Cryptocurrencies, Stocks, and Economic Policy Uncertainty: A FAVAR Analysis

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Abstract

We study the interactions between cryptocurrencies, stock markets, and economic policy uncertainty (EPU) by means of a Factor-Augmented Vector Autoregressive (FAVAR) framework. We rely on two market factors to model the comovements of returns within cryptocurrencies and stock markets. We document a greater heterogeneity across cryptocurrencies than stocks, with a fragmentation of the market by functional characteristics of the projects. We then use a structural analysis to explore cross-market spillover effects and how EPU affects the two markets. We find that stock returns positively respond to crypto shocks, but not vice versa. We also find that the effect of EPU on crytpo returns depends on the originating region of the policy uncertainty, with cryptocurrencies providing a safe haven against the Chinese and the U.K., but not the U.S., EPU.

Keywords: Cryptocurrencies, Blockchain, Financial Markets, Macroeconomic Shocks, FAVAR.

JEL Classification: G1, G11,G15,O16,O33, F31

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1 Introduction

In little more than a decade since the introduction of Bitcoin in 2009, cryptocurrencies went from a fringe type of asset, mostly suitable for a niche of specialized tech investors, to a global market that reached 3 trillion dollars of capitalization at its peak in 2021 before plummeting to 1 trillion during the so-called crypto winter of 2022. Although still a small market compared to the traditional equity markets,[1] the exponential pace at which the cryptocurrency space has grown since 2017-18 reflects the mounting interest for this type of investment by a very broad variety of investors, often attracted by the large gains it can offer. Crypto trading has turned into a mainstream activity, as all the media attention caused by the recent collapse of the FTX exchange has reminded us.

Despite this increase in trading, however, cryptocurrencies remain a risky and difficult asset category to understand. The widespread popularity of crypto trading raises numerous questions. How should these assets be correctly priced? What are the fundamentals driving the price of cryptocurrencies? Are we just witnessing another bubble? Can big players manipulate this market at the expense of smaller, unsophisticated investors? All these questions have spurred a rich academic literature analyzing cryptocurrencies, and especially Bitcoin.

In this paper, we study crypto markets from an aggregate prospective, and put them in relation to traditional equity markets and macroeconomic variables at weekly frequency in a unified Factor-Augmented Vector Autoregression (FAVAR) framework. The FAVAR model allows us to estimate a common crypto market factor extracted from a large set of 64 cryptocurrencies and a global stock market factor from 38 major international stock indexes. We use this model to analyze the interactions between the two market factors and to study the impact of economic policy uncertainty (EPU) of the U.S., as well as of China and the U.K., on the market factors. Our results illustrate three main points.

First, the use of a factor to represent the crypto market provides a convenient way to model a diverse set of assets without relying only on the return dynamics of Bitcoin or of a few other cryptocurrencies. We find that cryptocurrency returns are characterized by very large

[1] The crypto market has never represented more than 3% of the global stock market.

idiosyncratic cross-sectional differences. Cryptocurrencies can be grouped in a few clusters of projects with technological and functional similarities, and appear much less cohesive than their stock counterparts.

Second, we conduct a structural impulse response analysis identifying the structural shocks of the model with a recursive Cholesky scheme. The core identifying assumption is that the the financial sector variables respond on impact to the other shocks, while the response of the real sector variables occurs with a lag. In the real sector, we include an economic activity index, a policy rate, and an economic policy uncertainty index which is ordered last within the macro block.

We find that the crypto market factor does not respond to shocks to the traditional stock market factor. On the contrary, a positive shock to the crypto factor causes an increase in stock returns as well. The crypto shock also shows that crypto returns are autocorrelated and significantly persistent for three weeks, in violation of market efficiency. The response of the stock returns to the crypto shock also remains positive for up to four weeks. The lack of feedback from stocks to the crypto market reflects the hypothesis that cryptocurrencies are largely independent from traditional markets. However, the effect of crypto markets on traditional markets is a first indication that a broader transmission channel could be in place. We characterize this effect by showing that it could be explained by the correspondence with broader common shocks hitting financial investors across markets.

Third, we uncover a novel effect of economic policy uncertainty shocks on crypto markets. This effect takes different forms relative to the country of origin of the uncertainty. Cryptocurrencies can provide either hedging or safe-haven opportunities against EPU. On the one hand, cryptocurrencies and traditional stock returns move in opposite directions in response to an U.S. EPU shock. Cryptocurrencies can be used as a hedge against movements in the U.S. EPU. On the the other hand, an increase in the Chinese or U.K. EPU causes an increase of both traditional stock and crypto returns. In this case, cryptocurrencies (and traditional stocks) behave as a safe-haven against EPU shocks.

This third result is interesting for at least two reasons. First, we document that cryptocurrencies can actually be a useful diversification tool in portfolio management strategies in relation to economic policy uncertainty shocks. One of the main advantages that Bitcoin was expected to provide is a protection against inflation of traditional fiat currencies. The literature, however, has found limited evidence in support of this role of Bitcoin. Similar weak evidence has been found for the portfolio diversification properties of Bitcoin against EPU, mostly limited to extreme market conditions. Our structural analysis, on the contrary, obtains significant and robust results, which apply to a general, diverse time period.

The second reason is that the portfolio diversification properties of cryptocurrencies against economic policy uncertainty depends on the originating region of the uncertainty shocks. This reflects a higher segmentation of the crypto space, where investors from different countries with exposure to shocks from different regions of the world could invest in cryptocurrencies pursuing quite different goals and strategies. Similarly, Karau (2021) finds that the Bitcoin prices respond differently to monetary shocks from the ECB or the Fed. These differences, for example, have relevant implications for policy makers and international coordination in designing regulatory frameworks for cryptocurrencies.

Related Literature. We can identify at least three main strands of the cryptocurrency literature that are relevant for our study. First, early work studies the economics of cryptocurrencies, especially from a theoretical perspective. The focus of this strand is on how blockchain technology, the underlying technology which constitutes the backbone of cryptocurrencies, relates to the price of cryptocurrencies. This literature explores the role of incentives in mining and Proof-of-Work consensus protocols (Abadi and Brunnermeier, 2018; Auer, 2019; Huberman, Leshno, and Moallemi, 2021), the pricing dynamic in equilibrium models (Biais, Bisiére, Bouvard, Casamatta, and Menkveld, 2020; Choi and Rocheteau, 2021; Prat and Walter, 2021), and how adoption affects the price of cryptocurrencies in models with competing forms of currencies (Schilling and Uhlig, 2019a,b; Benigno, Schilling, and Uhlig, 2019; Bolt and Van Oordt, 2020). This body of work provides some of the theoretical background to understand crypto markets and on which we also rely in our analysis.

Second, a significant strand of the literature analyzes different aspects of the crypto market price dynamics. An important theme is price manipulation by large, sophisticated players in these markets and the impact on small, unsophisticated investors. For example, work in this area documents the influence of the supply of stablecoins, suspicious trading activity on the price of Bitcoin (Griffin and Shams, 2020; Gandal, Hamrick, Moore, and Oberman, 2018), and the concentration of crypto holdings in a small number of wallets (Sai, Buckley, and LeGear, 2021). It also demonstrates the pervasive use of pump-and-dump schemes in crypto markets (Li, Shin, and Wang, 2021) and the existence of recurrent arbitrage opportunities across exchanges, especially when Bitcoin appreciates (Makarov and Schoar, 2020). Finally, it also studies the similarities between tokens issued in Initial Coin Offerings and equity issued in Initial Public Offerings (Lyandres, Palazzo, and Rabetti, 2020). Our findings about the inefficiency and segmentation of the cryptocurrency markets directly speak to this strand.

Third, cryptocurrencies are also studied in the context of portfolio management and investment diversification. Empirical models relying on multiple quantitative techniques have been used to forecast crypto prices (Chevallier, Guégan, and Goutte, 2021; Bartolucci, Destefanis, Ortu, Uras, Marchesi, and Tonelli, 2020), for asset selection (Bartolucci and Kirilenko, 2020), and to identify fundamentals able to explain the cross-section variation of returns (Bhambhwani, Delikouras, and Korniotis, 2021; Zhang, Li, Xiong, and Wang, 2021). Similarly, this strand of the literature explores the relation between crypto markets, the traditional equity markets, and monetary policy (Karau, 2021; Kurka, 2019; Caporale, de Dios Mazariegos, and Gil-Alana, 2022; Koutmos, King, and Zopounidis, 2021), other macroeconomic variables, such as inflation (Conlon, Corbet, and McGee, 2021; Corbet, Larkin, Lucey, Meegan, and Yarovaya, 2020) and economic policy uncertainty (Wu, Tong, Yang, and Derbali, 2019; Wang, Xie, Wen, and Zhao, 2019), regulatory news (Auer and Claessens, 2020), consumers' preferences and government transaction policies (Hendrickson, Hogan, and Luther, 2016).

Our research question and modeling strategy are closely related to many of the papers in this group, especially Karau (2021). Karau (2021) studies the effect of monetary policy shocks on Bitcoin prices. They also use a VAR model in their analysis, but without considering the factor component as we do. This allows us to explicitly extend the analysis to the broad crypto markets rather than limiting it to Bitcoin. Nevertheless, we share with this strand of the literature the interest in the comovements across different asset categories and in the relation between crypto markets and macroeconomic outcomes.

2 A Model of Portfolio Comovements

Consider a panel of asset returns across both S traditional stock markets and C alternative cryptocurrencies. Our objective is to model the comovements of returns both across and within asset classes.

Let R_{st} and R_{ct} represent the period-t returns of a portfolio in the traditional stock market s and of cryptocurrency c, respectively. We assume that fluctuations in R_{st} and R_{ct} can be decomposed into two components: a factor driven by dynamics within a given asset class, F_t^S or F_t^C, and an idiosyncratic component ϵ_{st} or ϵ_{ct}. We assume that the class factors are latent. The class factors explain comovement within assets of that particular sector, potentially deviating from alternative asset classes.

The use of a factor structure is particularly helpful when comparing stock and crypto assets in the same model. Stock markets are defined at the national level, but also display significant cross-sectional linkages. The factor synthetically captures the international dimension of the country-specific stock markets. Cryptocurrencies, on the contrary, are already defined at the global level, since they are created to be borderlessly traded. In this case, the factor provides a way to obtain a market index that optimally incorporates the differences across currencies. The two factors, hence, represent conceptually comparable return dynamics for the international stock and crypto markets. We believe this approach allows for a fairer and richer comparison than simply comparing Bitcoin to a single stock market.

The asset returns for market $s = 1, ..., S$ and cryptocurrency $c = 1, ..., C$ can then be written as components of the measurement equation in a state-space model:

$$R_{st} = \lambda_s^F F_t^S + \epsilon_{st} \tag{1}$$

$$R_{ct} = \lambda_c^F F_t^C + \epsilon_{ct}, \tag{2}$$

where λ_i^F are factor loadings that determine the exposure of returns R_i to their respective class factor. We assume that $\epsilon_{st} \sim N(0, \sigma_s^2)$; $\epsilon_{ct} \sim N(0, \sigma_c^2)$; $E[\epsilon_{st}' \epsilon_{ct}] = 0$ for all $s \neq c$. These restrictions imply that comovements across stock portfolio and crypto returns result from the factor structure itself and there is no correlation between idiosyncratic shocks.

The dynamics of the factors are described as a VAR in which we allow for a relationship between returns, global and regional macroeconomic conditions, and policy variables. Let Y_t collect the N macro and policy variables. The reduced-form FAVAR represents the transition equation of the state space:

$$\mathbf{Z}_t = \Phi\left(L\right) \mathbf{Z}_{t-1} + \mathbf{e}_t \tag{3}$$

where $\mathbf{Z}_t = \left[Y_t, F_t^S, F_t^C\right]$, $\Phi\left(L\right)$ is an $(N+2) \times (N+2)$ matrix polynomial in the lag operator, and $\mathbf{e}_t \sim N\left(0, \Sigma\right)$.

In the dynamic factor model, we cannot separately identify the sign and scale of the factor from that of the loadings without additional restrictions. We utilize an approach similar to that of Bernanke, Boivin, and Eliasz (2005) and set the loading for one series in each asset class to be equal to 1. This allows us to pin down the sign as the loading is strictly positive for either the S&P500 or Bitcoin. Furthermore, given that the scale is identified based upon variability in the identifying series, we can estimate the full variance-covariance matrix Σ without restriction.

2.1 Identifying the VAR

We aim to examine the propagation of economic policy uncertainty shocks and financial market shocks through asset markets and assess whether investor behavior reflects the view that traditional and crypto assets are complements or substitutes. Portfolio reallocation patterns will likely depend on the nature of the shock, whether we can view these as conventional "supply-side" or "demand-side" shocks. Furthermore, the policy uncertainty channel induced by changes in economic policy in different economies may affect conditions in financial markets, and thus impact the flow in demand across or within asset classes.

In order to identify the relevant shocks in our specification, we estimate the reduced-form FAVAR and impose a Cholesky-style ordering in which the traditional stocks and crypto factors are ordered last, following measures of real economic activity, a short-term interest rate, and economic policy uncertainty (or stock market volatility in some specifications used for robustness).

3 Implementation

In this section, we describe the data and methods used to obtain our results.

3.1 Data

Our sample covers the period from January 2017 through May 2021 at weekly frequency ($T = 229$). The weekly returns for the stock market portfolios are calculated as the percentage weekly changes of the stock exchange indexes for 39 of the largest exchanges based on market capitalization in 2021. Time series of the stock market indexes are obtained from Bloomberg Terminal financial services, which was accessed on May 25, 2021. Table 1 reports the full list of exchanges in our sample. All stock market indexes are available for the entire sample of analysis.

The return rates of the cryptocurrencies are calculated for the prices of 64 of the largest crypto projects selected based on the ten-year market capitalization in 2021. The cryptocurrency prices are provided by the crypto data provider messari.io, accessed on May 27, 2021. Some of these currencies, however, do not come into existence until later in the sample. We treat the unbalanced panel as containing missing observations, which can easily be accommodated for within the Kalman filter algorithm used to extract the common factors. Table 2 lists the specific cryptocurrencies in our sample along with the dates of the initial observation in each series.

We consider several specifications for incorporating macroeconomic conditions and policy variables. The details of what is included in each model are described more fully in Sections 4 and 5. For the U.S-centric baseline model, we use the log of the U.S. Economic Policy

Bloomberg ticker Index	Description	Category	Country
SPX Index	The Standard & Poor's 500 Index	National	U.S.
DJI Index	Dow Jones Industrial Average	National	U.S.
NYA Index	NYSE Composite	National	U.S.
NDAQ Index	Nasdaq Inc	National	U.S.
RIY Index	Russell 1000 Index	National	United Kingdom
ACWI US Equity	MSCI ACWI ETF	Global	Developed and Emerging
MXEA Index	MSCI EAFE ETF	Global	Europe & Asia
CCMP Index	Nasdaq Composite	National	U.S.
GDOW Index	The Global Dow	Global	World
CBOE US Equity	Cboe Global Markets Inc	National	U.S.
W5000 Index	Wilshire 5000	National	U.S.
IBOV Index	IBOVESPA	National	Brazil
IBEX 35 Index	IBEX 35 Index	National	Spain
BURSA MK Equity	FTSE BURSA	National	Malaysia
AS51 Index	S&P/ASX 200	National	Australia
ASX Index	FTSE All Share Index	National	United Kingdom
DAX Index	DAX PERFORMANCE-INDEX	National	Germany
CAC 40 Index	CAC 40 Index	National	France
SPA50 Index	S&P Asia 50 Index	Regional	Asia
EB1X Index	FTSE Euro 100 Index	Regional	Europe
SPE Index	S&P Europe 350 Index	Regional	Europe
SPLAC Index	S&P Latin America 40 Index	Regional	Latin America
SHCOMP Index	SSE Composite Index	National	China
SZ399659 Index	SZSE Component Index	National	China
SHSZ300 Index	CSI 300 Index	National	China
TPX Index	TOPIX Index	National	Japan
JPNKMS Index	JPX-Nikkei Index 400	National	Japan
TDXP Index	TecDAX Index	National	Germany
TASX Index	FTSE techMark All-Share Index	National	United Kingdom
SENSEX Index	BSE SENSEX Index	National	India
FTSEMIB Index	FTSE MIB Index	National	Italia
ENXFP Copr Ticker	IBrX 100 Index	National	Brazil
SPTSX Index	S&P/TSX Composite Index	National	Canada
KOSPI Index	The Korea Composite Stock Price Index	National	Korean
IKOSDAQ Index	Kosdaq Composite Index	National	Korean
IMOEX Index	Moscow Exchange Index	National	Russia
XU100 Index	BIST 100	National	Turkey
HSI Index	Hang Seng Index	National	Hong Kong
ENXFP Copr Ticker	Euronext NV	Regional	Europe

Table 1: List of the stock exchanges included in the analysis, with scale category (Regional, National, Global) and country of reference. Data is obtained from Bloomberg Terminal. All series are available for the full sample of analysis from January 2017 to May 2021.

Cryptocurrency Name	Cryptocurrency Key	Start Date	Category
Bitcoin	btc	Full sample	1
Ethereum	eth	Full sample	2
BNB	bnb	2017-11-04	other
Polkadot	dot	2020-08-22	2
Cardano	ada	2017-10-28	2
XRP	xrp	Full sample	other
Litecoin	ltc	Full sample	1
Chainlink	link	2017-11-04	2
Bitcoin Cash	bch	2017-08-12	1
Stellar	xlm	Full sample	2
Dogecoin	doge	Full sample	1
Uniswap	uni	2020-09-19	2
Aave	aave	2017-12-23	2
EOS	eos	2017-08-12	2
Monero	xmr	Full sample	1
Cosmos	atom	2019-04-27	2
Huobi Token	ht	2018-02-10	other
Bitcoin SV	bsv	2018-11-17	1
NEM	xem	Full sample	1
TRON	trx	2017-11-11	3
IOTA	miota	2017-08-12	3
Tezos	xtz	2018-09-22	3
Theta Token	theta	2018-01-27	other
VeChain	vet	2018-08-04	3
NEO	neo	2017-08-12	3
Crypto.com Chain	cro	2019-03-09	other
Dash	dash	Full sample	1
Avalanche	avax	2020-10-03	2
FTX Token	ftt	2019-08-10	other
Solana	sol	2020-03-23	2
Terra	luna	2020-06-06	other
The Graph	grt	2020-12-19	other
Synthetix	snx	2020-04-04	other
Maker	mkr	2018-02-17	other
Algorand	algo	2019-06-22	3
Dai	dai	2018-04-07	other
Filecoin	fil	2019-07-20	other
Compound	comp	2020-06-20	other
PancakeSwap	cake	2021-01-23	1
Kusama	ksm	2020-08-22	other
Ethereum Classic	etc	Full sample	2
Zcash	zec	Full sample	1
SushiSwap	sushi	2020-09-05	1
Decred	dcr	Full sample	other
yearn.finance	yfi	2020-07-25	other
Unus Sed Leo	leo	2019-05-25	other
Ren	ren	2018-12-08	other
DeFi	dfi	2021-01-16	1
Zilliqa	zil	2018-02-10	2
UMA	uma	2020-07-18	other
Celsius Network	cel	2020-09-19	other
ICON	icx	2017-12-23	3
Waves	waves	Full sample	3
Nexo	nexo	2019-03-09	other
NEAR Protocol	near	2020-10-31	other
Ethos	ethos	2017-10-28	3
0x	zrx	2017-09-02	2
Ravencoin	rvn	2018-08-18	other
Celo	celo	2020-05-30	other
DigiByte	dgb	Full sample	1
Hedera Hashgraph	hbar	2019-09-21	other
Ontology	ont	2018-03-17	other
renBTC	renbtc	2020-12-05	1
Nano	nano	2018-02-10	3

Table 2: List of cryptocurrencies included in the analysis. Data is obtained from messari.io. The sample of availability of each project is reported in the third column. The full sample of analysis is from January 2017 to May 2021. Cryptocurrencies selected based on the ten-year market capitalization in 2021. The Category column classifies the generation of the underlying blockchain technology of a project – with “other” referring to projects with different characteristics, such as exchanges or stablecoin issuers.

Uncertainty Index (EPU) from Baker, Bloom, and Davis (2016). We also include the Lewis-Mertens-Stock Weekly Economic Index (Lewis, Mertens, Stock, and Trivedi, 2022) which is available on the Federal Reserve Economic Database (FRED) hosted by the Federal Reserve Bank of St. Louis. As a measure of short-term interest rates to capture the stance of monetary policy, we include the interest rate on the 3-month Treasury bill, also obtained from Bloomberg Terminal. For an alternative measure of uncertainty, more specifically focused on financial markets, we substitute the log of VIX (provided by FRED) for the EPU. To discern a demand channel for cryptocurrency holdings in asset portfolios, we use the Google trends web-search index for the key word "Bitcoin."

Beyond the U.S. baseline, we consider two international perspectives and build China-centric and U.K.-centric alternatives. For China, we include the interest rate on the 3-month Chinese government bond and the log China EPU (also from Baker, Bloom, and Davis, 2016). Similary for the U.K., we use the interest rate on the 3-month U.K. government bond and the log U.K. EPU (Baker, Bloom, and Davis, 2016). The short-term interest rates for these two countries are obtained from Bloomberg Terminal.

3.2 Estimation

We employ the methodology of Bernanke, Boivin, and Eliasz (2005) and estimate the FAVAR using a Bayesian approach via likelihood-based Gibbs sampling. In doing so, we treat the model parameters $\theta = \left(\lambda_s^F, \lambda_c^F, \sigma_s^2, \sigma_c^2, \Phi\left(L\right), \Sigma\right)$ as random variables. The Gibbs sampler proceeds by alternating between sampling the parameters in θ and the unobserved factors $\left[F^S, F^C\right]$. See the appendix of Bernanke, Boivin, and Eliasz (2005) for a full description of the estimation procedure.

For clarity, we provide more detail here regarding the prior on the FAVAR component itself. Taking the factors as given, the dynamics of $\mathbf{Z}$ can be estimated as a standard VAR. We impose a similar diffuse conjugate Normal-Wishart prior as is done in Bernanke, Boivin, and Eliasz (2005). To parameterize the prior, we adopt an approach in line with a Minnesota prior in which the coefficients on longer lags are more likely to be closer to zero. We also follow Kadiyala and Karlsson (1997) and set the prior for Σ to be diagonal with elements determined by the residual variances of univariate regressions for each element in the VAR. The prior variances for elements of $\Phi(L)$ are determined such that the coefficient on the k-th lag of the j-th variable in the i-th equation accounts for potential variation in the scale of the variables, i.e., the prior is set to $\frac{\sigma_i^2}{k\sigma_j^2}$. Finally, we draw the factors from the Kalman filter with a backward smoother. We present results for 10,000 draws after discarding the first 5,000 draws.

4 Results: The Market Factors

In this section, we discuss a baseline model focusing on the two market factors and their interactions. We then use other specifications to further understand the main effects illustrated by the baseline. Table 3 summarizes the variables in each model and guides us through this part of the analysis.

4.1 Baseline Model

We first study a baseline model in which only the two market factors are included along with the U.S. EPU as a control in the FAVAR. We rely on this simple model to make two key points of our analysis about the crypto market structure and the links between traditional stock and cryptocurrency markets. This block is also going to be an elemental part of all the models we study next. Importantly, the conclusions we draw from this baseline model remain valid in the other specifications as well.

Result 1. The first observation we make is about characteristics of the cryptocurrency market revealed by the crypto factor. The crypto market is commonly discussed by mainstream media in terms of just a couple of assets which dominate the capitalization of the market. Bitcoin usually gets most of the attention in the news, followed by the Ethereum blockchain. The general public and less specialized investors likely identify the crypto market with Bitcoin.

Our factor analysis makes it clear that although Bitcoin undoubtedly plays a big role in

Variable	**Model**		
	Baseline	+BTC Web	2 Sub-Samples
U.S. EPU	✓	✓	✓
Google search: Bitcoin		✓	
Money supply growth			
Stock Factor	✓	✓	✓
Crypto Factor	✓	✓	✓

Table 3: Models used in the analysis in Section 4 and the variables included in each model. The Baseline model only considers the two market factors with the EPU index as a control. In the two other specifications we add the Google searches of the keyword "Bitcoin" from Google Trends and alternatively split the sample of the baseline model into two periods pre/post January 1, 2020.

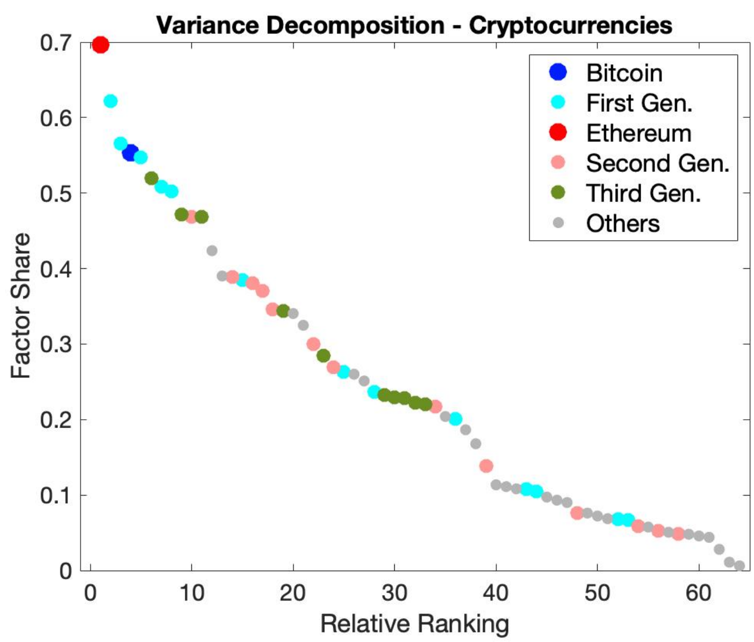

Figure 1: Variance Decomposition – Share of the variance of each cryptocurrency explained by the common market factor.

the dynamics of this market, the cryptocurrency market is much more heterogeneous and more complex than the strong emphasis put on Bitcoin would suggest. Figure 1 formally makes this point by showing the share of variance of each of the 64 currencies in our sample explained by the common factor.[2]

The currency with the highest factor share is Ethereum (.7) and not Bitcoin (.55). However, a group of tokens based on the Bitcoin protocol take six out of the first eight positions in the variance decomposition. This block of currencies is indicated in light blue in the figure, while Bitcoin is in dark blue. Bitcoin also exercises its influence on the market indirectly through this block.

A second group of currencies corresponds to the so-called second-generation projects. These are blockchains centered on the development of decentralized tools and applications like smart contracts. Except for Ethereum, these currencies are found in the mid range of the factor shares, with values between .3-.4. These are the pink dots in Figure 1, while Ethereum is represented by the red dot.

Currencies from third-generation projects constitute the third block. These correspond to the green dots in the figure. These are based on highly-performing blockchains especially suitable, for instance, for DeFi (Decentralized Finance) applications. Some display relatively high factor shares, but the bulk of them can be found in the range .2-.25. Finally, a mix of currencies, especially for younger projects, show large idiosyncratic components (in light gray).

Result 2. The second set of results is obtained from the impulse response functions of the two factors to the stock and crypto structural innovations. In this figure, as in all the other figures of the paper reporting impulse response functions, we consider one-standard-deviation innovations. The solid dark line corresponds to the median response of a variable to the shock, whereas the gray areas represent the 14/86th percentiles of the posterior distribution of the responses. We make three observations based on the results illustrated in Figure 2.

[2]Figure A1 in Appendix A also compares the variance decomposition of the stock market indexes and cryptocurrencies. As expected, the figure illustrates how crypto assets are also much more heterogeneous than the traditional stock markets, with dynamics depending on average on much larger idiosyncratic components.

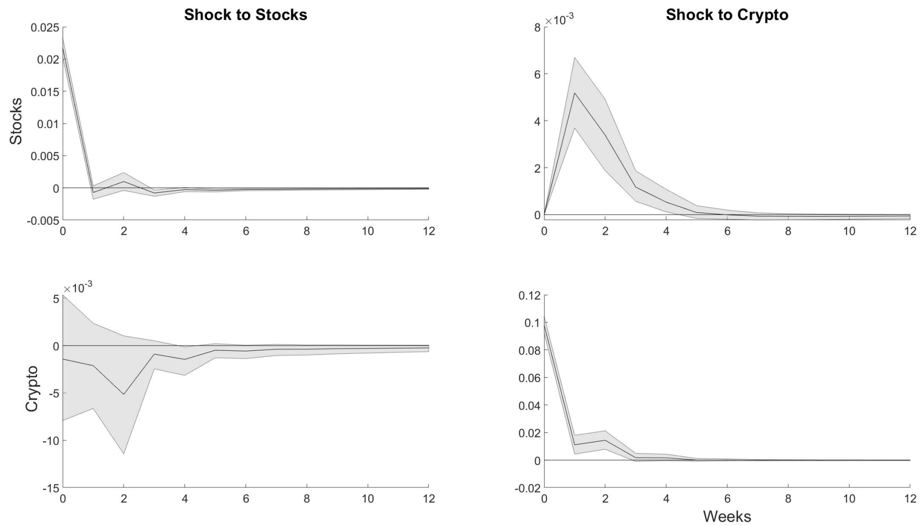

Figure 2: Impulse Response Functions – Baseline Model. VAR model with the U.S. EPU index and the two factors for the the stock markets and the crypto market. The IRFs are based on a recursive Cholesky scheme using this same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

First, the typical crypto factor shock is about five times as large as a shock to the stock factor. This reflects the higher volatility and risk of crypto markets. Second, while the stock shock is fundamentally white noise, the crypto shocks are persistent and predictable up to three/four weeks after the shock. This result points to a lack of efficiency in the crypto market, which corroborates the common opinion that this market is still largely associated with unsophisticated investors.

Third, we find that the stock market factor has a significant response to the crypto shocks, but not vice versa. The response of the stock markets is positive, economically quite sizable (with a peak around .5%), and strongly significant for an extended time period (up to five weeks). The lack of transmission from the traditional markets to the crypto market is not unexpected, as many observers believe in the independence and specificity of crypto investors' motivations. However, the feedback from the crypto into the traditional markets is a novel and interesting result.[3] We provide a further explanation of this effect next.

[3] For instance, Caporale, de Dios Mazariegos, and Gil-Alana (2022) do not find long-run equilibrium relation between cryptocurrencies and U.S. stock markets using fractional cointegration methods.

4.2 Interpretation of the Response of the Stock Factor to Crypto Shocks

The increase in stock returns following a positive shock to the crytocurrency returns requires some more discussion since a straightforward interpretation of this effect based on a portfolio substitution argument is clearly not suitable in this case. Other common strategy-based explanations that may introduce complementarity between the two types of investments do not, however, seem likely to apply either. For instance, profits from crypto investment strategies that exploit heterogeneity across investors, such as pump-and-dumps, could be reinvested in the traditional stock markets. But this interpretation would be at odds with the duration of the effects, since these strategies take place over very short time frames.

An explanation of this effect may alternatively reflect a broader transmission mechanism then, with richer economic and financial implications. We use the rest of the analysis in this section to investigate this possibility.

The first hypothesis we test is whether this effect is also capturing, at least in part, a more general increase in the appetite for risky assets by international investors. The exercise we conduct corresponds to model +BTC Web in Table 3, where the index for the web searches of the keyword "Bitcoin" from Google Trends is added to the model along with the U.S. EPU used as a control. The Google Trends index is assumed to approximate investor interest for cryptocurrencies.

We see in Figure 3 that Bitcoin web searches and crypto returns positively co-move with a bidirectional feedback. The Google Trends shock is then used to check whether the demand for crypto assets could also translate into demand for traditional stocks, causing the increase in returns in both markets. We don't find evidence supporting this hypothesis as the stock returns factor has a largely non-significant response to the Google Trends shock.

The second hypothesis we entertain is that these effects of the crypto shocks could be driven by other coincidental shocks that affect the two types of assets at the same time.[4] To test this hypothesis, we exploit the COVID-19 pandemic period and the large systemic shock

[4] Kurka (2019), for instance, studies volatility spillovers from Bitcoin to traditional assets and finds a substantial conditional transmission of crytpo shocks during periods of market disruption as well, while unconditional effects are negligible.

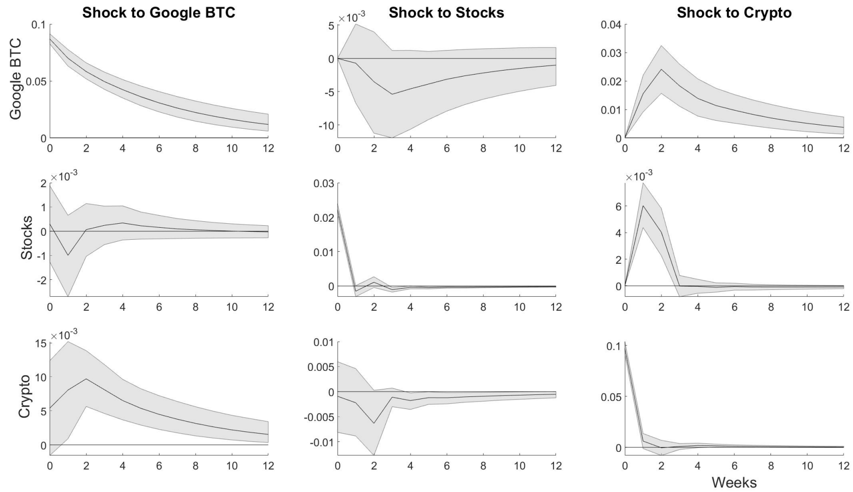

Figure 3: Impulse Response Functions – +BTC Web Model. VAR model with the U.S. EPU index, the Google Trends index of the web searches for the keyword "Bitcoin," and the two factors for the the stock markets and the crypto market. The IRFs are based on a recursive Cholesky scheme using this same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

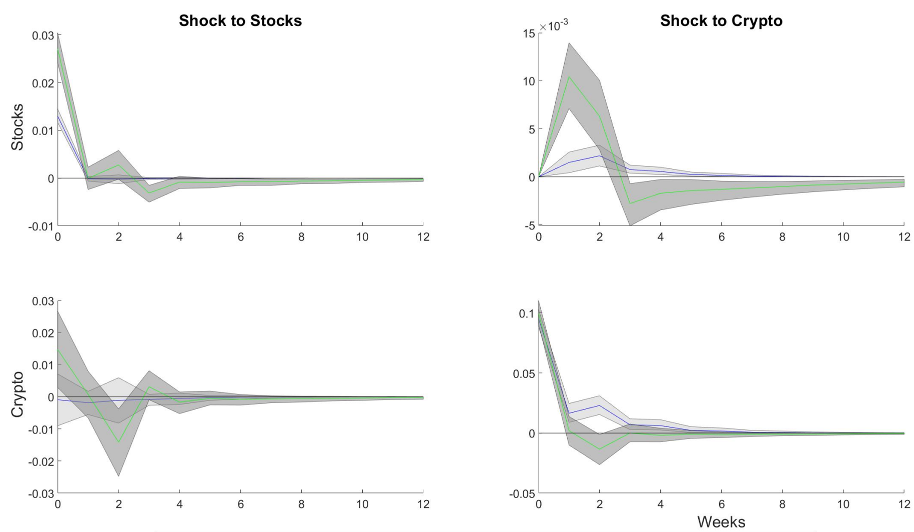

Figure 4: Impulse Response Functions – Baseline Model. VAR model with the U.S. EPU index and the two factors for the the stock markets and the crypto market. The sample is split in two parts: before 1-1-2020 (the black line) and after 1-1-2020 (the green line). The IRFs are based on a recursive Cholesky scheme using this same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

it caused. If this explanation is correct, we should observe a stronger response of the stock factor in the most recent part of the sample. We split the sample into two sub-periods, before and after January 1st, 2020, and we re-estimate the baseline model. Figure 4 illustrates the results for this exercise. Although the responses of the stock market factor are qualitatively consistent across the two sub-samples, the magnitude of the effect differs and the post-2020 response is about four times as large as the pre-2020 one.

The structural links between the two asset categories documented by the exercises in this section outline an interesting question about the role of cryptocurrencies in investment portfolio management. Cryptocurrencies were introduced as a new type of asset which was believed could provide some form of protection against conventional financial and economic shocks. The empirical literature, however, has only found limited support to this idea. Furthermore, as crypto markets experience a progressive assimilation into the global financial system, crypto assets may transform and even acquire more conventional traits. We further explore these aspects of cryptocurrencies in relation to economic policy uncertainty next.

5 Results: EPU and Cryptocurrencies

The second part of our analysis focuses on the effects of economic policy uncertainty on crypto markets. To do that, we enrich the structure of the baseline model by adding macroeconomic and policy variables, such as a real economic activity index or policy rates, to the EPU and the financial markets' block. Our main specification is for the U.S. economy, but we extend our analysis to China and the U.K. adapting the specification accordingly as illustrated in Table 4. Considering multiple countries allows us to highlight significant differences in the transmission of uncertainty from different regions of the World.

5.1 The U.S. case

The U.S. VAR model includes the weekly economic index (WEI), the U.S. 3-month T-Bill return rate, the U.S. EPU, and the two market factors. The structural shocks are identified with a recursive Cholesky scheme with ordering of the variables given by WEI, T-Bill rate,

Variable	**Model**				
	U.S. EPU	U.S. VIX	2 Sub-Samples	CHN EPU	U.K. EPU
WEI	✓	✓	✓		
U.S. Bond Rate	✓	✓	✓		
CHN Bond Rate				✓	
U.K. Bond Rate					✓
U.S. EPU	✓		✓		
CHN EPU				✓	
U.K. EPU					✓
VIX		✓			
Stock Factor	✓	✓	✓	✓	✓
Crypto Factor	✓	✓	✓	✓	✓

Table 4: Models used in the analysis in Section 5 and the variables included in each model. The Baseline model for the U.S. considers the two market factors, the EPU index, along with the U.S. 3-month T-Bill rate and a weekly economic index as a control. The specifications of the same model for the Chinese (CHN) and U.K. EPU replace the T-Bill rate with short term domestic bond rates. The benchmark model for the U.S. is also estimated for the pre/post January 1, 2020 sub-samples and with an alternative specification in which the VIX index replaces EPU.

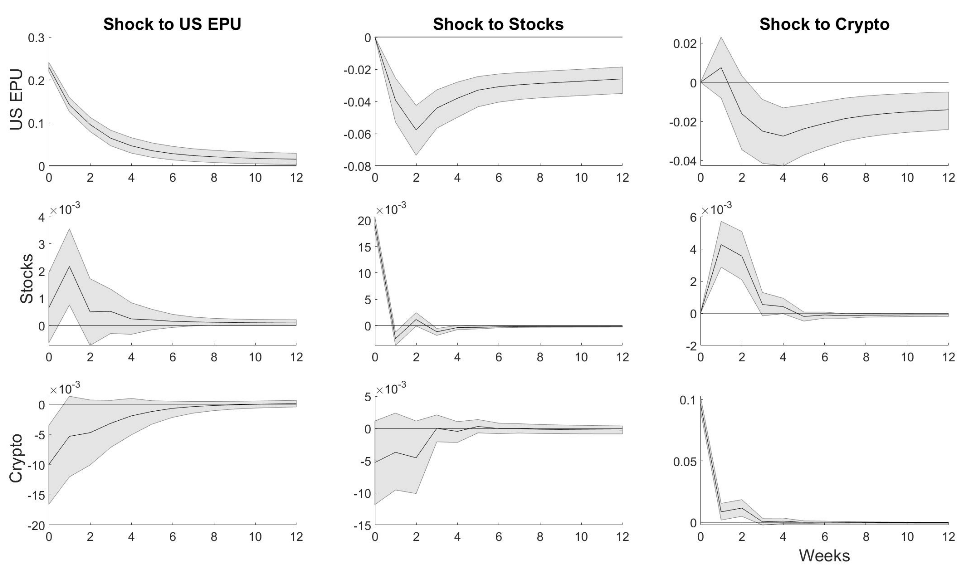

Figure 5: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, FFR, EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

EPU, factors.

The identification approach relies on two main assumption. First, the real and policy block of the model is separated from the financial block and ordered first so that it does not respond on impact to financial shocks, while financial markets are allowed to respond to the real sector shocks right away. This is a standard assumption in models estimated at lower frequency, which would fairly apply to weekly data as well.

Second, within the first block, policy uncertainty is assumed to be the most endogenous of the variables which responds on impact to the economic activity and the T-Bill rate. This is also a fair assumption in this context because being the EPU a news-based index, it can plausibly respond quickly to other macro and policy shocks. Nevertheless, the results we discuss in this section are robust to other orderings of the variables within the first block, especially to ordering EPU in the first position (as illustrated in Figure A6 of Appendix A).

The impulse response functions of the U.S. EPU model are reported in Figure 5. The EPU shock has opposite effects on the two markets. A positive one-standard deviation increase in EPU causes a positive response of the stock return factor for about three weeks, with a statistically significant response of .3% at peak one week after the shock. On the contrary, the response of the crypto factor is negative and significant on impact, reaching a 1% drop, and remains quite persistent although only marginally significant afterwards.

Theoretical results suggest that financial markets should typically respond negatively to a policy uncertainty shock (see Pástor and Veronesi, 2012). A new policy announcement can increase firms' profitability if it improves on the current policy. This has a positive impact on stock returns. At the same time, uncertainty about the new policy increases the discount factor, reducing stock prices. Pástor and Veronesi (2012) show that the latter effect normally dominates, especially if the policy change is anticipated and its effects have been already embedded in stock prices before the announcement.

EPU is a news-based index which not only tracks new economic policy announcements, but also and more generally accounts for the debate surrounding the policy decision-making process, the analysis of intended and unintended effects, and the uncertainty about the time-line of the policy implementation. The EPU shocks identified in our VAR, hence, may reflect some of the anticipated positive effects of a policy change on stock prices leading to the policy announcement, which could explain the brief increase of stock returns in response to an EPU increase found in Figure 5. Moreover, the EPU shock also causes a drop of the short term interest rate,[5] which impacts stock returns by decreasing the discount factor applied to future profits. This effect could in principle offset the direct increase in the discount factor due to the heightened economic policy uncertainty. This seems to be, at least in part, the empirical case in our model where the resulting net response of the stock factor is positive.[6]

While the U.S. EPU has a positive effect on global stock returns, the response of the crypto return factor to the U.S. policy uncertainty shocks is negative.[7] The result is interesting for a couple of reasons. First, one of the possible explanations of the interest of investors in crypto assets is that they could provide new instruments to diversify portfolios against shocks commonly affecting traditional financial markets. Cryptocurrencies, therefore, could be useful portfolio complements of traditional stocks. The negative conditional correlation of the two market factors in response to the policy uncertainty shocks in our result suggest this is the case for the U.S. EPU.

Second, the transmission mechanism that can explain the response of the stock factor might not work for the cryptocurrencies. Crypto fundamentals could simply be independent of changes in U.S. economic policy or even respond negatively to the uncertainty of the unfavorable regulatory stance of the American government towards crypto markets. Similarly, the American interest rate might not be a major component of the discount factor relevant

[5]See the full set of impulse response functions illustrated by Figure A5 in Appendix A.

[6]The empirical literature that studies the effects of economic policy uncertainty on stock returns usually finds quite heterogeneous results depending on the estimation techniques adopted, whether non-linear effects are considered, and the panel structure of the model (see, among others, Arouri, Estay, Rault, and Roubaud, 2016; Christou, Cunado, Gupta, and Hassapis, 2017; Chang, Chen, Gupta, and Nguyen, 2015; Kundu and Paul, 2022). All these papers indicate that the responses may vary across countries, stock markets, and states of the world. The main conclusion from this empirical literature is that the theoretical prediction that stock prices fall when a new policy is introduced is not unambiguously supported.

[7]A recent strand of the literature has focused on the effects of EPU and global uncertainty on Bitcoin (see, among the others Wang, Xie, Wen, and Zhao, 2019; Wu, Tong, Yang, and Derbali, 2019; Bouri, Gupta, Tiwari, and Roubaud, 2017). This literature generally finds weak average responses of Bitcoin to uncertainty, but it also documents how these effects are often non-linear and get stronger at the extremes of the uncertainty and return distributions. On the contrary, although we also find that the effects can be stronger in periods of higher uncertainty (see Figure 6), the results identified by our analysis apply more in general.

for the international crypto investors, allowing EPU to directly raise the discounting.

As a further step in the analysis and for robustness, we consider two other models in Figures 6 and 7.

In Figure 6 we split the sample in the pre- and post- COVID-19 pandemic period. The size of the policy uncertainty shocks are similar in the two sub-samples, but the responses of both market factors are much larger during the pandemic period as we could expect. The relative responses remain qualitatively similar though, with the stock market returns briefly increasing and the crypto returns briefly falling. Noticeably, however, the responses on impact are null and not significant and the effect takes one period to emerge. In a period of already extremely high global uncertainty, it seems that financial markets take longer to specifically parse out policy uncertainty.

In Figure 7 the VIX index replaces the U.S. EPU. The VIX is a measure of short-term implied stock market volatility, and it can be seen as an indicator of the degree of financial uncertainty in the stock markets. We find that a positive shock to the VIX, that is an increase in stock market volatility, is followed by a drop of the stock factor immediately on impact. The response reverts back to zero one week after the shock, taking on slightly positive, but still significant, values in a couple of periods. This effect is consistent with the sale of stocks to re-balance portfolio risk levels when financial risk increases, and with the decrease of the short term interest rate following the shock which then helps stock returns recover as in the EPU model.

The response of the crypto factor, on the contrary, is not significant at the beginning, but it turns persistently and significantly negative afterwards. If we interpret this result again in terms of the hedging properties of cryptocurrencies in the context of portfolio diversification strategies, this result implies this would not be the case for financial risk shocks. Moreover, crypto investments do not provide a safe-haven option against market volatility either.

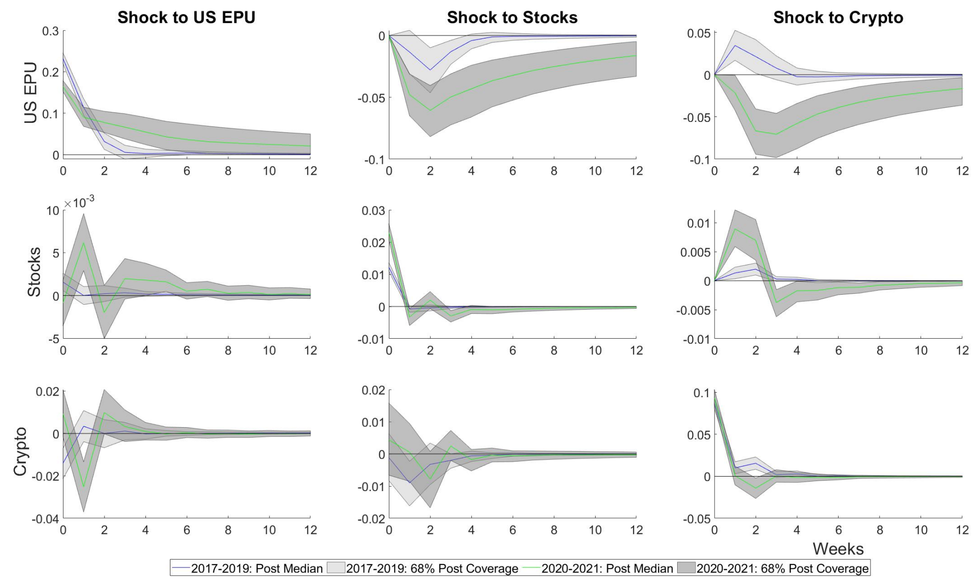

Figure 6: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, FFR, EPU, and the two market factors. The sample is split in two parts: before 1-1-2020 (the black line) and after 1-1-2020 (the green line). The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

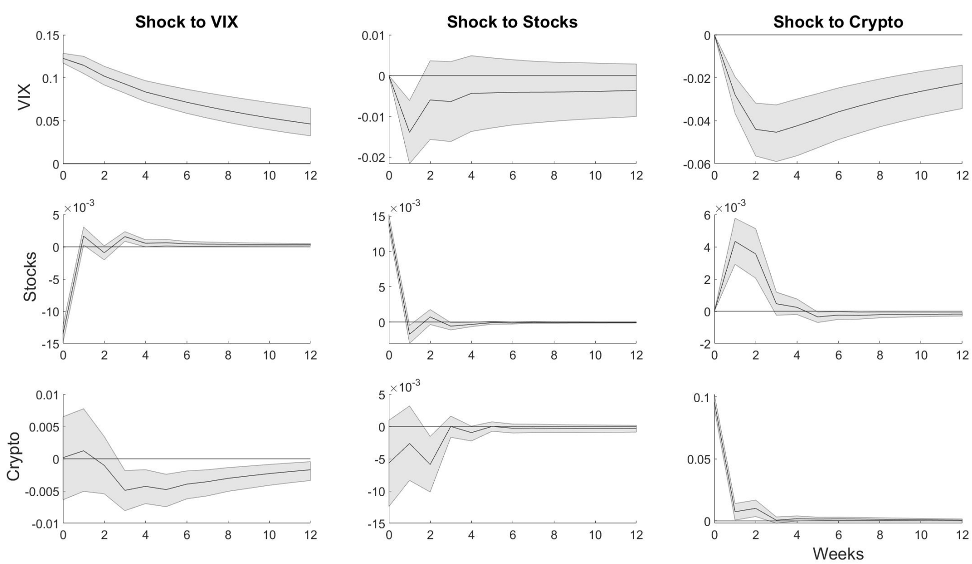

Figure 7: Impulse Response Functions – U.S. VIX Model. VAR model with WEI, FFR, VIX, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

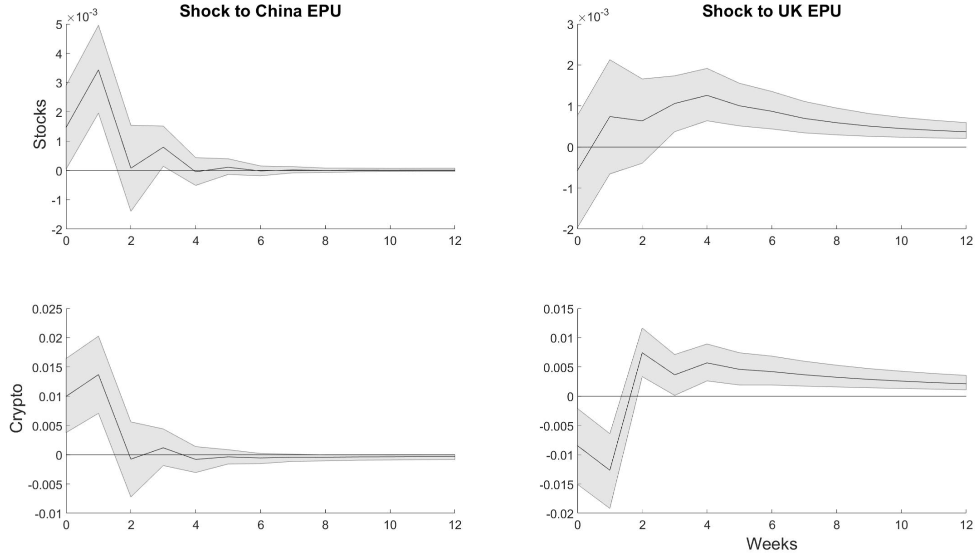

Figure 8: Impulse Response Functions – Comparison of the responses of stock and crypto factors to an EPU shock in the China and U.K. EPU Models. VAR models with short term interest rate, domestic EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis.

5.2 Comparison with China and the U.K.

In the previous section we focused on the U.S. EPU, but this is not the only source of economic policy uncertainty that may matter for the dynamics of crypto markets. With the available data, we can also explore the effects of the Chinese and the U.K. EPUs in Figure 8. We find two interesting results.

First, the uncertainty from these two countries affect traditional stock markets in the same way as the U.S. EPU. Positive EPU shocks from both China and the U.K. lead to significant increases of stock returns, which can even be quite persistent for the U.K. case. This result is not unexpected and it can be seen as one more testament of the strong international integration of global stock markets, as documented by the factor analysis as well and the variance decomposition in Figure A1 in the Appendix.

Second, and on the contrary of what found for the U.S. uncertainty, cryptocurrencies can provide a safe haven investment option against the Chinese EPU shocks. This is also the case for the U.K. EPU shocks for horizons longer than two weeks. Setting aside specific differences between the specifications of these models and their response functions, however, a clear conclusion emerges about the possible segmentation of the crypto space. Regional investors from different geographic areas, with different degrees of exposures to regional sources of uncertainty, do not necessarily share the same reasons to invest in cryptocurrencies.

This conclusion corroborates the view of crypto markets as a more heterogeneous and still evolving space to closely study. The result also bears some implications for the design choices of crypto market regulatory frameworks, especially at international level, which we discuss in the final section of the paper.

6 Conclusion

Our FAVAR approach allows us to explicitly embed heterogeneity within asset classes in the study of the comovements of crypto and traditional stock markets. We use this model to assess the effects of economic policy uncertainty on these two asset classes from a portfolio perspective.

Our main findings are three. First, we find that cryptocurrencies are characterized by large cross-sectional differences. Studying crypto markets by only focusing on Bitcoin, as often done in the literature, offers a narrower perspective of the overall crypto sector. Second, we find that stock returns respond to shocks to the crypto factor, but not vice-versa. This effect could be, at least in part, explained by global shocks hitting financial investors across markets. Third, we find that cryptocurrencies can provide an additional portfolio diversification tool against EPU shocks. Cryptocurrencies display hedging properties against the U.S. EPU movements, whereas behave as a safe-haven against the China and U.K. EPU shocks.

Our analysis provides relevant insights to formulate some policy recommendations. The first two results speak to the importance of recognizing and correctly dealing with the heterogeneity of crypto assets and their relation to other asset categories. As the use of cryptocurrencies as investments grows and the integration between crypto and traditional financial markets increases, more clear regulation of the crypto space is required to protect smaller, unsophisticated investors. Regulation, however, must be able to distinguish differences in quality and characteristics of various crypto projects to offset risks without limiting the development of new digital financial, DLT-based products.

The third set of results, which documents the regional differences in the effects of EPU on cryptocurrencies, has policy implications for the design of domestic and international regulatory systems for crypto markets. The regional segmentation of the crypto space reflected by this and similar results in the literature suggests that regulations that account for specific domestic features are required.

At the same time, however, the global nature of crypto trading implies that a good degree of international coordination is also necessary to avoid unintended consequences from the introduction of new rules. For instance, a policy maker could think that some forms of crypto trading should be limited in a country, but domestic investors could circumnavigate these restrictions by accessing crypto markets internationally, getting exposed to even less familiar foreign shocks. Further research would be beneficial to clearly understand the mechanisms explaining these regional differences and to effectively coordinate the international response of regulators to crypto market risks.

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Appendix

A Additional Figures & Full Sets of IRFs

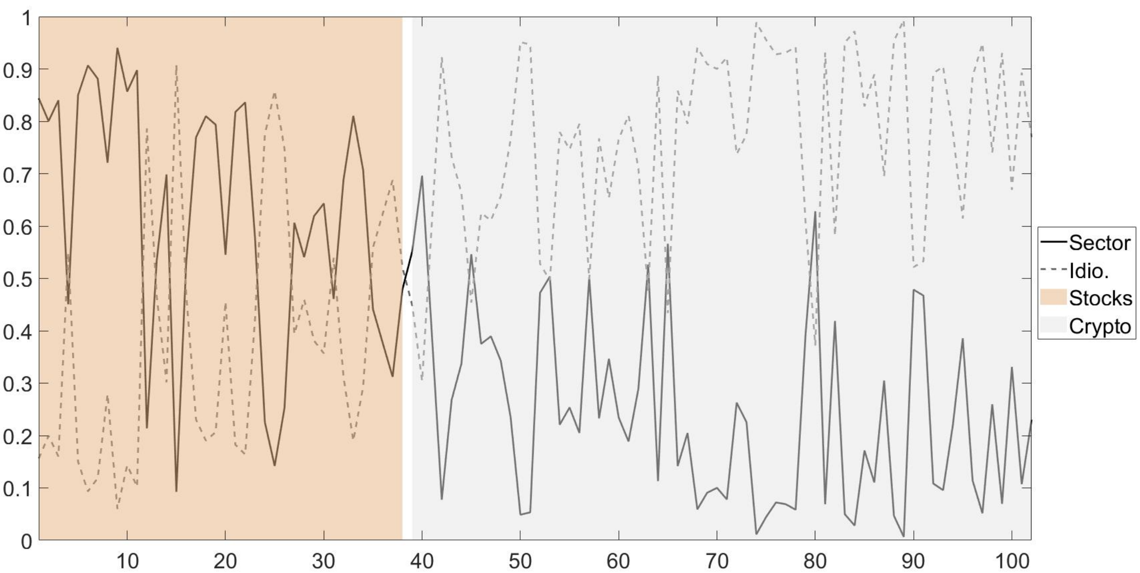

Figure A1: Variance Decomposition: Share of variance of each stock market index (left side panel) and of each cryptocurrency (right side panel) explained by their market factor and their own idiosyncratic component.

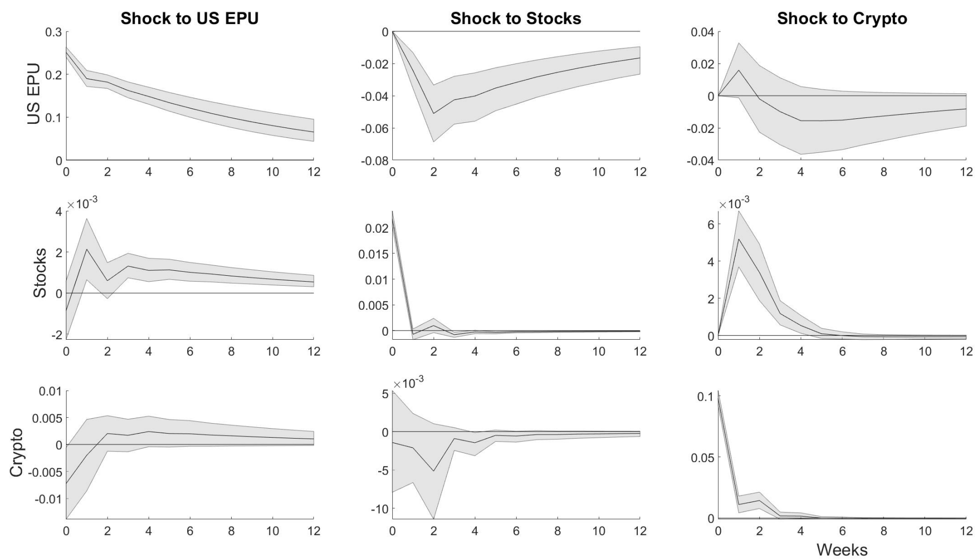

Figure A2: Impulse Response Functions – Baseline Model. VAR model with the U.S. EPU index and the two factors for the the stock markets and the crypto market. See Figure 2.

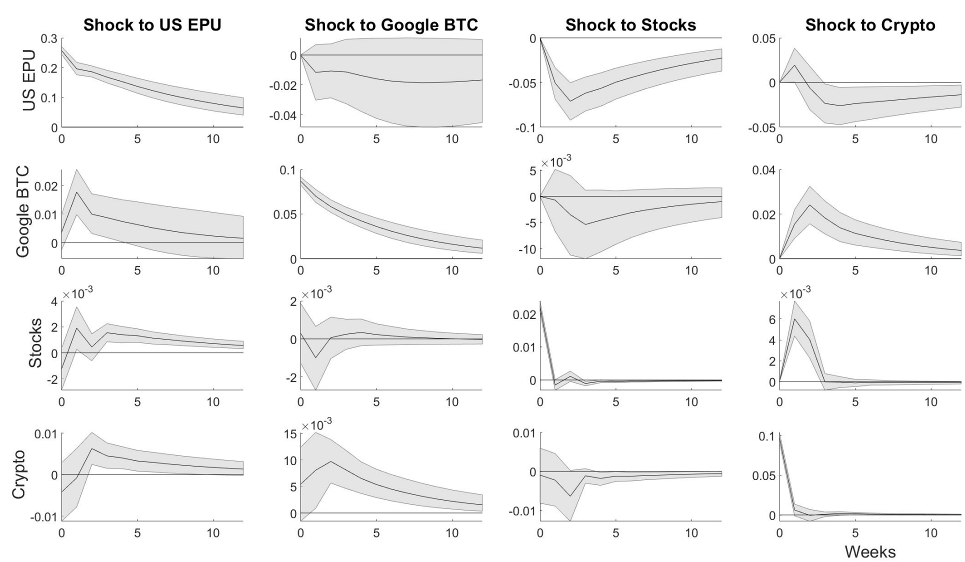

Figure A3: Impulse Response Functions – +BTC Web Model. VAR model with the U.S. EPU index, the Google Trends index of the web searches for the keyword "Bitcoin," and the two factors for the the stock markets and the crypto market. See Figure 3.

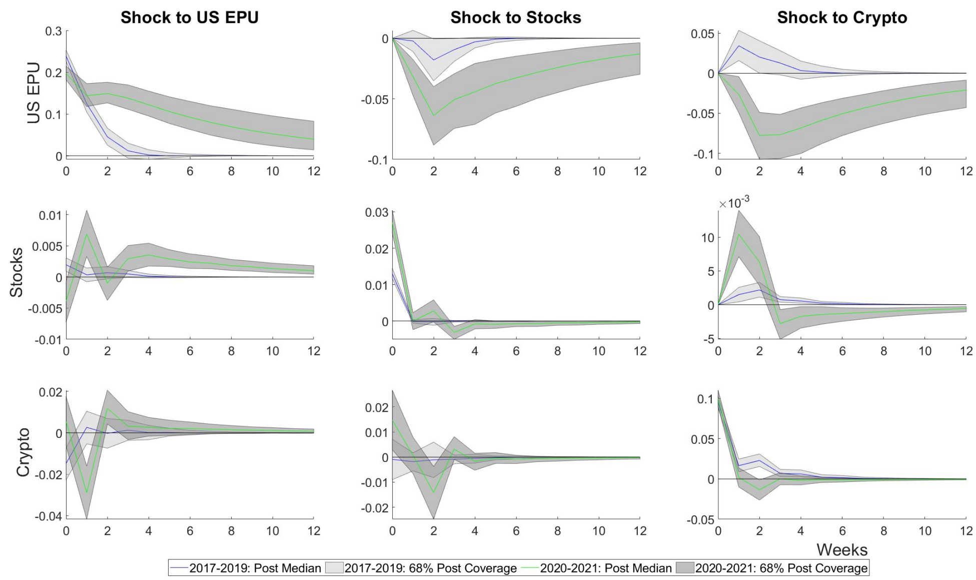

Figure A4: Impulse Response Functions – Baseline Model with split sample. See Figure 4.

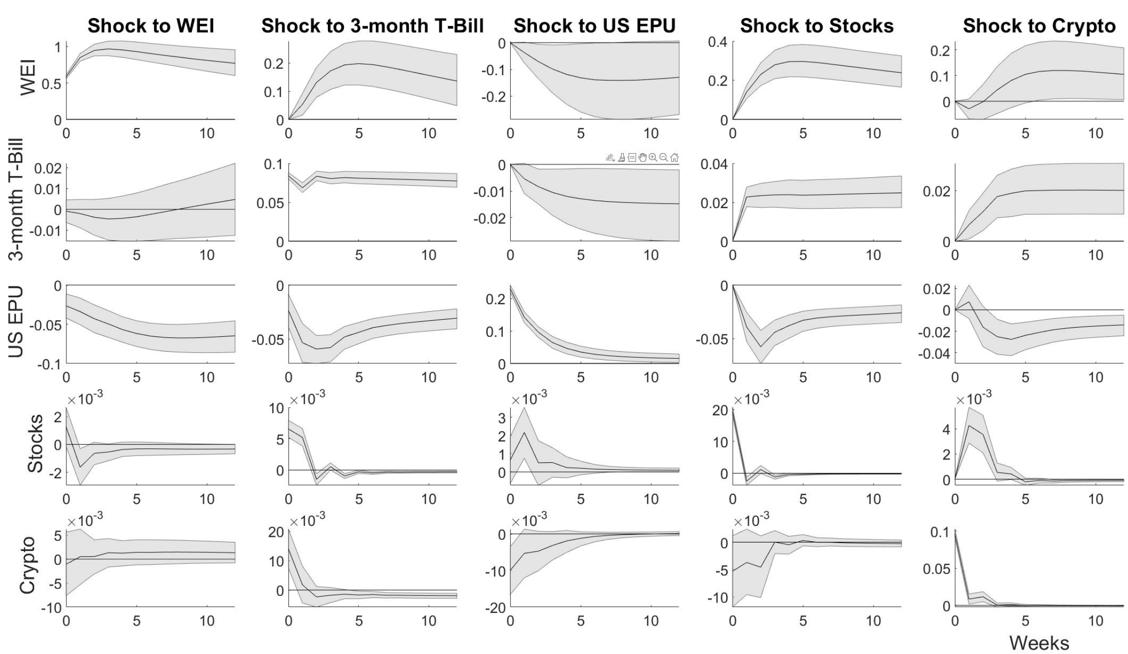

Figure A5: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, FFR, EPU, and the two market factors. See Figure 5.

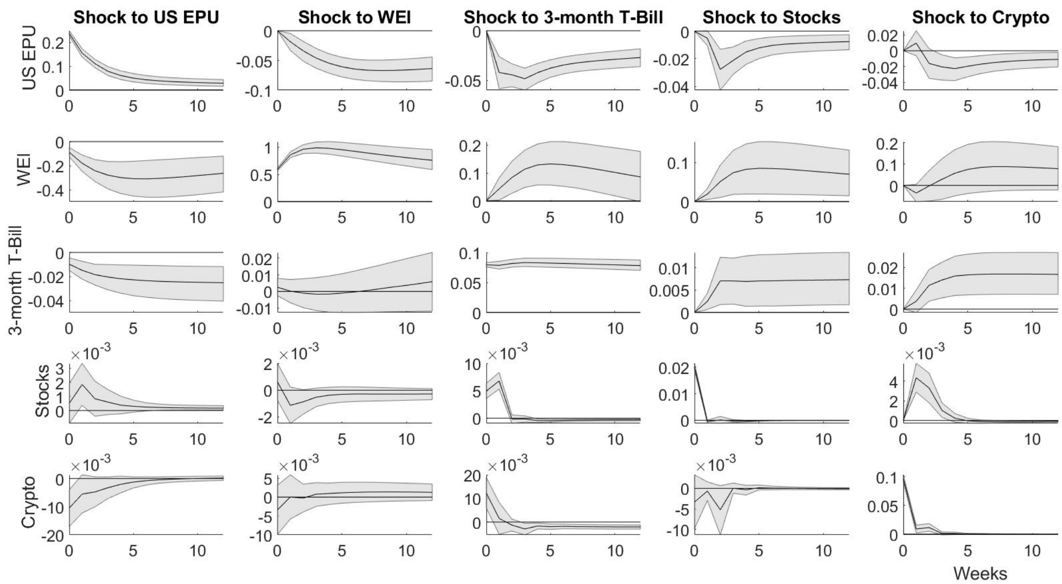

Figure A6: Impulse Response Functions – U.S. EPU Model. Robustness check of the benchmark structural identification scheme in Figure 5 in which EPU is ordered first.

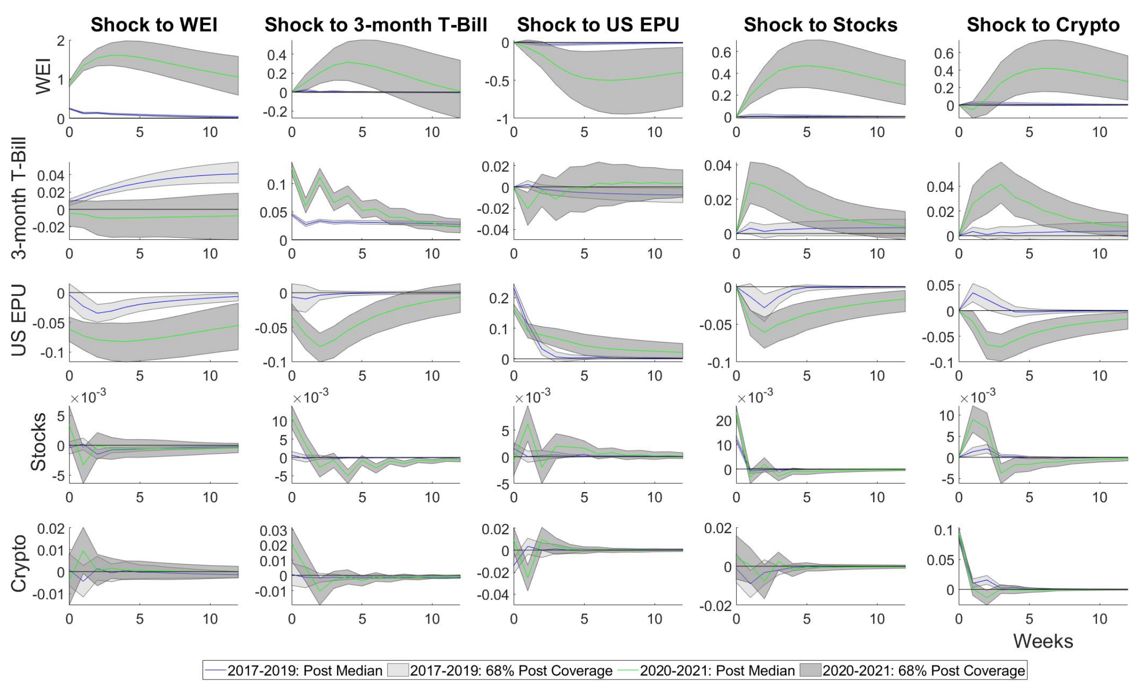

Figure A7: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, FFR, EPU, and the two market factors and sample split in two periods. See Figure 6.

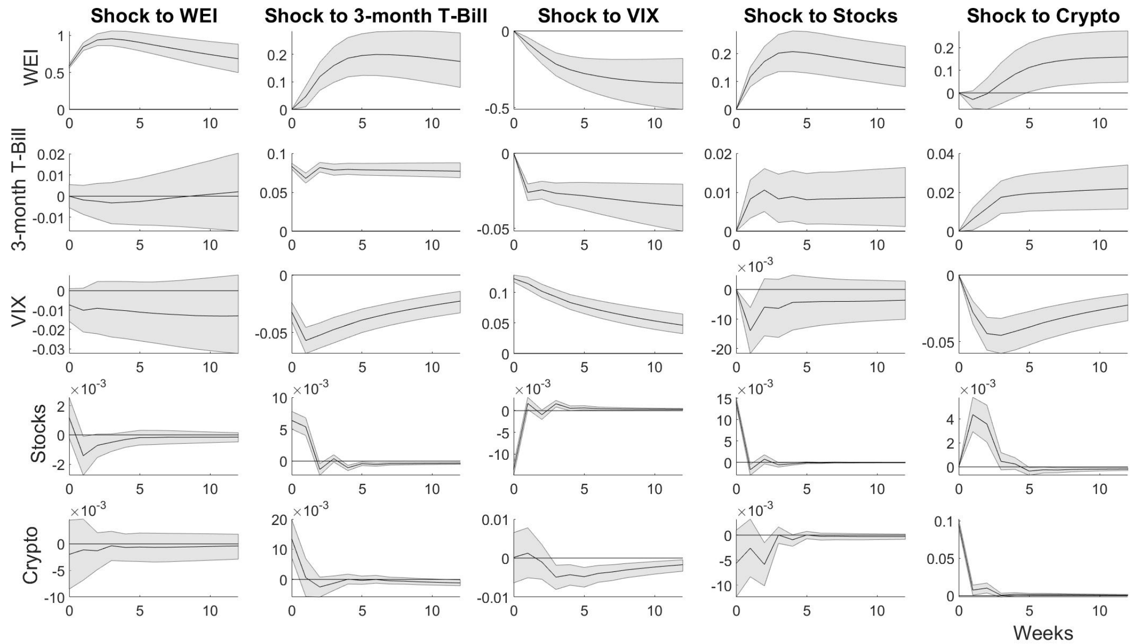

Figure A8: Impulse Response Functions – U.S. VIX Model. VAR model with WEI, FFR, VIX, and the two market factors. See Figure 7.

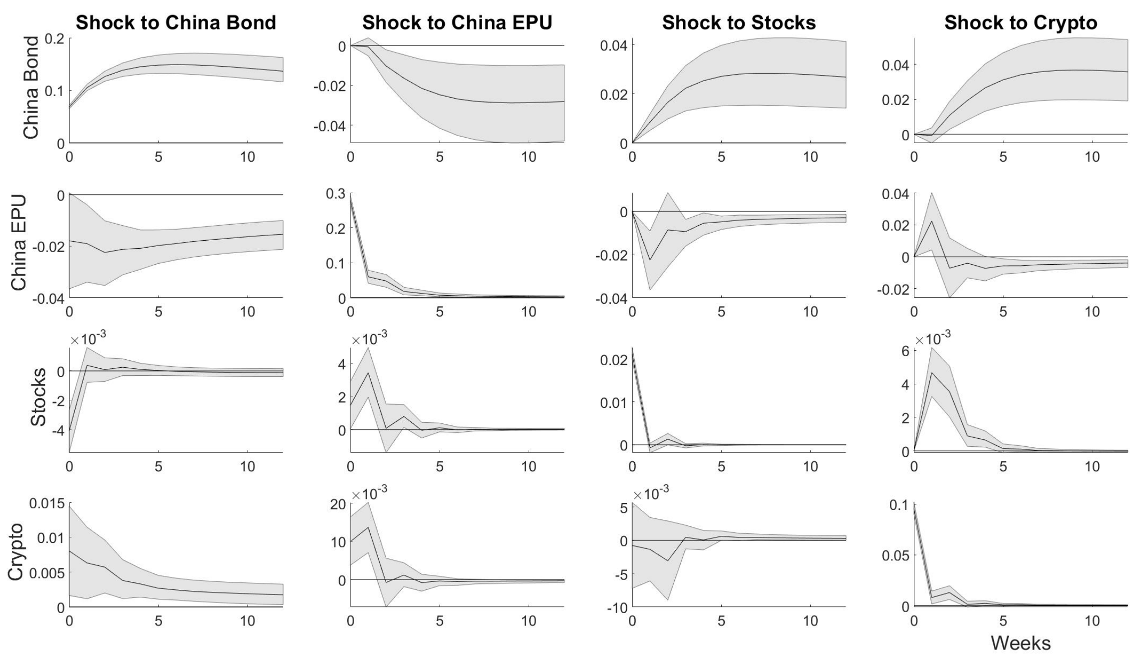

Figure A9: Impulse Response Functions – China EPU Model. VAR model with short term interest rate, EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis. See Figure 8.

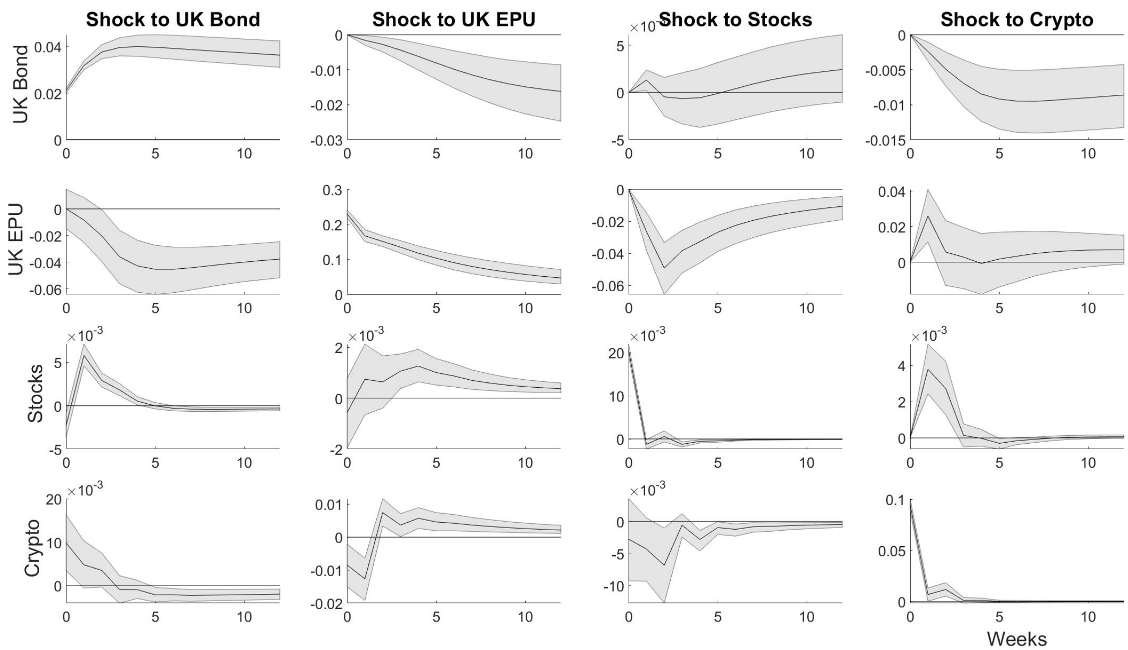

Figure A10: Impulse Response Functions – U.K. EPU Model. VAR model with short term interest rate, EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 14/86th percentile posterior bands; weeks from the shock on the x-axis. See Figure 8.