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by Iñaki Aldasoro, Giulio Cornelli, Massimo Ferrari Minesso, Leonardo Gambacorta, Maurizio Michael Habib

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Stablecoins, money market funds and monetary policy*

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Abstract

Using a new series of crypto shocks, we document that money market funds' (MMF) assets under management, and traditional financial market variables more broadly, do not react to crypto shocks, whereas stablecoin market capitalization does. U.S. monetary policy shocks, in contrast, drive developments in both crypto and traditional markets. Crucially, the reaction of MMF assets and stablecoin market capitalization to monetary policy shocks is different: while prime-MMF assets rise after a monetary policy tightening, stablecoin market capitalization declines. In assessing the state of the stablecoin market, the risk-taking environment as dictated by monetary policy is much more consequential than flight-to-quality dynamics observed within stablecoins and MMFs.

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1 Introduction

Stablecoins are crypto tokens that live on distributed ledgers (i.e., "on-chain") and promise to be worth always a dollar, providing par convertibility on demand. Stablecoin issuers defend this promise by holding (mostly) fiat-denominated (i.e., "off-chain") short-term assets, such as Treasuries, high-quality commercial paper, repurchase agreements and bank deposits.[1] The combination of money-like demandable liabilities with backing assets that may become illiquid implies that stablecoin issuers' liquidity transformation exposes them to runs.[2]

Stablecoins' balance sheet structure therefore closely resembles that of money market funds (MMFs). Indeed, Anadu et al. (2024) and Oefele et al. (2024) document that during episodes of stress in crypto markets, stablecoins exhibit flight-to-quality dynamics, much like those observed for MMFs during the great financial crisis and the COVID-19 pandemic (Cipriani and Spada, 2020).[3] During such episodes, perceived high-quality stablecoins receive inflows at the expense of their perceived low-quality peers, much like non-prime MMFs received inflows at the expense of prime MMFs during stress episodes in that market. However, on aggregate, there is no evidence of inflows into stablecoins during major crypto events (Anadu et al., 2024) and, in particular, during the March 2023 banking crisis (Oefele et al., 2024). Whether stablecoins act as crypto safe-haven is still an open question.

In this paper we document an important distinction between stablecoins and MMFs, namely their very different response to crypto and U.S. monetary policy shocks since 2019. Drawing on a new series of crypto market shocks and a standard measure of monetary policy shocks, we show that crypto shocks are inconsequential for MMFs and traditional financial markets but

[1]Herein we focus on USD-pegged stablecoins, which capture most of the market. Moreover, with one exception, we focus on stablecoins backed by off-chain financial assets. Algorithmic stablecoins are minor after the demise of TerraUSD, and crypto-backed stablecoins capture a small share of the market – mostly accounted for by Dai, which we include in our analysis.

[2]For stablecoin runs see Bertsch (2023), Lyons and Viswanath-Natraj (2023), d'Avernas et al. (2023) and Ahmed et al. (2024), among others.

[3]There are of course differences between stablecoins and MMFs, most notably that MMFs are well regulated whereas stablecoins are not, that stablecoin liabilities are on-chain rather than off-chain, and they do not pay interest. Other parallels are also possible as well, such as with wildcat banks (Gorton and Zhang, 2023), fixed exchange rate regimes (Levy Yeyati and Katz, 2022), exchange-traded funds (Ma et al., 2023) or eurodollars (Aldasoro et al., 2023).

negatively affect stablecoins. In contrast, U.S. monetary policy shocks significantly affect MMFs (especially prime MMFs in the roughly three-month horizon we consider) and stablecoins, but in opposite directions. While prime-MMF assets grow after contractionary monetary policy shocks, stablecoin market capitalization significantly declines.

Stablecoins, as a whole, do not act as “safe-haven” against crypto or standard financial shocks. As monetary policy tightens, crypto prices fall, the market turns bearish and investors demand less stablecoins (the settlement means in crypto markets) for speculative purposes. Dollar monetary policy therefore acts as the key nexus between traditional and crypto markets.

2 Data and Empirical Strategy

Our dataset comprises traditional financial market variables and standard indicators from crypto markets, as well as two shock series: one for monetary policy, which we take from the literature, and another for crypto, which we construct and make available with this paper. The data are at weekly frequency and run from January 2019 to July 2024, a period characterized by a number of events in crypto markets and a significant tightening of U.S. monetary policy.

Financial markets and crypto data. We collect data for the U.S. stock market (S&P 500), 3-month treasury yield, the VIX, the Citigroup Economic Surprise Index (CESI), the Brent price and the USD broad nominal effective exchange rate (NEER) from Haver Analytics. Data on U.S. MMF assets under management and yields, split between prime and non-prime, is sourced from iMoneyNet. In addition, we collect off-chain Bitcoin prices from CCData (formerly CryptoCompare) and stablecoin circulating market capitalization data for Tether, USDC and Dai, which jointly account for the lion’s share of the market, from Messari.[4]

[4]As of July 2024, these three stablecoins had a market capitalization of USD 150 billion and together accounted for 95% of the USD-pegged stablecoin market (or more than 90% of the total stablecoin market). Tether is by far the largest one with a capitalization exceeding USD 110 bn, followed by USDC, with around USD 35 bn, and Dai, with nearly USD 5 bn.

Crypto shocks. In the spirit of Iacoviello and Navarro (2019)[5] we construct "crypto shocks" as the unforecastable component of the Bloomberg Galaxy Crypto Index (BGCI) – an index that captures broad crypto-market developments.[6] Specifically, we compute crypto shocks by taking the orthogonal component of BGCI returns to contemporaneous and lagged traditional financial and crypto-market variables. We rely on a supervised learning algorithm – the elastic net – to select predictors from a (large) given set of candidates and estimate their coefficients. Importantly, elastic nets have a penalization term for the number of regressors, dropping predictors that do not improve model fit. The initial list of control variables includes: the change in the U.S. 3-month yield, the (log) gold price, the Citigroup economic surprise index, the term spread, the logarithm of VIX, oil prices, the U.S. dollar NEER and the S&P 500. We also include the lagged BGCI returns and dummies for years from 2019 to 2023. We estimate the following model:

$$\min_{\beta_0,\beta} \left[\frac{1}{2N} \sum_{t=1}^{N} \left(S_t - \beta_0 - X_t^T \beta \right)^2 + \lambda P_\alpha (\beta) \right], \tag{1}$$

with the penalization function:

$$P_\alpha (\beta) = \frac{(1-\alpha)}{2} ||\beta||^2 + \alpha ||\beta||. \tag{2}$$

the loss term in Equation 1 is augmented by the penalization term in Equation 2 to prune less relevant regressors. Appendix A provides more details on the estimation procedure. Shocks are computed as residuals from Equation 1.[7]

Reassuringly, our crypto shocks (Figure A6 in Appendix A) capture relevant episodes in crypto markets: for example, they drop in correspondence with Tesla's decision to suspend payments from the Bitcoin network and China's crackdown on cryptocurrencies (May 2021), the TerraUSD/Luna collapse (May 2022) and FTX's bankruptcy (November 2022). Consistently, the series spikes with the 12th anniversary of Bitcoin's creation and growing support by finan-

[5]In Iacoviello and Navarro (2019) U.S. monetary policy shocks are derived by purging changes in U.S. interest rates from the forecastable part, captured by lagged macro variables.

[6]The BGCI doesn't include stablecoins among its constituents. For the construction of the index see this documentation page and the Bloomberg Galaxy Crypto Index factsheet.

[7]Figure A2 shows the distribution of the residuals from Equation 1 while Table A3 shows that they are exogenous to financial market variables.

cial institutions (January 2021).[8]

The identification of crypto shocks implicitly relies on a Cholesky ordering assumption: that financial markets react – if anything – to crypto shocks with a lag. That assumption is relaxed in a robustness test reported in the Appendix B, where crypto shocks are computed using only purely exogenous control variables that correlate with financial market developments (monetary policy shocks, geopolitical risk and year dummies).

Monetary policy shocks. We identify monetary policy shocks as the surprise component in the 3-month U.S. future yield, defined as the change in the Fed funds futures in a tight window (10 minutes before and 20 minutes after) around Fed monetary policy announcements (Gürkaynak et al., 2005).[9] One should note that our derived crypto shocks and the monetary policy shocks are orthogonal (see Figure A3 in Appendix A).

Table A1 in the Appendix C reports summary statistics for the main variables used in our analysis.

Empirical strategy. We assess the dynamic response of stablecoins, money market funds and financial sector variables to crypto and U.S. monetary policy shocks. To be fully agnostic, we estimate impulse responses by local projections, so that the magnitudes and signs are driven by the data.

Baseline responses are estimated as in Jordà (2005):

$$y_{t+k} = \alpha^k + \beta^k S_t + \sum_{l=1}^{L} \delta_l^k y_{t-l} + X_t \Gamma^k + \vartheta S_t \times I_t + \varepsilon_{t+k} \tag{3}$$

where y_{t+k} is the log of the dependent variable (k periods ahead), which is alternatively MMFs assets and yields, stablecoin market capitalization or one of the variables otherwise used as controls and captured in X_t: the S&P500 index, the 3-month U.S. Treasury yield, the USD NEER and the price of Bitcoin. The regression includes a time trend, three lags of the dependent variable, as well as the variables in X_t together with their respective three lags as controls. The main coefficient of interest is β^k, which captures the dynamic reaction of the dependent variable to our shocks S_t, which are the crypto shocks or, alternatively, U.S. monetary policy shocks, as defined above. The COVID-19 pan-

[8]For example, see JPMorgan Says Bitcoin Could Surge to $146,000 in Long Term.

[9]The elasticity of the S&P 500 and U.S. yields to these shocks are in line with the results of (Gürkaynak et al., 2005); see Table A2 in the Appendix.

demic and the associated unprecedented market turmoil pose a challenge for identification, in particular in relatively small samples. In the spirit of Lenza and Primiceri (2022), we control for the COVID-19 pandemic by interacting the monetary policy shock with a dummy variable, I_t, that takes the value of 1 in February and March 2020. For comparability, impulse responses are scaled to generate a 10% contraction in the price of Bitcoin on impact, approximately one standard deviation of Bitcoin weekly returns in our sample (see Table A1 in the Appendix). That decrease in the Bitcoin price is generated by a 5 bps monetary policy shock and a 7 percentage points crypto shock.

3 Results

In this section we present the results of the empirical exercise, studying the reaction of MMF's assets and stablecoin capitalization to crypto and monetary policy shocks. As a preview of the results, we find that crypto shocks have no impact on traditional financial markets (including MMFs) and lead to a decline in stablecoin market capitalization, whereas U.S. monetary policy shocks are more important than crypto shocks, leading to inflows to prime MMFs and outflows from stablecoins. Stablecoins, as a whole, do not act as safe haven against crypto or traditional financial shocks.

3.1 Crypto shocks, asset markets and stablecoins

Crypto market shocks are irrelevant for traditional financial markets. Stock prices and the 3-month yield barely bulge following shocks to crypto markets. MMF yields and assets are generally unfazed by crypto market shocks: despite a (marginally) significant negative decline on impact and after two weeks for the non-prime MMF yield, the response of MMF, both relative to assets and yields, is not statistically significant at any horizon up to 12 weeks (Figure 1).

Stablecoins, the sum of the market capitalization of Tether, USDC and Dai in our analysis (see Figure A7 in Appendix C), do exhibit a significant reaction to crypto shocks. Stablecoin market capitalization drops by around 4 percentage points after three months following a negative crypto shock, driven by the significant response of Tether and USDC (see Figure A9 in Appendix C).[10] In a nutshell, our evidence does not support the claim that stablecoins, as a whole, may play a role as crypto safe-haven.[11]

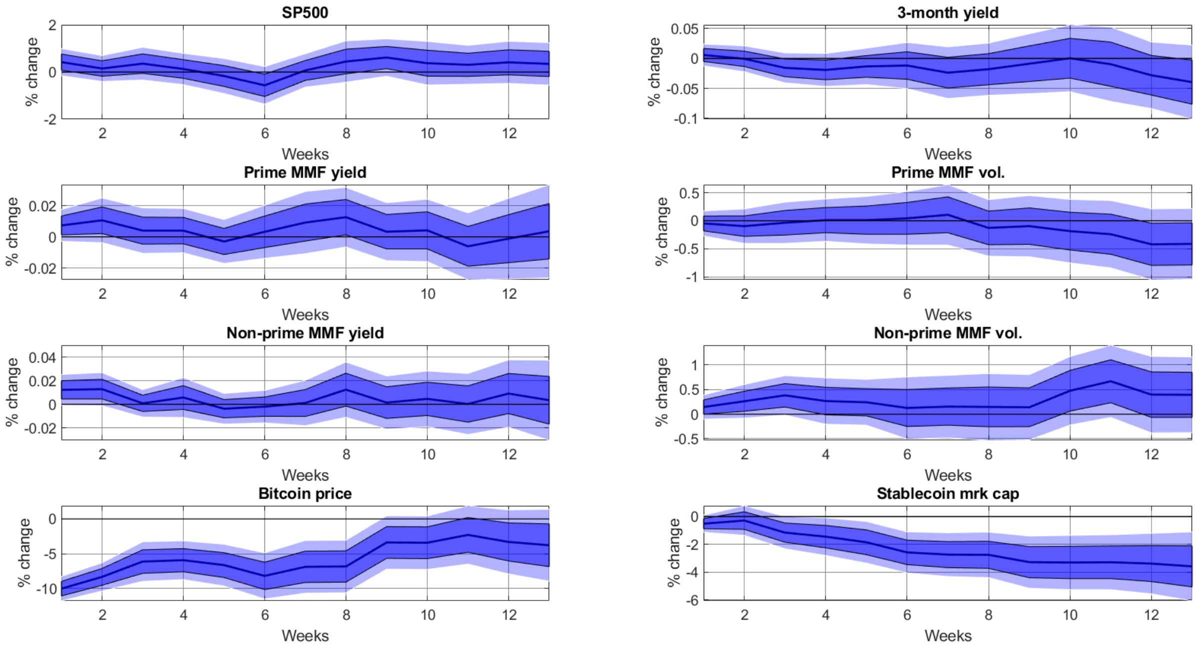

Figure 1: Impulse responses to a negative crypto shock.
Notes: the Figure reports impulse responses to a crypto shock, scaled to contract the price of Bitcoin by 10% (i.e. about a standard deviation). Shaded areas report the 68% and 90% confidence intervals. Impulse responses are computed as in equation 3.

3.2 Monetary policy shocks, asset markets and stablecoins

U.S. monetary policy shocks, in contrast, have a significant impact on both traditional financial markets and crypto markets. In line with existing evidence, we find that standard financial market variables react to monetary policy shocks. A contractionary monetary policy shock leads to a decline in the S&P 500 and an increase on impact in short-term U.S. rates (3-month yields) (Figure 2). Differences in the magnitude and speed of the reaction are due to

[10] The response of Dai is negative on impact and drop to zero thereafter. This dynamic likely reflects the specific characteristics of Dai, which, unlike Tether and USDC, is backed by crypto collateral.

[11] Note that negative crypto shocks are surprises to crypto asset prices and therefore do not reflect systematic bullish or bearish views on the market, of the type that could underpin volatile crypto convenience yields as documented in Schmeling et al. (2023). Our results, as discussed next, seem to be broadly in line with the view that monetary policy more strongly dictates systematic bearish/bullish crypto market sentiment.

the specific sample considered, where the stock market proved to be resilient to monetary policy surprises (BIS, 2023).

Yields and assets of prime-MMFs increase after a contractionary monetary policy shock (Figure 2). As monetary policy tightens, deposit rates lag policy rates, the opportunity cost of holding bank deposits increases and bank deposits thus decline (Drechsler et al., 2017). In turn, the rates paid by MMFs, a close substitute to bank deposits, track policy rates much more closely, and funding to MMFs – reflected in higher assets under management – increases (Chen et al., 2018; Xiao, 2020; Aldasoro and Doerr, 2023). Conversely, non-prime MMFs do not react to monetary policy shocks over a 13-week horizon. This result may be driven by two reasons: first and foremost, the horizon of our analysis is likely too short to capture the reaction of non-prime MMFs, which typically takes longer to materialize (Afonso et al., 2022); second, the elasticity of MMFs assets to monetary policy tightening has been weak in the most recent period (Afonso et al., 2023).

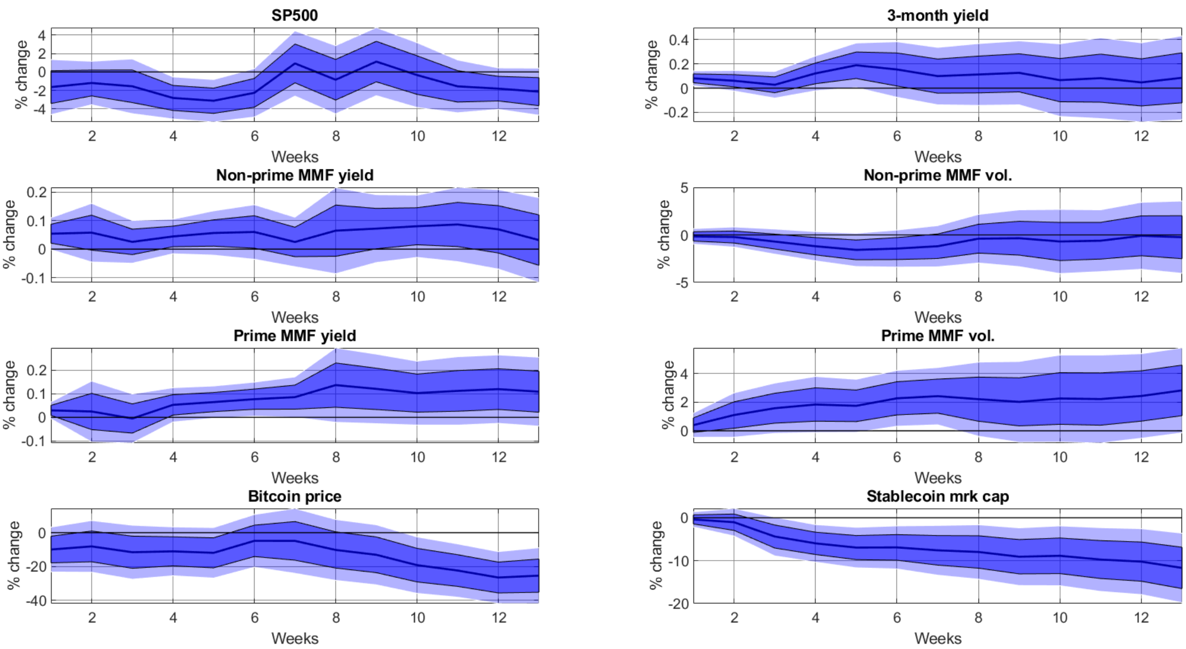

Figure 2: Impulse responses to a contractionary monetary policy shock.
Notes: the Figure reports impulse responses to a monetary policy shock scaled to contract the price of Bitcoin by 10% (i.e. about a standard deviation). Shaded areas report the 68% and 90% confidence intervals. Impulse responses are computed as in equation 3.

In contrast, stablecoins are *negatively* affected by monetary policy shocks (Figure 2). Stablecoin market capitalization drops by around 10 percentage points after three months. The decline is statistically significant, persistent and much larger than the impact of crypto shocks that lead to a decline in Bitcoin prices of a similar magnitude.[12] In particular, the fall in stablecoin capitalization is driven by Tether and USDC (see Figure A10 in Appendix C). Contractionary monetary policy shocks are thus negative for crypto: as the opportunity cost of holding unregulated non-interest bearing assets increases in a rising interest rate environment, investors move (on the margin) towards traditional investment assets.[13] These findings are in line with the argument developed in Aldasoro et al. (2023) about the role of monetary policy for stablecoin market developments. In other words, monetary policy, in particular for the U.S. dollar, is the linchpin that connects crypto and traditional financial markets. Finally, our findings are robust to controlling for the ZLB period and to alternative specifications of crypto shocks in Equation 1, in particular relaxing the assumption that financial variables are not contemporaneously impacted by crypto shocks (see Appendix B).

4 Conclusion

We find that negative crypto shocks have no impact on traditional financial markets, including MMFs, and negatively affect stablecoins. In turn, U.S. monetary policy shocks are more important, leading to inflows into prime MMFs and much more significant outflows from stablecoins. Our results suggest that, first, stablecoins' role as crypto safe-haven is questionable and does not extend to either crypto or traditional financial market shocks. Second, U.S. monetary policy not only affects traditional financial markets, but also exerts a significant influence on cryptocurrency markets, especially stablecoins.

[12] Karau (2023) also documents how Bitcoin prices fall after a U.S. policy tightening.

[13] This result is consistent with the slowdown in deposit inflows on DeFi protocols following a rise in interest rates off-chain documented by Cornelli et al. (2024).

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Appendix

A Crypto shock construction

We purge financial market developments from the Bloomberg Galaxy Crypto Index (BGCI) through a simple supervised learning algorithm, the elastic net. In practice we estimate the following model:

$$\min_{\beta_0,\beta}\left[\frac{1}{2N}\sum_{t=1}^{N}\left(S_t-\beta_0-X_t^T\beta\right)^2+\lambda P_\alpha\left(\beta\right)\right], \tag{A.4}$$

with the penalization function:

$$P_\alpha\left(\beta\right)=\frac{(1-\alpha)}{2}||\beta||^2+\alpha||\beta||. \tag{A.5}$$

in Equation A.4, S_t is the (log) change in the index at week t and X a matrix of candidate controls including the contemporaneous and lagged values of: the change in the U.S. 3-month yield, the (log) gold price, the Citigroup economic surprise index, the (log) of the VIX, the (log) of the oil price, the (log) of the U.S. dollar NEER, the (log) of the S&P 500 and the term spread. We also include the lag of the (log) change in the BGCI and dummies for the years from 2019 to 2023. β_0 is the loading of the constant and β is a vector of loadings for each variable in X. Critically, the model is estimated for a given value of α and λ, which govern the size of the penalty for including more regressors. The larger λ the more coefficients are set at or close to zero. Conversely, $\lambda\rightarrow 0$ delivers the maximum likelihood estimator.[14] α is instead a scaling parameter that determines the weights of the lasso ($||\beta||$) and the ridge ($\frac{1}{2}||\beta||^2$) terms inside the penalty function $P_\alpha(\beta)$ of Equation 2. The procedure by Zou and Hastie (2005) estimates the model for different values of the parameters and picks the specification that minimizes the mean squared error (MSE).

We estimate Equation A.4 following Zou and Hastie (2005) and Hastie et al. (2009). For a given value of α and λ we take subsequent draws of β to compute the loss function, $\frac{1}{2N}\sum_{t=1}^{N}\left(S_t-\beta_0-X_t^T\beta\right)^2+\lambda P_\alpha\left(\beta\right)$. For each draw, some values in β are 0 and the penalty function is augmented (proportional to λ) by the number of non-zero parameters in β. Via a coordinate descent algorithm,

[14] That is to say, the higher λ the fewer controls are included as explanatory variables.

we keep on drawing βs until we reach convergence at the draw that solves Equation A.4 by minimizing the penalty. The procedure allows to disentangle between relevant variables, that are associated to non-zero β parameters, and irrelevant variables, whose $\beta_j = 0$. We repeat the estimation for different values of α in the interval $(0, 1)$ and pick the combination that minimizes the MSE. These shocks are made available on the authors' websites.

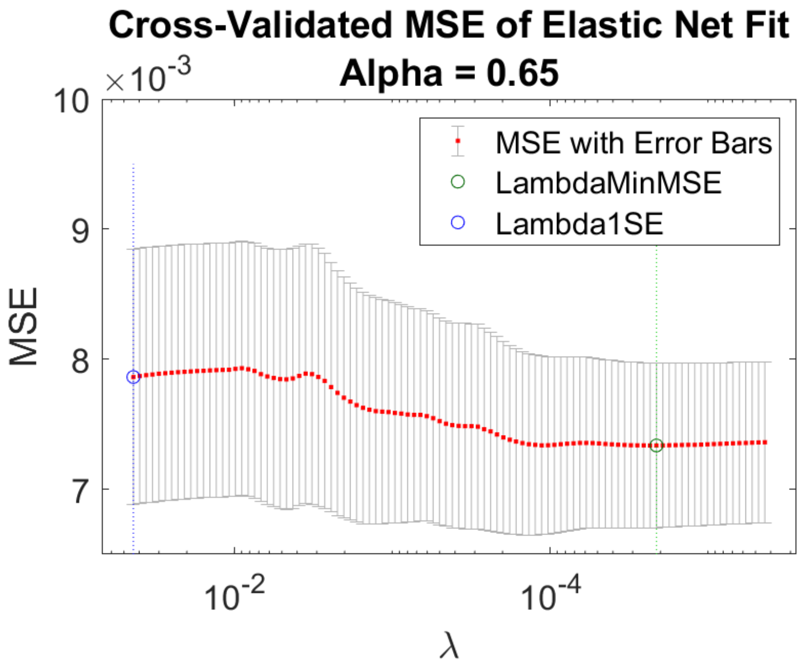

Figure A1: Estimation of λ.

Notes: the figure reports the values of λ for different iterations of the elastic-net.

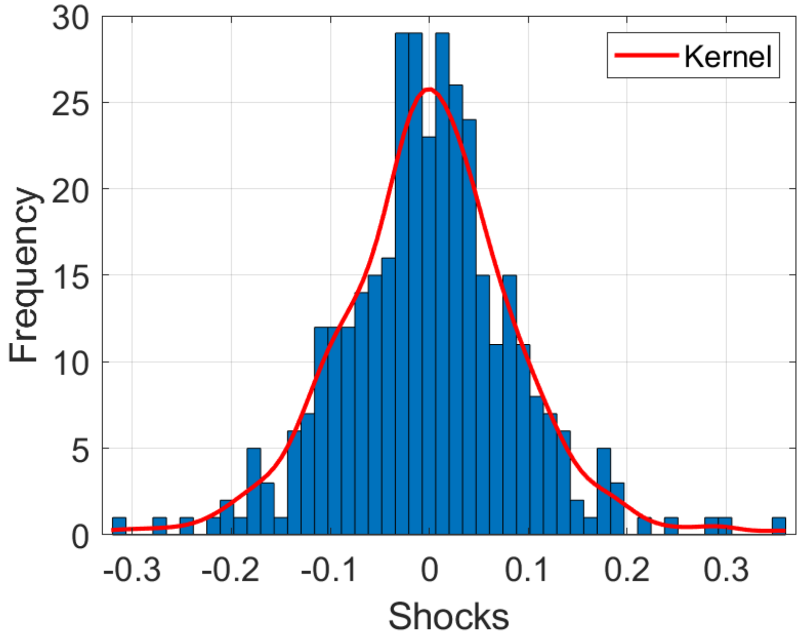

Figure A2: Distribution of residuals from the elastic net estimation.
Notes: the figure reports kernel distribution for the residuals of the elastic net model.

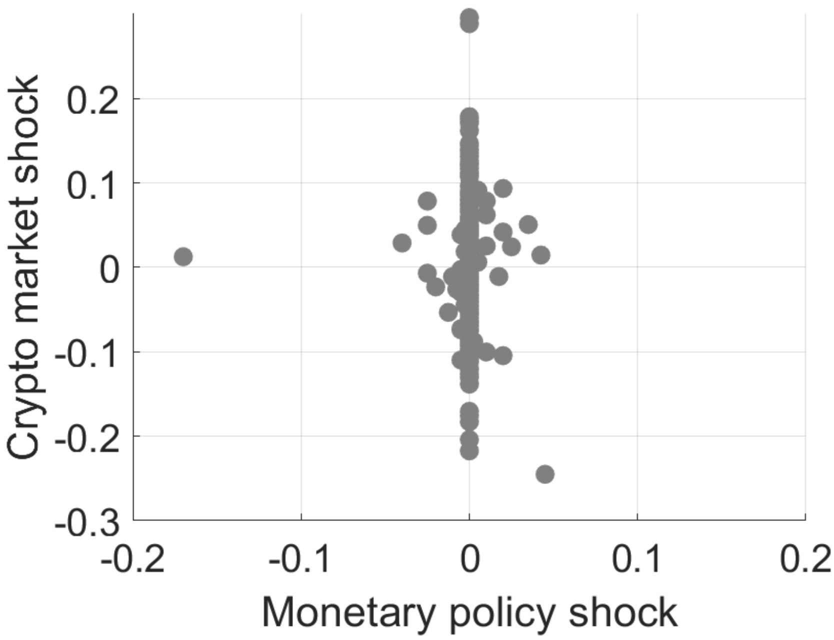

Figure A3: Correlation between monetary policy shocks and crypto shocks.
Notes: the figure reports the scatter plot between the surprise on the 3-month federal fund future around US monetary policy announcements and the crypto market shock we have constructed. Both shocks are expressed in percentage points.

B Robustness

We test the robustness of our findings along two dimensions: the impact of the zero lower bound (ZLB) period and the definition of the crypto shock.

We control for the ZLB period by controlling for the interaction of the monetary shock with a dummy equal to 1 between March 2020 and April 2022. This should absorb the impact of the ZLB period on the impulse responses. Figure A4 reports the impulse responses, which are broadly consistent with our main results.

In our baseline, we identify crypto shocks by implicitly assuming that financial variables react to crypto shocks with a lag. We also test for the robustness of this result by computing crypto shocks controlling for purely exogenous variables (i.e. not using financial market data in Equation 1 but only dummies, the monetary policy shock and the geopolitical risk index of Caldara and Iacoviello (2022)). These variables are correlated to financial market prices, but are exognous to them. Also in this case, as shown in Figure A5, results remain robust.

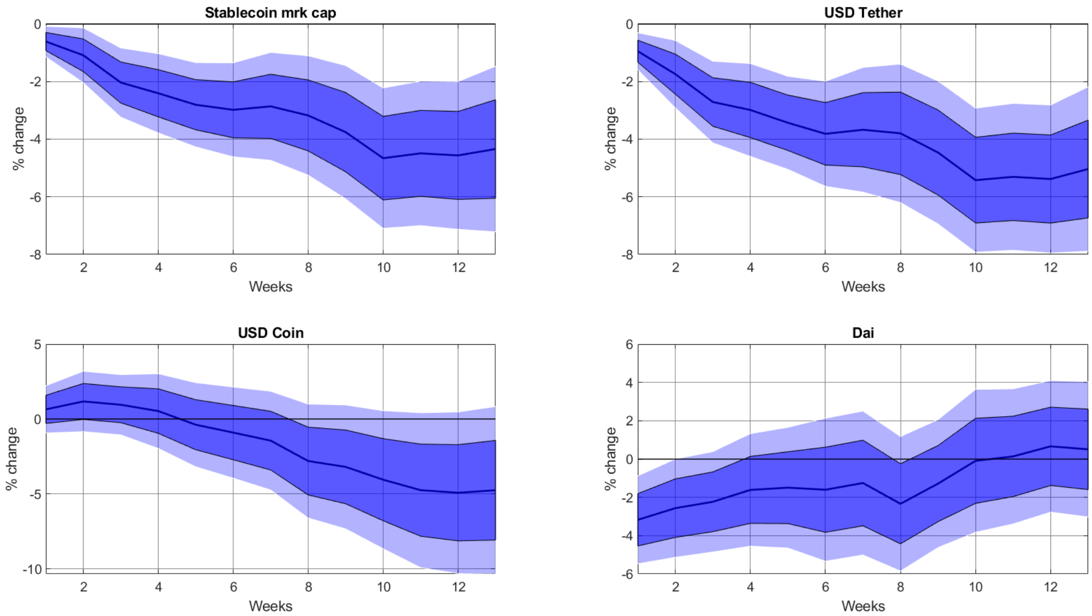

Figure A4: Crypto shocks robustness – zero lower bound.

Notes: the figure reports impulse responses to a monetary policy shock scaled to contract the price of Bitcoin by 10% (i.e. about a standard deviation). Shaded areas report the 68% and 90% confidence intervals. Impulse responses are computed controlling for the ZLB period.

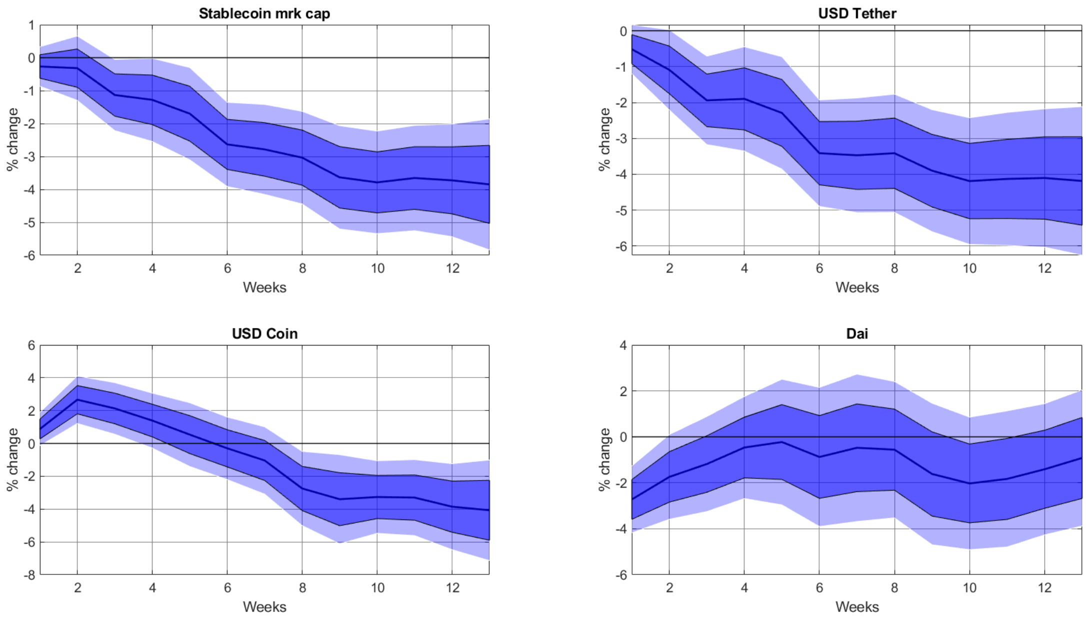

Figure A5: Crypto shocks robustness – alternative definition of crypto shocks with exogenous variables as controls.

Notes: the figure reports impulse responses to a crypto shock, scaled to contract the price of Bitcoin by 10% (i.e. about a standard deviation). Shaded areas report the 68% and 90% confidence intervals. The crypto shock is obtained controlling only for purely exogenous variables: the U.S. monetary policy shock, geopolitical risk and year dummies.

C Figures & Tables

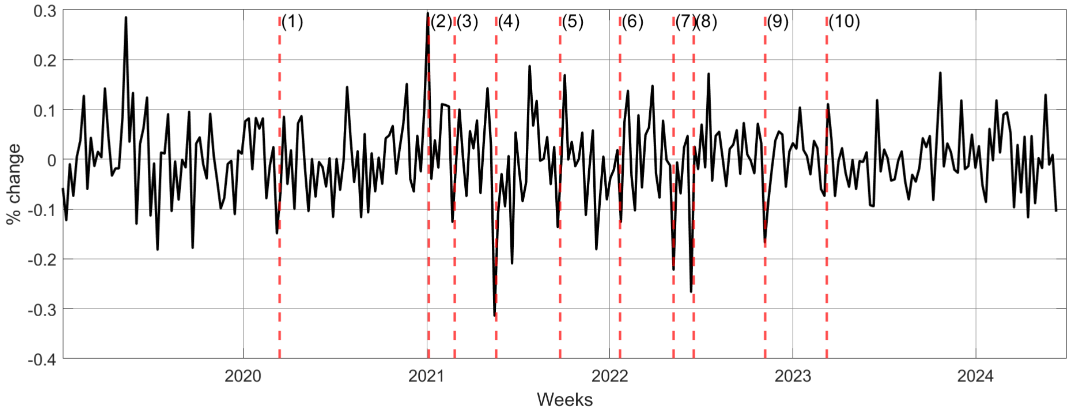

Figure A6: Crypto shocks.

Notes: the figure reports the crypto shock series that we estimate based on Equation 1. The vertical lines indicate: (1) BitMEX outage (week of 13 mar 2020); (2) the 12th anniversary of Bitcoin's creation and growing support by financial institutions (first two weeks of January 2021); (3) Market correction after peak (week of 26 Feb 2021); (4) Tesla's decision to suspend payments from the Bitcoin network and China's crackdown on cryptocurrencies (week of 19 May 2021); (5) China bans crypto (week of 24 Sep 2021); (6) Central bank of Russia proposes a ban on crypto use and mining and China makes all crypto transactions illegal (week of 21 Jan 2022); (7) Terra/Luna collapse (week of 8 May 2022); (8) Crypto market rout (week of 17 Jun 2022); (9) FTX bankruptcy (week of 7 Nov 2022); (10) SVB collapse (week of 10 Mar 2023).

Table A1: Summary statistics (weekly data)

	Mean	Std. deviation	Source
Δ S&P 500 (%)	0.26	2.69	Haver Analytics
Change in 3-month U.S. Treasury yield (b.p.)	2.26	2.15	Haver Analytics
Δ USD Broad NEER (%)	0.03	0.74	Haver Analytics
Change in yield, non-prime MMF assets (b.p.)	1.75	1.81	iMoneyNet
Δ non-prime MMF assets (%)	0.25	1.21	iMoneyNet
Change in yield, prime MMF assets (b.p.)	2.03	1.99	iMoneyNet
Δ prime MMF assets (%)	0.21	1.71	iMoneyNet
Δ Stablecoin market cap (%)	1.41	4.14	Messari
Δ USD Tether supply (%)	1.44	3.89	Messari
Δ USD Coin supply (%)	1.60	5.74	Messari
Δ USD Dai supply (%)	2.10	7.50	Messari
Δ Bitcoin close price (%)	1.03	9.29	CCData
U.S. monetary policy shock (b.p.)	-0.04	1.20	Gürkaynak et al. (2005)
Crypto shock (log)	0.00	0.08	Aldasoro et al. (2024)

Notes: the table reports summary statistics for the main variables used in the empirical analysis. Data are weekly. The sample begins in January 2019 and ends in July 2024. All variables excluding changes in yields, monetary policy shock and crypto shocks are expressed in percentage changes. Changes in yields and the monetary policy shocks are expressed in basis points (b.p.). The crypto shock is expressed in logs.

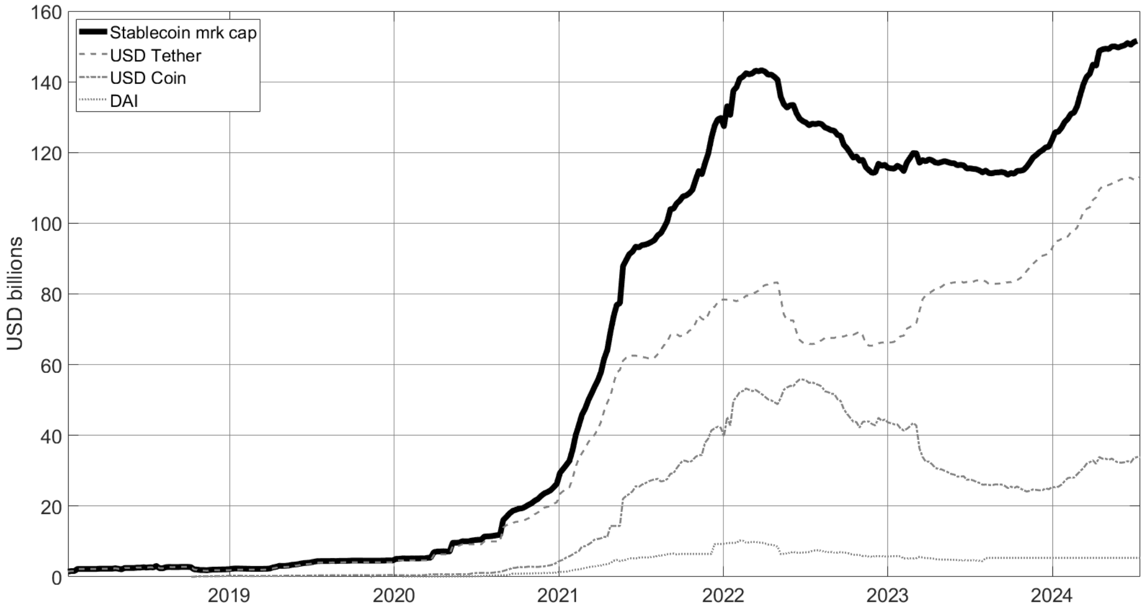

Figure A7: Stablecoin market capitalization.

Notes: the figure reports stablecoin market capitalization of the three major stablecoins (USD Tether, USD Coin and Dai) and their sum, in billions of U.S. dollars.

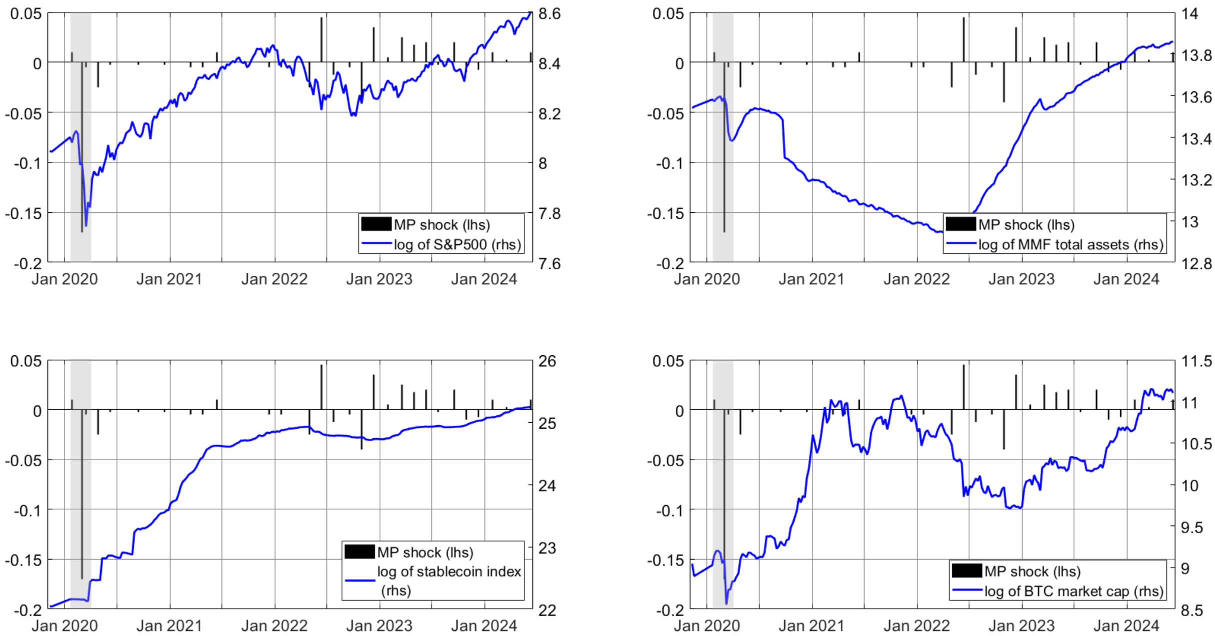

Figure A8: Monetary policy shocks and market data.

Notes: the Figure reports the monetary policy shocks (gray bars), measured as the 3-month future surprise, against the log of the S&P 500, money market funds total assets, the stablecoin index and Bitcoin market capitalization. The shaded areas highlight the COVID-19 period. For sources and construction see Table A1 and Section 2.

Table A2: Estimation of elasticities to monetary policy shocks

	S&P 500	2-year yield	5-year yield	10-year yield
	Intraday response			
β	-5.22	1.49	1.13	0.40
$p-value$	(0.06)	(0.00)	(0.00)	(0.01)
R^2	0.21	0.70	0.49	0.17
Obs.	45	45	45	45
	Daily response			
β	-28.72	0.61	0.31	-0.96
$p-value$	(0.00)	(0.10)	(0.40)	(0.00)
R^2	0.35	0.09	0.03	0.25
Obs.	44	44	44	44

Notes: the Table reports the estimated coefficients from estimating the following regression: $\Delta y_m = \alpha + \beta MPS_m + \varepsilon_m$, where Δy_m is the percent change in the variable of interest (columns) during the 30-minutes event window or the day of the monetary policy meeting m, and MPS_m is the monetary policy shock series, as described in Section 2. P-values, reported in parenthesis, are based on robust standard errors. The regression is at meeting frequency.

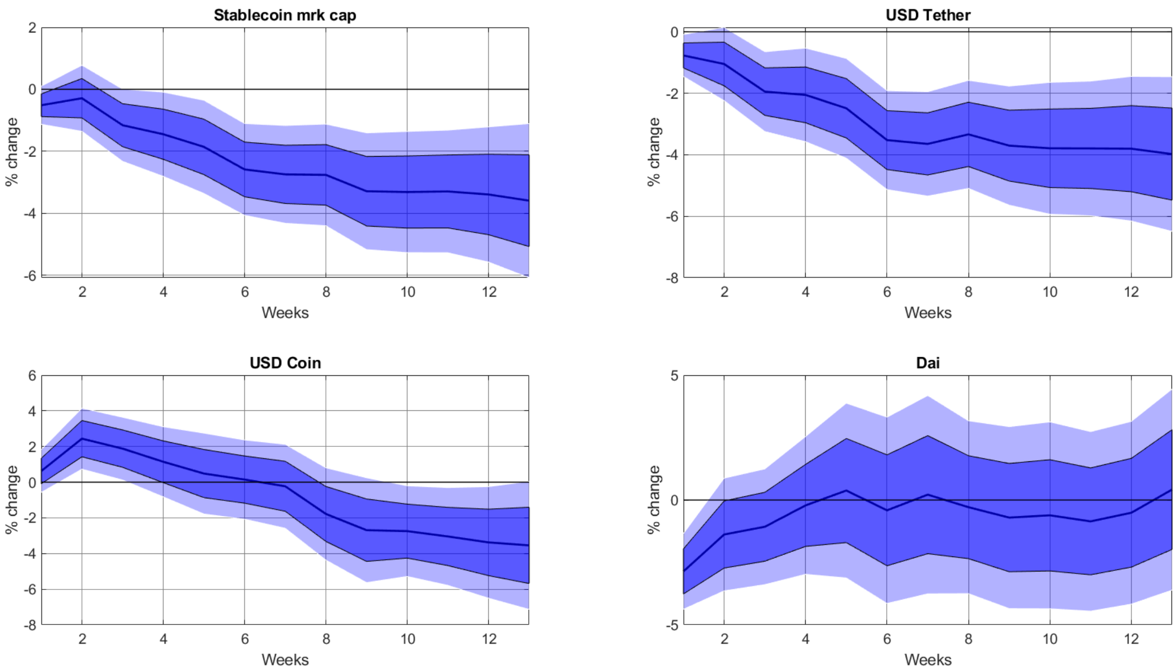

Figure A9: Impulse responses of individual stablecoins' supply to a negative crypto shock.

Notes: the figure reports impulse responses to a crypto shock, scaled to contract the price of Bitcoin by 10% (i.e. about a standard deviation). Shaded areas report the 68% and 90% confidence intervals. Impulse responses are computed as in equation 3 substituting the stablecoin market capitalization with that from individual stablecoins.

Table A3: Shock predictability

$$
\begin{aligned}
S_t = \alpha + \sum_{l=0}^{1} \beta_l \Delta S\&P500_{t-l} + \sum_{l=0}^{1} \gamma_l 2 - year\, yield_{t-l} + \\
+ \sum_{l=0}^{1} \delta_l 10 - year\, yield_{t-l} + \sum_{l=0}^{1} \theta_l \Delta USDNeer_{t-l} + \epsilon_t
\end{aligned}
\tag{C.7}
$$

	(1)	(2)
$\Delta S\&P500_t$	-0.102	-0.067
	(0.202)	(0.208)
$2 - yearyield_t$	-0.002	0.009
	(0.014)	(0.064)
$10 - yearyield_t$	0.004	0.005
	(0.019)	(0.062)
$\Delta USDNeer_t$	-1.388	-1.331
	(0.730)	(0.757)
$\Delta S\&P500_{t-1}$		0.122
		(0.227)
$2 - yearyield_{t-1}$		-0.012
		(0.064)
$10 - yearyield_{t-1}$		-0.000
		(0.062)
$\Delta USDNeer_{t-1}$		-0.092
		(0.788)
Constant	-0.004	-0.004
	(0.017)	(0.017)
Obs.	283	282
R-squared	0.013	0.015
F-test	1.014	0.555
F-test (p-value)	0.400	0.814

Notes: the Table reports the estimated coefficients from regressing the crypto shock on contemporaneous and lagged changes in the (log) S&P 500, the (log) USD NEER and the 2- and 10-year U.S. yield. Robust standard errors are in parenthesis.

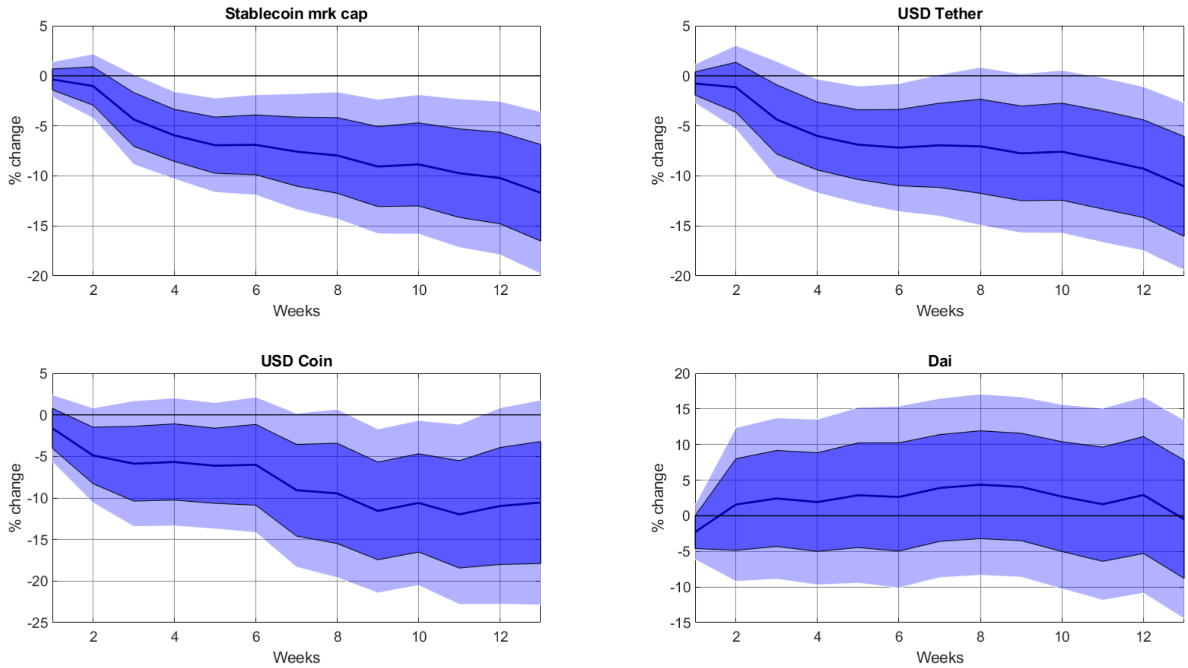

Figure A10: Impulse responses of individual stablecoins' supply to a contractionary monetary policy shock.

Notes: the figure reports impulse responses to a monetary policy shock scaled to contract the price of Bitcoin by 10% (i.e. about a standard deviation). Shaded areas report the 68% and 90% confidence intervals. Impulse responses are computed as in equation 3, substituting the stablecoin market capitalization with that from individual stablecoins.

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