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

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Abstract

We study the interactions between cryptocurrencies, stocks, and U.S. economic policy uncertainty (EPU) using a Factor-Augmented Vector Autoregressive framework, in which return comovements within each asset market are modeled by a single common factor. We document a greater heterogeneity across cryptocurrencies than stocks, with market fragmentation by functional characteristics of the projects. Through structural impulse-response analysis, we find that: (1) Stock returns positively respond to crypto shocks, but not vice versa; (2) Cryptocurrencies can be used to hedge against U.S. EPU, but display safe-haven characteristics against Chinese EPU. We interpret these results in light of recent crypto investment and pricing models.

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

JEL Classification: G1, G11, G15, F3, E44

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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 investors, to a global market of almost 3 trillion dollars of capitalization in early 2024. 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. Crypto trading has turned into a mainstream activity (Weber, Candia, Coibion, and Gorodnichenko, 2023).

Despite the widespread popularity of crypto trading, however, cryptocurrencies remain a challenging asset category to understand. As a consequence, a rich academic literature that aims to explain the pricing of cryptocurrencies and crypto investment decisions has recently developed (see, among the others, Weber, Candia, Coibion, and Gorodnichenko, 2023; Biais, Bisiére, Bouvard, Casamatta, and Menkveld, 2023; Kogan, Makarov, Niessner, and Schoar, 2023; Auer, Cornelli, Doerr, Frost, and Gambacorta, 2023; Liu, Tsyvinski, and Wu, 2022). In this paper, we contribute to this line of work with an empirical study of the aggregate dynamics of crypto markets, contrasted to that of traditional equity markets. We set up a Factor-Augmented Vector Autoregression (FAVAR) framework 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.[2] We use this model to analyze the interactions between the market factors and to study the impact of the U.S. economic policy uncertainty (EPU) on the two factors, which allows us to shed light on some of the motives and implications of including cryptocurrencies in investment portfolios.

Our analysis illustrates 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. Factors in asset pricing tests are routinely used to reduce the impact of idiosyncratic noise on parameter estimates. We, indeed,

[1] The crypto market roughly corresponds to, at most, 3% of the global stock market.

[2] Kogan, Makarov, Niessner, and Schoar (2023) find that investors trade gold very similarly to how they trade stocks in relation to crypto investment strategies. For this reason, and given the purpose of our paper, we focus on modeling the joint dynamics of stocks and crypto assets.

find that cryptocurrency returns are characterized by very large idiosyncratic cross-sectional differences, which strongly support the use of a factor representation. 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 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, consistent with the momentum trading hypothesis. 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 indicates that a broader transmission channel could be in place. We characterize this effect by showing that it could be explained by the concurrence of factors affecting crypto investors' beliefs about the general economic and financial conditions.

Third, we uncover a novel effect of economic policy uncertainty shocks on crypto markets. Cryptocurrencies and traditional stock returns move in opposite directions in response to a shock to the U.S. EPU. Cryptocurrencies can be used as a hedge against movements in the U.S. EPU. Alternatively, we also document that an increase in the Chinese EPU causes an increase of both traditional stock and crypto returns. In this case, cryptocurrencies (and traditional stocks) behave as a safe-haven against Chinese 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, however, 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 may depend on the originating region of the uncertainty shocks. This reflects a higher heterogeneity of the crypto space, where investors with exposure to shocks from different regions of the world could invest in cryptocurrencies pursuing quite different goals and strategies.[3] These differences, for example, have relevant implications for policymakers and international coordination in designing regulatory frameworks for cryptocurrencies.

We can interpret these results through the lenses of the crypto pricing models and the evidence about investment decisions in cryptocurrencies established in the current literature. Our results relate to three of the main conclusions provided by these models.

First, the dynamics of crypto prices are determined by the expectations about future adoption of a cryptocurrency, and the beliefs that higher current prices today facilitate higher adoption and higher prices tomorrow (Biais, Bisiére, Bouvard, Casamatta, and Menkveld, 2023; Kogan, Makarov, Niessner, and Schoar, 2023). These beliefs motivate investment strategies based on momentum trading (Kogan, Makarov, Niessner, and Schoar, 2023; Auer, Cornelli, Doerr, Frost, and Gambacorta, 2023; Weber, Candia, Coibion, and Gorodnichenko, 2023; Liu, Tsyvinski, and Wu, 2022), which explains the persistence of the crypto factor response to its own shocks. On the contrary, investment strategies in stocks are contrarian and portfolio positions are re-balanced after a price shock in a mean-reverting fashion.

Second, a large share of crypto investors is also active in the traditional stock markets –

[3]Similarly, Karau (2021) finds that the Bitcoin prices respond differently to monetary shocks from the ECB or the Fed.

Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023) find this share is 80% for U.S. investors. This characteristic of crypto investors provides a foundation for the transmission channel from crypto to stocks that we document here. In our analysis, we show that these comovements are not related to a higher appetite for risk among crypto investors' (consistent with the evidence of Kogan, Makarov, Niessner, and Schoar, 2023; Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter, 2023, who find that crypto and stock investors share similar characteristics), but more likely related to changes in crypto investors' expectations about the broader economic and financial conditions incorporated in their investment decisions. Moreover, evidence that cryptocurrencies have no exposure to common stock market factors (see Liu and Tsyvinski, 2020), corroborates our finding about the lack of response of the crypto factor to shocks to the stock factor.

Finally, crypto investors are more likely to be younger, wealthier, and more risk-seeking than the average population; however, their demographic characteristics do not fundamentally differ from those of the broader investor population (Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter, 2023; Weber, Candia, Coibion, and Gorodnichenko, 2023; Kogan, Makarov, Niessner, and Schoar, 2023). Portfolio diversification motives could hence play an important role in crypto investment decisions, as they do for other asset categories, and our results show that cryptocurrencies can be used to hedge against economic policy uncertainty. The mechanism behind this result can also be explained by the interplay between expectations about future prices, adoption, and current price dynamics (Biais, Bisiére, Bouvard, Casamatta, and Menkveld, 2023).

In recent years, regulatory frameworks in many countries have been intended to become stricter with respect to crypto markets, especially in the U.S. However, the timeline of the implementation of the new rules and their strictness have been characterized by a lot of uncertainty. If some of the underlying EPU components incorporate information about the risks of changes in the crypto regulatory framework and tax regimes that would negatively affect future adoption of cryptocurrencies, then crypto investors' beliefs would also be adjusted downwards leading to the response of the crypto factor to EPU that we observe.

1.1 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, 2023; 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 on which we also rely in the interpretation of our results.

Second, a significant strand of the literature analyzes different aspects of price dynamics in the crypto market. An important theme is price manipulation by large, sophisticated players in these markets and the impact on small, unsophisticated investors (Auer, Cornelli, Doerr, Frost, and Gambacorta, 2023). 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 crypto markets directly speak to this body of literature.

Third, cryptocurrencies are also studied in the context of portfolio management and investors' decisions. 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; Liu, Tsyvinski, and Wu, 2022; Liu and Tsyvinski, 2020). Similarly, this 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), or consumers' preferences and government transaction policies (Hendrickson, Hogan, and Luther, 2016). Finally, another strand of this literature relies on large-scale data sets at the retail level (Weber, Candia, Coibion, and Gorodnichenko, 2023; Kogan, Makarov, Niessner, and Schoar, 2023; Auer, Cornelli, Doerr, Frost, and Gambacorta, 2023; Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter, 2023) to uncover findings about the effects of expectations, momentum trading, and investors characteristics on crypto investment decisions.

Our research question and modeling strategy are closely related to many of the papers in this group. 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. As discussed earlier, our results are also consistent with the empirical evidence and the interpretation of the crypto investors' behavior put forward by these papers. From a methodological perspective, the paper closest to ours is Karau (2021), who uses a VAR model in their analysis to study the effect of monetary policy shocks on Bitcoin prices. We add the factor component to the VAR model, which allows us to explicitly extend the analysis to the broader crypto market, achieving conclusions that more generally apply to the overall category of crypto assets rather than just to Bitcoin.

2 Modeling 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 other hand, 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 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

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.

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 an international perspectives and build a China-centric alternative. In this specification, we include the interest rate on the 3-month Chinese government bond and the log China EPU (also from Baker, Bloom, and Davis, 2016). The short-term interest rates are obtained from the 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 $\Phi\left(L\right)$ 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 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.[4]

[4]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

Variable	Model		
	Baseline	+BTC Web	2 Sub-Samples
U.S. EPU	✓	✓	✓
Google search: Bitcoin		✓	
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.

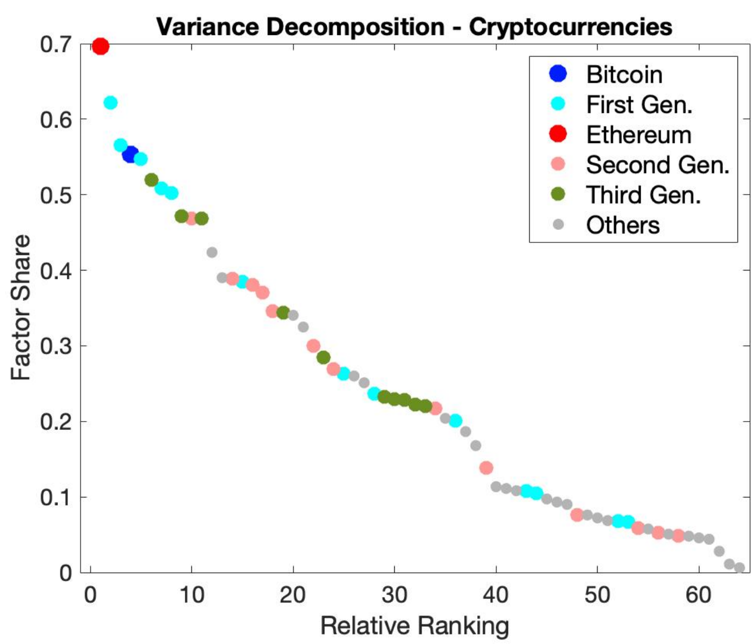

Figure 1: Variance Decomposition – Share of the variance of each cryptocurrency explained by the common market factor.

The 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 16/84th percentiles of the posterior distribution of the responses. We make three observations based on the results illustrated in Figure 2.

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 the implicitly higher riskiness, of crypto assets. This aspect is rationalized, for instance, by the Biais, Bisiére, Bouvard, Casamatta, and Menkveld (2023)'s model in which current crypto prices depend in equilibrium on the expectations about future prices and transactional benefits of the currency, which are endoge-

the traditional stock markets, with dynamics depending on average on much larger idiosyncratic components.

nous to the price itself. These feedback effects introduce "volatile-price" equilibria in which sunspots can drive random fluctuations of the price, regardless of changes in fundamentals.

Second, while the stock shock is fundamentally white noise, the crypto shocks exhibit persistence up to three to four weeks after the innovation. This result underscores the differences in crypto investment decisions relative to traditional stocks. Crypto investors adopt a momentum investment strategy, in which higher prices are an indicator of future higher adoption and positively influence expectations about future price growth as well. Investors, on the contrary, are typically contrarian in stocks (Kogan, Makarov, Niessner, and Schoar, 2023; Weber, Candia, Coibion, and Gorodnichenko, 2023; Auer, Cornelli, Doerr, Frost, and Gambacorta, 2023).

Third, we find that the stock market factor responds significantly to the crypto shocks, but not vice versa. The response of the stock markets is positive, economically quite sizable (with a peak around 0.5%), and strongly significant for an extended time period (up to five weeks). The lack of transmission from the stock to the crypto market is not unexpected, as many observers believe that crypto investors follow different investment models in the crypto market. Some empirical evidence by Liu and Tsyvinski (2020); Liu, Tsyvinski, and Wu (2022) also shows that cross-sectional returns of cryptocurrencies can be explained by crypto-specific factors and have no exposure to common stock market and macroeconomic factors.[5] However, the feedback from the crypto into the traditional markets is a novel and interesting result, for which we provide further discussion next.

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

[5]Similalry, 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.

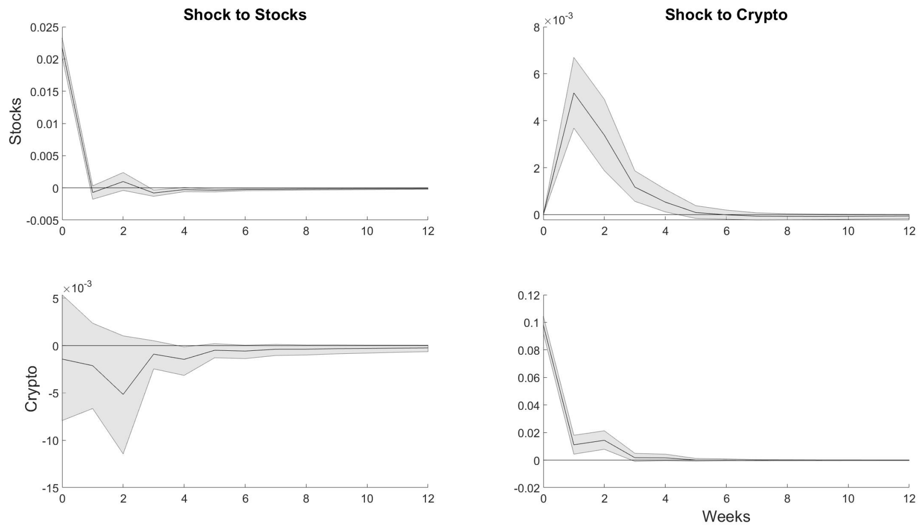

Figure 2: Impulse Response Functions – Baseline Model. VAR model with the U.S. EPU index and the two factors for the the stock markets and the crypto market. The IRFs are based on a recursive Cholesky scheme using this same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

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 then alternatively reflect a broader transmission mechanism, with richer economic and financial implications. The remainder of the analysis in this section investigates this possibility.

The first hypothesis we test is whether this effect captures an increase in the appetite for risky assets by international crypto investors who, in response to a positive shock to crypto returns, initially invest more in crypto (as prescribed by momentum trading), but then also turn to other types of risky assets such as stocks. To test this hypothesis we estimate model +BTCWeb in Table 3, where the index for the web searches of the keyword "Bitcoin" from Google Trends is included in the model, along with the U.S. EPU used as a control. The Google Trends index is assumed to approximate investor interest for cryptocurrencies.

Figure 3 shows 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 do not find evidence supporting this hypothesis, as the response of the stock factor to the Google Trends shock is not significant.

For this conjecture to work, two things must actually occur. First, crypto investors need to also hold traditional stocks in their portfolios. We know this is the case as Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023) show that a large share of crypto investors – 80% for the U.S. – is also active in the traditional stock markets. Second, crypto investors would need to exhibit a different attitude towards risk from traditional investors. Crypto investors are generally more risk-seeking than the average population; however, Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023); Weber, Candia, Coibion, and Gorodnichenko (2023); Kogan, Makarov, Niessner, and Schoar (2023) find that their characteristics are very similar to those of the general investor population. Our result is consistent with this evidence.

The second hypothesis we entertain is that the crypto shocks could embed changes in crypto investors' beliefs about the broader economic and financial conditions, which are incorporated in both their crypto and stock investment decisions determining these factor comovements. The rationale behind this hypothesis is that beliefs about future prices and adoption of cryptocurrencies are one of the main determinants of current prices (Biais, Bisiére, Bouvard, Casamatta, and Menkveld, 2023; Weber, Candia, Coibion, and Gorodnichenko, 2023; Kogan, Makarov, Niessner, and Schoar, 2023; Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter, 2023). Expectations about overall economic and financial prospects could be positively correlated with crypto investor beliefs about the growth of crypto ecosystems. Similarly, we can expect these expectations to correlate with stock expected returns and the investment decisions in stock markets. More generally, Giglio, Maggiori, Stroebel, and Utkus (2021) document that beliefs drive investors' expectations and are reflected in portfolio allocations, affecting both the direction and magnitude of trades.

We can test this hypothesis, at least indirectly, exploiting the COVID-19 pandemic period and the large systemic worsening of economic and financial conditions it caused. If this explanation is correct, we should expect a stronger response of the stock factor in the most recent

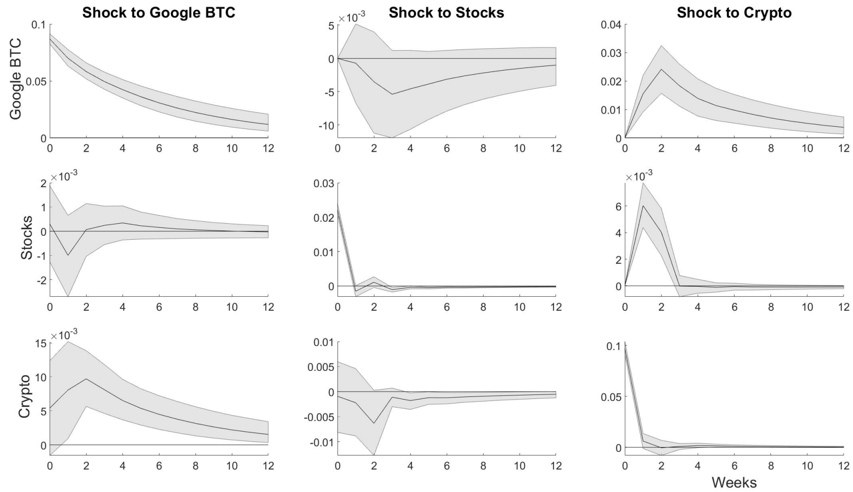

Figure 3: Impulse Response Functions – +BTC Web Model. VAR model with the U.S. EPU index, the Google Trends index of the web searches for the keyword "Bitcoin," and the two factors for the the stock markets and the crypto market. The IRFs are based on a recursive Cholesky scheme using this same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

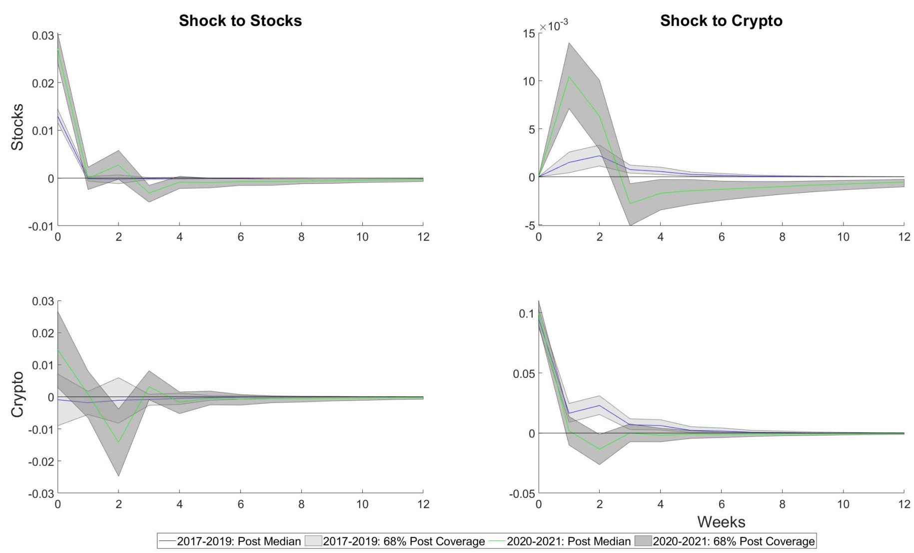

Figure 4: Impulse Response Functions – Baseline Model. VAR model with the U.S. EPU index and the two factors for the the stock markets and the crypto market. The sample is split in two parts: before 1-1-2020 (the black line) and after 1-1-2020 (the green line). The IRFs are based on a recursive Cholesky scheme using this same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

part of the sample.[6] 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. The responses of the stock market factor to the crypto shock are qualitatively consistent across the two sub-samples; however, the magnitude of the effect differs and the post-2020 response is about four times as large as the pre-2020 one, upholding this interpretation of the crypto shocks.[7]

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 this end, we enrich the structure of the baseline model by adding macroeconomic and policy variables, such as a real economic activity index and policy rates, to the EPU and the financial market block. Our main specification is for the U.S. economy, but we also extend our analysis to China, adapting the specification accordingly as illustrated in Table 4. Considering multiple countries allows us to highlight interesting differences in the effects of uncertainty from different regions of the World.

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

[7] Interestingly, this result is related to the work of Li and Miu (2023) who find that the unconditional correlation between crypto and stock returns is positive in regimes of high return volatility of both markets, but insignificant in other volatility regimes. Although the full dynamics of the return correlation likely depends on multiple factors, our interpretation of the crypto shock spillovers can contribute to explain Li and Miu (2023)'s results at least for the high-volatility regime in which higher market uncertainty makes the shifts in expectations about financial and economic conditions sharper.

Variable	**Model**			
	U.S. EPU	U.S. VIX	2 Sub-Samples	CHN EPU
WEI	✓	✓	✓	
U.S. Bond Rate	✓	✓	✓	
CHN Bond Rate				✓
U.S. EPU	✓		✓	
CHN 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) replaces 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.

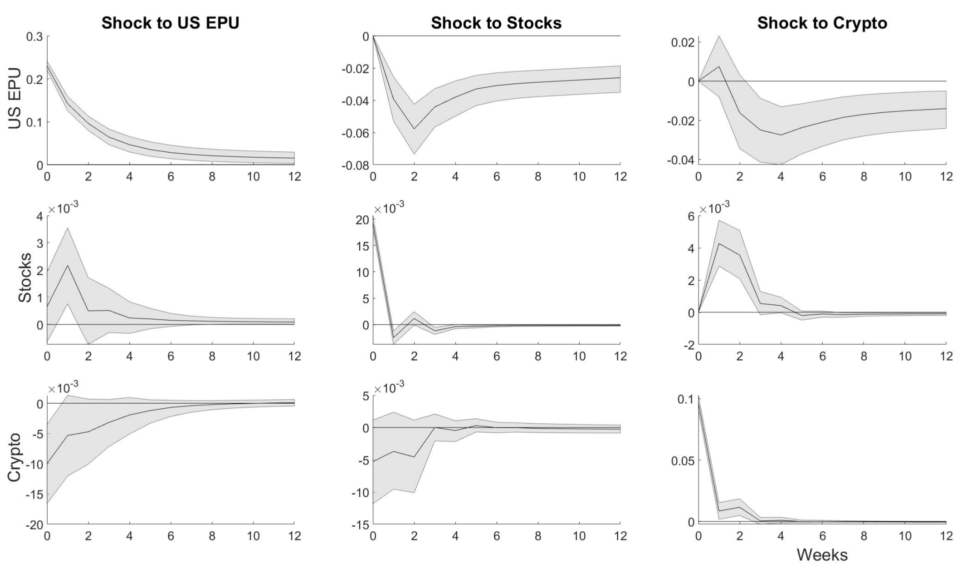

Figure 5: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, 3-month T-bill rate, EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

Main Result. 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, EPU, factors.

The identification approach relies on two main assumptions. 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 0.3% 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 timeline 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,[8] 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.[9]

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.[10] 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. Numerous papers, such as Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023); Weber, Candia, Coibion, and Gorodnichenko (2023); Kogan, Makarov, Niessner, and Schoar (2023), document that the typical crypto investor profile is quite similar to that of the broader investor population and crypto investors are also active in traditional financial markets. It is reasonable to believe that portfolio diversification can then motivate crypto investment decisions and cryptocurrencies can be

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

[9]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.

[10]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 EPU 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.

useful portfolio complements of traditional stocks. The negative conditional correlation of the two market factors in response to the policy uncertainty shocks suggest that cryptocurrencies can be used to hedge against U.S. EPU.

Second, the transmission mechanism that rationalizes the response of the stock factor would not work for cryptocurrencies. Crypto fundamentals, for instance, might not respond to changes in U.S. economic policy. Similarly, the American interest rate might not be a major component of the discount factor relevant for the crypto investors, allowing uncertainty to directly raise their discounting. In any case, this result can be more effectively interpreted through the lenses of the equilibrium crypto pricing theories that focus on the interplay between beliefs about future prices and adoption of cryptocurrencies, and current price dynamics (Biais, Bisiére, Bouvard, Casamatta, and Menkveld, 2023).

The negative response of the crypto factor to EPU shocks may reflect higher uncertainty about the regulatory framework and tax regimes of crypto investments in the U.S. The regulatory stance of the American government has become increasingly stricter towards crypto markets over the last decade. The predominant belief among crypto investors is that the American regulation will negatively affect adoption and prices of cryptocurrencies in the long run, lowering current prices as well. However, the timeline of the implementation and the strictness of a final regulatory system have been surrounded by great uncertainty. If EPU shocks capture new negative information about the American policy-makers' intentions on crypto markets, then crypto investors' expectations would also be adjusted downwards leading to negative returns.

Additional Analysis. 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

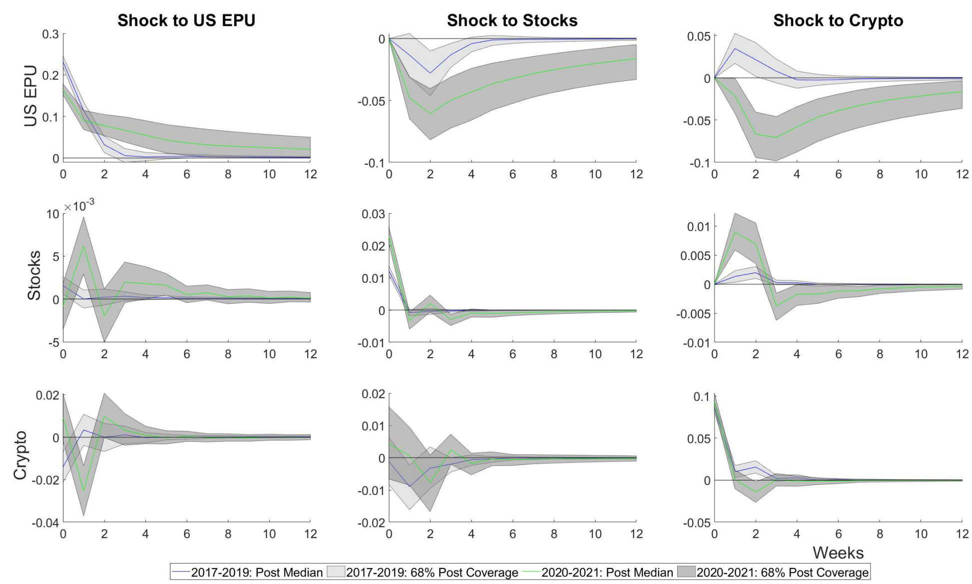

Figure 6: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, 3-month T-bill rate, EPU, and the two market factors. The sample is split in two parts: before 1-1-2020 (the black line) and after 1-1-2020 (the green line). The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

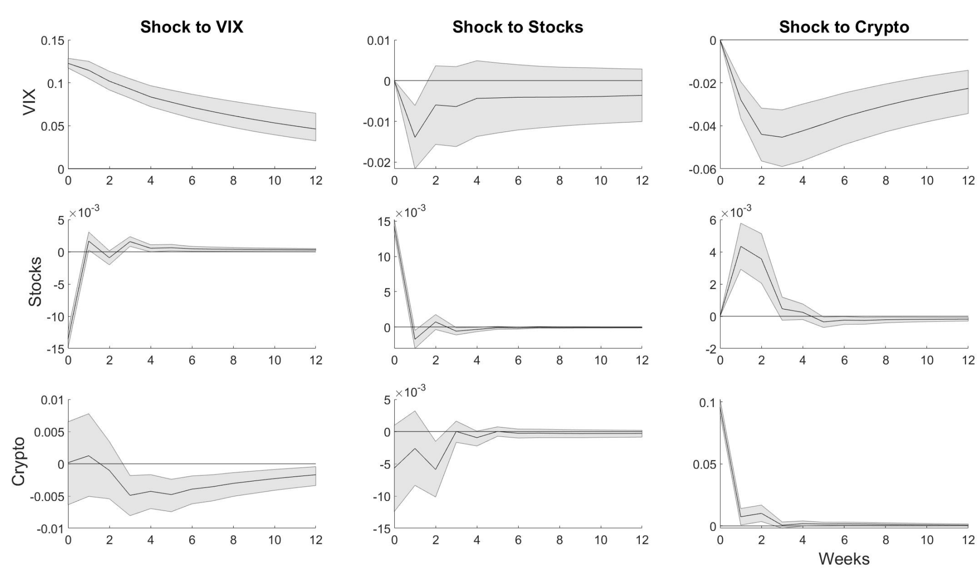

Figure 7: Impulse Response Functions – U.S. VIX Model. VAR model with WEI, 3-month T-bill rate, VIX, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

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-related 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 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 rates (see Figure A8) 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.

Chinese EPU. Finally, U.S. EPU may not be the only source of economic policy uncertainty that matters for the dynamics of crypto markets. Hence, we also explore the effects of the Chinese EPU in Figure 8. We find two interesting results.

First, the Chinese EPU affects traditional stock markets in the same way as the U.S. EPU. Positive EPU shocks from China lead to significant increases of stock returns. 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. Setting aside specific differences between the specifications of these models and their response functions, however, a

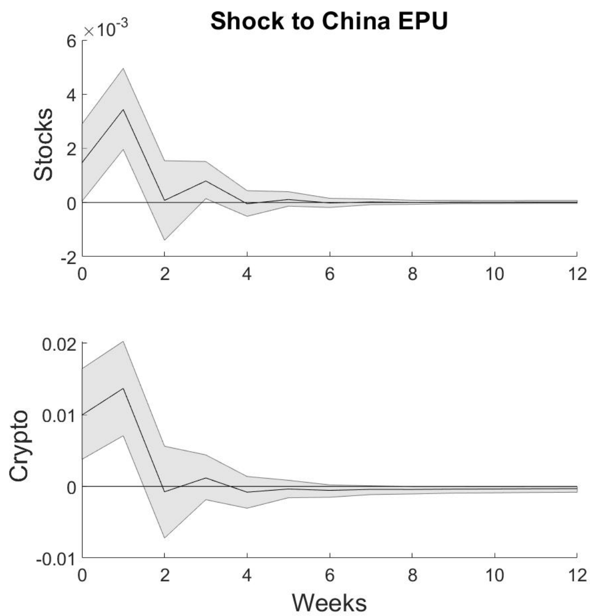

Figure 8: Impulse Response Functions – Comparison of the responses of stock and crypto factors to an EPU shock in the China-based VAR Model with a short-term interest rate, domestic EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis.

clear conclusion emerges about the possible segmentation of the crypto space. Investors with different degrees of exposures to regional sources of uncertainty may not necessarily face the same incentives to invest in cryptocurrencies.

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

6 Conclusions

We rely on a FAVAR approach to model the comovements of crypto and traditional stock markets, explicitly accounting for the heterogeneity within each asset class. We use this model to study the effects of economic policy uncertainty on these two types of investments.

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 interpreted in terms of changes in crypto investors' expectations about the broader economic and financial conditions reflected in their investment decisions. 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 they behave as a safe-haven against the Chinese EPU shocks.

Our analysis provides relevant insights to formulate policy recommendations. The first two results speak to the importance of recognizing and correctly dealing with the heterogeneity of crypto assets as well as their relation to other asset categories. As the use of cryptocurrencies as an investment grows and the integration between crypto and traditional financial markets increases, more clear regulation of the crypto space is required, especially to protect less sophisticated investors. Regulation, however, must be able to distinguish the 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 also includes some evidence about 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 clarify the reasons behind regional differences and to provide insights useful to effectively coordinate the international response of regulators to crypto market risks.

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Appendix

A Additional Figures & Full Sets of IRFs

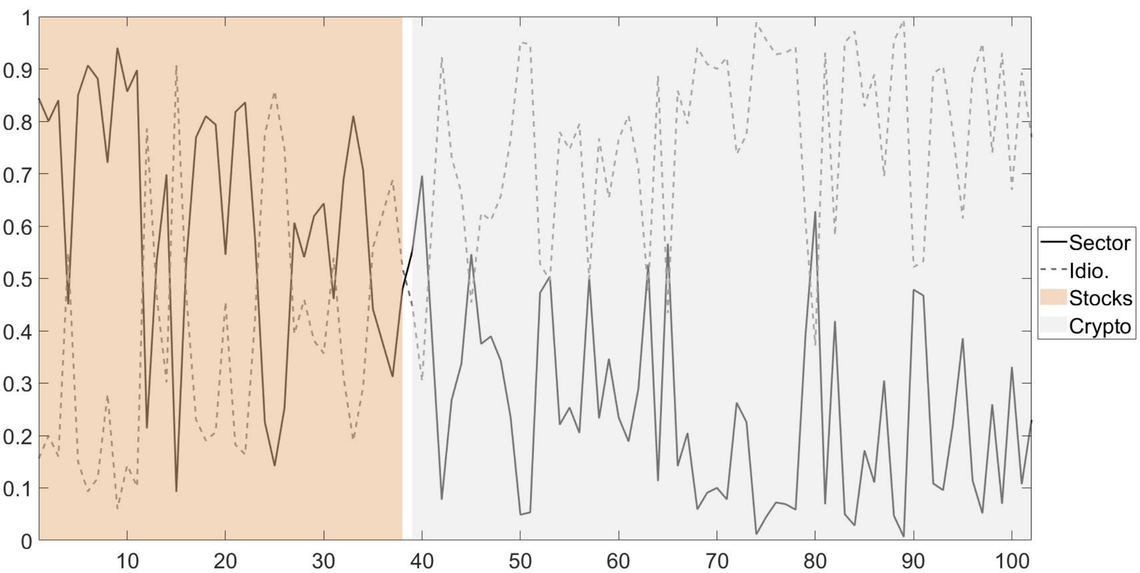

Figure A1: Variance Decomposition: Share of variance of each stock market index (left side panel) and of each cryptocurrency (right side panel) explained by their market factor and their own idiosyncratic component.

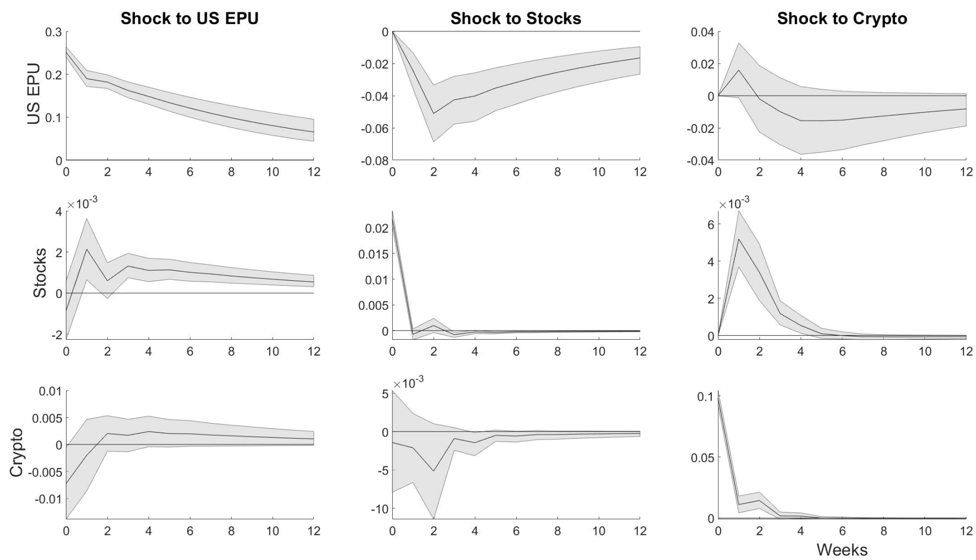

Figure A2: Impulse Response Functions – Baseline Model. VAR model with the U.S. EPU index and the two factors for the the stock markets and the crypto market. See Figure 2.

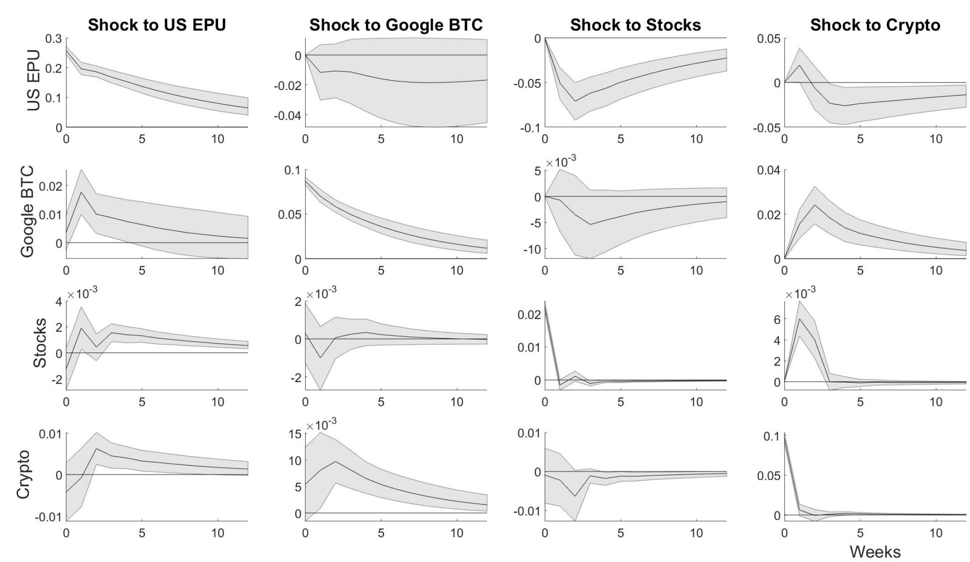

Figure A3: Impulse Response Functions – +BTC Web Model. VAR model with the U.S. EPU index, the Google Trends index of the web searches for the keyword "Bitcoin," and the two factors for the the stock markets and the crypto market. See Figure 3.

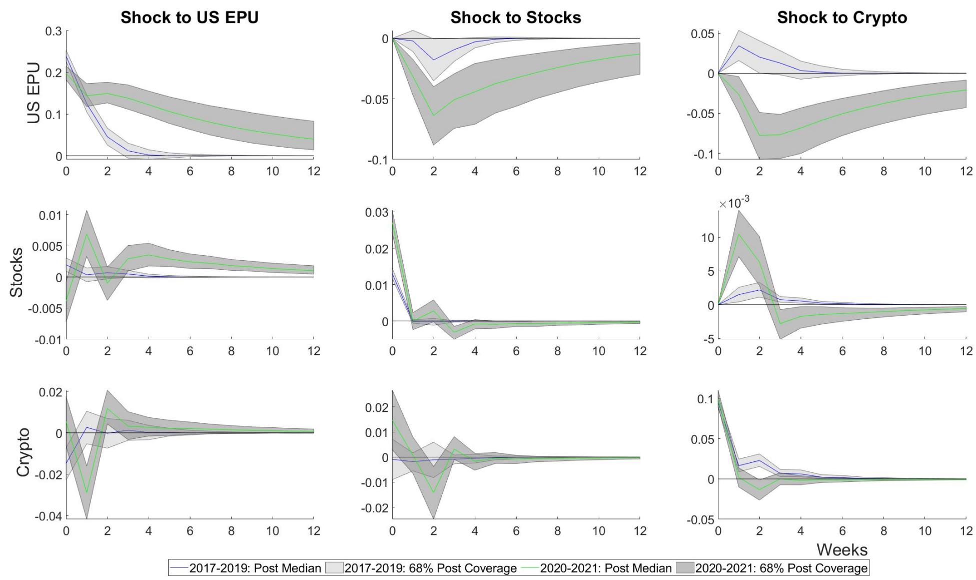

Figure A4: Impulse Response Functions – Baseline Model with split sample. See Figure 4.

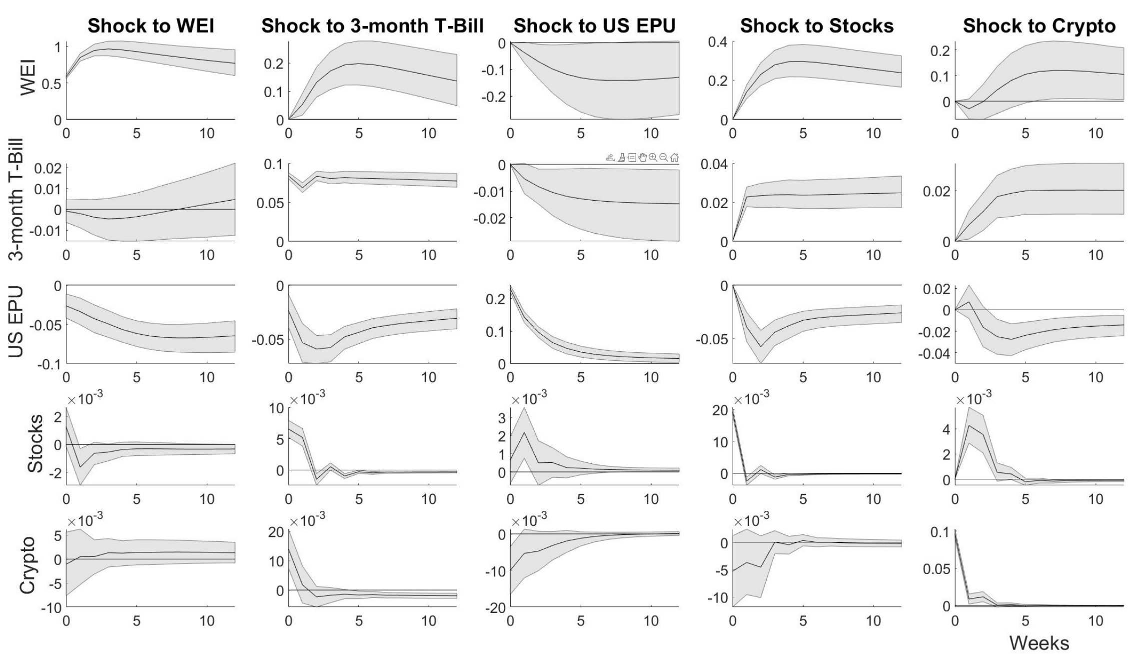

Figure A5: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, 3-month T-bill rate, EPU, and the two market factors. See Figure 5.

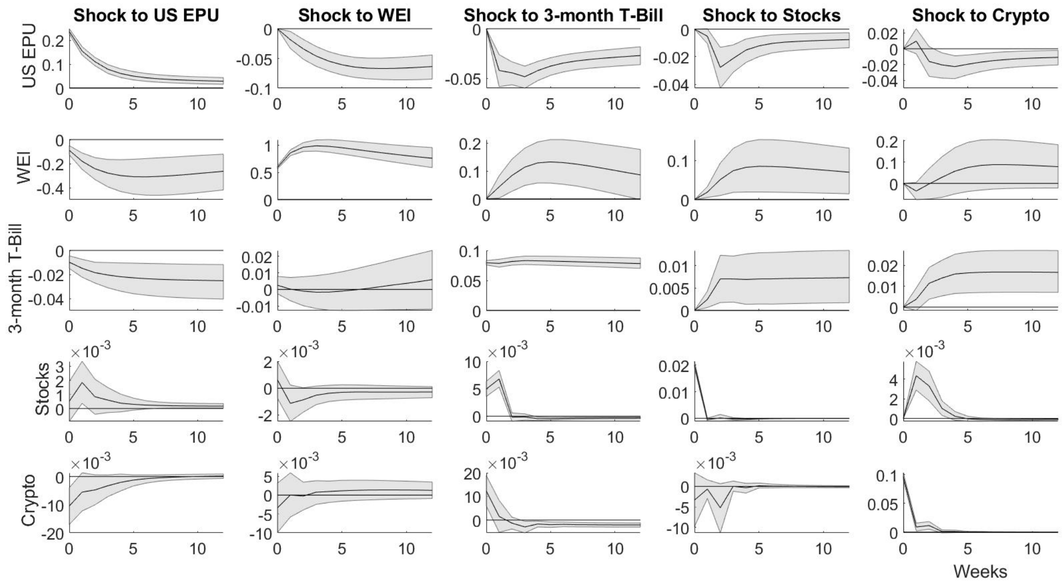

Figure A6: Impulse Response Functions – U.S. EPU Model. Robustness check of the benchmark structural identification scheme in Figure 5 in which EPU is ordered first.

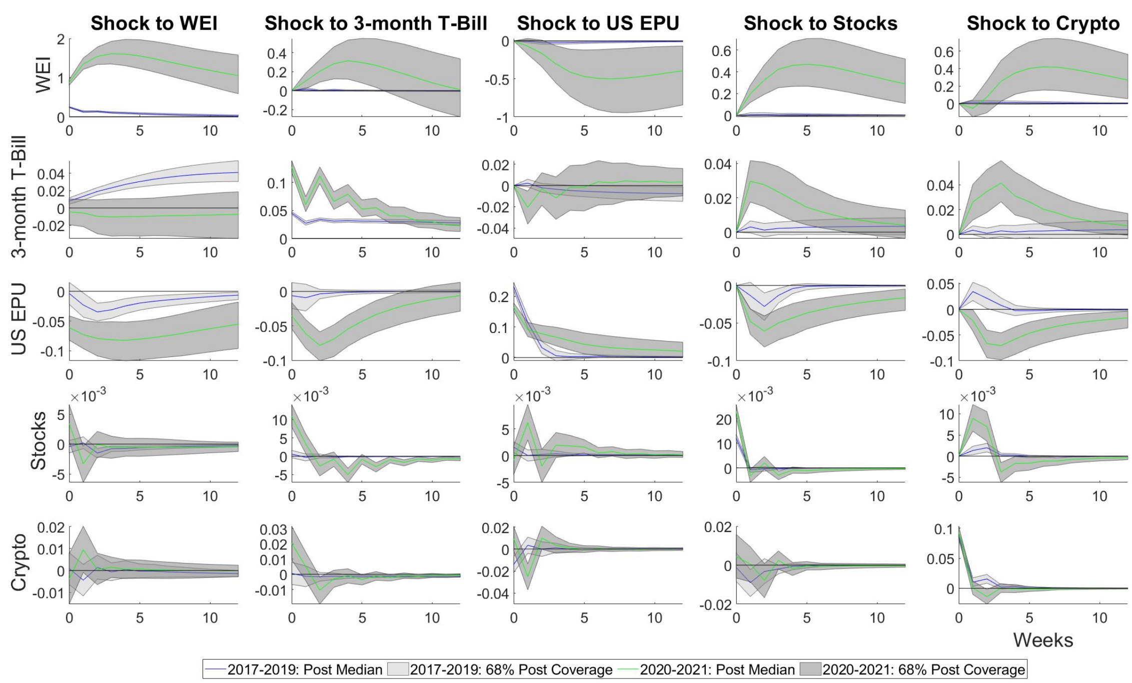

Figure A7: Impulse Response Functions – U.S. EPU Model. VAR model with WEI, 3-month T-bill rate, EPU, and the two market factors and sample split in two periods. See Figure 6.

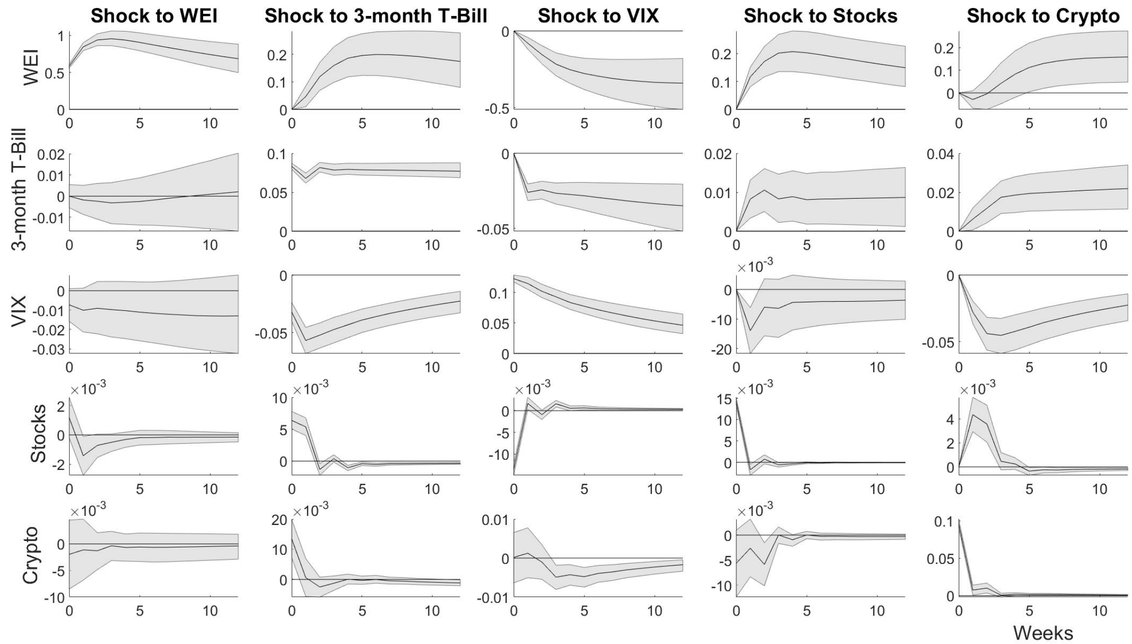

Figure A8: Impulse Response Functions – U.S. VIX Model. VAR model with WEI, 3-month T-bill rate, VIX, and the two market factors. See Figure 7.

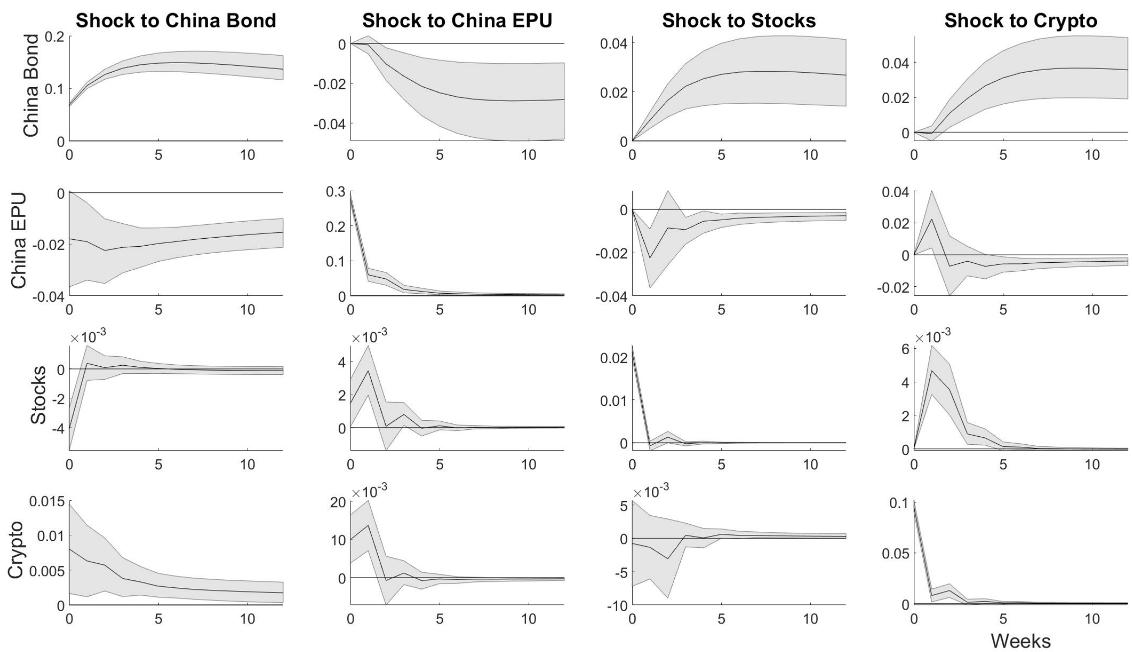

Figure A9: Impulse Response Functions – China EPU Model. VAR model with short term interest rate, EPU, and the two market factors. The IRFs are based on a recursive Cholesky scheme using the same ordering of the variables. One standard deviation shocks; 16/84th percentile posterior bands; weeks from the shock on the x-axis. See Figure 8.