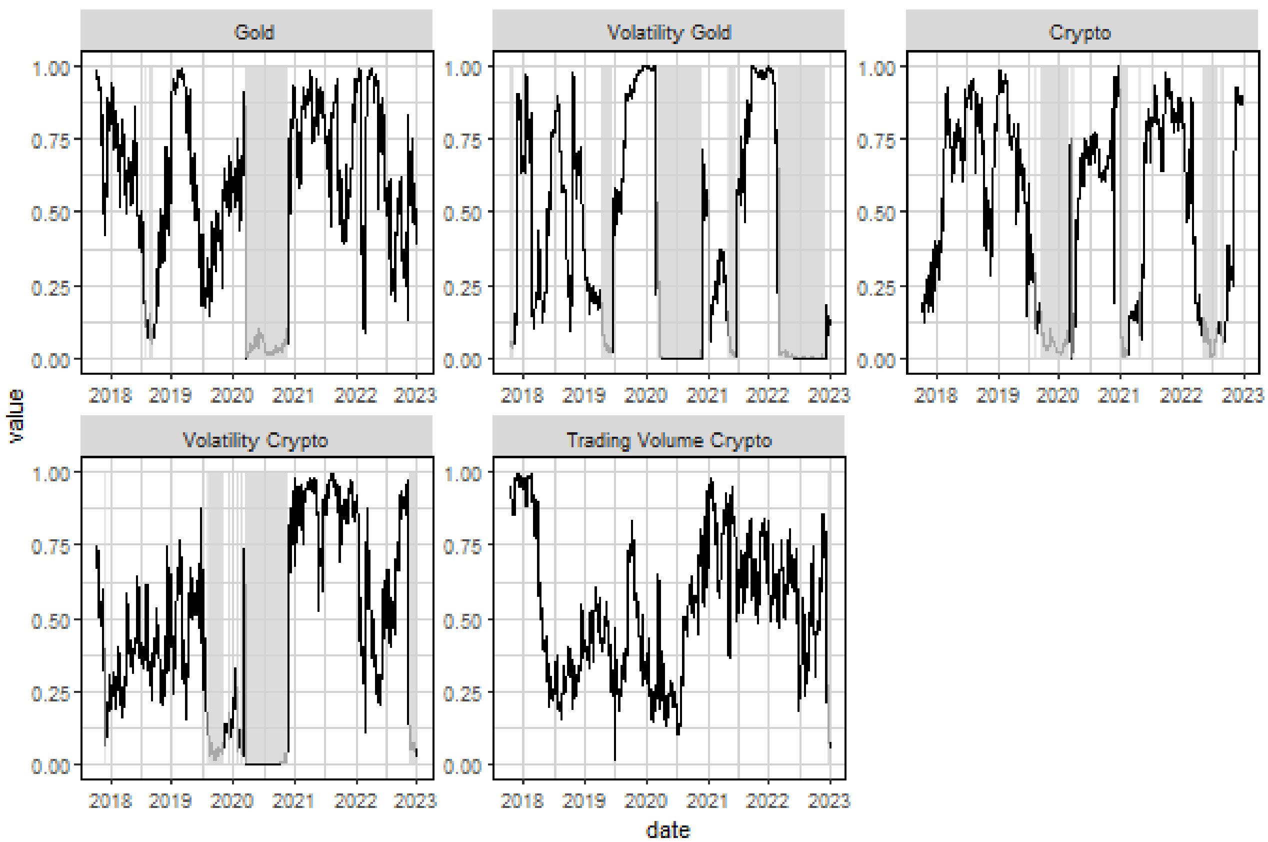


Table 8: Table VAR results

	USA 10Y	Volatility USA 10Y	Crypto	Volatility Crypto	Standardized TV	USA 10Y	Volatility USA 10Y	Crypto	Volatility Crypto	Standardized TV
USA_{t-1}	0.012	-0.022***	0.010	-0.002	-0.798	0.011	-0.023***	0.011	-0.002	-0.736
	(0.022)	(0.003)	(0.035)	(0.003)	(0.760)	(0.022)	(0.003)	(0.035)	(0.003)	(0.759)
Volatility USA_{t-1}	-0.027	0.383***	-0.274	-0.016	-21.790***	-0.060	0.368***	-0.246	-0.013	-20.208***
	(0.139)	(0.021)	(0.225)	(0.016)	(4.875)	(0.140)	(0.021)	(0.227)	(0.016)	(4.913)
$Crypto_{t-1}$	-0.020	0.000	-0.057**	-0.022***	0.921**	-0.019	0.001	-0.058**	-0.022***	0.893*
	(0.013)	(0.002)	(0.022)	(0.002)	(0.467)	(0.013)	(0.002)	(0.022)	(0.002)	(0.467)
Volatility $Crypto_{t-1}$	0.047	0.120***	-0.260	0.925***	-36.770***	0.051	0.122***	-0.264	0.925***	-36.975***
	(0.175)	(0.027)	(0.285)	(0.020)	(6.162)	(0.175)	(0.027)	(0.285)	(0.020)	(6.155)
Standardized TV_{t-1}	0.000	0.000**	0.001	0.002***	0.567***	0.000	0.000***	0.001	0.002***	0.564***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.021)	(0.001)	(0.000)	(0.001)	(0.000)	(0.021)
USA_{t-2}	0.014	-0.001	0.019	0.000	0.542	0.012	-0.001	0.021	0.000	0.636
	(0.022)	(0.003)	(0.035)	(0.003)	(0.767)	(0.022)	(0.003)	(0.035)	(0.003)	(0.767)
Volatility USA_{t-2}	-0.137	0.122***	-0.236	0.045**	-0.215	-0.164	0.109***	-0.213	0.047**	1.106
	(0.138)	(0.021)	(0.224)	(0.016)	(4.860)	(0.139)	(0.021)	(0.226)	(0.016)	(4.885)
$Crypto_{t-2}$	0.020	-0.001	0.040*	-0.010***	0.887*	0.020	-0.001	0.040*	-0.010***	0.854*
	(0.014)	(0.002)	(0.022)	(0.002)	(0.486)	(0.014)	(0.002)	(0.022)	(0.002)	(0.485)
Volatility $Crypto_{t-2}$	-0.079	-0.121***	0.412	0.054**	27.634***	-0.059	-0.112***	0.395	0.053**	26.700***
	(0.176)	(0.027)	(0.286)	(0.020)	(6.193)	(0.176)	(0.027)	(0.287)	(0.020)	(6.198)
Standardized TV_{t-2}	0.000	0.000**	0.001	-0.001***	0.097***	0.000	0.000*	0.001	-0.001***	0.094***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.022)	(0.001)	(0.000)	(0.001)	(0.000)	(0.022)
Constant	0.002	0.002***	-0.002	0.001**	0.468***	0.000	0.001*	0.000	0.001**	0.588***
	(0.002)	(0.000)	(0.003)	(0.000)	(0.069)	(0.002)	(0.000)	(0.004)	(0.000)	(0.085)
Num.Obs.	2159	2159	2159	2159	2159	2159	2159	2159	2159	2159
R2	0.004	0.227	0.013	0.942	0.411	0.005	0.238	0.013	0.942	0.413

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

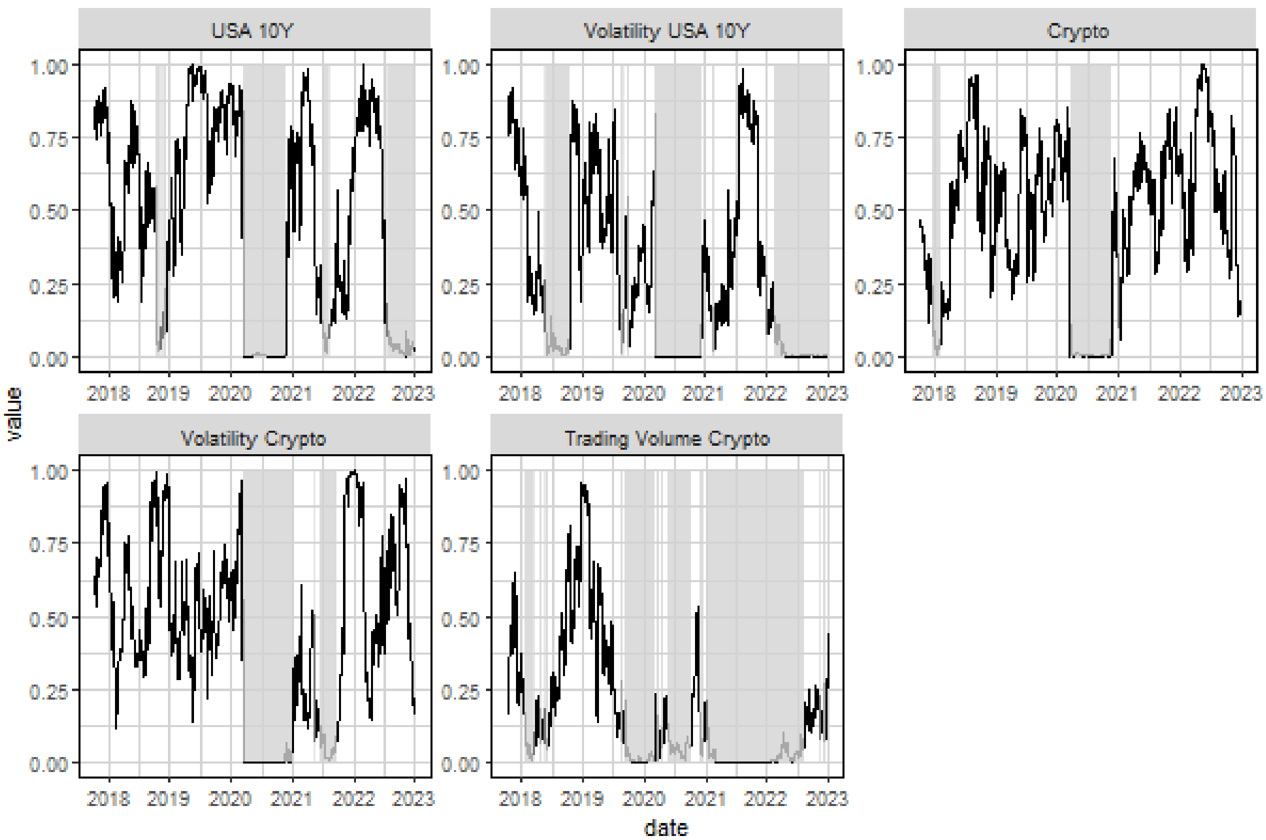
This table shows the results of the model (1)

Table 9: This table provides the results of the granger-causality test for the currency market. Each column is the outcome variable, and the coefficient associated with that variable is tested in each row. In the last row, the test is in the block, being the block formed by the variables in the market opposite of the outcome variable. Furthermore, the granger- causality uses the linear equation from the VAR(2). The variables being tested are the variation and volatility of the 10 year interest rate of the USA, return, volatility, and the standardized trading volume from the cryptocurrency index

	USA 10Y		Volatility USA 10Y		Crypto		Volatility Crypto		Standardize TV	
Variable	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
USA 10Y	0.715	0.699	45.011	0.000	0.382	0.826	0.857	0.652	1.578	0.454
Volatility USA 10Y	1.466	0.481	551.899	0.000	4.585	0.101	7.946	0.019	24.940	0.000
Crypto	4.452	0.108	0.189	0.910	10.827	0.004	227.274	0.000	6.874	0.032
Volatility Crypto	0.608	0.738	20.283	0.000	5.408	0.067	34385.518	0.000	60.638	0.000
Standardize TV	0.436	0.804	9.552	0.008	7.125	0.028	707.663	0.000	1282.891	0.000
ALL	5.583	0.472	35.607	0.000	5.141	0.273	8.932	0.063	27.957	0.000

Table 9 provides the granger-causality test for the model's VAR estimations, including the interest rate variables. Consistent with the coefficient in the estimation, the first column indicates that no variable granger causes the variation in the interest rate. The second column indicates that the return of the cryptocurrency does not granger-cause interest rate volatility. Nevertheless, this variable is granger-caused by crypto volatility and trading volume. The last row shows that all cryptocurrency variables together granger-cause interest volatility. At the same time, this is the only interest variable that granger-cause the crypto volatility and trading volume, both statistically significant at 5%. In extension, 13 shows the dynamic granger-causality test. Return and volatility across interest rates and cryptocurrency cause

Figure 13: This figure displays the Granger-causality test for the static VAR with a 252-day rolling window sample. The left axis shows the associated p-value of the test. The outcome variable is on top of each figure, and the predictive variables are all variables from other markets. The gray area denotes the periods in which the p-value is lower than 10%.



each other in the granger sense during the Covid period, similar to the findings in other markets. Furthermore, the trading volume of cryptocurrency is granger-caused in almost all intervals after 2020, except for the final half of 2020 and 2022. This pattern is similar to the granger-causality test in the Pound, and vaguely related to the SPX, but far from the granger-causality of Gold.

Figure 14 displays the IRFs for the VAR model that includes the interest rate variables. The first row on the left shows the response of the interest rate variation to a shock on the crypto return and the inverse at the right. Both plots indicate that no response is statistically significant at 5% confidence. The second row shows that the trading volume responds negatively to a shock in interest volatility. The effect is economically meaningful, achieving a lower value of -0.1 standard deviation around the three days and remains significant for at least ten days. The right panel shows the response of the cryptocurrency returns to a shock on the interest volatility. The initial impact is negative and only slightly significant around three and six days after the shock. The third row shows the response of the interest volatility to shocks in the crypto volatility and the standardized trading volume. Both plots are similar in the hump-shaped response and have a short-lived effect since the response is not statistically significant after two days. But the first is higher in magnitude, with the peak achieving 0.035 and the second 0.025. Therefore, the evidence from the IRfs indicates that cryptocurrency trading volume is large and negatively related to the volatility shock of the interest rate volatility. At the same time, the interest rate volatility is positively related to the crypto volatility and trading volume.

Figure 15 shows the time-varying IRFs for the interest rate market and cryptocurrency. Interestingly, in comparison with other markets, the IRFs are pretty similar over the years for most of the shocks. The exception is the response of the trading volume of cryptocurrency to a shock in the volatility of interest rates. The average response during 2022 is twice as negative as the impact during 2020, and both responses are only similar after almost ten days.

The literature has not explored the relationship between government bonds (i.e. interest rate) and the cryptocurrency market. It has been common to explore the connection with private bonds. In this context, Corbet et al., 2018 showed that bonds are more closely connected from Bitcoin in levels than Gold, SP500, and GSCI but lower in volatility. Our results indicate that the connection between the volatilities of both markets is tight, and the trading volume of cryptocurrency is also an essential channel to this connection.

Figure 14: This figure shows the principal IRF plots from the VAR(2) estimation. It uses a Cholesky decomposition of the shocks and identifies the errors. The order of the decomposition is the same as of the VAR(2), variation of the interest of ten years of USA its volatility, the return, volatility, and the standardized trading volume of the cryptocurrency index.

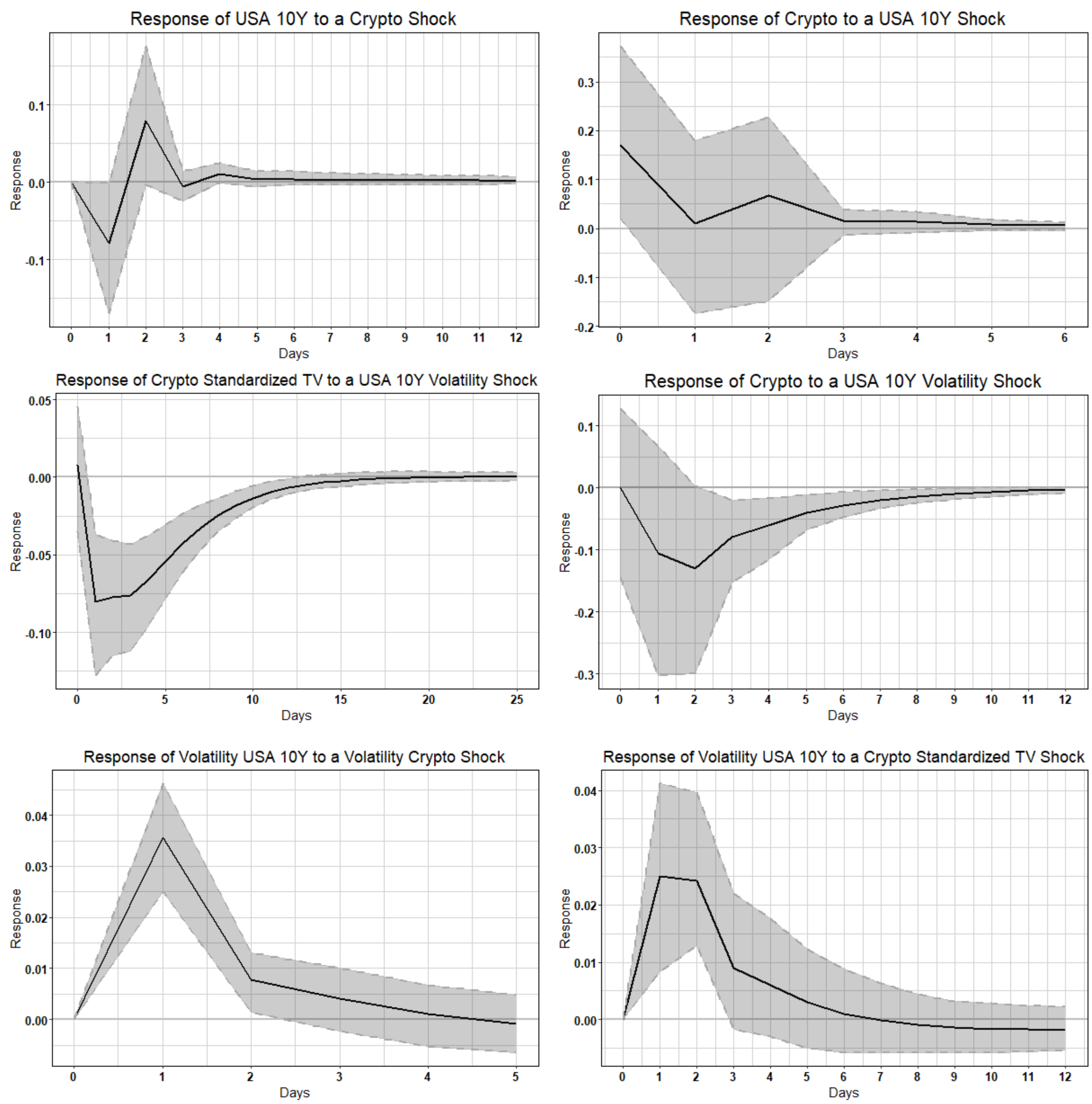
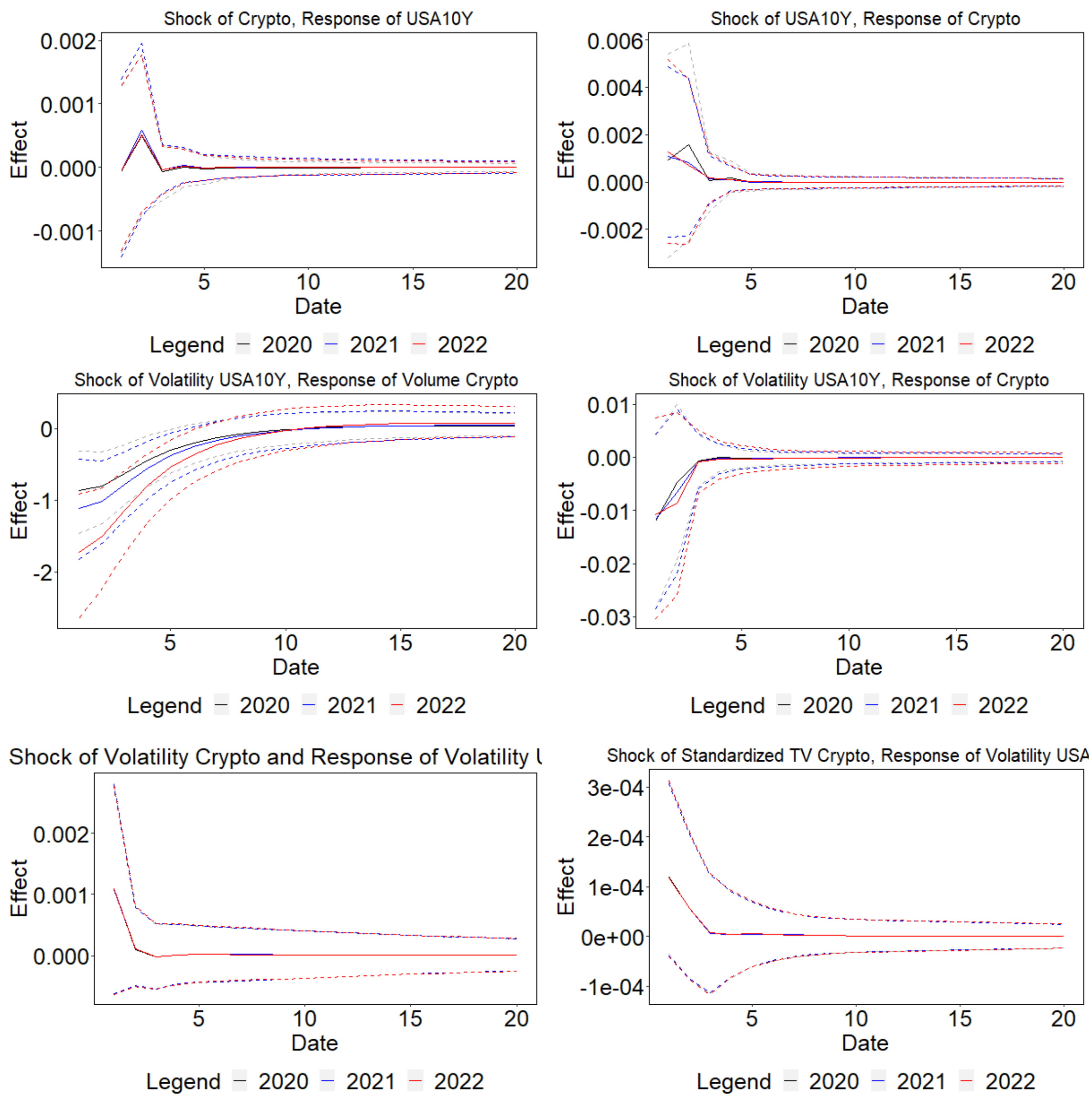


Figure 15: This figure shows the principal IRFs plots from the TVP-VAR(2) estimation. It uses a Cholesky decomposition of the shocks and identifies the errors. The order of the decomposition is the same as that of the VAR(2), the variation of the interest of the USA for ten years, its volatility, the return, volatility, and the standardized trading volume of the cryptocurrency index. Which line is the average and the 95% confidence interval for the average distribution over the year from 2020 to 2022.



6 Conclusion

In this study, we investigate which markets correlate with the cryptocurrency market. To summarize the crypto market, we constructed a cryptocurrency index from a universe of more than 9000 currencies. We extracted the return, volatility, and a measure of trading volume from this index. To uncover the leading and trailing among the variables, we use both a static VAR and a TVP-VAR estimation with the return, volatility, and trading volume from the cryptocurrency index and the return and volatility of the index from other markets, which are the equity, currency, and commodities sectors.

Our results indicate that the equity market and cryptocurrency are related. The return and our standardized measure of trading volume can predict the volatility of the SPX 500. Further, the main result in this market is the negative impact of the return and volatility of the SPX on the trading volume of the cryptocurrency index. Also, both responses vary over time, becoming more negative in the recent period.

Compared to the equities market, the currency market proxied by the British Pound is more disconnected from the cryptocurrency market. However, the Pound's volatility is impacted by two cryptocurrency variables volatility and trading volume. However, the impact of the former is significant in magnitude and lasts longer than the first. Furthermore, trading volume is also negatively impacted by a volatility shock of the Pound. Also, the effect is more negative in the recent period, this is similar to the response in volatility of SPX.

We also analyze the relationship between crypto and the commodities market proxied by gold. The main results indicate that cryptocurrency variables help predict the crypto's return and volatility. The opposite is not true except for trading volume, which is predicted only by gold volatility. Also, consistent with the results from other markets, a negative relation exists between the volatility of gold and the trading volume of crypto.

At last, we examine the variation of the ten-year interest rate of the USA and its relation with the cryptocurrency variables. Our results indicate a tight connection between the volatilities of interest and the crypto. Both have an essential leading impact on each other as they grange-cause one another. Furthermore, the standardized trading volume is negatively impacted by a shock of the volatility of the interest rate, as it was by shock on volatilities of the SPX, Pound, and Gold. If the trading volume responds to any volatility shocks and the trading volume generates large price movements, then the excessive volatility in the cryptocurrency market can be partially explained by spill-over volatilities. Moreover, similar to Pound and Gold, the volatility of the interest rates responds positively to shock on the standardized trading volume of crypto.

To conclude, our study disentangles the leading and trailing relation of cryptocurrency and equities, currency, and commodities markets. Our results indicate a cryptocurrency variable helps to predict volatility in other markets. Furthermore, we also document that volatility in other markets has a strong negative influence on the trading volume of the crypto index, and its response varies over time, being more negative in 2022 than in 2020. Since trading predicts volatility, there is a channel where the volatilities of other markets impact crypto, which helps to explain the excessive volatility in this market.

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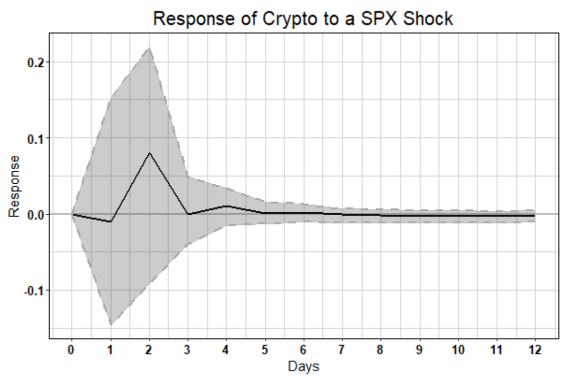
Appendix A - Robustness

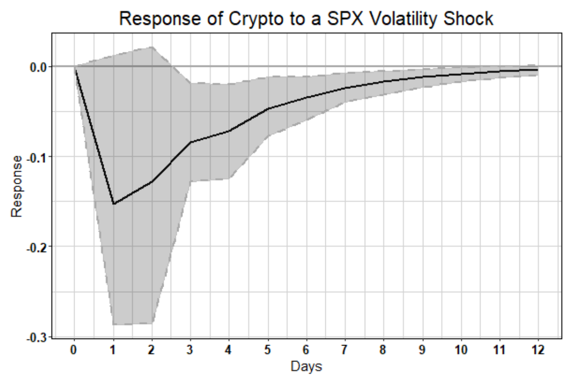
6.1 Equities

Figure 16: This figure shows the principal IRFs plots from the VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks to identify the errors. The order of the decomposition is the same as of the VAR(2), return and volatility of the SPX 500 index; return, volatility, and trading volume standardized of the cryptocurrency index.

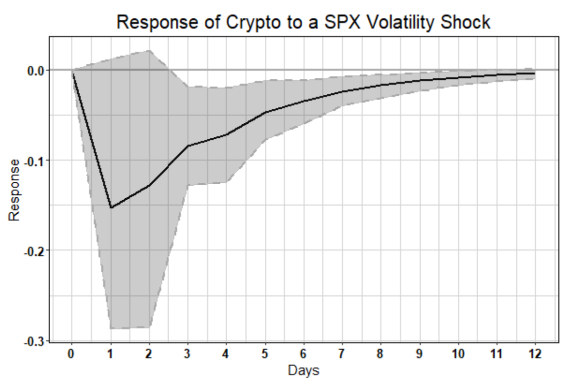
((a)) Figure



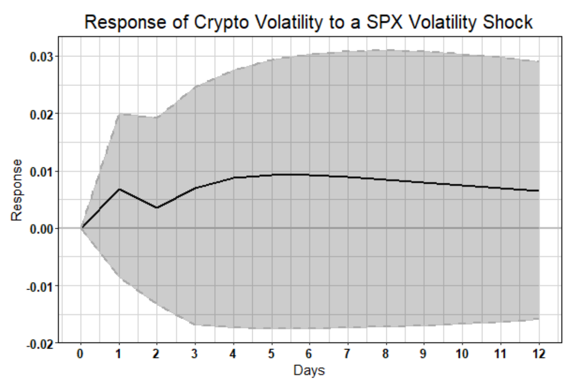
((b)) Figure



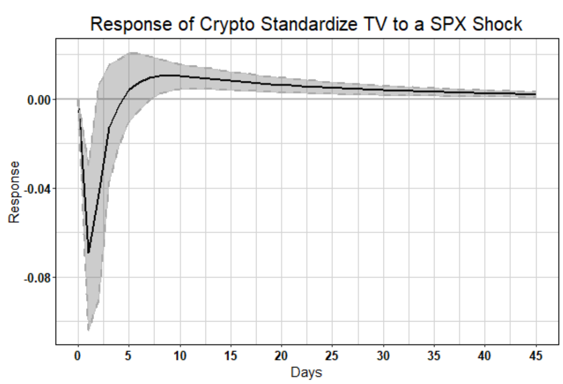
((c)) Figure



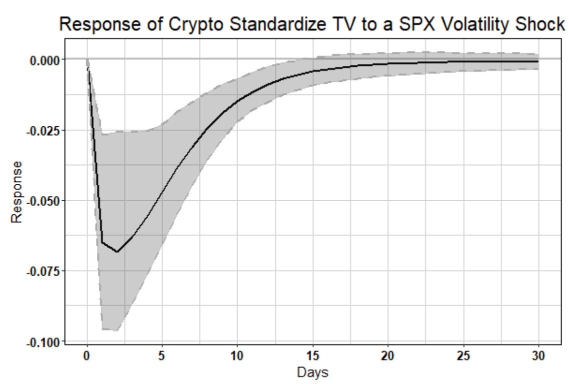
((d)) Figure



((e)) Figure



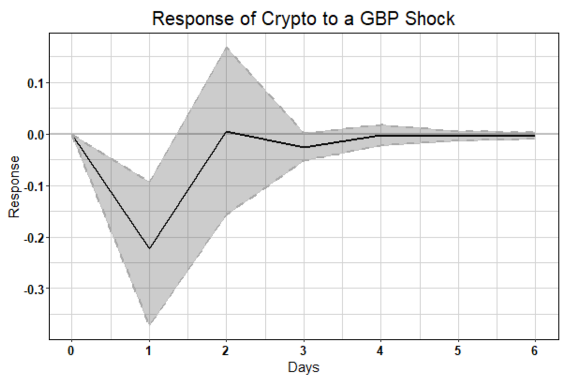
((f)) Figure



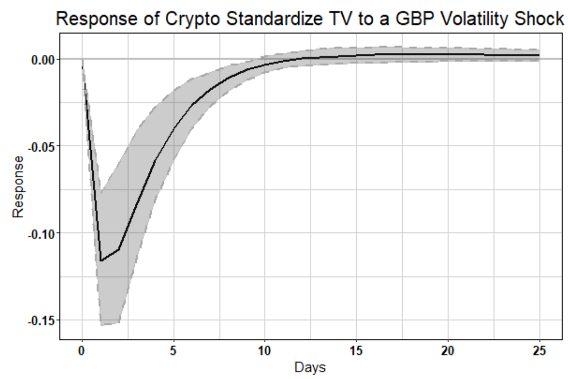
6.2 Currency

Figure 17: This figure shows the principal IRFs plots from the VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks to identify the errors. The order of the decomposition is return, volatility, and trading volume standardized of the cryptocurrency index and the return and volatility of the British pound.

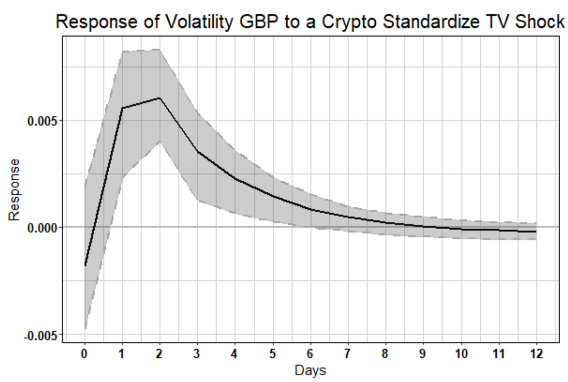
((a)) figure



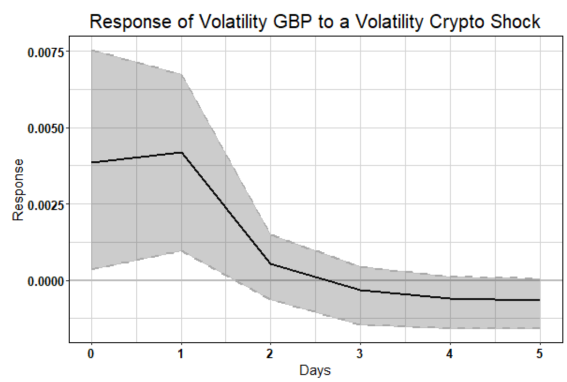
((b)) figure



((c)) figure



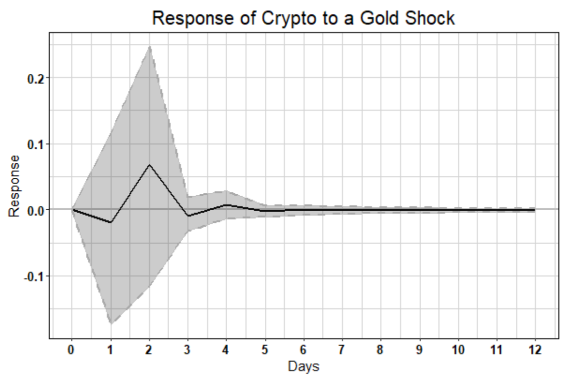
((d)) figure



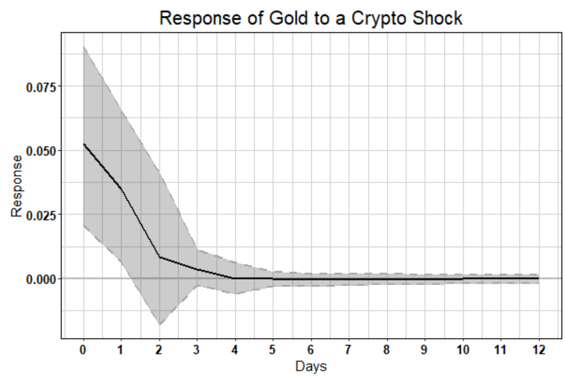
6.3 Commodities

Figure 18: This figure shows the principal IRFs plots from the VAR(2) estimation. It uses a Cholesky decomposition to decompose the shocks to identify the errors. The order of the decomposition is return, volatility, and trading volume standardized of the cryptocurrency index, return, and volatility of the Gold.

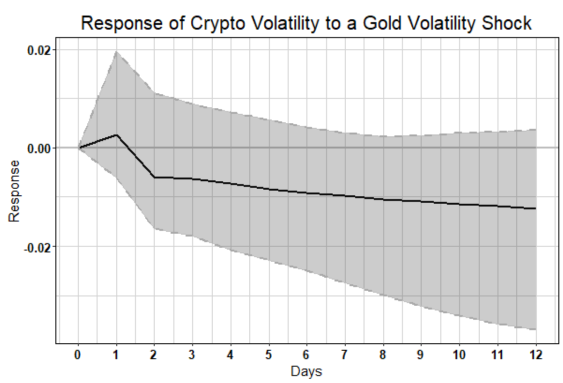
((a)) figure



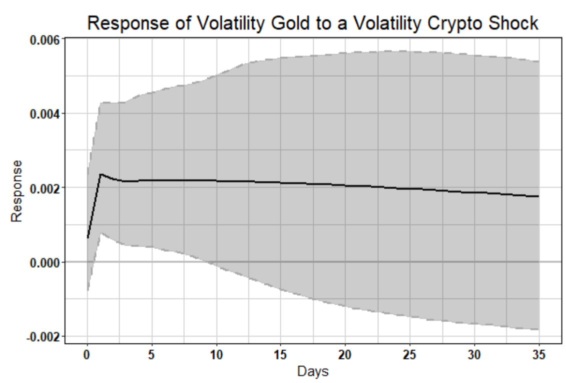
((b)) Figure



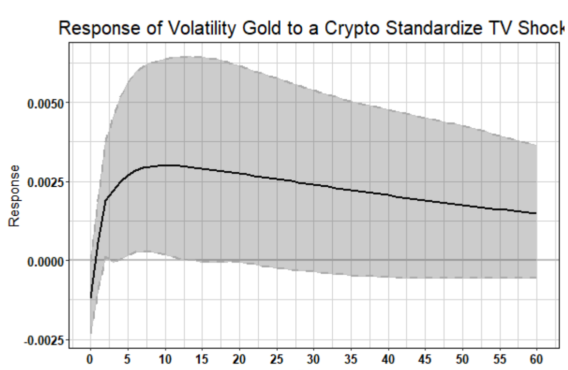
((c)) Figure



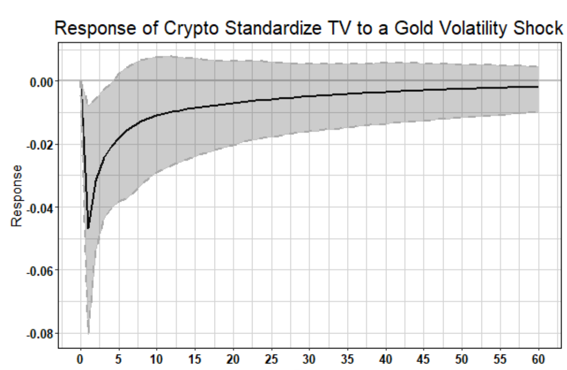
((d)) Figure



((e)) Figure



((f)) Figure



6.4 Interest

Figure 19: This figure shows the principal IRF plots from the VAR(2) estimation. It uses a Cholesky decomposition of the shocks to identify the errors. The order of the decomposition is the return, volatility, and the standardized trading volume of the cryptocurrency index. variation of the interest of ten years of USA its volatility.

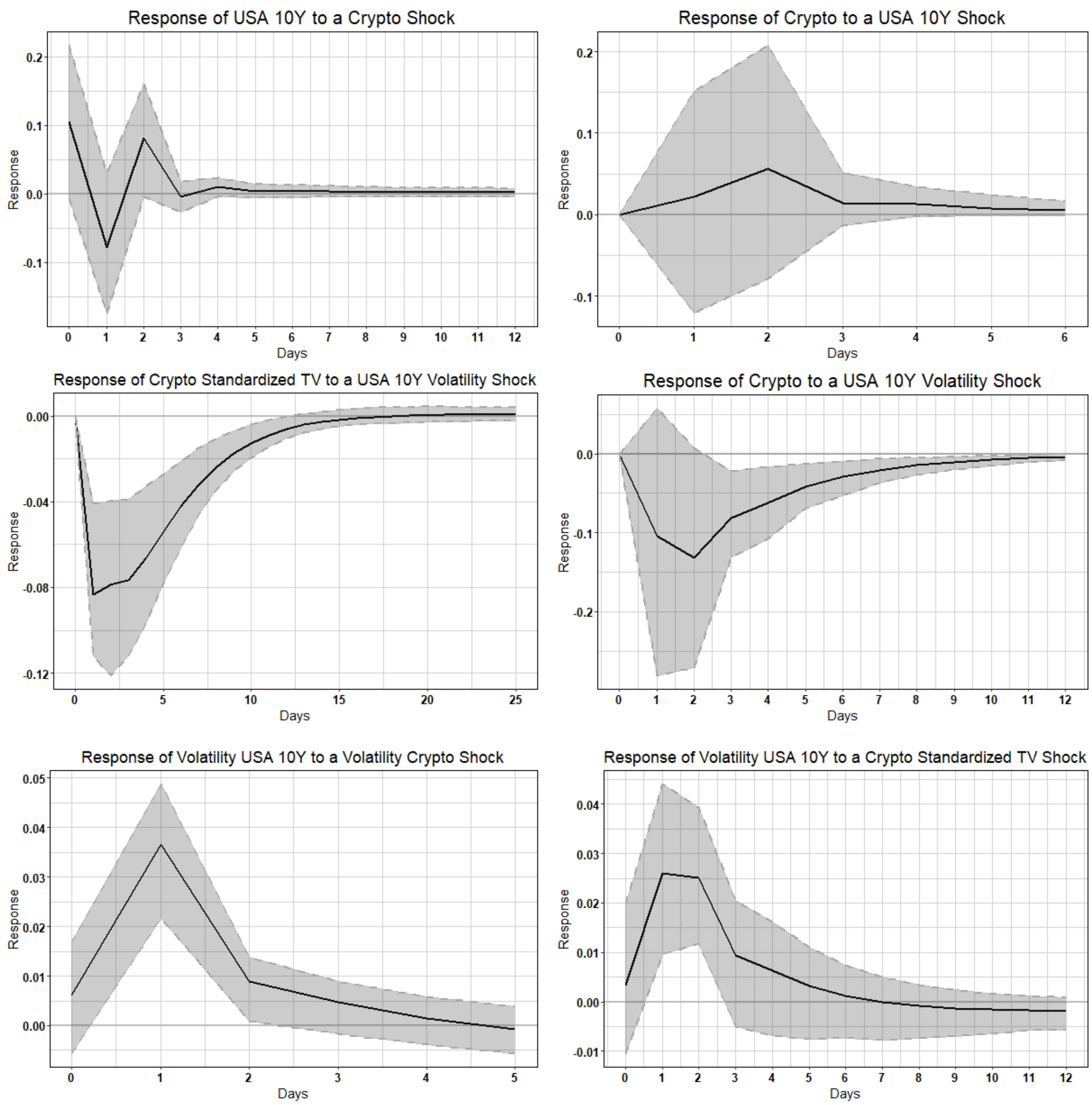


Table 10: Descriptive Statistics of the Estimated Volatility

Variable	Mean	Std	Median	Pct 25	Pct 75	Min	Max	Skewness	Kurtosis
Equity									
Volatility Equal Weighted CryptoIndex	0.122	0.123	0.081	0.040	0.158	0.024	1.501	3.001	18.923
Volatility Market Weighted CryptoIndex	0.629	0.189	0.595	0.494	0.727	0.312	1.539	1.123	4.743
Volatility Spx	0.021	0.027	0.012	0.006	0.026	0.005	0.384	4.243	34.092
Volatility Ccmp	0.027	0.031	0.015	0.008	0.032	0.006	0.371	3.182	19.106
Volatility Dji	0.021	0.027	0.011	0.006	0.024	0.005	0.396	5.023	46.123
Volatility Ndx	0.028	0.032	0.016	0.008	0.033	0.006	0.366	3.071	17.791
Volatility Mxwo	0.018	0.023	0.010	0.005	0.021	0.004	0.370	4.888	47.294
Currency									
Volatility Eur	0.009	0.009	0.006	0.003	0.012	0.002	0.076	2.303	10.544
Volatility Sdr	0.004	0.004	0.003	0.001	0.005	0.001	0.063	3.444	27.041
Volatility Jpy	0.009	0.011	0.006	0.003	0.012	0.002	0.141	4.005	31.483
Volatility Gbp	0.011	0.012	0.007	0.004	0.014	0.002	0.134	3.197	19.840
Volatility Cnh	0.006	0.007	0.004	0.002	0.008	0.001	0.074	3.290	19.883
Commodities									
Volatility Gold	0.107	0.025	0.100	0.092	0.112	0.084	0.285	3.069	15.511
Volatility Wti	0.250	0.128	0.236	0.236	0.236	0.236	2.283	11.010	136.498
Volatility Brent	0.045	0.055	0.026	0.014	0.054	0.010	0.904	5.088	50.756
Interest Rate									
Volatility Usa 10 Y	0.057	0.069	0.033	0.017	0.068	0.012	0.611	3.769	23.543
Volatility Eur 10 Y	0.387	1.164	0.198	0.172	0.292	0.166	23.204	14.595	257.335
Volatility Gbp 10 Y	0.123	0.165	0.064	0.038	0.138	0.029	1.878	4.683	36.609
Volatility Cny 10 Y	0.080	0.024	0.071	0.063	0.088	0.056	0.210	1.817	6.801
Volatility Jpy 10 Y	1.101	2.430	0.464	0.386	0.746	0.373	23.655	5.978	43.285

6.5 Descriptive and Diagnostics Volatility Table

Table 11: Diagnostic Volatility table

	LB Test			LB on Squared Residuals			ARCH Test		
Variable	Stat	P-value	Lag	Stat	P-value	Lag	Stat	P-value	Lag
Equity									
Equal Weighted CryptoIndex	4.45	0.20	5	2.44	0.52	5	2.00	0.68	5
Market Weighted CryptoIndex	5.38	0.12	5	2.93	0.77	9	2.96	0.52	5
Spx	6.57	0.07	5	6.35	0.07	5	3.76	0.34	5
Ccmp	5.54	0.12	5	5.98	0.09	5	3.09	0.45	5
Dji	4.08	0.24	5	5.51	0.12	5	7.03	0.07	5
Ndx	6.59	0.06	5	3.52	0.32	5	2.75	0.52	5
Mxwo	5.22	0.14	5	7.20	0.05	5	6.52	0.09	5
Currency									
Euro	4.93	0.16	5	6.80	0.06	5	3.35	0.41	5
Sdr	4.61	0.19	5	9.41	0.01	5	5.68	0.14	5
Jpy	6.56	0.07	5	6.37	0.07	5	3.29	0.42	5
Gbp	2.12	0.59	5	0.90	0.88	5	0.41	0.98	5
Cnh	5.22	0.14	5	4.80	0.17	5	2.88	0.49	5
Commodities									
Gold	9.51	0.01	5	5.08	0.42	9	6.24	0.13	5
WTI	36.93	0.00	5	5.54	0.12	5	1.53	0.79	5
Brent	1.12	0.83	5	4.04	0.25	5	2.77	0.51	5
Interest Rate									
USA 10 Y	8.46	0.02	5	3.30	0.36	5	1.07	0.88	5
Euro 10 Y	10.03	0.01	5	8.57	0.02	5	16.30	0.00	5
Gbp 10 Y	3.46	0.33	5	2.06	0.60	5	1.52	0.79	5
Cny 10 Y	10.76	0.01	5	15.57	0.02	14	9.84	0.02	5
Jpy 10 Y	2.96	0.41	5	0.37	1.00	9	0.45	0.98	5

Descriptive tables

Table 12: Descriptive Table Equities Index

	Mean	Std	Median	Pct 25	Pct 75	Min	Max	Skewness	kurtosis	DF Stat	DF Cvalue
Portfolio Cryptocurrency Index	0.0022	0.0406	0.0022	-0.0161	0.0217	-0.3678	0.2341	-0.4285	8.8054	-31.8461	-1.9500
Volume Cryptocurrency Index	154.8776	133.5684	139.4580	32.2835	225.0423	0.6668	660.1171	1.1386	4.3036	-4.0923	-1.9500
Standardized Volume Cryptocurrency Index	0.0928	1.1386	-0.0378	-0.7337	0.7601	-2.4525	5.0246	0.7922	3.7850	-19.2340	-1.9500
Spx	0.0003	0.0097	0.0004	-0.0023	0.0034	-0.0951	0.0938	-0.0068	20.7319	-33.1437	-1.9500
Ccmp	0.0004	0.0115	0.0007	-0.0031	0.0045	-0.0943	0.0935	-0.1260	12.3832	-33.3567	-1.9500
Dji	0.0003	0.0096	0.0003	-0.0024	0.0034	-0.0999	0.1137	0.0353	28.2657	-32.0300	-1.9500
Ndx	0.0004	0.0119	0.0008	-0.0036	0.0047	-0.0927	0.1007	-0.0521	11.9109	-34.1924	-1.9500
Mxwo	0.0002	0.0081	0.0003	-0.0022	0.0029	-0.0992	0.0877	-0.4560	25.9817	-29.4113	-1.9500
σ Portfolio Cryptocurrency Index	0.0396	0.0119	0.0375	0.0311	0.0457	0.0197	0.0969	1.1353	4.7742	-1.9168	-1.9500
σ Spx	0.0014	0.0017	0.0007	0.0004	0.0016	0.0003	0.0242	4.2407	34.2448	-14.2293	-1.9500
σ Ccmp	0.0017	0.0019	0.0010	0.0005	0.0020	0.0004	0.0233	3.1657	19.0878	-14.3773	-1.9500
σ Dji	0.0013	0.0017	0.0007	0.0004	0.0015	0.0003	0.0249	5.0285	46.3882	-13.8344	-1.9500
σ Ndx	0.0018	0.0020	0.0010	0.0005	0.0021	0.0004	0.0231	3.0535	17.7590	-14.3904	-1.9500
σ Mxwo	0.0011	0.0014	0.0006	0.0003	0.0013	0.0003	0.0233	4.8973	47.6335	-14.3048	-1.9500

Table 13: Descriptive Table Commodities

	Mean	Std	Median	Pct 25	Pct 75	Min	Max	Skewness	kurtosis	DF Stat	DF Cvalue
Portfolio Cryptocurrency Index	0.0022	0.0406	0.0022	-0.0161	0.0217	-0.3678	0.2341	-0.4285	8.8054	-31.8461	-1.9500
Volume Cryptocurrency Index	154.8776	133.5684	139.4580	32.2835	225.0423	0.6668	660.1171	1.1386	4.3036	-4.0923	-1.9500
Standardized Volume Cryptocurrency Index	0.0928	1.1386	-0.0378	-0.7337	0.7601	-2.4525	5.0246	0.7922	3.7850	-19.2340	-1.9500
σ Portfolio Cryptocurrency Index	0.0396	0.0119	0.0375	0.0311	0.0457	0.0197	0.0969	1.1353	4.7742	-1.9168	-1.9500
Gold	0.0002	0.0070	0.0003	-0.0024	0.0029	-0.0463	0.0595	-0.1093	12.0286	-31.1149	-1.9500
Brent	0.0004	0.0198	0.0011	-0.0062	0.0077	-0.2440	0.2102	-0.2661	27.2986	-29.5423	-1.9500
σ Gold	0.0067	0.0016	0.0063	0.0058	0.0070	0.0053	0.0180	3.1093	15.7050	-0.9635	-1.9500
σ Brent	0.0028	0.0035	0.0017	0.0009	0.0034	0.0006	0.0569	5.1115	51.2665	-16.2720	-1.9500

Table 14: Descritive Table Currency

	Mean	Std	Median	Pct 25	Pct 75	Min	Max	Skewness	kurtosis	DF Stat	DF Cvalue
Portfolio Cryptocurrency Index	0.0022	0.0406	0.0022	-0.0161	0.0217	-0.3678	0.2341	-0.4284	8.8014	-31.8448	-1.9500
Volume Cryptocurrency Index	22.8991	1.3014	23.3587	21.8972	23.8372	18.0153	24.9131	-1.0233	3.6976	0.1811	-1.9500
Standardized Volume Cryptocurrency Index	0.0932	1.1387	-0.0373	-0.7328	0.7602	-2.4525	5.0246	0.7915	3.7842	-19.2296	-1.9500
Eur	0.0000	0.0036	0.0000	-0.0016	0.0014	-0.0204	0.0213	0.1371	6.8801	-31.2752	-1.9500
SDR	0.0000	0.0017	0.0000	-0.0007	0.0006	-0.0124	0.0187	0.4426	14.6656	-30.6847	-1.9500
GBP	0.0000	0.0046	0.0000	-0.0018	0.0018	-0.0371	0.0315	-0.0492	11.2270	-30.8107	-1.9500
Jpy	0.0001	0.0039	0.0001	-0.0012	0.0016	-0.0378	0.0320	-0.5366	17.2393	-32.0363	-1.9500
Cnh	0.0000	0.0025	0.0000	-0.0009	0.0010	-0.0198	0.0113	-0.7938	10.9556	-33.0836	-1.9500
σ Eur	0.0006	0.0006	0.0004	0.0002	0.0008	0.0001	0.0048	2.2970	10.5569	-16.0381	-1.9500
σ GBP	0.0007	0.0008	0.0004	0.0002	0.0009	0.0001	0.0085	3.2206	20.1821	-16.4488	-1.9500
σ Sdr	0.0003	0.0003	0.0002	0.0001	0.0003	0.0001	0.0040	3.4705	27.7249	-16.6021	-1.9500
σ Jpy	0.0006	0.0007	0.0003	0.0002	0.0007	0.0001	0.0089	4.1178	33.4838	-16.6795	-1.9500
σ Cnh	0.0004	0.0004	0.0002	0.0001	0.0005	0.0001	0.0047	3.2856	20.3482	-16.3785	-1.9500
σ Portfolio Cryptocurrency Index	0.0396	0.0119	0.0375	0.0311	0.0457	0.0197	0.0969	1.1349	4.7739	-1.9324	-1.9500

Table 15: Descriptive Table Currency Interest Rates

	Mean	Std	Median	Pct 25	Pct 75	Min	Max	Skewness	kurtosis	DF Stat	DF Cvalue
Portfolio Cryptocurrency Index	0.0022	0.0406	0.0022	-0.0161	0.0217	-0.3678	0.2341	-0.4284	8.8014	-31.8448	-1.9500
Volume Cryptocurrency Index	22.8991	1.3014	23.3587	21.8972	23.8372	18.0153	24.9131	-1.0233	3.6976	0.1811	-1.9500
Standardized Volume Cryptocurrency Index	0.0932	1.1387	-0.0373	-0.7328	0.7602	-2.4525	5.0246	0.7915	3.7842	-19.2296	-1.9500
Usa 10 Y	0.0004	0.0249	0.0008	-0.0080	0.0090	-0.1637	0.1775	-0.3045	14.5309	-32.1775	-1.9500
Eur 10 Y	-0.0098	0.3338	0.0000	-0.0291	0.0296	-6.2392	2.7548	-10.7918	219.4167	-30.9571	-1.9500
σ Eur 10 Y	0.0243	0.0736	0.0124	0.0108	0.0183	0.0105	1.4617	14.6401	257.7606	-22.1890	-1.9500
σ Usa 10 Y	0.0036	0.0043	0.0021	0.0011	0.0043	0.0008	0.0385	3.7724	23.6595	-14.9463	-1.9500
σ Portfolio Cryptocurrency	0.0396	0.0119	0.0375	0.0311	0.0457	0.0197	0.0969	1.1349	4.7739	-1.9324	-1.9500