Are Stablecoins Stabilizing or Destabilizing the Crypto Market?

by

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Abstract

Different from traditional cryptocurrencies with extreme price fluctuations, stablecoin is a special kind of cryptocurrencies pegged to non-crypto assets and thus remains stable price ranges. While existing literature focus on the stability of stablecoins, we turn to examine the "destabilizing" effect instead. We argue that stablecoins have bridged the gap between crypto and non-crypto markets, and focus on the risk spillovers among three asset categories: stablecoins, traditional cryptocurrencies, and the non-crypto assets such as US dollars. Utilizing the copula based CoVaR approaches, we find significant bidirectional risk spillovers among all pairs of assets considered, indicating the integration of stablecoins, traditional crypto market and the non-crypto markets. More importantly, we provide empirical evidence for asymmetric effects, where the risk spillovers from the non-crypto market to traditional crypto market through stablecoins are stronger than the opposite direction. Our findings suggest the role of stablecoins both as a risk transmitter and also as a risk amplifier for the crypto markets.

Keywords: crypto assets; stablecoins; risk spillovers

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

1 Introduction

Different from traditional cryptocurrencies characterized by extreme price fluctuations, stablecoin is a special kind of cryptocurrencies pegged to non-crypto assets to maintain relatively stable price ranges. It has become the "digital fiat" in crypto markets (Kristoufek, 2021) , facilitating more than 60% of the cryptocurrency trading(Cermak et al., 2021), and reaching a trading volume of over 700 billion dollars[1] which is even larger than Paypal. Given the strong evidence supporting the stabilizing effect of stablecoins (Gu et al., 2020; Lyons and Viswanath-Natraj, 2019; Corbet et al., 2020; Baumöhl and Vyrost, 2020; Baur and Hoang, 2021) , together with the exploding supply of stablecoins from less than 5 billion dollars in 2019 to more than 100 billion dollars in 2021, it is puzzling why the volatility in crypto markets has still remained the same, if not increased.

Despite lack of empirical evidence on the risky aspect of stablecoins, the potential risks that stablecoins might pose on the financial system have received increasing attentions recently (G7WorkingGroup, 2019). In July 2021, US Treasury Secretary Yellen has summoned a meeting to discuss stablecoins and their potential risks to the financial system, with the heads of Federal Reserve, the Securities and Exchange Commission and the Commodity Futures Trading Commission.[2] In this backdrop, this paper aims to fill the gap by examining the potential role of stablecoins to "destabilize" the crypto markets and even the financial system.

To capture the destabilizing effect, we focus on the risk spillovers among three asset categories: stablecoins, traditional cryptocurrencies such as Bitcoins and Ethereums, and the non-crypto assets. We mainly use US dollars to represent the non-crypto assets, because more than 90% of stablecoins are pegged to US dollars. The economic intuitions for risk

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

[2] Accessed from https://www.wsj.com/articles/risks-of-crypto-stablecoins-attract-attention-of-yellen-fed-and-sec-11626537601 on 28 July,2021.

spillovers are straightforward as follows. Although crypto and non-crypto markets used to be isolated with each other, now with stablecoins both pegged to non-crypto assets and frequently used in cryptocurrencies trading, there would be a "stablecoins-bridging effect" leading to risk spillovers between the two markets. Moreover, since stablecoins follow their non-crypto pegs and function as "digital fiat" for settlements in crypto markets, we expect the risk spillovers to be asymmetric. The dominating risk transmitting direction would be from non-crypto pegs to stablecoins, and then to traditional crypto assets. Thus we argue that stablecoins could function as both a risk transmitter but also a risk amplifier for the crypto market. The following evidence is of great importance not only to regulating stablecoins, but also to the overall financial stability.

More specifically, to quantify the risk spillover effects, we utilize copula-based CoVaR approaches based on the daily transaction prices of different assets from February 2019 to May 2021. To begin with, following Girardi and Ergün (2013) and Reboredo et al. (2016), we test for the risk spillover by testing whether the differences between VaR and CoVaR for various asset pairs are significant. We find significant evidence of bilateral risk spillover effects between US dollars and stablecoins, and between stablecoins and traditional cryptocurrencies.Figure 1 illustrates the test results. The solid line arrows indicate the existence of spillover effects and the direction of arrows indicates the direction of spillover effects.

Figure 1: Risk spillovers among stablecoins, US dollar, and major crypto assets

Furthermore, we conduct the tests for the 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 1 represent the direction of stronger spillover effects. Finally, we also conduct similar analyses on a type of stablecoin pegged to gold instead of US dollars.

The empirical results lend supportive evidence to our conjectures and carry important policy implications. First, although the crypto market and non-crypto markets used to be isolated from each other, stablecoins now transmit risks between non-crypto and crypto markets, calling for regulators to build more effective firewalls between the two markets. Second, with countries around the world seeking to establish a regulatory framework for crypto markets, our finding of stablecoins' risk amplifier role suggests that regulators should pay more attention to the supervision of stablecoin-related exchanges and enterprises. Third, the asymmetric effects warn about the "re-dollarization" of crypto markets, where the US monetary policies would lead to significant price flucations in cryptocurrencies. One recent example is that the overall crypto market falls soon after the Fed announces plans to increase interest rates on 21st June, 2021.[3]While the development of crypto markets is usually interpreted as de-dollarization, exemplified by El Salvador' experiment decreeing bitcoin to be legal tender[4], our results raise doubts for this interpretation.

Our study contributes to the emerging field of stablecoins in three aspects: First, most existing literature focuses on the stability nature of stablecoins (Gu et al., 2020; Lyons and Viswanath-Natraj, 2019; Baur and Hoang, 2021; Corbet et al., 2020; Baumöhl and Vyrost, 2020), and little attention has been paid to the destablizing characteristics of stablecoins. Our paper aims to fill this gap by offering a comprehensive analysis on risk spillovers among stablecoins, non-crypto pegs and the traditional cryptocurrencies. Second, the majority of research on crypto markets focus on the traditional cryptocurrencies like Bitcoin(Makarov

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

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

and Schoar, 2020; Foley et al., 2019; Griffin and Shams, 2020). We extend the existing literature by focusing on the interaction between stablecoins and the traditional cryptocurrencies. Lastly, there has been growing concerns over the potential challenges stablecoins pose on the regulation since 2017(Arner et al., 2020; FSB, 2020; USPresident'sWorkingGroup, 2020), while academic work is scarce. The results presented in this paper provide empirical evidence for the potential risks stablecoins may bring into financial market.

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. Section 4 presents the methodology. Section 5 presents the main empirical results and provide evidence for the existence of bidirectional spillover effects. Section 6 tests for asymmetry in spillover effects and provides the robustness analysis. Finally, section 7 concludes.

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 destabilizing effect 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 and amplifier calls for valid regulatory firewalls against stablecoins to block risk spillovers between different markets.

2.3 Hypotheses development

In this section, we develop testable hypotheses for the existence of risk spillovers and the asymmetric effects. First, we examine whether risk spillovers significantly exist among stablecoins, traditional cryptocurrencies and non-crypto assets. Second, we discuss whether the risk spillovers are asymmetric, being particular stronger in the direction from non-crypto markets to crypto markets. In exploring the two hypothese, we emphasize the “risk transmitter” and “risk amplifier” roles that stablecoins play.

To begin with, we focus on the “risk transmitter” role of stablecoins. Since stablecoins can be viewed as the bridge between non-crypto and crypto markets (Cermak et al., 2021). The interaction between the two markets through stablecoins means that the turbulence in one market will influence the other. Firstly, 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, not to mention that a large propotion of stablecoins use non-crypto assets as their collateral, then a shock to their peg would naturally lead to price fluctuations in stablecoins. On the other hand, runs on stablecoins could spur sell-off of the assets used as their collateral, and directly signal intentional investors on the relative prices of their non-crypto pegs compared with cryptocurrencies, which might affect the confidence and stability of broader financial system in the non-crypto market (Arner et al., 2020). So we expect a bidirectional risk spillover between stablecoins and the related non-crypto assets.

Secondly, 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 lend supportive evidence to our argument. Therefore, we also expect significant risk spillovers between stablecoins and traditional cryptocurrencies. The above discussions lead to our first hypothesis on the “risk transmitter” role of stablecoins:

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

Next, we explore the risk amplifier role of stablecoins. First, 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. Second, 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. Collectively, these studies and our related discussion lead to our second hypothesis:

Hypothesis 2 (H2): The risk spillovers among stablecoins, non-crypto assets, and traditional cryptocurrencies are asymmetric.

3 Data description

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 [5]. 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 2 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 2(a) and 2(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,

[5] 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.

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: The asterisk ** and *** indicates rejection of the null hypothesis at the 5% level and 1% significance levels.

and partially due to different market mechanisms of crypto market and foreign exchange markets. As seen from Figure 2(b)-2(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.

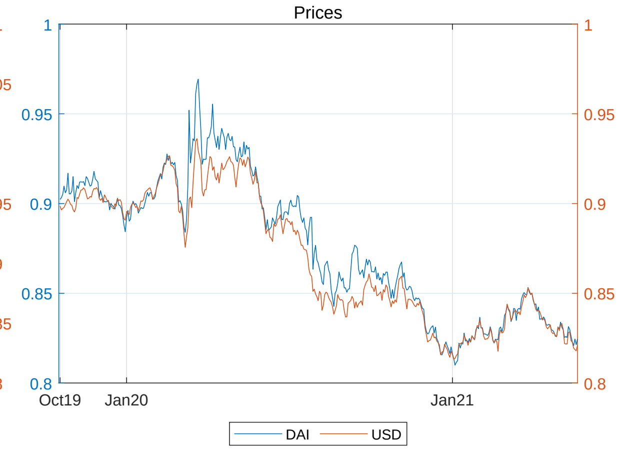
Table 2 presents the summary statistics for the asset returns. All the return series are skewed and exhibit excess kurtosis. The Jarque-Bera test of normality rejects the normality assumption of these return series at the 1% significance level. Moreover, the autoregressive conditional heteroskedasticity-Lagrange 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 Methodology

4.1 Measurements of risk spillovers

To capture the spillover effects, we adopt the CoVaR approach proposed by Adrian and Brunnermeier (2016) and Girardi and Ergün (2013).

(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 2: Dynamics of stablecoins, non-crypto pegs and cryptocurrencies

Let r_{it} denote the return of asset i. We use the downside and upside VaR measures to capture the downside and upside risks of r_{it}. The downside VaR for asset i is defined as the maximum expected loss 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 $Pr(r_{it} > VaR^{i}_{1-\alpha,t}) = \alpha$.

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.

To capture the possible negative risk spillover effects between asset returns, we propose the downside-to-upside CoVaR given by,

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

The downside-to-upside CoVaR incorporates the additional upside risk in asset j resulted from asset i being in extreme downside market conditions. Similarly, we can propose the upside-to-downside CoVaR given by,

$$\Pr(r_t^j \leq CoVaR_{\beta,t}^{j|i} | r_t^i \geq VaR_{1-\alpha,t}^i) = \beta \tag{5}$$

The upside-to-downside CoVaR incorporates the additional downside risk in asset j conditional on asset i experiencing extreme upside market movements. 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 Reboredo et al. (2016) and Jin (2018), we compare the empirical distribution functions for the downside-to-downside (or upside-to-upside) CoVaR and corresponding 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 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 VaR, respectively.

4.2 CoVaR in copula representation

The VaR and CoVaR measures are implicitly defined as the unconditional and conditional quantiles of the joint distribution of asset returns. We adopt the copula approach to construct the joint distribution of asset returns. 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,

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

The copula approach is attractive due to its flexibility to choose the marginal distributions and copula function separately.

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}, $t = 1, ..., T$,

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

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).

The CoVaR measures in (2) to (4) can be represented in terms of copulas as,

$$C\left(F_j(CoVaR_{\beta,t}^{j|i}), F_i(VaR_{\alpha,t}^i)\right) = \alpha\beta \tag{12}$$

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

$$F_i(VaR_{\alpha,t}^i) - C\left(F_j(CoVaR_{\beta,t}^{j|i}), F_i(VaR_{\alpha,t}^i)\right) = \alpha\beta \tag{14}$$

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

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

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

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

5 Empirical results for risk spillovers

5.1 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.

5.2 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

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 for the null hypothesis that the probability integral transform series follow the uniform distributions by using 1000 simulations. The asterisk *, ** and *** indicates significance at the 10%, 5% and 1% level.

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[6].

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 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 coefficients of the best-fitting copulas for the pairs of USDT-USD and DAI-USD are positive, which suggests that the 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 stablecoins and the 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 the same set of copula families as those reported in Table 4. However, to save the space, we only report the estimation results of four time varying copulas[7]. 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. 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

[6]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 $c_R(u, v; \alpha) = c(1-u, v; \alpha)$. Note that our parameter estimates for the rotated Clayton and rotated Gumbel are opposite in sign to those by using the VineCopula package.

[7]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 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%, 5% and 1% levels, respectively.

copula provides the best fit for the pairs of DAI-USDEURO, USDT-BTC and USDT-ETH, and the time-varying normal copula performs best for the pair of USD-USDEURO. However, for the pairs of DAI-BTC and DAI-ETH, the static Student's t copula is preferred.

Table 5: Estimation 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

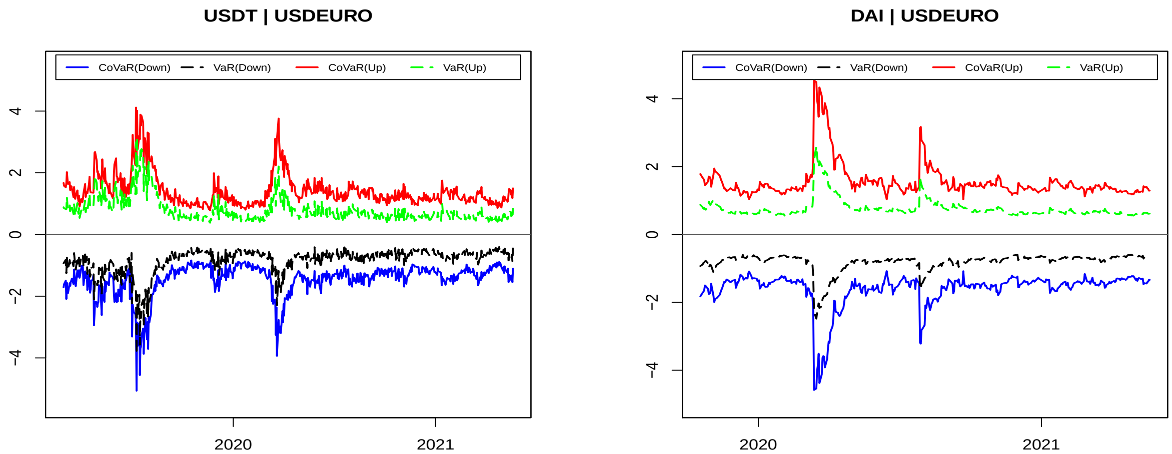
Note: This table reports maximum likelihood estimates and their asymptotic standard errors (in parentheses) of the parameters of the time varying copula models. The lowest AIC value (in bold) indicates the best-fitting time varying copula model. *, ** and *** indicate significance at the 10%, 5% and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

5.3 Spillover effects between stablecoins and non-crypto assets

We use the selected ARMA-GARCH models combined with the best-fitting copulas to construct the conditional joint distributions of asset returns, based on which we can calculate the VaR and CoVaR measures.

Panel I and Panel II of Figure 3 represent the VaR and CoVaR dynamics for the stablecoins and US dollars, respectively. Since the stablecoins and their pegs, i.e. US dollars, are positively dependent, we report the downside-to-downside and upside-to-upside CoVaR measures defined in (2) and (3). Table 6 reports the summary statistics of VaR and CoVaR values and the test results for the null hypothesis of no spillover effects between stablecoins and non-crypto assets. 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 significantly lower than the downside VaR values, and the upside-to-upside CoVaR values are significantly higher than the upside VaR values, which implies that there exist significant downside-to-downside and upside-to-upside risk spillovers between stablecoins and non-crypto assets transmitted in both directions. The graphical evidence is confirmed by the KS bootstraping test results reported in Table 6. To sum up, there exists significant risk spillovers between stablecoins and non-crypto assets, which is in accordance with our arguments.

Panel I: Spillover from USDEURO to stablecoins



Panel II: Spillover from stablecoins to USDEURO

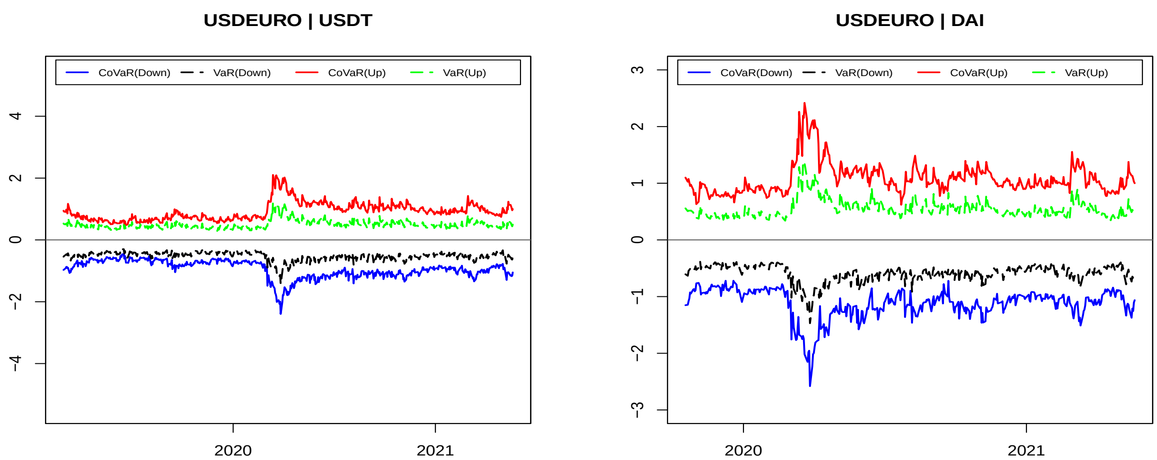


Figure 3: VaR and CoVaR dynamics for stablecoins and non-cypto pegs

Table 6: Descriptive statistics and test results of VaR and CoVaR measures for stablecoins and non-crypto assets

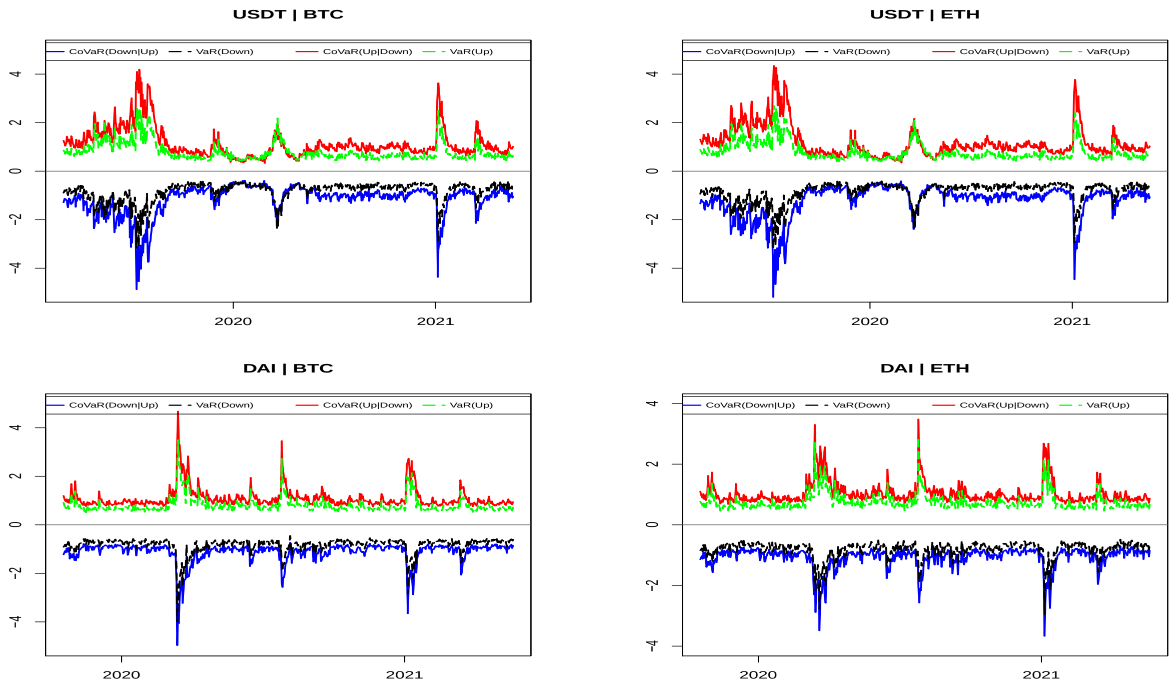
	Downside			Upside		
	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR > VaR$
Panel I: VaR of stablecoins and CoVaR from USDEURO to stablecoins						
USD $\Rightarrow$ USDT	-0.847	-1.468	0.726	0.804	1.426	0.735
	(0.429)	(0.552)	[0.000]	(0.408)	(0.532)	[0.000]
USD $\Rightarrow$ 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: VaR of USDEURO and CoVaR from stablecoins to USDEURO						
USDT $\Rightarrow$ 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 $\Rightarrow$ 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. "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.

5.4 Spillover effects between stablecoins and traditional cryptocurrencies

Panel I and Panel II of Figure 4 represent the VaR and CoVaR dynamics for the stablecoins and traditional cryptocurrencies, respectively. Since the stablecoins and traditional cryptocurrencies are negatively dependent, we report the upside-to-downside and downside-to-upside CoVaR measures defined in (4) and (5). 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. The graphical evidence is confirmed by the KS bootstraping test results reported in Table 7. In summary, we find significant risk spillovers between stablecoins and traditional cryptocurrencies. Combined with results in Table 6, our findings lend supportive evidence to Hypothesis 1, that stablecoins have bridged the gap between crypto and non-crypto markets and transmit risks to each other.

Panel I: Spillover from traditional cryptocurrencies to stablecoins



Panel II: Spillover from stablecoins to cryptocurrencies

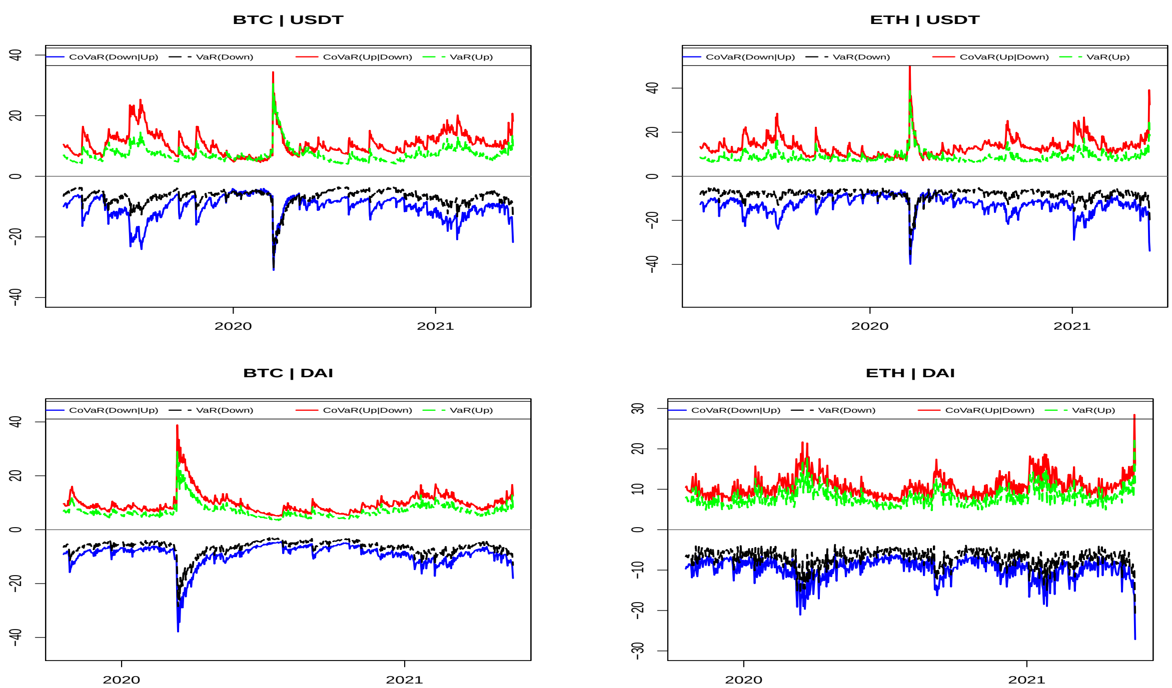


Figure 4: VaR and CoVaR dynamics for stablecoins and traditional cryptocurrencies

Table 7: Descriptive statistics and test results of VaR and CoVaR measures for stablecoins and traditional cryptocurrencies

	Downside			Upside		
	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR < VaR$	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR > VaR$
Panel I: VaR of stablecoins and CoVaR from traditional cryptocurrencies to stablecoins						
BTC ⇒ 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 ⇒ 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 ⇒ 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 ⇒ 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: VaR of cryptocurrencies and CoVaR from stablecoins to traditional cryptocurrencies						
USDT ⇒ 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 ⇒ 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 ⇒ 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 ⇒ 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. "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.

6 Further discussions

6.1 Asymmetric effects of risk spillovers

We examine whether the spillover effects from stablecoins to non-crypo assets 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. Panel I of Table 8 shows that the downside-to-downside risk spillovers from the USDT to the USD rates are symmetric to those from the USD rates to the USDT. However, the results in Panel II show that the magnitude of the upside-to-upside spillover risks from the USD rates to the USDT was greater than that from the USDT to the USD rates. Regarding the DAI-USD pair, the spillover effects from the USD rates to the DAI were greater than those from the DAI to the USD rates, regardless of downside-to-downside or upside-to-upside risks. The dominating direction of risk spillovers is from USD to stablecoins. Such results are intuitive, since stablecoins are designed to follow their pegs and the volume of US dollars in foreign exchange markets are much larger than stablecoins in crypto markets.

Then 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 the stablecoins is significantly different from the CoVaR normalized by the VaR for the cryptocurrencies. The results of the KS test reported in Panel I of Table 9 show that the upside-to-downside spillovers from stablecoins to cryptocurrencies are greater than the downside-to-upside spillovers from cryptocurrencies to stablecoins.

As the results of the KS test reported in Panel II of Table 9 reveals, the downside-to-upside spillovers from stablecoins to cryptocurrencies are greater than the upside-to-downside spillovers from cryptocurrencies to stablecoins. The dominating direction of risk spillovers is from Stablecoins, which is in accordance with previous literature(Kristoufek, 2021) and

Table 8: Test results for symmetries in the risk spillovers from stablecoins to non-crypto assets and from non-crypto assets to stablecoins

	USDT-USD	DAI-USD
Panel I: $H_0 : \frac{CoVaR_{DN\|DN}}{VaR_{DN}}\mathbf{(A\|B)} = \frac{CoVaR_{DN\|DN}}{VaR_{DN}}\mathbf{(B\|A)}$		
$H_1 : \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{A\|B}) < \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{B\|A})$	0.043	0.04
	[0.321]	[0.499]
$H_1 : \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{A\|B}) > \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{B\|A})$	0.057	0.38
	[0.144]	[0.000]
Panel II: $H_0 : \frac{CoVaR_{UP\|UP}}{VaR_{UP}}\mathbf{(A\|B)} = \frac{CoVaR_{UP\|UP}}{VaR_{UP}}\mathbf{(B\|A)}$		
$H_1 : \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{A\|B}) < \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{B\|A})$	0.027	0.071
	[0.663]	[0.117]
$H_1 : \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{A\|B}) > \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{B\|A})$	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 the risk spillovers from stablecoins to non-crypto pegs and from non-crypto pegs to stablecoins. $\frac{CoVaR_{DN|DN}}{VaR_{DN}}$ denotes the downside-to-downside CoVaR normalized by the downside VaR. $\frac{CoVaR_{UP|UP}}{VaR_{UP}}$ denotes the upside-to-upside CoVaR normalized by the upside VaR.

Table 9: Test results for symmetries in the downside and upside risk spillovers between stablecoins and traditional cryptocurrencies

A-B	USDT-BTC	USDT-ETH	DAI-BTC	DAI-ETH
Panel I: $H_0 : \frac{CoVaR_{UP\|DN}}{VaR_{UP}}(\text{A}\|\text{B}) = \frac{CoVaR_{DN\|UP}}{VaR}(\text{B}\|\text{A})$				
$H_1 : \frac{CoVaR_{UP\|DN}}{VaR}(\text{A}\|\text{B}) < \frac{CoVaR_{DN\|UP}}{VaR}(\text{B}\|\text{A})$	0.275	0.238	0.467	0.378
	[0.000]	[0.000]	[0.000]	[0.000]
$H_1 : \frac{CoVaR_{UP\|DN}}{VaR}(\text{A}\|\text{B}) > \frac{CoVaR_{DN\|UP}}{VaR}(\text{B}\|\text{A})$	0.015	0.007	0.002	0.002
	[0.849]	[0.952]	[0.997]	[0.998]
Panel II: $H_0 : \frac{CoVaR_{DN\|UP}}{VaR}(\text{A}\|\text{B}) = \frac{CoVaR_{UP\|DN}}{VaR}(\text{B}\|\text{A})$				
$H_1 : \frac{CoVaR_{DN\|UP}}{VaR}(\text{A}\|\text{B}) < \frac{CoVaR_{UP\|DN}}{VaR}(\text{B}\|\text{A})$	0.214	0.179	0.356	0.234
	[0.000]	[0.000]	[0.000]	[0.000]
$H_1 : \frac{CoVaR_{DN\|UP}}{VaR}(\text{A}\|\text{B}) > \frac{CoVaR_{UP\|DN}}{VaR}(\text{B}\|\text{A})$	0.016	0.007	0.002	0.003
	[0.808]	[0.949]	[0.999]	[0.990]

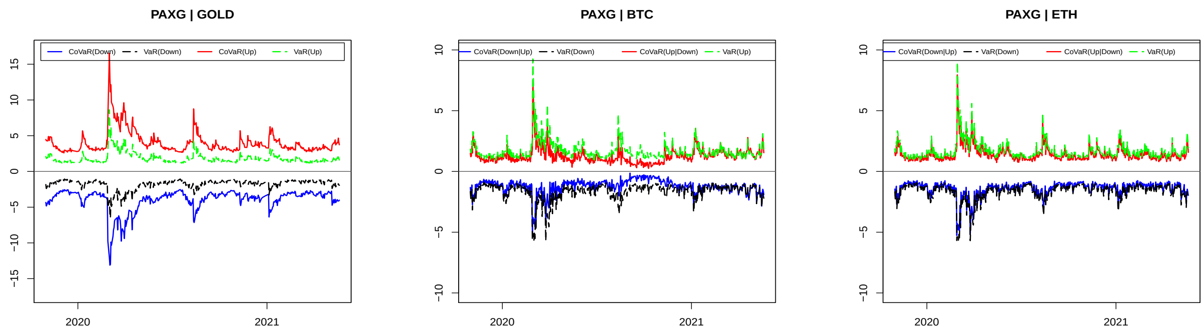
Note: This table reports the KS test statistics with p values (in squared brackets) for the null hypothesis of symmetries in the risk spillovers from stablecoins to crypocurrencies and from crypocurrencies to stablecoins. $\frac{CoVaR_{DN|UP}}{VaR_{DN}}$ denotes the upside-to-downside CoVaR normalized by the downside VaR. $\frac{CoVaR_{UP|DN}}{VaR_{UP}}$ denotes the downside-to-upside CoVaR normalized by the upside VaR.

the currency trading pattern in crypto markets. With stablecoins being the "digital fiat" in crypto tradings, the changes in stablecoins prices would transmit into other cypto assets, similar as the transmission of monetary policies.

6.2 Tests on stablecoins pegged to Gold

For comparison purpose, we also consider PAXG, which is the stablecoin backed by GOLD. Panel I and Panel II of Figure 5 represent the VaR and CoVaR dynamics for the PAXG and other assets, respectively. For the pair of PAXG and gold, we report the downside-to-downside and upside-to-upside CoVaR measures. For the pairs of PAXG and BTC and PAXG and ETH, we report the upside-to-downside and downside-to-upside CoVaR measures.

Panel I: Spillover from other assets to PAXG



Panel II: Spillover from PAXG to other assets

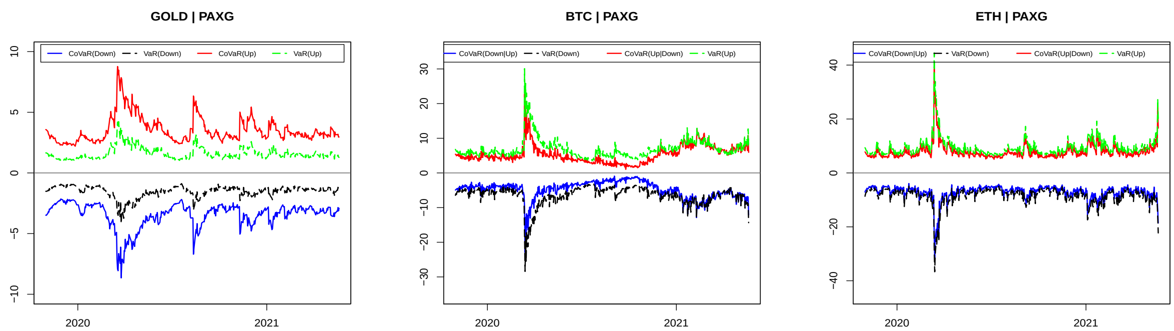


Figure 5: VaR and CoVaR dynamics for PAXG and other assets

Two observations are in order: (1) for the pair of PAXG-gold, the downside-to-downside CoVaR values are significantly lower than the downside VaR values, and the upside-to-upside CoVaR values are significantly higher than the upside VaR values, implying that there exist significant downside and upside risk spillovers between the PAXG and gold transmitted in both directions. (2) for the pairs of PAXG-BTC and PAXG-ETH, the upside-to-downside CoVaR values are not significantly lower than the downside VaR values, and the downside-to-upside CoVaR values are not significantly higher than the upside VaR values, implying that there were no upside-to-downside and downside-to-upside risk spillovers between the PAXG and cryptocurries transmitted in both directions. The graphical evidence is confirmed by the KS bootstraping test results reported in Table 10.

Table 10: Descriptive statistics and test results of downside and upside VaR and CoVaR for PAXG

	Downside			Upside		
	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR < VaR$	VaR	CoVaR	$H_0 : CoVaR = VaR$ $H_1 : CoVaR > VaR$
Panel I: VaR of PAXG and CoVaR from other assets to PAXG						
GOLD $\Rightarrow$ PAXG	-1.796	-3.976	0.882	1.865	4.048	0.887
	(0.739)	(1.571)	[0.000]	(0.796)	(1.630)	[0.000]
BTC $\Rightarrow$ PAXG	-1.655	-1.232	0	1.702	1.281	0.000
	(0.704)	(0.602)	[1.000]	(0.771)	(0.659)	[1.000]
ETH $\Rightarrow$ PAXG	-1.653	-1.422	0.000	1.705	1.447	0.000
	(0.705)	(0.624)	[1.000]	(0.766)	(0.675)	[1.000]
Panel II: VaR of other assets and CoVaR from PAXG to other assets						
PAXG $\Rightarrow$ GOLD	-1.551	-3.484	0.9	1.621	3.555	0.905
	(0.501)	(1.076)	[0.000]	(0.516)	(1.093)	[0.000]
PAXG $\Rightarrow$ BTC	-6.497	-4.846	0	6.968	5.31	0.000
	(2.826)	(2.579)	[1.000]	(2.850)	(2.541)	[1.000]
PAXG $\Rightarrow$ ETH	-8.545	-7.235	0.000	9.418	7.981	0.000
	(3.267)	(2.828)	[1.000]	(3.431)	(2.957)	[1.000]

Note: This table reports mean and standard errors (in parentheses) for VaR and CoVaR values for the pairs of PAXG-GOLD, PAXG-BTC and PAXG-ETH. "A $\Rightarrow$ B" denotes spillover effects from asset A to asset B. For the pair PAXG-GOLD, the KS test statistics with p values (in square brackets) for the null hypothesis of no downside-to-downside or upside-to-upside risk spillovers from asset A to asset B are also reported; For the pairs of PAXG-BTC and PAXG-ETH, 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.

We examine whether the spillover effects from PAXG to other assets and from other assets to PAXG are symmetric by testing whether the CoVaR normalized by the VaR for the PAXG is significantly different from the CoVaR normalized by the VaR for the other assets. The results of the KS test reported in Panel I and Panel II of Table 11 show that the risk spillovers from PAXG to gold are greater than the spillovers from gold to PAXG, regardless of the downside-to-downside or upside-to-upside risks. As Panel III of Table 11 reveals, the downside-to-upside spillover effects from cryptocurrencies (including BTC and ETH) to the PAXG are symmetric to the upside-to-downside spillovers effects from PAXG to cryptocurrencies (including BTC and ETH). Panel IV of Table 11 shows that the upside-to-downside spillovers from BTC to PAXG are symmetric to the downside-to-upside spillovers from PAXG to BTC; however, the upside-to-downside spillovers from ETH to PAXG are greater than the downside-to-upside spillovers from PAXG to ETH.

Table 11: Test results for symmetries in the downside and upside risk spillovers between PAXG and other assets

A-B	PAXG-GOLD
Panel I: $H_0: \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{A}\|\mathrm{B}) = \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{B}\|\mathrm{A})$	
$H_1: \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{A}\|\mathrm{B}) < \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{B}\|\mathrm{A})$	0.154
	[0.000]
$H_1: \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{A}\|\mathrm{B}) > \frac{CoVaR_{DN\|DN}}{VaR_{DN}}(\mathrm{B}\|\mathrm{A})$	0.036
	[0.604]
Panel II: $H_0: \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{A}\|\mathrm{B}) = \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{B}\|\mathrm{A})$	
$H_1: \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{A}\|\mathrm{B}) < \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{B}\|\mathrm{A})$	0.123
	[0.003]
$H_1: \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{A}\|\mathrm{B}) > \frac{CoVaR_{UP\|UP}}{VaR_{UP}}(\mathrm{B}\|\mathrm{A})$	0.044

[0.470]

Note: This table reports the KS test statistics with p values (in squared brackets) for the null hypothesis of symmetries in the risk spillovers from PAXG to other assets and from other assets to PAXG. $\frac{CoVaR_{DN|DN}}{VaR_{DN}}$ and $\frac{CoVaR_{DN|UP}}{VaR_{DN}}$ denote the downside-to-downside and upside-to-downside CoVaR normalized by the downside VaR, respectively. $\frac{CoVaR_{UP|UP}}{VaR_{UP}}$ and $\frac{CoVaR_{UP|DN}}{VaR_{UP}}$ denotes the upside-to-upside and downside-to-upside CoVaR normalized by the upside VaR, respectively.

To sum up, Table 11 illustrates the risk spillovers among PAXG, Gold, and major traditional crypto assets. The dashed line arrows in Figure 6 indicate no risk spillovers between PAXG and traditional cryptocurrencies. As the bold arrows indicates, the risk spillovers from PAXG to its peg gold are larger than that in the opposite direction, which is intuitive since the trading volume of Stablecoins (over 700 billion dollars daily) overpassing the trading volume of Gold[8] (around 150 billion dollars daily). This result suggests the importance of trading volumes in determining the dominant risk spillover direction, indicating that the strength of spillovers from crypto market to non-crypto market might be stronger than spillovers in the opposite direction through the channel of stablecoins in the future.

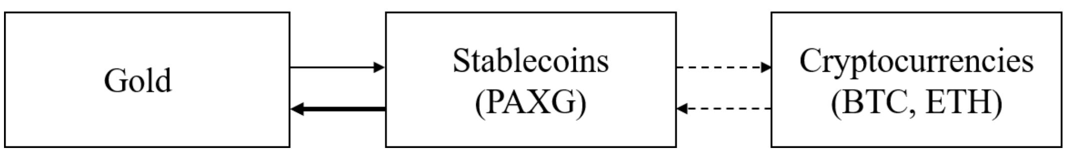


Figure 6: Risk spillovers among PAXG, Gold, and major crypto assets

7 Conclusions

In this paper, we examine the "(de)stabilizing" nature of stablecoins, paying particular attention to the risk spillovers among stablecoins, non-crypto assets and traditional cryptocurrencies. By using the copula-based CoVaR approaches, we find significant bidirectional risk spillover effects between US dollars and stablecoins, with stronger risk spillovers from

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

US dollar to stablecoins than vice-versa. We also find the spillovers between stablecoins and traditional cryptocurrencies in both directions, with spillovers from stablecoins to traditional crypto currencies larger than that in the opposite direction. Risks are channeled by stablecoins between crypto and non-crypto markets, and further amplifier for traditional cryptocurrencies. A similar argument is provided in Baumöhl and Vyrost (2020) and Baur and Hoang (2021), who find stablecoins are not consistently and reliably stable at all time and thus do not always live up to their names. However, they conclude that stablecoins offer significant diversification benefits for cryptocurrency traders and appear to have very good safe haven properties. We take a different, complementary perspective and emphasize that stablecoins could cause financial instability by propagating and amplifying the risks from non-crypto assets to the crypto markets.

In the legendary Volsunga Saga, the dragon slayer turned in to a dragon in the end[9]. Stablecoins ,designed as a solution to high volatility in crypto markets, could also bring in new sources of instability and risks to the financial system. Our evidence of the destabilizing aspect of stablecoins have important policy implications for both regulators and investors. First, in addition to their stability characteristics, stablecoins could bring in more risks to both the traditional crypto market and the non-crypto financial market by transmitting and amplifying the risks. Early in 2021, Visa became the first major payment network to settle transactions in stablecoins[10]. Our study suggests that thorough investigations should be conducted before further acceptance of stablecoins by regulated financial institutions. Second, with a majority of stablecoins pegged to US dollars and the wide use of stablecoins in crypto trading, there is a tendency of "dollarization" in the crypto markets. Our findings on the stronger risk spillovers from US dollars to crypto market through the channel of stablecoins are a signal of "dollarization", partly explaining the optimistic attitudes for stablecoins of

[9]Accessed from https://en.wikipedia.org/wiki/Dragonslayer on 28 July, 2021.

[10]Accessed from https://www.bloomberg.com/press-releases/2021-03-29/visa-becomes-first-major-payments-network-to-settle-transactions-in-usd-coin-usdc on 28 July, 2021.

the vice Chair of US Fed (Quarles, 2021). While some small developing countries are counting on stablecoins or other crypto currencies to "de-dollarize" their economy[11], our results instead suggest that these economies might be more vulnerable to the 'digital dollarization'. Third, in light of the rapid growth in stablecoins, central banks and regulators should consider setting fire wall between stablecoins and the non-crypto financial system in pursuit of financial stability.

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[11]For example, Venezuela accepted foreign aids 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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