The Crumbling Wall Between Crypto and Non-Crypto Markets: Risk Transmission Through Stablecoins

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Abstract

The crypto market and non-crypto market used to be separate from each other. Now, with a new type of cryptocurrency called stablecoins, which is pegged mainly to US dollars, we argue that the wall between crypto and non-crypto markets is crumbling. Utilizing copula-based CoVaR approaches, we investigate the risk spillovers for three categories: stablecoins, traditional cryptocurrencies, and non-crypto assets. In the sample period of 2019-2021, when stablecoins became widely adopted, we find significant bidirectional risk spillovers among all pairs of assets considered, in contrast to the insignificant risk spillovers in 2015-2017, when stablecoins were not popular. Our findings suggest stablecoins transmit risk between crypto and non-crypto markets, which has important policy implications for financial regulators. We find that the risk spillovers from the US dollar to the traditional crypto market through stablecoins are stronger than that from the crypto market to US dollars. Despite the

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traditional perception of cryptocurrencies as de-dollarizied currencies, the asymmetric risk spillover warns about the ongoing re-dollarization of crypto markets.

Keywords: crypto assets; stablecoins; risk spillovers

JEL Classifications: E5, F3, F4, G11, G15

1 Introduction

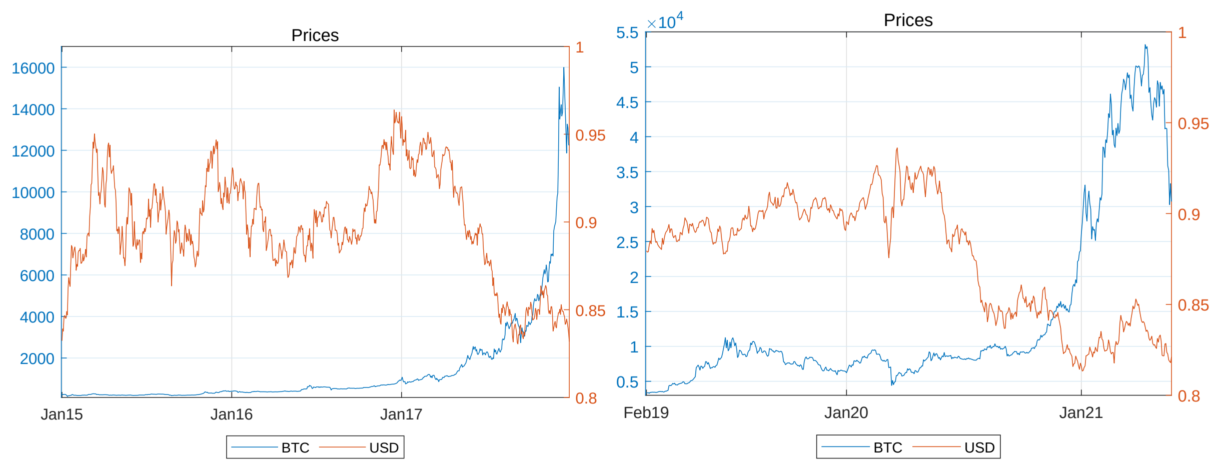
Given that cryptocurrencies are based on fundamentally new technology enabling decentralized payments, the general perception has been that the crypto market has made itself totally independent of central banks, and it even has been perceived as an island isolated from the existing financial system. However, if an invisible wall existed to block the risks between the crypto and non-crypto markets, that wall seems to be crumbling. On June 21, 2021, the overall crypto market fell soon after the Federal Reserve Board announced plans to increase interest rates. [1] The recent responsiveness of crypto markets to US monetary policies is not only contrary to the de-dollarized nature of cryptocurrencies but also goes against existing academic findings. For example, Liu and Tsyvinski (2021) find that cryptocurrencies are only influenced by crypto market-specific factors and do not co-move with stocks, currencies, or macroeconomic factors in non-crypto markets. What is now causing the recent breach of the traditional wall between the crypto and non-crypto worlds?

In this paper, we consider the recent development of stablecoins as an explanation for the emerging link between the crypto and non-crypto markets. Unlike typical cryptocurrencies characterized by extreme price fluctuations, stablecoins are a special type of cryptocurrency pegged to non-crypto assets to maintain relatively stable price ranges, thus naturally bonding them to the non-crypto market. Due to the price stability, stablecoins now facilitate more than 60% of cryptocurrency trading (Cermak et al., 2021) and have reached a trading volume

[1] Accessed from https://coindesk.cc/bitcoin-price-falls-after-fed-shifts-interest-rate-hikes-forward-amid-inflation-fears-27978.html

of over 700 billion dollars,[2] which is even larger than PayPal. In this sense, stablecoins have become the "digital fiat" in the crypto market (Kristoufek, 2021). Combining the pegging mechanism and the "digital fiat" function, stablecoins have the potential to bridge the gap between the crypto and non-crypto markets.

Figure 1 displays the evolution of the prices for typical crypto and non-crypto assets, that is, Bitcoin and US dollars, in the different periods of stablecoins' development. In the recent years of 2019-2021, when stablecoins became widely used in the crypto market, there is a negative correlation between the price of Bitcoin and US dollars. In contrast, in years of 2015-2017, when stablecoins were not popular, the prices of crypto and non-crypto assets seem totally uncorrelated.



(a) Pre-stablecoin period

(b) Post-stablecoin period

Figure 1: Evolution of the prices for Bitcoin and US dollars, in the different stages of stablecoins' development

To formally capture stablecoins' bridging effect between the crypto and non-crypto markets, we begin by investigating the risk spillovers among three asset categories: stablecoins, traditional cryptocurrencies such as Bitcoin and Ethereum, and non-crypto assets. We mainly use US dollars to represent the non-crypto assets because more than 90 percent of

[2] Accessed from https://coincodex.com/cryptocurrencies/sector/stablecoins/ on July 27, 2021.

stablecoins are pegged to US dollars. Following methods proposed by Girardi and Ergün (2013) and Reboredo et al. (2016), we utilize copula-based CoVaR approaches based on the daily transaction prices of different assets for two separate periods. In the period before stablecoins' wide adoption, the risk spillover between US dollars and traditional cryptocurrencies is not significant. In contrast, in the period after stablecoins' wide adoption, we find significant risk spillovers between US dollars and traditional cryptocurrencies, which could be explained by bilateral risk spillovers between US dollars and stablecoins, and between stablecoins and traditional cryptocurrencies. As shown in Figure 2, the solid line arrows indicate the existence of spillover effects and the direction of the arrows indicates the direction of the spillover effects.

Figure 2: Risk spillovers among stablecoins, US dollar, and major crypto assets

Moreover, since stablecoins follow their non-crypto pegs and function as a "digital fiat" for settlements in crypto markets, we expect the risk spillovers to be asymmetric. The dominant risk-transmitting direction would be from non-crypto pegs to stablecoins and then to traditional crypto assets. We then conduct the tests for asymmetry in risk spillovers among asset pairs. As expected, we find that the spillovers originating from non-crypto assets (mainly US dollars) through the channels of stablecoins, to traditional crypto assets are stronger than that in the opposite direction. The bold arrows in Figure 2 show the direction of stronger spillover effects. Finally, we also conduct several robustness checks by employing other financial market indexes to proxy the non-crypto markets and considering a type of stablecoin pegged to gold instead of US dollars. The main results remain unchanged, indicating an integration of the crypto and non-crypto markets, which are both influenced by US monetary policies.

The empirical results carry important policy implications. First, although the crypto market and non-crypto market used to be isolated from each other, stablecoins now transmit risks between non-crypto and crypto markets. As the crypto market integrates into traditional financial markets, it is more urgent to establish a regulatory framework for the crypto market. Second, the asymmetric effects warn about the "re-dollarization" of crypto markets, where US monetary policies would lead to significant price flucations in cryptocurrencies. While the development of crypto markets is usually interpreted as one way towards de-dollarization, as exemplified by El Salvador' experiment decreeing bitcoin to be legal tender,[3] our results raise doubts about this interpretation.

Our study contributes to the emerging field of cryptocurrencies in two aspects. First, while most research has reached consistent conclusions on the uniqueness and isolation of the crypto market (Makarov, 2020; Foley et al., 2019; Griffin, 2020; Liu and Tsyvinski, 2020), we capture the changing trading patterns brought by the entrance of stablecoins to the crypto market and provide new evidence on the recent integration of the crypto market to the traditional financial system. Second, concern has been growing over the potential challenges stablecoins pose on regulation (Arner et al., 2020; FSB, 2020; PWG, 2020), but most existing literature only focuses on the stable nature of stablecoins (Gu et al., 2020; Lyons,2019a; Baur, 2021; Corbet, 2020; Baumohl, 2020). Our paper attempts to fill the gap by revealing a new aspect of stablecoins, that is, as a risk transmitter between the crypto and non-crypto markets.

The remainder of the paper is organized as follows. Section 2 introduces the background and related literature, and develops the hypotheses to be tested. Section 3 describes the dataset and presents the methodology. Section 4 presents the main empirical results. Section 5 provides the robustness analysis. Finally, section 6 concludes.

[3]https://www.forbes.com/sites/lawrencewintermeyer/2021/08/05/could-developing-nations-follow-el-salvadors-move-to-bitcoin/?sh=77017b0728b7

2 Background, related literature and hypotheses

2.1 Background

Contrary to traditional cryptocurrencies, such like Bitcoin and Ethereum, which are characterized by wide price volatility, stablecoins aim to maintain a stable price facilitating crypto investors' transaction needs (Chohan, 2019). Emerged in 2014 and developed rapidly, stablecoins' trading volume now has already surpassed that of Bitcoin, the most well-known cryptocurrency. In Q1 2017, when crypto assets were gradually coming into investors' sight, 50% of cryptocurrency exchange was done by Bitcoin, while only about 5% was done by Tether, a stablecoin with the largest trading volume and market capacity (Cermak et al., 2021). As stablecoin's impact growing, the fraction of Bitcoin trading in all cryptocurrency trading has declined rapidly within just a few years, while stablecoins' trading volume surged. By January 2021, the situation changed tremendously: about 60% of cryptocurrency trading was accomplished by Tether while only 11% was done by Bitcoin (Cermak et al., 2021).As stablecoins become the transaction medium while Bitcoin's price fluctuate violently, Bitcoin is more like an investment, or even a speculation, while stablecoins begin to function as the "digital fiat" in crypto asset market (Kristoufek, 2021).

In practice, stablecoins peg their prices to non-crypto assets and usually have US dollars, gold or even crypto assets as collateral to maintain their prices stable to their pegs. ECB (2019) classifies stablecoins into four groups according to their price stabilizing mechanism: tokenized funds, off-chain collateralized stablecoins, on-chain collateralized stablecoins and algorithmic stablecoins. Due to the extreme small market share of existing algorithmic stablecoins and the similarity of tokenized funds and off-chain collateralized stablecoins, Gu et al. (2020) further classifies Stablecoins into two major types: off-chain stablecoins that are collateralized off-chain by non-crypto assets such as fiat currencies and commodities, and on-chain stablecoins that are collateralized on-chain by crypto assets.

Among thousands of different types of stablecoins, a large proportion of stablecoins are off-chain stablecoins, where Tether enjoys the largest market capitalization (Lyons and Viswanath-Natraj, 2019). Among on-chain stablecoins, DAI is the most popular one. That is why we use Tether and DAI to represent major stablecoins in the empirical setting. More than 90% of stablecoins peg their prices to US dollars, with a small number of stablecoins pegging their prices to other fiat currencies or gold. Both Tether and DAI are pegged to US dollars. Thus, in this paper US dollar is with no doubt the most important non-crypto peg assets to be investigated.

2.2 Related literature

Our study is related to several streams of literature. First, our paper adds to the ongoing discussion of cryptocurrencies. In studies of cryptocurrencies, Bitcoin is the most representative one and raises most attentions. Pioneering studies have been conducted on Bitcoin rules and the regulatory challenges (Böhme et al., 2015), the market inefficiency (Urquhart, 2016; Nadarajah and Chu, 2017), and the price formation (Ciaian et al., 2016). Given that Bitcoin's price has fluctuated wildly, the debate on whether Bitcoin is a qualified currency as a medium of exchange or just a speculative investment has not been settled. Schilling and Uhlig (2019) provide a model of a dollar and Bitcoin as mediums of exchange to study the Bitcoin speculation and find that wild price fluctuation does not invalidate Bitcoin's function as a medium of exchange. Hui et al. (2020) study Bitcoin exchange rate dynamics and find that from the view of exchange rates, Bitcoin acts like a combination of fiat money and a crypto commodity. Gandal et al. (2018) find that Bitcoin's USD price (or the USD/BTC exchange rate) is vulnerable to manipulation as shown by suspicious trades, as there is lack of regulation on Bitcoin trading markets. White et al. (2020) argue that Bitcoin has failed to perform the necessary functions of a unit of account. Cheah and Fry (2015) go as far as to say Bitcoin is simply a bubble and its fundamental price is zero. Indeed, when Bitcoin's price fluctuates wildly, Bitcoin holders are not able to use it for transactions (Katsiampa, 2017).Therefore, examplified by Bitcoin, traditional cryptocurrencies are more like an investment or even a speculation, rather than a medium of exchange, justifying the emergence of stablecoins, which have successfully remained stable price ranges and become widely used as a medium of exchange in crypto markets.

With a special focus on the role of stablecoins, our paper is built on literature investigating the mechanism and nature of stablecoins. Lyons and Viswanath-Natraj (2019) employs the Tether issuance data from Omni Explorer and Etherscan and transaction and order-book data on stablecoins/USD pairs from Coinapi, and finds collateral and arbitrage are the main mechanism through which stablecoins keep prices stable. Lyons and Viswanath-Natraj (2019) exploits the introduction of Tether on the Ethereum blockchain as a quasi-natural experiment to test whether the investor-driven flows stabilize the stablecoins' prices. Adrian (2019) and Kristoufek (2021) exploit the payment and settlement role of Stablecoins in crypto markets and pin down the "digital fiat (currency)" function for stablecoins. Our study is enlightened by the collateral and pegging mechanism discussed above to investigate the bridging effect of stablecoins. We also further explore the "digital fiat" role of stablecoins in developing the asymmetric risk spillover hypothesis.

Our paper is also related to the literature of stablecoins interacting with other traditional cryptocurrencies. There have been several studies focusing on the interaction between stablecoin and Bitcoin; more specifically, whether the Tether issuances have pushed up Bitcoin prices. Wei (2018) argues that Tether issuance did not "Granger-cause" Bitcoin prices to rise and was unlikely to have caused the 2017 Bitcoin rally. On the contrary, Griffin and Shams (2020) find that the rapid growth of Tether has been supplied to investors with the purpose of pushing up Bitcoin and other cryptocurrencies prices. To put it another way, the company issuing Tether manipulates the Bitcoin prices on purpose. Without further evidence, we choose not to join the ongoing discussion above, but rather explore the risk spillover effects between stablecoins with Tether included and traditional cryptocurrencies with Bitcoin included. So we join the discussion initiated by a few studies looking into stablecoins' stabilizing function in the crypto market and how stablecoins behave during the turbulence of traditional cryptocurrencies. The existing literature on this topic mainly focused on how stablecoins provide a port in the crypto-price-fluctuation storms (Gu et al., 2020; Lyons and Viswanath-Natraj, 2019) and on its function as a safe haven in the crypto world (Corbet et al., 2020; Baumöhl and Vyrost, 2020; Baur and Hoang, 2021). For example, Baur and Hoang (2021) find that when Bitcoin's price drops precipitously, stablecoins can serve as safe havens in particular situations, which is similar to the conclusion of Wang et al. (2020). Wang et al. (2020) employ DCC-GARCH model and dummy variable regression to study the risk-dispersion abilities of stablecoins with USD-peg or gold-peg against traditional crypto assets. We aim to complete the discussion by providing evidence for the risky aspect of stablecoins to traditional cryptocurrencies and the financial system.

We utilize the standard financial econometric methods on risk spillovers, which are usually applied to the non-crypto financial markets (Engle et al., 1990; Hamao et al., 1990; King and Wadhwani, 1990; King et al., 1994; Cheung and Ng, 1996; Campbell and Cochrane, 1999; Hong et al., 2009; Diebold and Yilmaz, 2009, 2012; Diebold and Yılmaz, 2014). Beneki et al. (2019) have extended the methods to crypto markets, employing the bivariate diagonal BEKK-GARCH model to study the risk spillover effect within traditional cryptocurrencies, Bitcoin and Ethereum. They find a volatility transmission from Ethereum to Bitcoin and that i.e. the reverse influence is weaker. We extend the discussion to broader asset categories, putting Bitcoin and Ethereum into the same asset group to represent traditional crypto markets, and investigate the risk spillovers among three markets: stablecoin, traditional crypto market and the non-crypto markets.

Last but not least, our study contributes to the ongoing discussion on regulation of stablecoins. As stablecoins' issuance has surged, stablecoin's trading volume has grown to a level that regulators cannot ignore. What is more, stablecoins are more similar to the established fiat currencies; thus, the threat and potential regulation problem posed to governments by stablecoins' replacing the established fiat currencies is much larger (BIS, 2019). For example, with more trading using stablecoins such as Tether, the control of capital flow will be weaker (Makarov and Schoar, 2020). Our finding on the stablecoins' role as risk transmitter calls for valid regulatory firewalls against stablecoins to block risk spillovers between different markets.

2.3 Hypotheses development

In this section, we develop several testable hypotheses regarding the spillover effects among stablecoins, traditional cryptocurrencies and non-crypto assets.

To begin with, we focus on the interaction between stablecoins and the non-crypto market. Stablecoins are closely related to the non-crypto real financial markets. On one hand, to maintain price stability, stablecoins are pegged to the non-crypto assets. As a result, a shock to their peg would naturally lead to price fluctuations in stablecoins. On the other hand, since a large proportion of stablecoins directly use non-crypto assets as their collateral, runs on stablecoins could spur sell-off of the assets used as their collateral, which might affect the confidence and stability of broader financial system in the non-crypto world (Arner et al., 2020). We formally state the first testable hypothesis as follows.

Hypothesis 1 (H1): There exist significant bidirectional risk spillovers between stablecoins and non-cypto assets.

Moreover, we expect the risk spillover to be asymmetric. Since stablecoins are pegged to the prices of non-crypto assets, the price of stablecoins would follow the price of their pegs, rather than the reverse direction. For example, both DAI and Tether are pegged to US dollars, then a depreciation in US dollars would be followed by a depreciation in DAI and Tether, and a tightening monetary policy of US Fed will lead to a drop in the liquidity of these stablecoins. Thus we expect a stronger risk spillover in the direction from the non-crypto market to stablecoins.

Hypothesis 2 (H2): The risk spillover from non-crypto assets to stablecoins is stronger than that from stablecoins to non-crypto assets.

Then we move to explore the risk spillovers between stablecoins and traditional cryptocurrencies. Stablecoins serve as the "digital fiat" currencies in the crypto markets (Kristoufek, 2021). They are used by traders and investors both as a means of payment to buy other traditional cryptocurrencies, and as a place to hold funds to avoid exchanging back and forth for fiat currencies when cryptocurrencies experience large price fluctuations. Therefore, a decrease in traditional cryptocurrencies' prices will induce investors to exchange into stablecoins, which in turn pushes up stablecoins prices. Similarly, a decrease in stablecoins' prices will lead investors to hold more traditional cryptocurrencies, which would push up the overall prices in crypto markets. Griffin and Shams (2020) has documented that the increasing supply of a stablecoin Tether has pushed up Bitcoin and other cryptocurrencies prices, which lends supportive evidence to our argument. Therefore, we also expect significant risk spillovers between stablecoins and traditional cryptocurrencies. Collectively, these studies and our related discussion lead to our third hypothesis:

Hypothesis 3 (H3): There exist significant bidirectional risk spillovers between stablecoins and the traditional cryptocurrencies.

Finally, we discuss the asymmetric nature of the spillover effects between stablecoins and traditional cryptocurrencies. Given the "digital fiat" function of Stablecoins, a shock to stablecoins is like a change in quasi monetary policies in crypto markets which, as a result would lead to large fluctuations of traditional crypto currencies. Thus the price of stablecoins follows their pegs, and influence the overall liquidity of crypto trading. The above discussion leads to our last hypothesis on the "risk transmitter" role of stablecoins:

Hypothesis 4 (H4): The risk spillover from stablecoins to traditional cryptocurrencies are stronger than that from traditional cryptocurrencies to stablecoins.

3 Data and methodology

3.1 Data

We will look into the risk spillovers among three asset categories: stablecoins, traditional cryptocurrencies, and the non-crypto assets. Here we define non-crypto assets such as assets in the real world including the fiat currencies, commodities, and precious metals. Non-crypto assets are used and traded in the real financial world, come into existence before the creation of cryptocurrencies, and do not depend on blockchain or other crypto primitives to facilitate market exchanges. We use "non-crypto assets" or "non-crypto markets" to refer to assets in the real financial world described as above. Moreover, we define stablecoins as a special kind of cryptocurrencies which peg their prices to non-crypto assets, maintain a relatively stable price ranges and use collaterals to back up their values. Finally, the traditional cryptocurrencies in this paper refer to the cryptocurrencies other than stablecoins, such as Bitcoin and Ethererum. Traditional cryptocurrencies are characterized by extreme price fluctuations, with neither collaterals nor any price pegs. Given that traditional cryptocurrencies are the majority in crypto markets, and that unlike stablecoins, they seldom serve as exchange medium as a real currency, we would interchangeably use "crypto assets", "(traditional) cryptocurrencies" and "(traditional) crypto markets" to refer to traditional cryptocurrencies in the following context.

More specifically, to examine the risk spillovers between traditional crypto currencies and stablecoins, we consider Bitcoin (BTC for short) and Ethereum (ETH for short), which are the top two crypto assets with highest market values and account for more than 60% of total crypto market capitalization. We use Tether (USDT for short), the largest offchain collateralized stablecoin and DAI, the largest onchain collateralized stablecoins to proxy stablecoins. Tether is backed by the offchain collateral, US dollars. DAI is backed by the onchain collateral, a basket of crypto assets. Both of them are pegged one-to-one to U.S. dollar. We also include PAXG for further analysis, which is a stablecoin collateralized and pegged to gold. Table 1 presents the details of stablecoins and traditional crypto assets covered in this study.

Table 1: Details of cryptocurrencies and stablecoins

	USDT	DAI	BTC	ETH	PAXG
Lauch date	2014/10/6	2019/11/18	2009/1/3	2015/7/30	2019/8/29
Market Cap.	$69.2B	$6.21B	$884B	$408B	$309M
Peg	USD	US dollar	None	None	Gold
Collateral	USD	ETH and other ETH-based assets	None	None	Gold

Note: ‘B’ represents billion.

To capture the risk spillover effects among stablecoins and non-crypto assets, we need to find some representative assets to proxy the non-crypto markets. Here we mainly use US dollars in the empirical investigation, further adding in gold for robustness checks. Due to the significant importance of US dollars as global reserve currencies in global financial markets, it would do a better job than other assets to track the movements of non-crypto financial market. Considering that more than 90% of stablecoins, Tethre and DAI included, are pegged to US dollars, a natural conjecture is that US dollars maintain a closer link than other non-crypto assets with stablecoins. So if we are to spot the spillover effects between non-crypto markets and stablecoins, the prices of US dollars would be more informative and responsive.

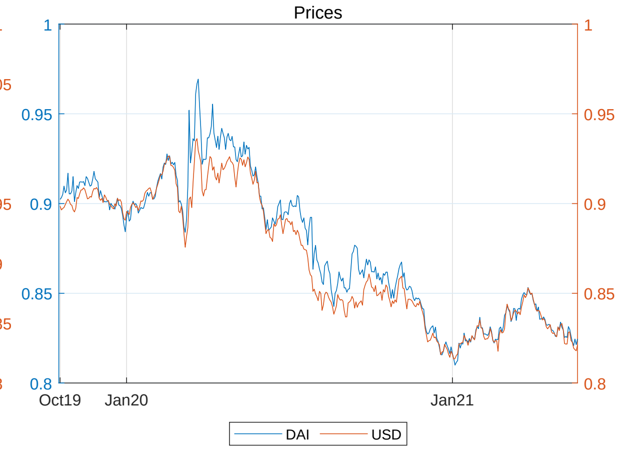
In light of Jeger et al. (2020), we need to find a numeraire currency to measure the values of all assets considered in this paper, including the US dollars, stablecoins and other cryptocurrencies. The daily prices of all assets above denominated in numeraire currency should be available and valid. Thus we resort to Euro as the numeraire currency, and the prices of all assets are measured in Euro. Specifically, the prices of crypto assets denominated in Euro are obtained from Cryptocompare.[4] The USD/EUR exchange rates are measured as units of Euro per U.S. dollar and obtained from the Federal Reserve of United States.

Due to the availability of the data, we consider three pairs related to USDT (USDT-USD/EUR, USDT-BTC and USDT-ETH) from February 27, 2019 to May 21, 2021 and three pairs related to DAI (DAI-USD/EUR, DAI-BTC and DAI-ETH) from October 17, 2019 to May 21, 2021. Figure 3 displays the prices of stablecoins and traditional cryptocurrencies, and the exchange rates of U.S. dollar against the Euro throughout the sampling period. It's not surprising that the USD/EUR exchange rates, show similar patterns as shown in Figure 3(a) and 3(b), since USDT and DAI are designed to be pegged to the U.S. dollar. However, both offchain collaterized USDT and onchain collaterized DAI would deviate from USD/EUR exchange rates, partially due to the different natures of cyptocurrencies and fiat currency, and partially due to different market mechanisms of crypto market and foreign exchange markets. As seen from Figure 3(b)-3(d), stablecoins and traditonal crypto currencies show the opposite trend. While Bitcoin and Ethereum share a general increasing trend, the two stablecoins follow a decreasing trend over time.

Table 2 presents the summary statistics for the asset returns. All the return series are skewed and exhibit excess kurtosis. The Jarque-Bera test of normality rejects the normality assumption of these return series at the 1% significance level. Moreover, the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic indicates that ARCH effects were present in all return series at the 5% significance level with the exception of the BTC. The stablecoins and cryptocurrencies trade 24 hours a day and 7 days in a week. However, the federal reserve does not maintain the USD rates on weekends.

[4]Cryptocompare has been collecting transaction data from more than 250 important exchanges around the world since 2017. The major crypto assets covered by Cryptocompare include Bitcoin (BTC), Ethereum(ETH), Ripple(XRP), Solana(SOL), Binance Coin(BNB), Tether(USDT), DAI, PAXG, etc.

(a) USDT and USD/EUR



(b) DAI and USD/EUR

(c) USDT and BTC

(d) USDT and ETH

(e) DAI and BTC

(f) DAI and ETH

Figure 3: Dynamics of stablecoins, non-crypto pegs and cryptocurrencies

Table 2: Summary Statistics

	USDT	DAI	BTC	ETH	USDEURO
Mean	-0.013	-0.015	0.272	0.347	-0.012
Std. Dev.	0.612	0.606	4.085	5.196	0.388
Skewness	0.571	0.55	-1.679	-1.798	0.171
Kurtosis	10.062	13.916	26.381	22.406	5.104
Jarque-Bera stat.	1747.7***	2944.3***	19028.7***	13285.4***	107.7***
ARCH-LM stat.	154.1***	129.5**	18.1	29.2**	107.9***
nObs	814	582	814	814	559

Notes: This table documents the summary statistics of the stablecoins returns, traditional cryptocurrency returns and USD/EUR exchange returns. The asterisk ** and *** indicates rejection of the null hypothesis at the 5% level and 1% significance levels. The USDT returns, BTC returns, ETH returns and USD/EUR exchange returns are from February 28, 2019 to May 21, 2021. The DAI returns are from October 18, 2019 to May 21, 2021.

3.2 Measurements of risk spillovers

In this paper, we focus on extreme market risks which are the major concerns of regulators and investors. Extreme market movements could increase financial system vulnerabilities and even lead to social instability. Market participants, who might suffer large losses under extreme adverse market conditions, exhibit a strong aversion to extreme market fluctuations.

Let r_{it} denote the return of asset i. We use the downside and upside VaR to measure the risks of individual assets. The downside VaR for asset i is defined as the maximum expected losses that asset i may experience with a confidence level $1 - \alpha$,

$$Pr(r_{it} \leq VaR^i_{\alpha,t}) = \alpha, \tag{1}$$

where α is usually a small number. The upside VaR for asset i is given by $Pr(r_{it} > VaR^i_{1-\alpha,t}) = \alpha$. The downside (upside) VaR measures are used to capture the extreme downside (upside) risks of r_{it} for long (short) position holders.

To capture extreme risk spillover effects, we adopt the CoVaR approach proposed by Adrian and Brunnermeier (2016) and Girardi and Ergün (2013). We distinguish between positive and negative risk spillover effects. To capture positive risk spillover effects from asset i to asset j, following Reboredo et al. (2016), we consider the downside-to-downside CoVaR given by,

$$Pr\left(r_{jt} \leq CoVaR^{j|i}_{\beta,t} | r_{it} \leq VaR^{i}_{\alpha,t}\right) = \beta, \tag{2}$$

and upside-to-upside CoVaR given by,

$$Pr\left(r_{jt} \geq CoVaR^{j|i}_{\beta,t} | r_{it} \geq VaR^{i}_{1-\alpha,t}\right) = \beta. \tag{3}$$

where β is usually a small number. The CoVaR measure is directional in the sense that it allows to capture the spillover effects from asset i to asset j and vice versa. Since stablecoins and their non-crypto pegs are positively dependent, we use the downside-to-downside and upside-to-upside CoVaR measures to capture their spillover effects.

On the other hand, since stablecoins and traditional cryptocurrencies are negatively dependent, we propose the upside-to-downside and downside-to-upside CoVaR measures to capture their spillover effects. The downside-to-upside CoVaR is given by,

$$\Pr(r^{j}_{t} \geq CoVaR^{j|i}_{\beta,t} | r^{i}_{t} \leq VaR^{i}_{\alpha,t}) = \beta. \tag{4}$$

and the upside-to-downside CoVaR is given by,

$$\Pr(r^{j}_{t} \leq CoVaR^{j|i}_{\beta,t} | r^{i}_{t} \geq VaR^{i}_{1-\alpha,t}) = \beta \tag{5}$$

The downside-to-upside (upside-to-downside) CoVaR incorporates the additional upside (downside) risk in asset j resulted from asset i being in extreme downside (upside) market conditions. In this paper, $\alpha = \beta = 0.1$.

To test for the null hypothesis of no significant positive risk spillovers from asset i to asset j, reformulated as,

$$H_0 : CoVaR_{\beta,t}^{j|i} = VaR_{\alpha,t}^{j} \tag{6}$$

following Bernal et al. (2014), Reboredo et al. (2016) and Mensi et al. (2017), we compare the empirical distribution functions for the downside-to-downside (or upside-to-upside) CoVaR and downside (upside) VaR using the KS bootstrapping test as proposed in Abadie (2002),

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{1/2} \sup_x |F_m(x) - G_n(x)|, \tag{7}$$

where F_m and G_n are the empirical cumulative distribution functions of the downside-to-downside (or upside-to-upside) CoVaR and downside (upside) VaR, respectively. Similarly, we can test for the null hypothesis of no significant negative risk spillovers from asset i to asset j by comparing the empirical distribution functions of the upside-to-downside (or downside-to-upside) CoVaR and downside (upside) VaR, respectively.

3.3 CoVaR in copula representation

To calculate the VaR and CoVaR measures, which are implicitly defined as the unconditional and conditional quantiles, one need to model the joint distribution of asset returns. We adopt the copula approach to construct the joint distribution of asset returns due to its flexibility to model the marginal distributions of individual asset returns and their dependence structure separately.

Let Ω_{t-1} denote the information set available at time $t-1$. Patton (2006) show that the conditional joint distribution function $F(r_{1t}, r_{2t}|\Omega_{t-1})$ can be decomposed into the conditional marginal distribution functions F_j and a conditional copula C, such that,

$$F(r_{1t}, r_{2t}|\Omega_{t-1}) = C\left(F_1(r_{1t}|\Omega_{t-1}), F_2(r_{2t}|\Omega_{t-1})|\Omega_{t-1}\right), \tag{8}$$

Before modeling the copula function, one must first specify the conditional marginal distributions. For $j = 1, 2$, consider the following ARMA-GARCH specification for r_{jt}, $t = 1, ..., T$,

$$r_{jt} = \mu_{jt}(\theta_{01}) + e_{jt},$$
$$e_{jt} = \varepsilon_{jt}\sigma_{jt}(\theta_0),$$

where $\mu_{jt}(\theta_{01}) = E[r_{jt}|\Omega_{t-1}]$ is the conditional mean of r_{jt} given Ω_{t-1}, $\sigma^2_{jt}(\theta_0) = E[(r_{jt} - \mu_{jt}(\theta_{01}))^2|\Omega_{t-1}]$ is the conditional variance of r_{jt} given Ω_{t-1}, ε_{jt} is the standardized innovation, and $\theta_0 = (\theta'_{01}, \theta'_{02})'$ is a vector of finite-dimensional unknown parameters to be estimated.

We next fit the copula model to the filtered asset returns. To accommodate possible time-varying dependence between asset returns, we use the copula model with the Generalized Autoregressive Score (GAS) dynamics proposed by Creal et al. (2013). Let $U_{jt} = F_j(\varepsilon_{jt}|\Omega_{t-1})$, $j = 1, 2$ denote the probability integral transform (hereinafter 'PIT') of the standardized residuals. To deal with parameters that are constrained in a restricted range, we use a monotone increasing transformation to the copula parameter δ_t such that $h_t = g(\delta_t)$ is not range restricted. We then update the transformed parameter by exploiting the information implied by the scaled score of the copula likelihood function,

$$h_{t+1} = \omega + \beta h_t + \alpha I_t^{-1/2} s_t, \tag{9}$$
$$s_t = \frac{\partial}{\partial \delta_t} \log c(U_{1t}, U_{2t}; \delta_t) \tag{10}$$
$$I_t = E_{t-1}[s_t s_t'], \tag{11}$$

where s_t is the score of the log copula density and I_t its information matrix. The parameter β is designed to capture persistence in the copula parameter. The standardized score of the copula log-likelihood $I_t^{-1/2} s_t$ is intended to improve the model's local fit in terms of the likelihood or density in the steepest ascent direction. For a detailed review of copula based methods, please refer to Patton (2012).

With a well-specified copula function, the CoVaR measures in (2) to (4) can be represented in terms of copulas as,

$$C\left(F_j(CoVaR^{j|i}_{\beta,t}), F_i(VaR^i_{\alpha,t})\right) = \alpha\beta \tag{12}$$

$$1 - F_i(VaR^i_{1-\alpha,t}) - F_j(CoVaR^{j|i}_{\beta,t}) + C\left(F_j(CoVaR^{j|i}_{\beta,t}), F_i(VaR^i_{1-\alpha,t})\right) = \alpha\beta \tag{13}$$

$$F_i(VaR^i_{\alpha,t}) - C\left(F_j(CoVaR^{j|i}_{\beta,t}), F_i(VaR^i_{\alpha,t})\right) = \alpha\beta \tag{14}$$

$$F_j(CoVaR^{j|i}_{\beta,t}) - C\left(F_j(CoVaR^{j|i}_{\beta,t}), F_i(VaR^i_{1-\alpha,t})\right) = \alpha\beta \tag{15}$$

The copula representation (12) to (15) facilitates to calculate $CoVaR^{j|i}_{\beta,t}$ in a two-step procedure,

Step 1: Given the confidence levels α and β, we can obtain $F_j(CoVaR^{j|i}_{\beta,t})$ by solving (12) - (15);

Step 2: We can obtain $CoVaR^{j|i}_{\beta,t} = F_j^{-1}\left(F_j(CoVaR^{j|i}_{\beta,t})\right)$ by inversing the quantile function of $F_j(CoVaR^{j|i}_{\beta,t})$.

4 Empirical results for risk spillovers

4.1 Models for the marginal distributions

We fit the univariate ARMA-GARCH models to individual asset returns with innovations assumed to follow the Student's t distribution. Based on the AIC criterion, our preferred model turns out to be an AR(1,2,5,9)-GARCH(1,1) for the USDT, an AR(1,12)-GARCH(1,1) model for the DAI, AR(1,2)-GARCH(1,1) for the BTC, AR(1,10)-GARCH(1,1) for the ETH, AR(1,6)-GARCH(1,1) for the USD/EURO rate. To reduce the number of parameters to be estimated, we use the AR model with the nonconsecutive lags following Patton (2006). For example, AR(1,2,5,9) denotes the AR model with the nonzero AR coefficients at lags 1, 2, 5 and 9. Table 3 presents the estimation results of the marginal distribution models with the asymptotic standard errors in parentheses. Most of the parameters are statistically significant at the 5% level. The Ljung-box test and the weighted portmanteau test results support the adequacy of the fitted ARMA-GARCH process. The KS and CvM tests fail to reject the null hypothesis that the Student's t distribution provides a good fit for the standardized residuals of the return series.

4.2 Results from copula estimation

In this subsection, we explore the dependence structure between the filtered asset returns using the copula approach. We first perform a static copula analysis under the assumption that the dependence structure remained constant. We consider a variety of commonly used copulas: the normal, Student's t, Plackett, Frank, SJC, Clayton and Gumbel. The Gaussian, Plackett and Frank copulas are symmetric and admit no tail dependence; the Student t copula is also symmetric but allows tail dependence. All the four copula functions can be used to model either positive or negative association. The Gumbel copula allows upper tail dependence and zero lower tail dependence; the Clayton copula allows lower tail dependence and zero upper tail dependence; and finally the more flexible SJC copula allows either asymmetric or symmetric tail dependence. To account for possible negative dependence between asset returns, we also consider 90° rotated Clayton and 90° rotated Gumbel copulas.[5]

Table 4 presents the estimated parameters and multistage MLE standard errors of the parameters and values of the log-likelihood and AIC for the static copula models. Most of the

[5]The 90° rotated version of the bivariate copula is obtained by applying the transformation $C_R(u, v; \alpha) = v - C(1-u, v; \alpha)$ and $c_R(u, v; \alpha) = c(1-u, v; \alpha)$, where C_R and c_R are the cumulative distribution function and probability density function of the rotated version of bivariate copula. Note that our parameter estimates for the rotated Clayton and rotated Gumbel are opposite in sign to those by using the VineCopula package.

Table 3: Results for the marginal distributions

	USDT	DAI	BTC	Ethereum	USDEURO
Constant	-0.013	-0.016	0.273**	0.343**	-0.012
	(0.018)	(0.02)	(0.138)	(0.174)	(0.017)
AR(1)	-0.093***	-0.151***	-0.104***	-0.131***	0.15***
	(0.035)	(0.041)	(0.035)	(0.035)	(0.042)
AR(2)	0.073**		0.074**		
	(0.035)		(0.035)		
AR(4)					
AR(5)	-0.082**				
	(0.035)				
AR(6)					-0.092**
					(0.042)
AR(9)	-0.103***				
	(0.035)				
AR(10)				0.102***	
				(0.036)	
AR(12)		-0.089**			
		(0.041)			
GARCH cons.	0.013***	0.041**	0.47	2.41**	0.004
	(0.005)	(0.02)	(0.423)	(1.053)	(0.003)
Lagged var.	0.829***	0.719***	0.898***	0.822***	0.915***
	(0.04)	(0.107)	(0.034)	(0.051)	(0.042)
Lagged e^2	0.137***	0.15**	0.101***	0.118***	0.06**
	(0.037)	(0.07)	(0.023)	(0.04)	(0.031)
Shape	4.843***	4.313***	2.847***	3.096***	9.111***
	(0.803)	(0.893)	(0.284)	(0.381)	(3.095)
LB test	[0.846]	[0.487]	[0.467]	[0.147]	[0.766]
WLM test	[0.271]	[0.816]	[0.871]	[0.064]	[0.139]
KS test	[0.548]	[0.622]	[0.627]	[0.363]	[0.414]
CvM test	[0.332]	[0.691]	[0.682]	[0.327]	[0.477]

Note: This table reports the maximum likelihood estimates, with asymptotic standard errors in parentheses, of the parameters of the marginal distribution models for individual asset returns. 'LB test' reports the p-values for the Ljung-box test statistic for the null hypothesis of no serial correlation in the standardized residuals up to 12 lags. 'WLM test' reports the p-values for the weighted portmanteau test for the null hypothesis of no ARCH effects in the standardized residuals up to 12 lags. 'KS test' and 'CvM test' report the simulation-based p-values for the Kolmogorov-Smirnov and Cramer-von Mises goodness-of-fit tests under the null hypothesis that the probability integral transform series follow the uniform distributions by using 1000 simulations. The asterisk ** and *** indicates significance at the 5% and 1% levels.

dependence parameters are statistically significant. Based on the AIC criterion, the Student's t copula provides the best fit for all pairs, except for the pair USDT-USD, where the Plackett copula performs better. The parameter of Plackett copula for the pair of USDT-USD is greater than 1 and correlation coefficient of Student's t copula for the pair of DAI-USD is positive, which suggests that the returns of stablecoins and their non-crypto pegs are positively dependent; However, the correlation coefficients of the Student's t copulas for the pairs of USDT-BTC, USDT-ETH, DAI-BTC and DAI-ETH are negative, which suggests that the returns of stablecoins and traditional cryptocurrencies are negatively dependent. One interesting observation is that the 90° rotated copulas outperform their original copula versions for the negatively correlated pairs, while the opposite holds for the positively correlated pairs.

We next turn to use the dynamic copula functions to capture the possible time variation in the dependence structure of asset returns. We consider the same set of copula families as those reported in Table 4. For the Student's t copula, we assume for simplicity that the degrees of freedom parameter is constant and allow the correlation parameter to vary over time. To save space, we only report the estimation results of four time varying copulas, e.g. time varying normal, Student's t, Plackett and Frank copulas. [6] Table 5 presents the estimated results of four time-varying copula models. Among all the constant and time-varying copulas considered, the time varying Student's t copula provides the best fit for the pairs of DAI-USD, USDT-BTC and USDT-ETH, the time-varying normal copula performs best for the pair of USD-USD, while the static Student's t copula is preferred for the pairs of DAI-BTC and DAI-ETH.

[6]Time varying normal, Student's t, Plackett and Frank copulas are the four best performing time varying copulas for all pairs of asset returns, except for the pair DAI-BTC, whose best performing copula is time varying Student's t, followed by the time varying Plackett, 90° rotated Clayton and Normal copulas. The estimation results for the full set of copula families are available from the authors upon request.

Table 4: Estimation results of constant copula models

		USDT - USD	DAI-USD	USDT-BTC	USDT-ETH	DAI-BTC	DAI-ETH
Normal	ρ	0.605***	0.596***	-0.151***	-0.160***	-0.149***	-0.147***
		(0.046)	(0.053)	(0.038)	(0.036)	(0.038)	(0.048)
	AIC	-252.6	-172.1	-16.7	-19.0	-11.1	-10.7
Student's t	ρ	0.610***	0.618***	-0.140***	-0.158***	-0.147***	-0.145***
		(0.045)	(0.048)	(0.040)	(0.039)	(0.038)	(0.053)
	ν^{-1}	0.073*	0.195***	0.131***	0.150***	0.063	0.100***
		(0.044)	(0.061)	(0.034)	(0.044)	(0.046)	(0.033)
	AIC	-254.0	**-190.6**	**-28.4**	**-32.0**	**-11.9**	**-14.8**
Plackett	γ	7.571***	7.979***	0.647***	0.597***	0.637***	0.632***
		(1.309)	(1.396)	(0.080)	(0.077)	(0.078)	(0.136)
	AIC	**-258.8**	-185.6	-13.6	-19.1	-10.9	-10.9
Frank	γ	4.645***	4.647***	-0.828***	-0.962***	-0.899***	-0.897**
		(0.506)	(0.517)	(0.247)	(0.255)	(0.233)	(0.379)
	AIC	-252.5	-175.4	-12.7	-17.5	-10.8	-10.5
SJC	τ_U	0.280***	0.345***	0.000**	0.000***	0.000***	0.000***
		(0.076)	(0.094)	(0.000)	(0.000)	(0.000)	(0.000)
	τ_L	0.484***	0.467***	0.000***	0.000***	0.000***	0.000***
		(0.059)	(0.059)	(0.000)	(0.000)	(0.000)	(0.000)
	AIC	-241.7	-179.2	18.4	19.0	15.1	14.3
Clayton	γ	1.092***	1.075***	0.000	0.000	0.000	0.000
		(0.169)	(0.182)	(0.203)	(0.007)	(0.040)	(0.006)
	AIC	-213.8	-156.1	2.0	2.0	2.0	2.0
Gumbel	γ	1.594***	1.651***	1.010***	1.010***	1.010***	1.010***
		(0.100)	(0.116)	(0.016)	(0.017)	(0.018)	(0.018)
	AIC	-214.9	-163.7	3.6	4.5	3.8	29.2
R-Clayton	γ	0.000	0.000	0.170***	0.200***	0.166***	0.166***
		(0.049)	(0.042)	(0.046)	(0.045)	(0.051)	(0.052)
	AIC	2.0	2.0	-17.7	-23.4	-10.5	-10.5
R-Gumbel	γ	1.01***	1.01***	1.093***	1.102***	1.076***	1.084***
		(0.006)	(0.005)	(0.036)	(0.040)	(0.027)	(0.036)
	AIC	10.9	8.2	-16.9	-19.3	-7.0	-9.7

Note: This table reports maximum likelihood estimates and their asymptotic standard errors (in parentheses) of the parameters of the constant copula models. The lowest AIC value (in bold) indicates the best-fitting static copula model. * and *** indicate significance at the 10% and 1% levels, respectively.

Table 5: Estimation results of time-varying copula models

		USDT - USD	DAI-USD	USDT-BTC	USDT-ETH	DAI-BTC	DAI-ETH
Normal	ω	0.013	0.045	-0.006	-0.005	-0.067	-0.111***
		(0.041)	(0.039)	(0.034)	(0.007)	(0.129)	(0.025)
	α	0.056	0.072**	0.039	0.033	-0.043	-0.033
		(0.091)	(0.037)	(0.077)	(0.031)	(0.121)	(0.080)
	β	0.993***	0.971***	0.982***	0.984***	0.778*	0.631***
		(0.029)	(0.027)	(0.059)	(0.016)	(0.439)	(0.088)
	AIC	**-327.6**	-187.8	-25.5	-26.1	-8.0	-7.1
Student's t	ω	0.023***	0.382**	-0.004**	-0.004	-0.091***	-0.038***
		(0.009)	(0.164)	(0.002)	(0.003)	(0.024)	(0.007)
	α	0.093	0.289**	0.056***	0.054***	-0.051**	0.018
		(0.121)	(0.144)	(0.013)	(0.003)	(0.025)	(0.015)
	β	0.986***	0.749***	0.984***	0.984***	0.695***	0.876***
		(0.010)	(0.099)	(0.008)	(0.003)	(0.061)	(0.038)
	ν^{-1}	0.045***	0.191***	0.132***	0.156***	0.061*	0.103***
		(0.013)	(0.068)	(0.016)	(0.005)	(0.035)	(0.033)
	AIC	-327.2	**-205.5**	**-40.1**	**-44.3**	**-8.5**	**-11.0**
Plackett	ω	0.118***	0.144***	-0.006	-0.006	-0.035***	-0.066**
		(0.040)	(0.023)	(0.004)	(0.044)	(0.010)	(0.031)
	α	0.128***	0.032	0.083*	0.092	-0.018	0.070
		(0.036)	(0.079)	(0.047)	(0.060)	(0.050)	(0.102)
	β	0.932***	0.928***	0.986***	0.983***	0.924***	0.868***
		(0.022)	(0.015)	(0.005)	(0.061)	(0.006)	(0.035)
	AIC	-303.6	-186.5	-30.0	-37.1	-7.1	-8.2
Frank	ω	0.039	0.194***	-0.014	-0.013	0.875***	-0.133
		(0.021)	(0.050)	(0.019)	(0.038)	(0.229)	(0.123)
	α	0.251***	0.511***	0.168	0.175	-0.065	0.098
		(0.072)	(0.039)	(0.445)	(0.392)	(0.149)	(0.264)
	β	0.994***	0.959***	0.985***	0.984***	0.016	0.859***
		(0.004)	(0.015)	(0.009)	(0.045)	(0.027)	(0.206)
	AIC	-317.2	-185.9	-26.8	-35.8	-6.7	-7.1

Note: This table reports maximum likelihood estimates and their asymptotic standard errors (in parentheses) of the parameters of the time varying copula models. The lowest AIC value (in bold) indicates the best-fitting time varying copula model. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

4.3 Spillover effects between stablecoins and non-crypto assets

After specifying the ARMA-GARCH models and copula functions, we can calculate the CoVaR measures according to equations (12) - (15).

We use the US dollar as the proxy of non-crypto assets. Panel I and Panel II of Table 6 report the summary statistics of downside (upside) VaR and downside-to-downside (upside-to-upside) CoVaR values for the returns of stablecoins and the US dollar. The KS bootstrapping test results for the spillover effects between stablecoins and the US dollar are also reported. The null hypothesis of no spillover effects is overwhelmingly rejected in favor of the alternative of significant downside-to-downside and upside-to-upside risk spillovers between stablecoins and the US dollar transmitted in both directions.

Table 6: Descriptive statistics and tests for VaR and CoVaR for stablecoins and the dollar

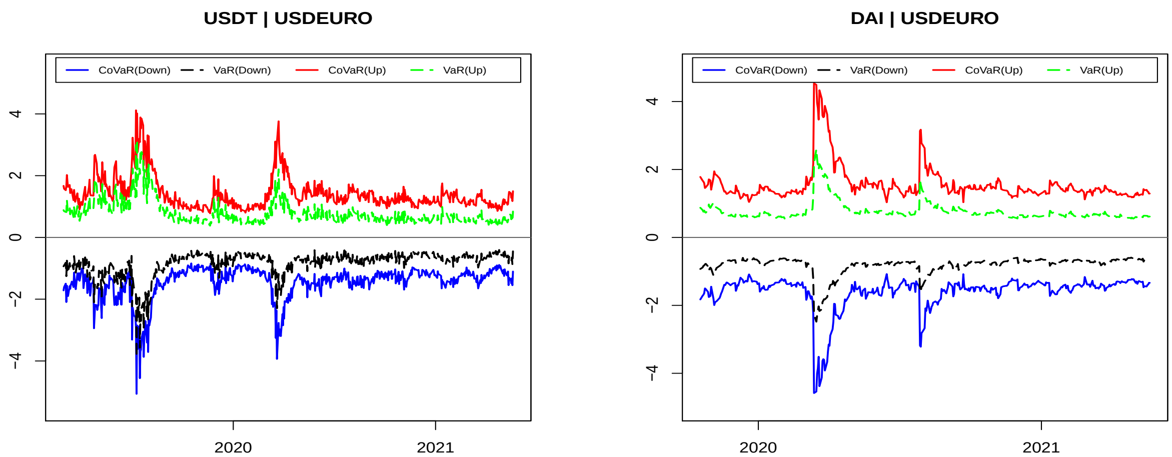
	Down-to-down Spillover			Up-to-up Spillover		
	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR < VaR$	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR > VaR$
Panel I: Spillovers from the US Dollar to stablecoins						
USD ⇒ USDT	-0.847	-1.468	0.726	0.804	1.426	0.735
	(0.429)	(0.552)	[0.000]	(0.408)	(0.532)	[0.000]
USD ⇒ DAI	-0.82	-1.617	0.914	0.776	1.572	0.912
	(0.280)	(0.529)	[0.000]	(0.283)	(0.529)	[0.000]
Panel II: Spillovers from stablecoins to the US Dollar						
USDT ⇒ USD	-0.524	-0.949	0.741	0.5	0.924	0.751
	(0.137)	(0.290)	[0.000]	(0.140)	(0.293)	[0.000]
DAI ⇒ USD	-0.597	-1.129	0.887	0.552	1.083	0.882
	(0.150)	(0.267)	[0.000]	(0.163)	(0.276)	[0.000]

Note: This table reports mean and standard errors (in parentheses) for downside (upside) VaR and downside-to-downside (upside-to-upside) CoVaR values for the returns of stablecoins and the US dollar. "A ⇒ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) for the null hypothesis of no downside-to-downside (4th column) or upside-to-upside (7th column) risk spillovers from asset A to asset B are also reported.

To further illustrate the test results, Panel I and Panel II of Figure 4 represent the VaR and CoVaR dynamics for stablecoins and the US dollar, respectively. The graphs in both panels show similar patterns: (1) the VaR and CoVaR values generally move in tandem over time; (2) the downside-to-downside CoVaR values are systemically lower than the downside VaR values, and the upside-to-upside CoVaR values are systemically greater than the upside VaR values, which is consistent with the KS bootstraping test results reported in Table 6.

To sum up, there exist significant risk spillovers between stablecoins and non-crypto pegs, which is in accordance with our Hypothesis 1.

Panel I: Spillovers from the US dollar to stablecoins



Panel II: Spillovers from stablecoins to the US dollar

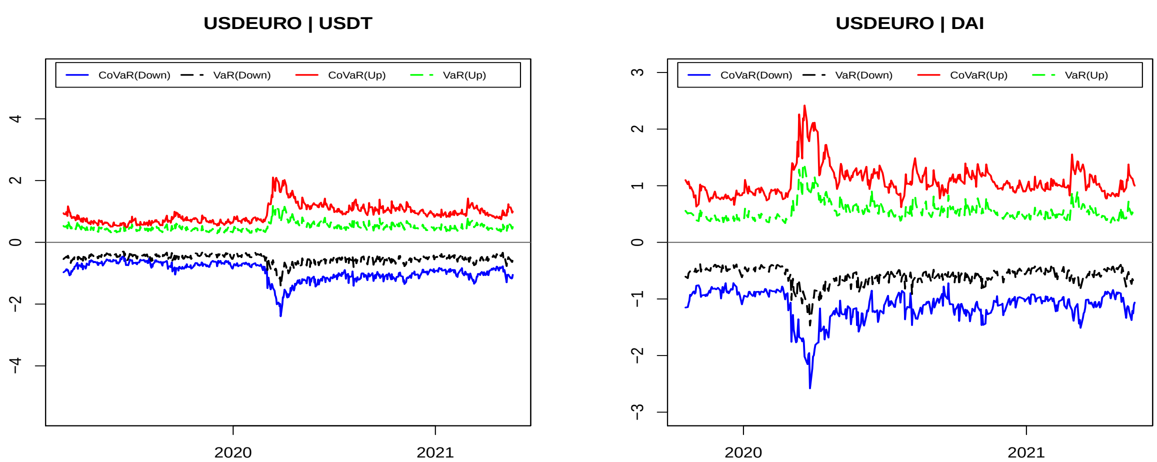


Figure 4: VaR and CoVaR dynamics for the returns of stablecoins and the US dollar

We examine whether the spillover effects from stablecoins to non-crypo pegs (e.g. US dollar) and from non-crypo pegs to stablecoins are symmetric by testing whether the CoVaR normalized by the VaR for the stablecoins is significantly different from the CoVaR normalized by the VaR for the non-crypo pegs. The KS test results reported in Table 7 indicate

Table 7: Test results for symmetries in the risk spillovers between stablecoins to the US dollar

	USDT-USD	DAI-USD
Panel I: H_0: $\text{CoVaR}^{normal}_{DN\|DN}(\text{s}\|\text{d}) = \text{CoVaR}^{normal}_{DN\|DN}(\text{d}\|\text{s})$		
H_1: $\text{CoVaR}^{normal}_{DN\|DN}(\text{s}\|\text{d}) < \text{CoVaR}^{normal}_{DN\|DN}(\text{d}\|\text{s})$	0.043	0.04
	[0.321]	[0.499]
H_1: $\text{CoVaR}^{normal}_{DN\|DN}(\text{s}\|\text{d}) > \text{CoVaR}^{normal}_{DN\|DN}(\text{d}\|\text{s})$	0.057	0.38
	[0.144]	[0.000]
Panel II: H_0: $\text{CoVaR}^{normal}_{UP\|UP}(\text{s}\|\text{d}) = \text{CoVaR}^{normal}_{UP\|UP}(\text{d}\|\text{s})$		
H_1: $\text{CoVaR}^{normal}_{UP\|UP}(\text{s}\|\text{d}) < \text{CoVaR}^{normal}_{UP\|UP}(\text{d}\|\text{s})$	0.027	0.071
	[0.663]	[0.117]
H_1: $\text{CoVaR}^{normal}_{UP\|UP}(\text{s}\|\text{d}) > \text{CoVaR}^{normal}_{UP\|UP}(\text{d}\|\text{s})$	0.077	0.267
	[0.033]	[0.000]

Note: This table reports the KS test statistics with p values (in squared brackets) for the null hypothesis of symmetries in risk spillovers from stablecoins (e.g. USDT and DAI) to the US dollar and from the US dollar to stablecoins. $CoVaR^{normal}_{DN|DN} = \frac{CoVaR_{DN|DN}}{VaR_{DN}}$ denotes the downside-to-downside CoVaR normalized by the downside VaR. $CoVaR^{normal}_{UP|UP} = \frac{CoVaR_{UP|UP}}{VaR_{UP}}$ denotes the upside-to-upside CoVaR normalized by the upside VaR. 's' and 'd' in the brackets represent stablecoins and the US dollar, respectively.

that downside-to-downside risk spillovers from USDT to the US dollar are symmetric to those from the US dollar to USDT (Panel I), whereas the upside-to-upside spillovers from the US dollar to USDT were greater than those from USDT to the US dollar. Regarding the DAI-USD pair, the spillover effects from the US dollar to DAI were greater than those from DAI to the US dollar, regardless of downside-to-downside or upside-to-upside risks.

In sum, the risk spillovers from the US dollar to stablecoins (e.g. USDT and DAI) are stronger than those from stablecoins to the US dollar, which is in line with Hypothesis 2. These results are intuitive since USDT and DAI are designed to peg their market values to the US dollar, and the US dollar trading volumes in foreign exchange markets are much larger than stablecoin trading volumes in crypto markets.

4.4 Spillover effects between stablecoins and traditional cryptocurrencies

Panel I and Panel II of Table 8 report the summary statistics of downside (upside) VaR and upside-to-downside (downside-to-upside) CoVaR values for the returns of stablecoins (e.g., USDT and DAI) and traditional cryptocurrencies (e.g., BTC and ETH). The KS bootstrapping test results for the spillover effects between stablecoins and traditional cryptocurrencies are also reported. The null hypothesis of no spillover effects is overwhelmingly rejected in favor of the alternative of significant upside-to-downside and downside-to-upside risk spillovers between stablecoins and traditional cryptocurrencies transmitted in both directions.

To further illustrate the test results, Panel I and Panel II of Figure 5 represent the VaR and CoVaR dynamics for the stablecoins and traditional cryptocurrencies, respectively. The graphs in both panels show that the upside-to-downside CoVaR values are significantly lower than the downside VaR values, and the downside-to-upside CoVaR values are significantly higher than the upside VaR values, implying that there exist significant upside-to-downside and downside-to-upside risk spillovers between the stablecoins and traditional cryptocurrencies transmitted in both directions. This findings are consistent with Hypothesis 3.

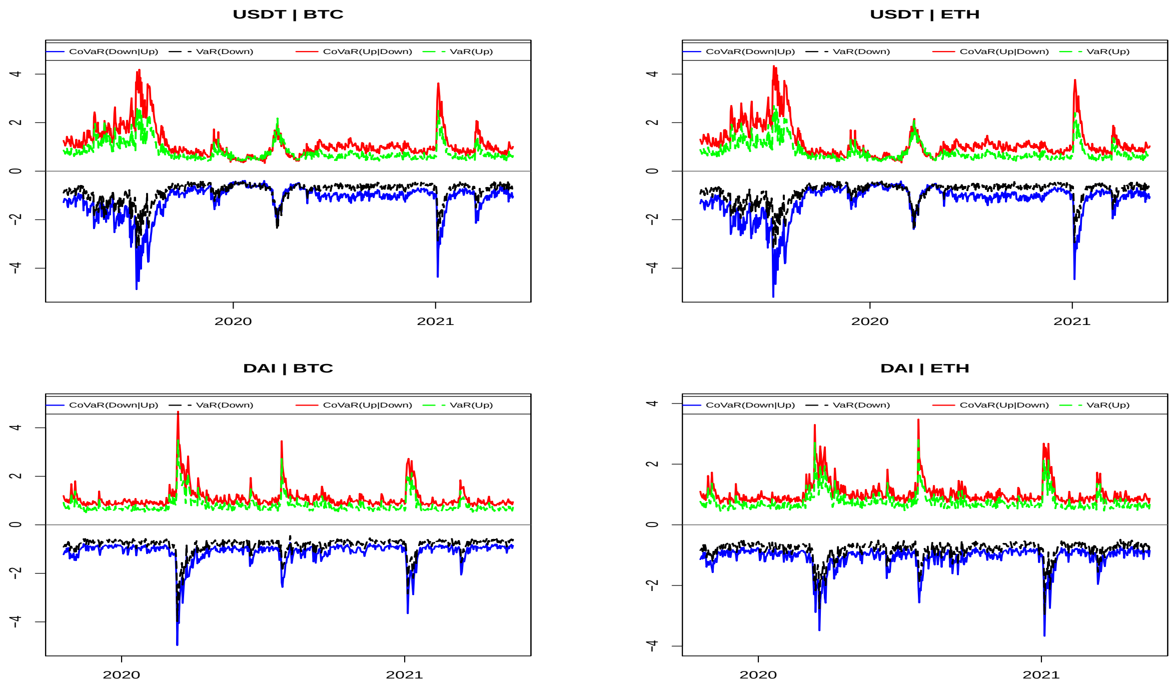
In summary, we find significant risk spillovers between stablecoins and traditional cryptocurrencies. Combined with results in Table 6, our findings lend supportive evidence that stablecoins bridge the gap between crypto and non-crypto (e.g. the US dollar) markets and transmit the risks between these two markets.

Table 8: Descriptive statistics and tests for VaR and CoVaR for stablecoins and traditional cryptocurrencies

	Up-to-Down Spillover			Down-to-Up Spillover		
	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR > VaR$
Panel I: Spillovers from traditional cryptocurrencies to stablecoins						
BTC $\Rightarrow$ USDT	-0.825	-1.163	0.43	0.801	1.137	0.434
	(0.390)	(0.620)	[0.000]	(0.384)	(0.614)	[0.000]
ETH $\Rightarrow$ USDT	-0.829	-1.209	0.445	0.801	1.183	0.451
	(0.392)	(0.657)	[0.000]	(0.381)	(0.651)	[0.000]
BTC $\Rightarrow$ DAI	-0.834	-1.119	0.663	0.803	1.088	0.674
	(0.327)	(0.426)	[0.000]	(0.313)	(0.414)	[0.000]
ETH $\Rightarrow$ DAI	-0.835	-1.156	0.703	0.803	1.125	0.72
	(0.326)	(0.440)	[0.000]	(0.316)	(0.427)	[0.000]
Panel II: Spillovers from stablecoins to traditional cryptocurrencies						
USDT $\Rightarrow$ BTC	-6.761	-10.116	0.493	7.3	10.66	0.499
	(2.628)	(3.755)	[0.000]	(2.654)	(3.766)	[0.000]
DAI $\Rightarrow$ BTC	-6.522	-9.216	0.469	7.023	9.711	0.464
	(2.828)	(3.874)	[0.000]	(2.763)	(3.834)	[0.000]
USDT $\Rightarrow$ ETH	-8.214	-12.672	0.63	8.904	13.368	0.623
	(2.623)	(4.019)	[0.000]	(2.741)	(4.173)	[0.000]
DAI $\Rightarrow$ ETH	-8.125	-11.829	0.641	8.975	12.701	0.696
	(3.041)	(4.212)	[0.000]	(3.140)	(4.378)	[0.000]

Note: This table reports mean and standard errors (in parentheses) for downside (upside) VaR and upside-to-downside (downside-to-upside) CoVaR values for the returns of stablecoins and traditional cryptocurrencies. "A $\Rightarrow$ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) under the null hypothesis of no upside-to-downside or downside-to-upside risk spillovers from asset A to asset B are also reported.

Panel I: Spillovers from traditional cryptocurrencies to stablecoins



Panel II: Spillovers from stablecoins to cryptocurrencies

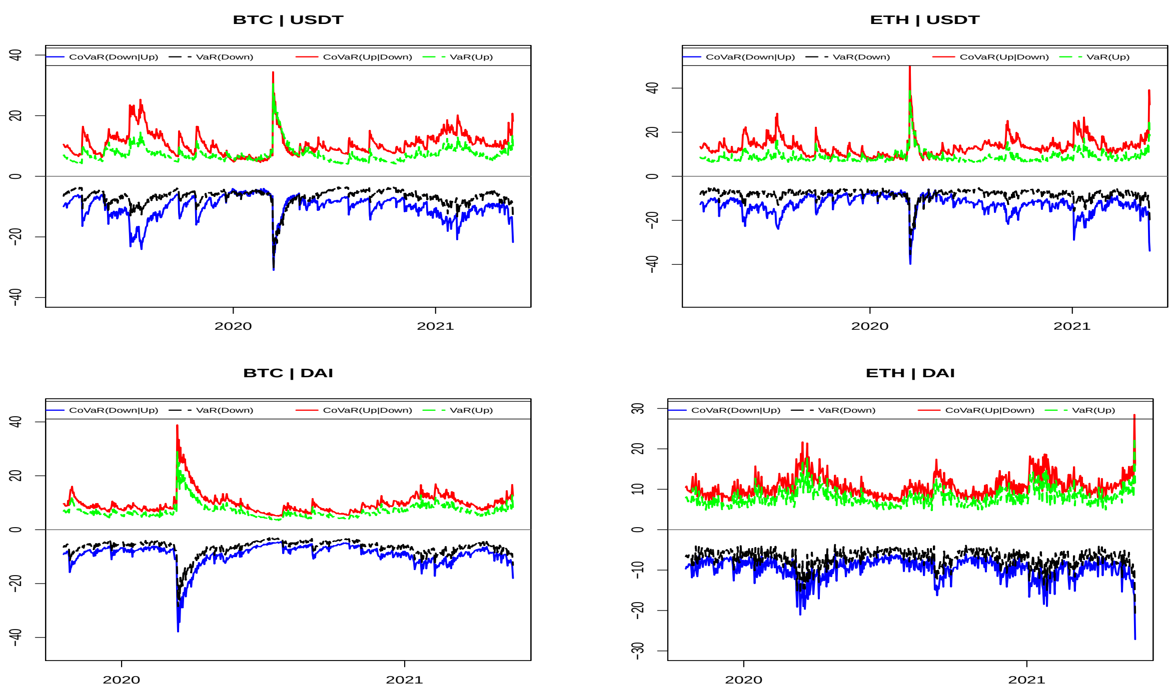


Figure 5: VaR and CoVaR dynamics for stablecoins and traditional cryptocurrencies

Next, we examine whether the spillover effects from stablecoins to cryptocurrencies and from cryptocurrencies to stablecoins are symmetric by testing whether the CoVaR normalized by the VaR for stablecoins is significantly different from the CoVaR normalized by the VaR for cryptocurrencies. The KS test results reported in Panel I and Panel II of Table 9 indicate that the upside-to-downside spillovers from stablecoins to cryptocurrencies are greater than the downside-to-upside spillovers from cryptocurrencies to stablecoins, whereas the downside-to-upside spillovers from stablecoins to cryptocurrencies are greater than the upside-to-downside spillovers from cryptocurrencies to stablecoins. These results are consistent with Hypothesis 4. The stronger risk spillovers from Stablecoins to cryptocurrencies are in accordance with the findings of Kristoufek (2021). One possible explanation for this finding is the role of stablecoins as the “digital fiat” in crypto tradings. The change in stablecoin supply, similar to the change in the money supply in the financial market, would have a great impact on the prices of traditional cyptocurrencies.

Table 9: Test results for symmetry in the risk spillovers between stablecoins and traditional cryptocurrencies

	USDT-BTC	USDT-ETH	DAI-BTC	DAI-ETH
Panel I: H_0: CoVaR$^{normal}_{UP\|DN}$ (s|c) = CoVaR$^{normal}_{DN\|UP}$ (c|s)				
H_1: CoVaR$^{normal}_{UP\|DN}$(s|c) < CoVaR$^{normal}_{DN\|UP}$ (c|s)	0.275	0.238	0.467	0.378
	[0.000]	[0.000]	[0.000]	[0.000]
H_1: CoVaR$^{normal}_{UP\|DN}$(s|c) > CoVaR$^{normal}_{DN\|UP}$(c|s)	0.015	0.007	0.002	0.002
	[0.849]	[0.952]	[0.997]	[0.998]
Panel II: H_0: CoVaR$^{normal}_{DN\|UP}$ (s|c) = CoVaR$^{normal}_{UP\|DN}$ (c|s)				
H_1: CoVaR$^{normal}_{DN\|UP}$(s|c) < CoVaR$^{normal}_{UP\|DN}$(c|s)	0.214	0.179	0.356	0.234
	[0.000]	[0.000]	[0.000]	[0.000]
H_1: CoVaR$^{normal}_{DN\|UP}$(s|c) > CoVaR$^{normal}_{UP\|DN}$(c|s)	0.016	0.007	0.002	0.003
	[0.808]	[0.949]	[0.999]	[0.990]

Note: This table reports the KS test statistics with p values (in squared brackets) for the null hypothesis of symmetric risk spillovers from stablecoins to crypocurrencies and from crypocurrencies to stablecoins. $CoVaR^{normalized}_{DN|UP} = \frac{CoVaR_{DN|UP}}{VaR_{DN}}$ denotes the upside-to-downside CoVaR normalized by the downside VaR. $CoVaR^{normalized}_{UP|DN} = \frac{CoVaR_{UP|DN}}{VaR_{UP}}$ denotes the downside-to-upside CoVaR normalized by the upside VaR. 's' and 'c' in the brackets represent stablecoins and traditional cryptocurrencies, respectively.

5 Robustness checks

In this section, we perform several robustness checks to firmly establish that the stablecoins play an important role in transmitting risks between non-crypto world and crypto world.

5.1 Alternative proxies for the non-crypto market

As a robustness check, we consider two alternative proxies for the non-crypto market: S&P500 index and MSCI world index. We examine the risk spillovers between the stablecoins (e.g. USDT) and two stock indices over the same sample period considered in Section 4 (from February 27, 2019 to May 21, 2021). Since the returns of stablecoins (e.g. USDT) and stock indices are negatively dependent, we use the upside-to-downside and downside-to-upside CoVaR to capture the spillover effects. Table 10 reports the KS bootstrapping test results for the spillover effects between USDT and two stock indices. The descriptive statistics of VaR and CoVaR for USDT and stock indices are also reported. The null hypothesis of no risk spillovers is overwhelmingly rejected in favor of the alternative of significant bidirectional risk spillovers between USDT and major stock indices.

Table 10: Descriptive statistics and tests for VaR and CoVaR for stablecoins and stock indices

	Up-to-Down Spillover			Down-to-Up Spillover		
	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR > VaR$
Panel I: Spillovers from stock indices to USDT						
SP500 $\Rightarrow$ USDT	-0.841	-1.046	0.392	0.802	1.007	0.396
	(0.426)	(0.443)	[0.000]	(0.417)	(0.430)	[0.000]
MSCI $\Rightarrow$ USDT	-0.884	-1.218	0.494	0.845	1.176	0.508
	(0.441)	(0.452)	[0.000]	(0.424)	(0.434)	[0.000]
Panel II: Spillovers from USDT to stock indices						
USDT $\Rightarrow$ SP500	-1.632	-2.086	0.273	1.773	2.229	0.27
	(1.368)	(1.428)	[0.000]	(1.387)	(1.450)	[0.000]
USDT $\Rightarrow$ MSCI	-1.489	-2.187	0.385	1.614	2.312	0.37
	(1.205)	(1.383)	[0.000]	(1.158)	(1.355)	[0.000]

Note: This table reports mean and standard errors (in parentheses) for downside (upside) VaR and upside-to-downside (downside-to-upside) CoVaR values for USDT and two stock indices, e.g. S&P500 index and MSCI world index. "A $\Rightarrow$ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) for the null hypothesis of no upside-to-downside (4th column) or downside-to-upside (7th column) risk spillovers from asset A to asset B are also reported.

As noted in Section 4, there exist the bidirectional spillover effects between stablecoins and traditional cryptocurrencies. This means that if stablecoins play a role in transmitting risks between crypto world and non crypto world, we would expect that the bidirectional spillover effects exist between traditional cryptocurrencies (e.g., Bitcoin) and two major stock indices. We now test for the spillover effects between Bitcoin and two stock indices. Since the returns of Bitcoin and stock indices are positively dependent, we use the downside-to-downside and upside-to-upside CoVaR to capture the spillover effects. Table 11 reports the KS bootstrapping test results for the spillover effects between Bitcoin and two stock indices. The null hypothesis of no risk spillovers is overwhelmingly rejected in favor of the alternative of significant bidirectional risk spillovers between Bitcoin and two stock indices.

Table 11: Descriptive statistics and tests for VaR and CoVaR for Bitcoin and stock indices

	Down-to-down Spillover			Up-to-up Spillover		
	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR > VaR$
Panel I: Spillovers from stock indices to Bitcoin						
SP500 ⇒ BTC	-8.529	-12.888	0.577	9.318	10.007	0.153
	(3.195)	(4.706)	[0.000]	(3.211)	(3.441)	[0.000]
MSCI ⇒ BTC	-9.088	-14.313	0.649	9.944	10.747	0.182
	(3.290)	(5.024)	[0.000]	(3.300)	(3.541)	[0.000]
Panel I: Spillovers from Bitcoin to stock indices						
BTC ⇒ SP500	-1.631	-2.246	0.293	1.774	1.879	0.076
	(1.370)	(1.735)	[0.000]	(1.390)	(1.447)	[0.042]
BTC ⇒ MSCI	-1.477	-2.137	0.326	1.605	1.713	0.084
	(1.196)	(1.612)	[0.000]	(1.153)	(1.217)	[0.022]

Note: This table reports mean and standard errors (in parentheses) for downside (upside) VaR and downside-to-downside (upside-to-upside) CoVaR values for Bitcoin and two stock indices, e.g. S&P500 index and MSCI world index. "A ⇒ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) for the null hypothesis of no downside-to-downside (4th column) or upside-to-upside (7th column) risk spillovers from asset A to asset B are also reported.

Taken together, the findings provide additional support for our earlier conclusion that stablecoins provide a channel that transmits the risks between crypto world and non crypto world.

5.2 Comparing spillover effects for pre- and post- stablecoin periods

One may doubt that the risk spillovers between the crypto world and non-crypto world already existed before a boom in stablecoins in 2019. We therefore consider two subperiods: the pre-stablecoin period from January 1, 2015 to December 31, 2017 (when the stablecoins were not popular while the trading volume of Bitcoin has grown rapidly), and the post-stablecoin period from February 27, 2019 to May 21, 2021. We exclude year 2018 when the stablecoins started gaining popularity.

As noted in Section 4, the returns of U.S. dollar and stablecoins are positively dependent, while the returns of stablecoins and Bitcoin are negatively dependent, we would expect that the returns of U.S. dollar and Bitcoin are negatively dependent. We use the upside-to-downside and downside-to-upside CoVaR to capture the spillover effects between Bitcoin and U.S. dollar. The descriptive statistics and test results of VaR and CoVaR measures for Bitcoins and U.S. dollar in two subperiods are reported in Table 12. The null hypothesis of no risk spillovers cannot be rejected in the first subperiod, while this null hypothesis is overwhelmingly rejected in favor of the alternative of significant bidirectional risk spillovers between Bitcoin and U.S. dollar in the second subperiod.

Table 12: Descriptive statistics and tests for VaR and CoVaR for Bitcoins and U.S. dollar in two subperiods

	Up-to-down Spillover			Down-to-up Spillover		
	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR > VaR$
Panel I: Pre-stablecoins period						
USD $\Rightarrow$ BTC	-6.25	-5.523	0	7.253	6.535	0
	(3.547)	(3.191)	[1.000]	(3.571)	(3.202)	[1.000]
BTC $\Rightarrow$ USD	-1.001	-0.921	0.047	0.904	0.823	0.045
	(0.239)	(0.288)	[0.180]	(0.240)	(0.288)	[0.206]
Panel II: Post-stablecoins period						
USD $\Rightarrow$ BTC	-8.579	-12.733	0.533	9.351	10.5	0.222
	(3.275)	(4.874)	[0.000]	(3.205)	(3.626)	[0.000]
BTC $\Rightarrow$ USD	-0.525	-0.692	0.485	0.5	0.549	0.181
	(0.137)	(0.185)	[0.000]	(0.140)	(0.156)	[0.000]

Note: This table reports mean and standard errors (in parentheses) for downside (upside) VaR and upside-to-downside (downside-to-upside) CoVaR values. "A $\Rightarrow$ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) for the null hypothesis of no upside-to-downside (4th column) or downside-to-upside (7th column) risk spillovers from asset A to asset B are also reported.

Furthermore, Section 5.1 provides evidence of bidirectional spillover effects between Bitcoin and stock indices (e.g. S&P 500 and MSCI) in the post-stablecoin period. In contrast, Bitcoin was not statistically correlated with stock indices in the pre-stable period from January 1, 2015 to December 31, 2017. The Pearson's and Spearman's correlation coefficients between Bitcoin and SP500 are 0.052 and 0.013 (the corresponding p-values are 0.155 and 0.727), respectively. For Bitcoin and MSCI, the values are -0.009 and -0.001 (the corresponding p-values are 0.817 and 0.985), respectively. Overall, these results suggest that the wall between crypto world and non-crypto world has only started to crumble since the rise of stablecoins.

5.3 Tests on stablecoins pegged to Gold

We consider USDT and DAI in Section 4, which are pegged to U.S. Dollar. As a robustness check, we include PAXG, which is the stablecoin backed by GOLD. Due to the data availability, we examine spillover effects between PAXG and non-crypto assets (e.g. gold), and between PAXG and traditional cryptocurrencies (e.g. BTC and ETH) over the period from October 30, 2019 to May 21, 2021.

Table 13 presents the descriptive statistics for downside (upside) VaR and downside-to-downside (upside-to-upside) CoVaR for PAXG and gold. The KS bootstrapping tests result in significant rejection of no spillover effects between PAXG and gold.

Table 13: Descriptive statistics and tests for VaR and CoVaR for PAXG and gold

	Down-to-down spillover			Up-to-up spillover		
	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR > VaR$
GOLD $\Rightarrow$ PAXG	-1.792	-3.976	0.887	1.87	4.048	0.882
	(0.738)	(1.571)	[0.000]	(0.802)	(1.630)	[0.000]
PAXG $\Rightarrow$ GOLD	-1.55	-3.484	0.905	1.625	3.555	0.9
	(0.500)	(1.076)	[0.000]	(0.521)	(1.093)	[0.000]

Note: This table reports mean and standard errors (in parentheses) for downside (upside) VaR and downside-to-downside (upside-to-upside) CoVaR values for PAXG and gold. "A $\Rightarrow$ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) for the null hypothesis of no downside-to-downside (4th column) or upside-to-upside (7th column) risk spillovers from asset A to asset B are also reported.

We also test for asymmetry in the spillover effects between PAXG and gold by testing whether the CoVaR normalized by the VaR for PAXG is significantly different from the

CoVaR normalized by the VaR for gold. Despite evidence in Table 7 pointing to stronger risk spillovers from U.S. dollar to USDT and DAI than those in the opposite direction, the KS test results reported in Table 14 suggest that the risk spillovers from PAXG to its peg gold are stronger than those from gold to PAXG, regardless of the downside-to-downside or upside-to-upside risks. This finding seems reasonable because the trading volume of Stablecoins (over 700 billion dollars daily) overpasses the trading volume of Gold (around 150 billion dollars daily)[7].

Table 14: Test results for symmetry in risk spillovers between PAXG and gold

	PAXG-GOLD
Panel I: H_0: $\text{CoVaR}^{normal}_{DN\|DN}(\text{p}\|\text{g}) = \text{CoVaR}^{normal}_{DN\|DN}(\text{g}\|\text{p})$	
H_1: $\text{CoVaR}^{normal}_{DN\|DN}(\text{p}\|\text{g}) < \text{CoVaR}^{normal}_{DN\|DN}(\text{g}\|\text{p})$	0.141
	[0.000]
H_1: $\text{CoVaR}^{normal}_{DN\|DN}(\text{p}\|\text{g}) > \text{CoVaR}^{normal}_{DN\|DN}(\text{g}\|\text{p})$	0.044
	[0.469]
Panel II: H_0: $\text{CoVaR}^{normal}_{UP\|UP}(\text{p}\|\text{g}) = \text{CoVaR}^{normal}_{UP\|UP}(\text{g}\|\text{p})$	
H_1: $\text{CoVaR}^{normal}_{UP\|UP}(\text{p}\|\text{g}) < \text{CoVaR}^{normal}_{UP\|UP}(\text{g}\|\text{p})$	0.17
	[0.000]
H_1: $\text{CoVaR}^{normal}_{UP\|UP}(\text{p}\|\text{g}) > \text{CoVaR}^{normal}_{UP\|UP}(\text{g}\|\text{p})$	0.044
	[0.455]

Note: This table reports the KS test statistics with p values (in squared brackets) for the symmetry in spillover effects between PAXG and gold. $CoVaR^{normalized}_{DN|DN} = \frac{CoVaR_{DN|DN}}{VaR_{DN}}$ denotes the downside-to-downside CoVaR normalized by the downside VaR. $CoVaR^{normalized}_{UP|UP} = \frac{CoVaR_{UP|UP}}{VaR_{UP}}$ denotes the upside-to-upside CoVaR normalized by the upside VaR. 'p' and 'g' in the brackets represent PAXG and gold, respectively.

Furthermore, Table 15 presents the descriptive statistics for downside (upside) VaR and

[7] Accessed from https://www.statista.com/statistics/625422/daily-trading-volumes-of-major-financial-assets-worldwide/ on 27 July, 2021.

upside-to-downside (downside-to-upside) CoVaR for PAXG and traditional cryptocurrencies (e.g. BTC and ETH). Despite evidence in Table 9 pointing to significant bidirectional spillover effects between stablecoins pegged to U.S. dollar (e.g., USDT and DAI) and traditional cryptocurrencies, the KS bootstrapping test results reported in Table 13 cannot reject the null hypothesis of no spillover effects between PAXG and traditional cryptocurrencies. This may be attributed to much smaller trading volumes of PAXG compared to trading volumes of stablecoins pegged in U.S. dollar.

Table 15: Descriptive statistics and tests for VaR and CoVaR for PAXG and traditional cryptocurrencies

	Up-to-Down			Down-to-Up		
	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR < VaR$	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR > VaR$
Panel I: Spillovers from traditional cryptocurrencies to PAXG						
BTC ⇒ PAXG	-1.653	-1.232	0	1.707	1.281	0
	(0.704)	(0.602)	[1.000]	(0.771)	(0.659)	[1.000]
ETH ⇒ PAXG	-1.653	-1.452	0	1.706	1.483	0
	(0.702)	(0.634)	[1.000]	(0.770)	(0.688)	[1.000]
Panel II: Spillovers from PAXG to traditional cryptocurrencies						
PAXG ⇒ BTC	-6.487	-4.846	0	6.955	5.31	0
	(2.855)	(2.579)	[1.000]	(2.847)	(2.541)	[1.000]
PAXG ⇒ ETH	-8.295	-7.192	0	9.153	7.973	0
	(3.310)	(2.961)	[1.000]	(3.121)	(2.795)	[1.000]

Note: This table reports mean and standard errors (in parentheses) for VaR and CoVaR values for PAXG and traditional cryptocurrencies (e.g., BTC and ETH). "A ⇒ B" denotes spillover effects from asset A to asset B. The KS test statistics with p values (in square brackets) for the null hypothesis of no upside-to-downside or downside-to-upside risk spillovers from asset A to asset B are also reported.

To sum up, Figure 6 illustrates the risk spillovers among PAXG, Gold, and major traditional crypto assets. We use the solid line arrow indicates the existence of risk spillovers, while the dashed line arrow instead indicates no risk spillovers in the direction. The direction of the bold arrows indicates the direction of stronger spillover effects. Different from our earlier conclusion that the largest off-chain and on-chain USD-backed stablecoins, USDT and DAI, plays an important role of transmitting risks between non-crypto and crypto world, gold-backed stablecoin PAXG instead does not function as a risk transmitter between non-crypto and crypto world, probably due to its low trading volumes. One important implication from this finding is that the role of stablecoins as the risk transmitter between non-crypto and crypto world might be strengthened with the increased trading of stablecoins in the future.

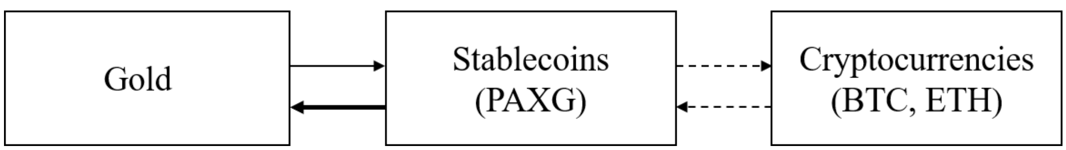


Figure 6: Risk spillovers among PAXG, Gold, and major crypto assets

6 Conclusions

In this paper, we examine the role of stablecoins as a bridge between the crypto and non-crypto markets and pay particular attention to the risk spillovers among three types of assets: stablecoins, non-crypto assets, and traditional cryptocurrencies. By using the copula-based CoVaR approaches, we find significant bidirectional risk spillovers among all pairs of assets considered in the sample period of 2019-2021, when stablecoins became widely adopted. In contrast, in the 2015-2017 period, when stablecoins were not popular, the risk spillovers between non-crypto assets and traditional cryptocurrencies were insignificant. Our findings suggest risks are transmitted between crypto and non-crypto markets through the channel of stablecoins. We also find that the risk spillovers from the US dollar to the traditional crypto market through stablecoins are stronger than those from the traditional crypto market to the US dollar.

Our findings have important policy implications for both regulators and investors. First, they must pay attention to the risks that stablecoins might pose to the financial system and the broader economy. Early in 2021, Visa became the first major payment network to settle transactions in stablecoins.[8] Our finding that stablecoins serve as risk transmitters suggests that regulators should thoroughly investigate the potential risks of stablecoins before regulated financial institutions further accept stablecoins in payments. Second, with a majority of stablecoins pegged to the US dollar and the wide use of stablecoins in crypto trading, the crypto markets have a tendency toward "re-dollarization." Our findings on the stronger risk spillovers from the US dollar to the crypto market through the channel of stablecoins are a signal of "dollarization," which partly explains the optimistic attitude for stablecoins by the vice chair of US Federal Reserve (Quarles, 2021). While some small developing countries are counting on stablecoins or other crypto currencies to "de-dollarize" their economy,[9] our results suggest that these economies might be more vulnerable to "digital dollarization." Third, in light of stablecoins' rapid growth, central banks should bring stablecoins into their regulatory perimeter and develop rules and standards for stablecoin trading.

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[9] For example, Venezuela accepted foreign aid in stablecoins in 2020 and considered stablecoins as a payment solution countrywide. El Salvador announced Bitcoin as the legal tender in 2021.

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