Contagious Volatility

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Abstract

How does uncertainty of crypto-assets affect traditional asset classes? Using a vector autoregression (VAR) methodology, I answer this question by analyzing volatility spillovers between five asset classes (crypto-assets, stocks, bonds, fiat-currencies, and commodities). Given the vast heterogeneity within each asset class, my VAR specification accounts for cross sectional variation across and within each asset class. By transforming the VAR residuals into sectoral shocks, I am able to distinguish between *volatility spillovers* across, and *volatility co-movements* within asset classes. I find that on average volatility of crypto-assets accounts for 15% of the volatility contagion received by traditional asset classes. The directional spillovers from crypto-asset to bonds and to fiat-currencies are particularly strong, capturing the *wealth* channel and the *remittance* channel, respectively.

Keywords: Crypto-assets, Financial Stability, Contagion and Co-movement

JEL Classification: G19, G23

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1 Introduction

In light of the continued growth of the crypto-asset ecosystem, numerous central banks express concerns that this newly emerging asset class may impact financial stability.[1] As pointed out by these institutions, the main challenge in quantifying the potential impact of crypto-assets on the financial system stems from the lack of available data, as well as the novelty of the risk to be assessed. To fill this gap, this paper identifies volatility shocks specific to crypto-assets in order to analyze how this risk materializes, and how it reverberates across financial markets. To do so, I develop a new methodology that quantifies directional *volatility spillovers* across asset classes, and *volatility co-movements* within asset classes.

In line with the literature (see e.g. Yermack (2017), Abadi and Brunnermeier (2018), and Buchwalter (2018)) I define crypto-assets as all assets that are based on a distributed blockchain. Crypto-assets exhibit a high degree of volatility and are considered an immature asset-class given the lack of standardization/regulation and constant evolution. Further, crypto-assets display high co-movement in volatility, i.e., volatility quickly reverberates across this emerging asset class (Corbet et al., 2019). This comes in addition to the fact that it is difficult to hedge a position in crypto-assets as only few derivatives are available. Hence, while crypto-assets are small in terms of market capitalization compared to stock, bond, fiat-currencies (FX),

[1] This standpoint is expressed in the financially stability reports of central banks from, e.g. the United States (Federal Reserve System, 2019), Canada (Bank of Canada, 2019), the Euro-Zone (European Central Bank, 2019), and the United Kingdom (Bank of England, 2019). Similarly, international organizations regrouping national bodies of financial supervision such as the Bank for International Settlements (Bank for International Settlements, 2018), and the Financial Stability Board (Financial Stability Board, 2018) share akin concerns.

and commodity markets, the high co-movement together with the absence of hedging opportunities imply large fluctuations in the market capitalization of crypto-assets. This paper investigates how this uncertainty impacts traditional asset classes.

Crypto-asset returns in general present little to no correlation with traditional assets. However, this absence of correlation does not imply the lack of any linkages between the emerging and traditional asset classes. Indeed, linkages of assets can be measured by looking at volatility transmissions among them.

Using a vector autoregression (VAR) framework, Sims (1980) introduces a spillover measure based on the decomposition of the variance forecasting error (VFE). More precisely, the VFE decomposition captures how much of the H-step-ahead VFE of some variable i is due to shocks of another variable j. As pointed out by Koop et al. (1996) and Pesaran and Shin (1998), the VFE decomposition approach allows to distinguish between two types of spillovers: *contagion* and *co-movements*. In line with Forbes and Rigobon (2002), I define contagion as the impact a shock to one asset has on another asset. Conversely, co-movement simply captures interdependence across assets without being able to attribute the origin of the shock to a given asset.

The residuals of a VAR correspond to *systemic* shocks as they contain both idiosyncratic shocks and shocks that are common to other assets. Using these *systemic* shocks to study spillovers implies an interpretation in terms of co-movements as all shocks are correlated. Conversely, the reverberation of *reduced* shocks captures *contagion* across assets. Reduced shocks only contain idiosyncratic variation and have no correlation with other shocks. Obtaining reduced shocks, however, requires an identification strategy. To implement an identification strategy, previous papers (see, e.g., Diebold and Yilmaz, 2009) rely on the Cholesky decomposition which implicitly imposes an identification strategy by the ordering of the variables in the VAR. While it is straightforward to obtain reduced shocks by implementing identification strategies with a Cholesky decomposition, this approach bears two drawbacks.

First, the number of possible identification strategies explodes with the number of assets. That is, N assets imply $N!$ different possible orderings of variables, i.e. identification strategies. It becomes, hence, challenging to select the correct (or at least a commonly agreed) identification strategy. *Second*, the Cholesky decomposition implicitly imposes an asset-by-asset identification strategy, i.e., all reduced shocks are uncorrelated. Therefore, such identification strategy is not able to allow for tighter linkages in different market segments (i.e., asset classes, regional markets, etc.).

This paper aims at overcoming both of these drawbacks by introducing a new type of shocks coined as *sectoral* shocks. As opposed to the Cholesky decomposition, which requires asset-by-asset identification strategies, the decomposition proposed in this paper (implemented with series of linear projections) is able to accommodate sectoral linkages as the identifications strategies are only formulated across asset classes. That is, while the Cholesky decomposition removes the correlation between individual assets, my approach only removes the correlation across asset classes but not within asset classes. Residuals of assets within a same asset class are therefore correlated, capturing the tighter linkages within asset classes. My paper thus contributes to literature of spillovers by introducing a new decomposition of the VFE into three components: own variance share, co-movement share and contagion share. These three measures capture, respectively, how much of the VFE of an asset is due to shocks occurring to itself, due to shocks occurring to the remaining assets in the same asset class (co-movement), and due to shocks occurring to assets of other asset classes (contagion).

Not defining identification strategies within asset classes, drastically reduces the number of potential identification strategies while at the same allowing for tighter linkages with in asset class. In the case of five asset classes (crypto-assets, stocks, bonds, FX and commodities), there are a total of $5! = 120$ possible identification strategies. Rather than aiming to select a single identification strategy, I compute the spillovers measures for all 120 possible identification strategies, hence obtaining a range of estimates of the estimated spillover measures. The resulting range of spillover estimates being small, illustrates the robustness of the analysis to various identification strategies. Further, as each asset class is represented by several assets, I am able to pinpoint for which asset the contagion is strongest, and, hence, identify the channels through which crypto-assets affect traditional asset classes.

This paper presents several noteworthy findings. *First*, I show that crypto-assets account on average for 15% of the contagion received by traditional asset classes. This responds to the concern of the central banks and other financial institutions regarding the challenge to quantify the aggregate impact of crypto-assets on traditional asset classes. *Second*, as each asset class is represented by several assets, I'm able to identify two channels through volatility reverberates to the traditional system; the *wealth* channel, and the *remittance* channel. If each class were only represented by a single variable, the VFE decomposition would not have been able to identify these channels as they capture the linkages between the subgroups of different asset classes.

To illustrate the *wealth* channel, I highlight two results: (i) Crypto-asset account for 16.57% of the volatility contagion received by the bond market on average. Because the methodology developed in this paper allows to represent each asset class by several variable I can quantify the impact that crypto-assets have on each of the assets representing the bond market. In particular, I notice a strong link between crypto-assets and the U.S. corporate bond index. That is, 27.51% of the total volatility contagion received from U.S. corporate bonds stems from crypto-assets. This number drops to 14.22% (11.54%) for the Chinese (European) corporate bond indices. I can therefore conjecture that the investors who are active on in the crypto-asset ecosystem are also active on the U.S. corporate bond market. This intuition is in line with the second result. (ii) The sub-categories of crypto-assets named service crypto-assets and decentralized applications (dapps) explain, respectively, 12.72% and 13.24% of the volatility contagion received by the U.S. corporate bonds. As explained in more detail below, both service crypto-assets and dapps provide services such as cloud storage and other services that are also provided by established industries. Hence, to some extend they might attract similar investors and consumers. The volatility of service crypto-assets and dapps reverberating back to the corporate bond index, captures a flow of capital. More precisely, high volatility of crypto-assets corresponds to a higher probability of a decline market, therefore investors reallocate their wealth to the traditional markets where we observe a lower volatility which captures the probability of a rising market. Indeed, looking at the impulse responses (IR), I notice that a 1% increase in the volatility of service crypto-assets (dapps) decreases the volatility of the corporate bond index spread by 18 (47) basis points. This decrease in volatility of the U.S. corporate bond index captures that investors reallocate their financial wealth from the crypto-asset ecosystem back to the traditional asset classes.

The contagion between crypto-assets and FX markets capture the *remittance* channel. Indeed, I notice that volatility in the crypto-space reverberates particularly to the lower income countries. That is, payment crypto-assets account for as much as 17.02% of the contagion received by currencies of the lower middle income countries. Sending remittance via crypto-assets or via the traditional banking system are two substitutive ways. When there is high volatility in the exchange rates, banks (or other financial institutions) take higher margins on the exchange rate in order to cover potential losses due to fluctuations in the exchange rate. Accordingly, using crypto-assets to transfer money becomes relatively more interesting. Conversely, if crypto-assets are very volatile, people rather rely on the traditional system. This substitutive linkages is capture by a negative IR. More precisely, a 1% increase in the volatility of payment-crypto-assets yields a 38 basis point decrease in the volatility of the currencies of the lower middle income countries. The net contagion between payment crypto-assets and lower middle income currencies (defined as the different of the impact of payment crypto-assets on lower middle income currencies and the impact of lower middle income currencies on payment crypto-assets) is positive. In other words, volatility in the crypto-space pushes more customers to the traditional system, than volatility in the traditional system pushes customers to the crypto-space.

The remainder of the paper is structured as follows. Section 2 briefly highlights the heterogeneity of crypto-assets. This sections is intend for novices of the crypto-asset literature as it explains the different nature of subcategories of crypto-asset which are used in the analysis. Section 3 describes the methodology and introduces the measures for contagion and co-movement. Section 4 present the summary statistics of the data. Section 5 presents the results in three parts. Section 6 contains some robustness checks. Section 7 concludes.

2 Crypto-assets, not Crypto-currencies

This section aims at providing a brief overview of heterogeneity of crypto-assets. Readers familiar with the subcategories of crypto-assets (payment crypto-assets, platform crypto-assets, stable coins and decentralized applications) should feel free to skip this section. This section shall help the reader to understand the nature of the different subcategories of crypto-assets used in the VAR analysis.

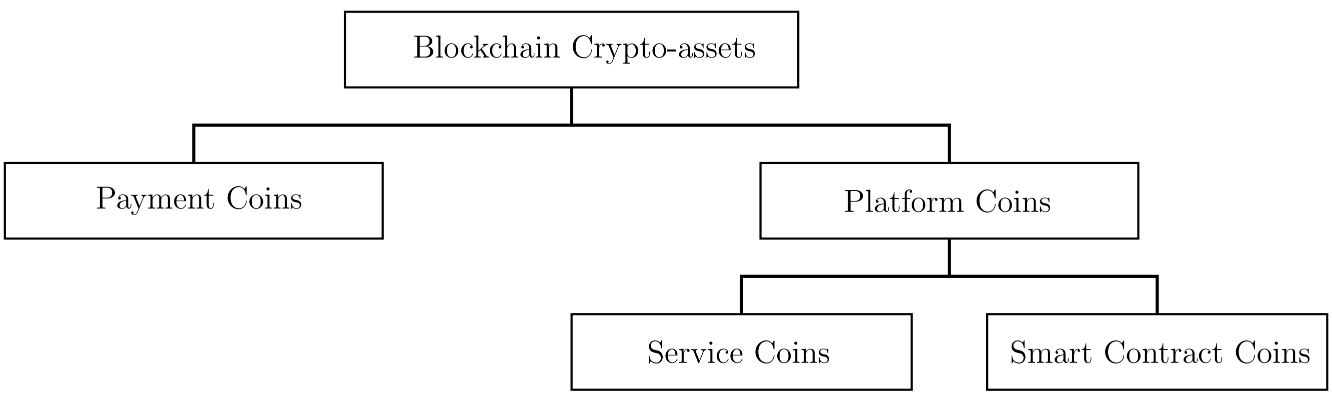
There are many misconceptions towards the crypto-asset ecosystem. The most prominent one is that not all crypto-assets are crypto-currencies. Indeed, only a minority of crypto-assets provide the service of a payment system. However, most people refer to all crypto-assets as crypto-currencies. This is most likely because the first and most prominent crypto-asset, Bitcoin, is a crypto-currency (more precisely, a payment crypto-asset). In his seminal paper, Nakamoto (2008) introduces Bitcoin as the first digital currency based on a distributed peer-to-peer payment system. Since then, we did not only witness the creation of other crypto-currencies (such as

Litecoin, Bitcoin Cash, etc.), but we also witnessed the creation of other crypto-assets that extend the peer to peer framework far beyond payments.

Today, there are two main categories of crypto-assets: blockchain crypto-assets and protocol crypto-assets. Each asset of the former category has its own blockchain, while protocol crypto-assets do not have their own blockchain. Instead, they 'live' on the blockchain of blockchain crypto-assets.

I distinguish between two kinds of blockchain crypto-assets: *Payment* coins and *Platform* coins. The latter is composed of two groups: *Service* coins and *Smart Contract* coins (see Figure 1).

Figure 1: **Classification of Blockchain Crypto-assets**



The most well-known crypto-asset of payment crypto-assets is Bitcoin. While all crypto-assets are referred to as crypto-currency, this term actually only applies to this subcategory of blockchain crypto-assets. These assets constitute a peer-to-peer electronic payment system.

Platform crypto-asset, however, allow for a more general interaction between individuals which is not limited to a peer-to-peer transfer of money. That is, platform crypto-assets can be seen as the generalized counterpart to payment crypto-assets given that they do not only allow for a transfer of money but also provide other service such as cloud storage or cloud computing to implement smart contracts. There are two subcategories of platform crypto-assets; service crypto-assets and smart contract platforms.

An illustration for a service crypto-assets is Filecoin. Filecoin provides the service of cloud storage based on a distributed blockchain. Rather than using cloud storage provided by centralized providers such as Google, Apple, Dropbox, etc., Filecoin provides the possibility of storing information on a distributed network. The fact that this category of crypto-asset provides a service that differs from a simple means of payments, highlights that not all crypto-assets can be described as crypto-currencies. It is also important to notice that service coins are to some extent a competitor to traditional industry as they provide a similar service (e.g., cloud storage). The only difference is that while traditional industries are organized in centralized fashion, service crypto-assets are based on distributed blockchain. In other words, it is not the service per se which is new, but rather the way in which the service is provided. User who would like to store their data on the Filecoin network would need to pay for this service with the native currency of that platform, i.e. Filecoins.

The second subcategory of platform crypto-assets are smart contract platforms. These assets are specific to the crypto-asset ecosystem and do have an counterpart in the traditional system. This blockchain-based platform allows for the implementation of "smart contracts." The New York Times[2] described Ethereum as "a single shared

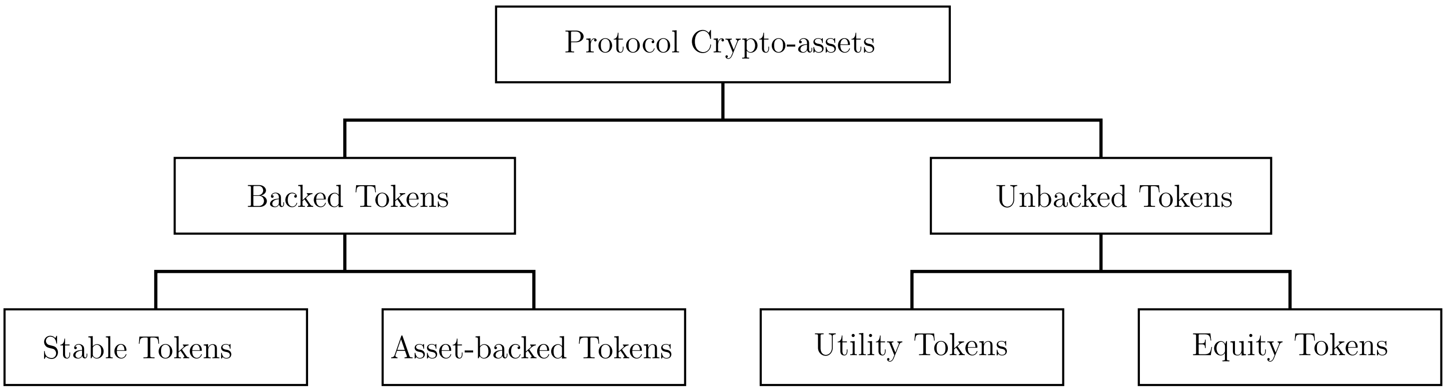
[2] See https://www.nytimes.com/2016/03/28/business/dealbook/ethereum-a-virtual-currency-enables-transactions-that-rival-bitcoins.html (last accessed November 1, 2019).

computer that is run by the network of users and on which resources are parceled out and paid for by Ether" where Ether is native currency of the Ethereum platform. Smart contract platforms provide the necessary foundation for protocol crypto-assets which constitutes the second major subcategories of crypto-assets: protocol crypto-assets.

As mentioned above, protocol crypto-assets do not have their own blockchain, but they rely on the blockchain of smart contract platforms. The fact that protocol crypto-assets are issued on an already existing network of its host blockchain rather than creating a new network carries several benefits. In contrast to blockchain crypto-assets that need to establish an entire network in order to ensure the maintenance of the blockchain, protocol crypto-assets simply benefit from an already existing network that already tackled issues of maintenance and safety. However, this comes with a trade-off, while this allows for a quicker adoption,[3] it also constraints users and developers to the rules of the host blockchain. Protocol crypto-assets can be split into two subcategories (see Figure 2).

[3] A comparison would be a smartphone and the application on it. It is easier for an app developer to create an app within an existing framework (Android or iOS) rather than building a new phone from the ground up and creating a consumer base simply to distribute a game.

Figure 2: **Classification of Protocol Crypto-assets**



Backed tokens are similar to payment coins in the sense that their primary objective is to allow for the transfer of wealth. In contrast to payment coins that do not represent a claim on any asset, backed tokens, as the name indicates, are backed by an asset. This is referred to as the *tokenization* of assets. I distinguish between two types of backed tokens: stable tokens[4] and equity tokens.

The most well-known stable token is Tether. Every Tether is always 100% backed by reserves of USD such that one unit of Tether equals one USD. The advocated benefit of Tether vis-a-vis the USD is that it can be transferred almost instantly anywhere in the world with little or no fees. Tether itself has no speculative value as it simply represents a claim on a fiat-currency. Hence, when studying the impact crypto-assets have on traditional asset classes I exclude this subcategory, as its volatility is not specific to the crypto-asset ecosystem. Further, asset-backed tokens give users the opportunity to transfer claims of any kind of assets including derivatives, private equity, real estate, collectibles, and other assets. Supporters argue that the tok-

[4]Stable tokens are sometimes also referred to as 'stable coins' in the literature

enization of these assets may improve their liquidity as transfers are faster and less expensive.

An unbacked token is referred to as a *decentralized application* or *dapp*. A dapp consists of one or more smart contracts. As such, a dapp can fulfill various functions such as a database or a small program. For example, Augur is a large database established in decentralized way. Individuals can rely on the database to make a bet on any event including an election, sports, financial markets, etc. Another dapp is called Golem. It basically allows individuals to rent out their computational power of the computer when they are not using it. Similar to the case of service crypto-assets, dapps are also to some extent a competitor to traditional industry as they provide similar services (e.g., cloud storage, gambling, etc.). Again, the only difference is that while traditional industries are organized in centralized fashion, dapps are based on distributed blockchain. It is important to notice, however, that dapps and service crypto-assets differ from one another.

In contrast to blockchain crypto-assets (that issue new money with each new block), the issuance of the native currency of protocol assets is controlled by the developing team of a given dapp. To finance their idea, developers can organize an initial token offering[5] (ITO) by selling some tokens of their dapp in exchange for the native currency of the blockchain where the dapp will be executed. Once the dapp is up and running, the early investors can sell the tokens they obtained from their investment to the customers who would like to use the service provided by the dapp or hold a stake in it. Hu et al. (2018) highlight the distinction between two

[5]The literature sometimes also refers to this as intitial coin offering (ICO).

kinds of tokens: utility tokens and security tokens. The former is used pay for the provided service, i.e., the token is spent. The later can be interpreted as a stock of that company. Intuitively, the utility token can be seen as a ticket to watch a sports event in a stadium, whereas the security token represents ownership of the stadium where the sport event takes place. As such, individuals can use the service provided by a dapp while still holding 'shares' of it. There is a growing literature that investigates the workings of ITOs; see, e.g., Howell et al. (2018), Li and Mann (2018), and Cong et al. (2018).

Hence, investing in service crypto-assets or decentralized applications can be seen as an investment in start-ups (or small companies) providing a service similar to the one of established industries. Conversely investing in smart contract platform crypto-assets is an investment specific to the crypto-asset ecosystem.

To sum up, in the present paper four subcategories of crypto-assets are relevant for the analysis of volatility contagion

- **Payment crypto-asset (pay)**: they provide a peer to peer payment system. In the analysis I consider Bitcoin separately, as it is unique both in terms of market capitalization and popularity.

- **Service crypto-assets (ser)**: they provide services such as cloud storage and hence constitute to some extent a competition to traditional industries.

- **Smart contract platform crypto-assets (smc)**: these assets are specific to the crypto-asset ecosystem and do not have an counterpart in the traditional system. They allow for the implementation of "smart contracts" and provide the necessary foundation for dapps.

- **Decentralized applications (dapps)**: they can fulfill various functions such as a database or a small program. Similar to the case of service crypto-assets, apps are also to some extent a competitor to traditional industry as they provide similar services. However dapps and service crypto-assets differ in how new money is issued. While the issuance of new money of service crypto-assets is tightly regulated by the blockchain, the issuance of money in case of dapps is done with ITO and is at the discretion of the developping team. As we will see below dapps present a much higher volatility and on average suffer of a negative return.

3 Methodology

This section starts by explaining the empirical framework. In particular, I explain how sectoral shocks are obtained, and how the differ from systemic and reduced shocks. Further, I describe the measures to quantify co-movement within asset classes, and contagion across asset classes.

3.1 Empirical Framework

I consider a covariance stationary N-variable vector autoregression with P lags,

$$X_t = \sum_{p=1}^{P} \Phi_p X_{t-p} + u_t$$

$$=\Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + u_t$$

where $X_t = [\ X_{1,t}\ X_{2,t}\ \ldots\ X_{N_t}\ ]$ and $X_i\ \forall i \in [\ 1,\ 2,\ \ldots, N]$ is a vector of asset return volatilities. Further, Φ_p is a $N \times N$ parameter matrix for lag p. Lastly, the variance-covariance (VCV) matrix of VAR residuals, u_t, which corresponds to systemic shocks, is given by $\mathbb{V}[u_t] = \Sigma$. Using the moving average representation yields

$$X_t = \sum_{i=0}^{\infty} A_i u_{t-i} \tag{1}$$

where A_0 is a $N \times N$ identity matrix and $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$ with $A_i = 0$ for $i < 0$. I follow the approach of Koop et al. (1996) and Pesaran and Shin (1998). They define the VFE decomposition which captures how much of the H-step-ahead VFE of an asset i is due to shocks of an asset j as follows

$$\theta_{ij} = \frac{\frac{1}{\sigma^2_{Q,jj}} \sum_{h=0}^{H-1} (e_i^\top A_h Q^{-1} \mathbb{V}[Qu_t] e_j)^2}{\sum_{h=0}^{H-1} (e_i^\top A_h \mathbb{V}[u_t] A_h^\top e_i)} \tag{2}$$

where $\sigma^2_{Q,jj}$ is the jth element on the diagonal of $\mathbb{V}[Qu_t]$ and e_i is a selection vector with one as the ith element and zero otherwise. The time horizon for which the linkages are computed is denoted by H. Lastly, Q relates to the nature of the shocks used to calculate linkages (see Table 1).

Table 1: Different types of shocks and their components

This table highlights the different types of shocks; systemic, sectoral, and reduced. Systemic shocks corresponds to the residuals of the VAR. Reduced shocks are computed by multiplying the systemic shocks with the unique lower triangular Cholesky matrix obtained from the decomposition of the variance covariance matrix of systemic shocks. Sectoral shocks are obtained with a series of linear projections of the systemic shocks.

Shocks	Computation	VCV matrix	Correlation with assets in		idiosyncratic
			other asset classes	same asset class	shocks
Systemic	u_t	$\mathbb{V}[u_t] = \Sigma$	✓	✓	✓
Sectoral	$\bar{z}_t = \bar{C}u_t$	$\mathbb{V}[\bar{z}_t] = \Omega$	·	✓	✓
Reduced	$z_t = Cu_t$	$\mathbb{V}[z_t] = I$	·	·	✓

In the case of *systemic* shocks, Q is defined as an $N \times N$ identity matrix which implies that the VCV matrix of systemic shocks is a fully symmetric positive semi-definite matrix. This approach carries the benefits that the results are invariant to the ordering of the variables. However, the resulting spillovers, as calculated with equation (2), contain both idiosyncratic shocks and elements which are common to other assets. I can therefore not clearly identify contagion. Conversely, in case of *reduced* shocks, I set $Q = C$ where C^{-1} is the unique lower triangular Cholesky decomposition of Σ. Hence, the VCV matrix of reduced is a diagonal matrix.[6] The resulting spillovers, as calculated with equation (2), can therefore clearly be identified as contagion. However, the implementation of identification strategies with the Choleky decomposition carries two drawbacks.

First, the number of possible identification strategies explodes with the number

[6]More precisely, it is an identity matrix as $\mathbb{V}[\epsilon_t] = C\mathbb{V}[u_t]C^\top = C\Sigma C^\top = CC^{-1}{C^{-1}}^\top C^\top = I$ given that C is defined by the Cholesky decomposition of $\Sigma = C^{-1}{C^{-1}}^\top$.

of assets. That is, N assets imply $N!$ different possible orderings of variables, i.e. identification strategies. In order to keep the number of identification strategies reasonably small, the number of assets under consideration should be kept relatively small. Consequently, when looking at interconnectedness of assets it is likely to omit some variables that may carry relevant information. For instance, when analyzing the linkages across U.S. stock, bond, FX and commodity markets, Diebold and Yilmaz (2012) only represent each asset class by a single index. The analysis would be more complete if stock markets were for instance also represented by the Russel 2000 to account for small stocks, or any other index as opposed to solely relying on the S&P500. Similarly, the bond market dynamics would be better captured if the analysis would also include bond indices for different maturities. The same intuition applies to FX and commodity markets, however, this increasing number of assets goes hand in hand with a larger number of possible identification strategies.

Second, the Cholesky decomposition implicitly imposes an asset-by-asset identification strategy, i.e., all reduced shocks are uncorrelated. Therefore, such identification strategy is not able to allow for tighter linkages in different market segments (i.e., asset classes, regional markets, etc.). However, representing each asset class with several asset and allowing for tighter linkages among those assets might prove useful when studying the linkages of the U.S. stock, bond, FX and commodity markets. In addition to the issue of the vast number of possible identification strategies that arise in that case, the Cholesky decomposition implies that shocks within an asset class are completely orthogonalized. Intuitively, however, it would be preferable to allow for some tighter linkages within an asset class in order to accommodate the similarities of related assets. From an investor perspective, this allows to accommodate the fact that portfolio rebalancing within an asset class might also yield higher correlation among those assets. From a regulatory perspective, it could be that changes in regulation yield a shock for a certain asset class as a whole.

This is why I propose a new approach that finds a middle-ground between *systemic* and *reduced* shocks. I achieve this with the concept of *sectoral* shocks.

Sectoral shock are able to accommodate tighter linkages within asset classes. The present paper considers $M = 5$ different asset classes: stocks, bonds, fiat-currencies, commodities and crypto-assets. It proves, hence, useful to regroup residuals according to assets classes $u_t = [u_{1,t}\ u_{2,t}\ \dots\ u_{N,t}] = [u_{k_1,t}\ u_{k_2,t}\ \dots\ u_{k_M,t}]$ where k_1, k_2, ... k_M form a partition of the individual assets $\{1, 2, \dots N\}$. I then obtain the reduced shocks, denoted $\bar{z}$, with a series of linear projection of the systemic shocks

$$
\begin{aligned}
\bar{z}_{k_1,t} =& u_{k_1,t} - L[\ u_{k_1,t} \mid u_{k_2,t}\ u_{k_3,t}\ u_{k_4,t}\ u_{k_5,t}] \\
\bar{z}_{k_2,t} =& u_{k_2,t} - L[\ u_{k_2,t} \mid u_{k_3,t}\ u_{k_4,t}\ u_{k_5,t}] \\
\bar{z}_{k_3,t} =& u_{k_3,t} - L[\ u_{k_3,t} \mid u_{k_4,t}\ u_{k_5,t}] \\
\bar{z}_{k_4,t} =& u_{k_4,t} - L[\ u_{k_4,t} \mid u_{k_5,t}] \\
\bar{z}_{k_5,t} =& u_{k_5,t}
\end{aligned}
\tag{3}
$$

where $L(a \mid b)$ denotes the linear projection operator. It captures all the correlation the asset (or the group of assets) a has with with the asset (or the group of assets) b. Intuitively it removes all common components of a and b from a. As results a $a - L(a \mid b)$ and b are orthogonal. In the appendix, I derive the matrix notation so that equations (3) can be rewritten as $\bar{z}_t = \bar{C}u_t$.

Intuitively, the first linear projection removes all correlation that residuals from an asset class k_1 have with residuals from all other asset classes. The obtained reduced shocks $\bar{z}_{k_1,t}$ have no correlation with residuals from any of the other asset classes. The second linear projection similarly orthogonalizes all residuals from the asset class k_2 with respect to all the *remaining* asset classes, as the reduced shocks $\bar{z}_{k_1,t}$ are already orthogonal to $u_{k_2,t}$. I repeat this procedure until the last asset class k_M. Since the residuals of the previous asset classes have been orthogonalized with respect to $u_{k_M,t}$, the sectoral shocks of the last asset class k_M are simply defined as $\bar{z}_{k_5,t} = u_{k_5,t}$.

This orthogonalization of residuals implicitly requires an identification strategy across asset classes. That is, the results of projecting the residuals u_{t,k_1} of the asset class k_1 on the the residuals u_{t,k_2} of the asset class k_2, crucially depends on the order of the projections. As such, to cover all possible identification strategies I conduct the linear projection with $5! = 120$ different orderings. I do not select a single identification strategy. Instead, I argue that a total of 120 identification strategies is reasonable in the sense that it provides a wide range of estimates for the sectoral shocks $\bar{z}_t$ while keeping the computational burden low.

In each case (i.e. independent of the ordering of the linear projections) the VCV matrix of the sectoral shocks is block-diagonal as shown in equation (4)

$$\mathbb{V}\left[\bar{C}\ u_t\right] = \begin{pmatrix} \sigma_{\bar{C},11} & \sigma_{\bar{C},12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \sigma_{\bar{C},21} & \sigma_{\bar{C},22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \sigma_{\bar{C},33} & \sigma_{\bar{C},34} & \sigma_{\bar{C},35} & \sigma_{\bar{C},36} & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \sigma_{\bar{C},43} & \sigma_{\bar{C},44} & \sigma_{\bar{C},45} & \sigma_{\bar{C},46} & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \sigma_{\bar{C},53} & \sigma_{\bar{C},54} & \sigma_{\bar{C},55} & \sigma_{\bar{C},56} & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \sigma_{\bar{C},63} & \sigma_{\bar{C},64} & \sigma_{\bar{C},65} & \sigma_{\bar{C},66} & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\bar{C},77} & \sigma_{\bar{C},78} & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\bar{C},87} & \sigma_{\bar{C},88} & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\bar{C},99} & \cdots & \sigma_{\bar{C},9N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\bar{C},N9} & \cdots & \sigma_{\bar{C},NN} \end{pmatrix} = \begin{pmatrix} \boxed{\Omega_{11}} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boxed{\Omega_{22}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boxed{\Omega_{33}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \boxed{\Omega_{44}} \end{pmatrix} \tag{4}$$

where each light gray block represents the VCV matrix of the sectoral shocks of an asset class.[7] The identification strategy implemented with $\bar{C}$ is such that I allow for correlation between asset of same asset class. However, I remove all correlation of shocks across asset classes. This means that all shocks can be attributed to a given asset class. Consequently, the spillovers across asset classes, as computed with equation (2), can then be solely interpreted as contagion while spillovers within an asset class contain both co-movement with assets from the same category and idiosyncratic shocks. Equation (5) graphically illustrates these different types of spillovers

[7]Please note that here I illustrate the case with $M = 4$ asset classes

$$
\Theta = \begin{pmatrix}
\theta_{11} & \theta_{12} & \theta_{13} & \theta_{14} & \theta_{15} & \theta_{16} & \theta_{17} & \theta_{18} & \theta_{19} & \cdots & \theta_{1N} \\
\theta_{21} & \theta_{22} & \theta_{23} & \theta_{24} & \theta_{25} & \theta_{26} & \theta_{27} & \theta_{28} & \theta_{29} & \cdots & \theta_{2N} \\
\theta_{31} & \theta_{32} & \theta_{33} & \theta_{34} & \theta_{35} & \theta_{36} & \theta_{37} & \theta_{38} & \theta_{39} & \cdots & \theta_{3N} \\
\theta_{41} & \theta_{42} & \theta_{43} & \theta_{44} & \theta_{45} & \theta_{46} & \theta_{47} & \theta_{48} & \theta_{49} & \cdots & \theta_{4N} \\
\theta_{51} & \theta_{52} & \theta_{53} & \theta_{54} & \theta_{55} & \theta_{56} & \theta_{57} & \theta_{58} & \theta_{59} & \cdots & \theta_{5N} \\
\theta_{61} & \theta_{62} & \theta_{63} & \theta_{64} & \theta_{65} & \theta_{66} & \theta_{67} & \theta_{68} & \theta_{69} & \cdots & \theta_{6N} \\
\theta_{71} & \theta_{72} & \theta_{73} & \theta_{74} & \theta_{75} & \theta_{76} & \theta_{77} & \theta_{78} & \theta_{79} & \cdots & \theta_{7N} \\
\theta_{81} & \theta_{82} & \theta_{83} & \theta_{84} & \theta_{85} & \theta_{86} & \theta_{87} & \theta_{88} & \theta_{89} & \cdots & \theta_{8N} \\
\theta_{91} & \theta_{92} & \theta_{93} & \theta_{94} & \theta_{95} & \theta_{96} & \theta_{97} & \theta_{98} & \theta_{99} & \cdots & \theta_{9N} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
\theta_{N1} & \theta_{N2} & \theta_{N3} & \theta_{N4} & \theta_{N5} & \theta_{N6} & \theta_{N7} & \theta_{N8} & \theta_{N9} & \cdots & \theta_{NN}
\end{pmatrix} \tag{5}
$$

where the off-diagonal elements (i, j) capture the directional spillover from asset i to asset j. More precisely, the elements in the white boxes capture contagion across asset classes, while the elements in the light gray boxes capture co-movements of asset within a same asset class. The diagonal elements (i, i) as depicted by dark grey boxes represent asset-specific shocks. The total VFE of asset i is the given by

$$
\theta_i = \sum_{j=1}^{N} \theta_{ij}
$$

and, as shown in Equation (5), θ_i is composed of three elements: own variance share, co-movement share and contagion share. These three measures capture, respectively, how much of the VFE of an asset is due to shocks occurring to itself, due to shocks occurring to the remaining assets in the same asset class (co-movement), and due to shocks occurring to assets of other asset classes (contagion).

3.2 Measuring Co-movement and Contagion

With VFE matrix as depicted in equation (5), I can compute a series of measures to capture linkages both within, and across asset classes. Let us start with measures that capture links within an asset class.

First, I can compute the average *own variance share*. It captures how much of the VFE of an asset class k_1 is due to shocks occurring to assets themselves.

$$Own\_Variance\_Share_{k1} = \frac{1}{N_{k_1}} \sum_{i \in k_1} \theta_{ii} \tag{6}$$

I normalize by N_{k_1} which is the number of assets in asset class k_1, in order to accommodate that each asset class may be represented by a different number of assets.

Second, I can compute the *co-movement share*. It captures how much of the variance of the asset class k_1 is due to co-movements among assets in that same specific asset class.

$$Comovement\_Share_{k_1} = \frac{1}{N_{k_1}} \sum_{i \in k_1} \left(\sum_{j \in k_1, j \neq i} \theta_{ij} \right) \tag{7}$$

I can hence compute is the *Feedback share*. It captures to which extent the own variance share is due to co-movement of assets. This captures how important reverberation of shocks is within asset classes.

$$Feedback\ Share_{k_1} = \frac{Comovement\_Share_{k_1}}{Own\_Variance\_Share_{k_1} + Comovement\_Share_{k_1}} \tag{8}$$

The higher this number the more the VFE is driven my co-movement of assets within the same asset class.

Now let us define the measures that capture the contagion across asset classes. I start by computing the *cross variance shares.* They capture to which extent the VFE of asset class k_1 is driven by shocks of k_2. I denote this measure by $\Theta_{k_1 k_2}$

$$\Theta_{k_1 k_2} = \frac{1}{N_{k_1}} \sum_{i \in k_1} \underbrace{\left(\frac{1}{N_{k_2}} \sum_{j \in k_2} \theta_{ij} \right)}_{\substack{\text{Average impact of all} \\ \text{assets in } k_2 \text{ on asset } i \text{ in } k_1}} \tag{9}$$

The total *cross variance share*, i.e., the share of the VFE of the asset class k_1 that is due to shocks occurring in all other asset classes is given by $\sum_{j \neq 1} \Theta_{k_1 k_j}$.

Lastly I can compute the *Contagion Shares.*

$$Contagion\_Share_{k_1 k_2} = \frac{\Theta_{k_1 k_2}}{\sum_{j \neq 1} \Theta_{k_1 k_j}} \tag{10}$$

While the cross variance share, $\Theta_{k_1 k_2}$ captures how much of the total VFE of k_1 is due to k_2, the contagion share captures how much of the contagion received by k_1 is due to k_2. This measure provides useful insights to capture the linkages across markets, and the relative importance of each asset class in the context of volatility contagion.

4 Data

I want to quantify the volatility contagion between five asset classes; crypto-assets, stock, bonds, FX and commodities. While there is no obvious reasons to think that crypto-assets present a tight link with each of the four traditional asset classes, I believe that it is important to represent all asset classes in order to avoid the issue of missing variables. The aim is to avoid to wrongly attribute a shock to a given asset class simply because the asset (class) from which the shock actually originates, is lacking. The parsimonious methodology developed in this paper allows me to represent each asset class with many variables, without increasing the number of possible identification strategies, as identification strategies are only formulated across (and not within) asset classes. Table (2) contains the summary statistics for all variables of interest to the analysis.

The focus of the present paper is to understand volatility spillovers across individual assets and asset classes. While Table (2) provides insights on the variables, Table (3) presents the summary statistics of the volatility measures used in the VAR analysis.

4.1 Crypto-assets

Crypto-assets are represented with a total of five assets. The data of crypto-assets is extracted from coinmarketcap.com. To determine the subcategory for each crypto-asset, I rely on the information provided by coingecko.com (for more details see Buchwalter, 2018).

Table 2: Summary Statistics

Measures are annualized and expressed in percent. The sample period goes from January 1, 2014 to August 16, 2019. The first order autocorrelation is given by $\alpha_1[\,\cdot\,]$. The variable 'Format' correspond to nature of the variable used in the VAR.

		T	Mean	Std. Dev.	Skewness	Kurtosis	$\alpha_1[\,\cdot\,]$	Format
Cryptos	Bitcoin	1468	37.35	888.07	-0.18	4.04	0.04	logvol
	Payment	1468	27.89	1263.86	0.31	4.23	0.09	logvol
	Service	1468	26.94	1462.25	0.17	4.15	0.01	logvol
	SMC	1468	45.12	1460.99	0.16	3.65	0.05	logvol
	dapps	1468	-117.64	1782.77	-0.61	4.23	0.02	logvol
Stocks	VIX	1468	15.00	4.18	1.60	6.69	0.94	loglevel
	US	1468	27.67	331.10	-0.17	3.96	0.00	logvol
	EU	1468	3.33	222.06	-0.10	4.35	0.02	logvol
	China	1468	3.70	287.85	-0.12	3.53	0.10	logvol
Bonds	MOVE	1468	64.39	12.56	0.46	2.35	0.98	loglevel
	US	1468	0.26	25.25	-0.27	3.63	-0.06	logvol
	EU	1468	3.21	26.29	-0.25	3.48	0.04	logvol
	China	1468	5.05	20.57	0.12	10.50	0.05	logvol
FX	High	1468	3.60	83.45	-0.02	3.03	0.17	logvol
	Up. Mi.	1468	5.32	43.24	0.77	5.49	0.10	logvol
	Low Mi.	1468	3.22	25.88	-0.15	4.64	0.09	logvol
	Low	1468	5.65	80.19	0.27	5.29	-0.31	logvol
Cmdt	OilVIX	1468	34.23	11.77	0.72	3.18	0.99	loglevel
	GoldVIX	1468	14.75	3.36	0.50	2.76	0.97	loglevel

As explained in section 2, there are four asset classes that are relevant to the present analysis: payment crypto-assets, service crypto-assets, smart contract platform crypto-assets and decentralized applications. Hence, I do not consider stable tokens as these do have no speculative value specific to crypto-assets. Similarly, I also exclude asset backed tokens as they also represent claims on assets (such as, e.g., gold, fiat-currencies, etc.), which do not derive their value from the crypto-asset

Table 3: Summary Statistics of Volatility Measures

Measures are annualized and expressed in percent. The sample period goes from January 1, 2014 to August 16, 2019. The first order autocorrelation is given by $\alpha_1[\,\cdot\,]$.

		T	Mean	Std. Dev.	Skewness	Kurtosis	$\alpha_1[\,\cdot\,]$
Cryptos	Bitcoin	1468	3.94	0.32	-0.25	2.38	0.96
	Payment	1468	4.29	0.29	0.24	2.31	0.91
	Service	1468	4.42	0.32	0.26	2.42	0.95
	SMC	1468	4.47	0.24	0.07	2.62	0.93
	dapps	1468	4.67	0.22	0.27	2.85	0.98
Stocks	VIX	1468	2.67	0.25	0.76	3.50	0.95
	US	1468	2.99	0.19	0.55	2.73	0.91
	EU	1468	2.51	0.33	0.33	2.52	0.96
	China	1468	2.86	0.18	0.24	2.41	0.98
Bonds	MOVE	1468	4.15	0.19	0.15	2.07	0.98
	US	1468	0.47	0.09	-0.06	2.23	0.96
	EU	1468	0.51	0.11	0.71	3.20	0.98
	China	1468	0.09	0.46	0.52	2.61	0.97
FX	High	1468	1.64	0.13	-0.02	1.99	0.99
	Up. Mi.	1468	0.90	0.30	0.25	2.80	0.99
	Low Mi.	1468	0.44	0.27	-0.78	3.35	0.99
	Low	1468	1.39	0.51	-0.05	2.55	0.97
Cmdt	OilVIX	1468	3.48	0.34	-0.03	2.48	0.99
	GoldVIX	1468	2.67	0.23	0.07	2.20	0.97

ecosystem. Further, I decided to consider Bitcoin individually and not together with other payment crypto-assets due to its uniqueness in terms of market capitalization and popularity. Hence, crypto-assets are represented with five variables: one individual asset, Bitcoin, and four indices that capture the average return payment crypto-assets, service crypto-assets, smart contract platform crypto-assets and decentralized applications.

I compute the logarithmic volatility with exponential garch(1,1), commonly referred to as egarch(1,1), introduced by Nelson (1991). I use the logarithm to avoid possible misspecification issues with VAR. That is, while volatility is per definition always positive, in extreme cases the VAR could yield a negative forecast for the volatility. By using the logarithm of the volatility I conveniently avoid such issues while at the same time getting the benefit of a more intuitive interpretation in terms of relative changes. We also notice that crypto-assets exhibit a very high volatility, and that the subgroups of crypto-assets differ in the level of the volatility. In particular, apps exhibit the highest volatility, and the lowest return. This is due to inherent nature of how money is issued for these assets (see section 2). Hence, representing an asset class with several variable allows to account for heterogeneity in the cross-section of an asset class.

4.2 Stocks

To capture the dynamics of the stock market I consider a total of four variables; the VIX as well as three Morgan Stanley Capital International (MSCI) indexes for the U.S., Europe, and China. All four indices are downloaded from Bloomberg.

The VIX is calculated by the Chicago Board Options Exchange and defined as a measure of expected price fluctuations in the S&P 500 Index options over the next 30 days. The VIX is a leading indicator of the stock market uncertainty as it captures the overall investor sentiment. It is also referred to the "fear index", i.e. higher measures of the VIX imply higher uncertainty in the market. In other words, the VIX index is a proxy for volatility. In the VAR analysis, however, I use the logarithm of the VIX which implies that it could theoretically also be negative.

I implement this transformation to avoid potential misspecification issues steaming from the VAR, as predicted measures could in some cases be negative.

Further, I also represent the stock market with three international stock market indices: U.S., Europe, and China. I decided to focus on international indices as crypto-assets can be seen as a global asset. The three stock indices are provided by MSCI and dowloaded from Bloomberg. I use these daily return series to compute daily volatility measurers with an egarch(1,1). Again, in order to avoid possible misspecification issues I use the logarithm of the daily volatility measures.

4.3 Bonds

To capture the dynamics of the bond market I use a total of four variables; the Merrill Lynch Option Volatility Estimate (MOVE), as well as three corporate bond indexes for the U.S., Europe, and China. All four indices are downloaded from Bloomberg.

The MOVE index can be seen as the bond market's counterpart to the VIX index for the stock market. The MOVE is often called "the VIX for bonds". It represents U.S. treasury yield volatility implied by current prices of one-month over-the-counter options on 2-year, 5-year, 10-year and 30-year treasuries. As such it captures the overall bond market sentiment. Notice that, similar to the case of the VIX for stocks, the MOVE is a proxy for volatility.

I further represent the bond market by three additional corporate bond indices. I decided to use corporate bond indices for two reasons: (i) the dynamic for U.S. government bonds is already well captured with the MOVE index, (ii) it is unlikely to see any significant linkage between government bonds and crypto-assets. Instead, as I will discuss in more detail below, there significant linkages between corporate bonds and crypto-assets.

Similar to the stock market, I also use international indices for the bond markets, i.e. U.S., European and Chinese corporate bonds. More precisely, for the U.S. I rely on the short term corporate bond index provided by Vanguard. For Europe and China, I use short-term corporate bond index provided by S&P.[8] I use these daily return series to compute daily volatility measurers with an egarch(1,1). Again, in order to avoid possible misspecification issues I use the logarithm of the daily volatility measures.

4.4 Fiat-currencies

To capture the dynamics of the FX markets, I construct a total of four currency baskets using 126 fiat-currencies. I use the classification of the World Bank[9] to regroup countries according to high, upper middle, lower middle and low income countries. I first compute the average return series in each currency basket and then I compute the logarithm of the volatility as measured by egarch(1,1).

Again, the motivation here is to take a a global approach and take into consideration fiat-currencies from around the world, as crypto-assets are also accessible on a global scale and are not limited to a subset of countries. Below I will highlight

[8] There is also an S&P index for U.S. corporate bonds. However, it only focuses on the subcategory companies which constitute the S&P 500 stock index. Therefore, the vanguard index appear more appropriate as it captures the whole cross section of corporate bonds.

[9] Classification available on https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups. Last accessed November 1, 2019.

the *remittance* channel which captures the link between payment crypto-assets and lower middle income countries. As pointed out by the world bank[10] in the recent years the amount of remittances sent towards low and lower middle income countries has steady grown and reached an all time high in 2018.

According to the Overseas Development Institute (2014) Remittances Report the average remittance fee of the amounts sent to sub-Saharan Africa is equal to 12%. In other words, 12% of the amount send is lost to transfer fees. The Oversees Development Institute argues that this amount would be enough to pay for primary school education for 14 million children in the region. It hence comes as no surprise that people are constantly looking for new ways to send remittances in a cheaper fashion. In this context crypto-asset provide an alternative way as they allow to transfer wealth on a global scale. Against general believe, transaction fees on the Bitcoin network are low. As shown by Figure 3, the transaction fees on the bitcoin blockchain are less than 0.05% most of the time and only exceed 0.1% during the bubble period in late 2017 and early 2018.

When acquiring bitcoin via an exchange further fees apply. The amount and structure of the fees obviously depends on the service provider. Nonetheless, people familiar with the technology can avoid fees charged by intermediaries.

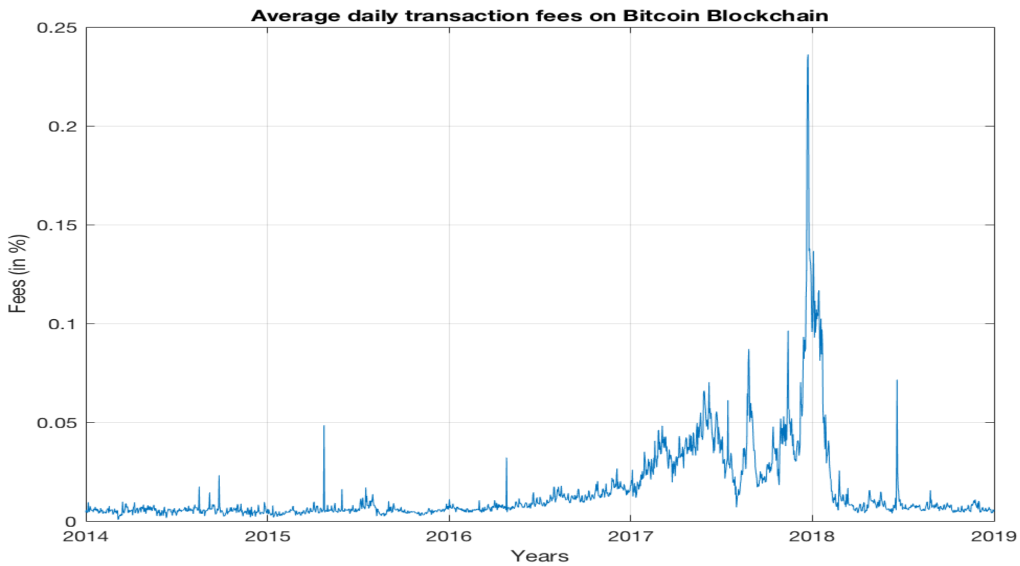
4.5 Commodities

Lastly, to capture the dynamics of the commodities market, I rely on the Oil VIX and Gold VIX which are proxies for volatility. I decided, however, not to include

[10] see https://www.worldbank.org/en/news/press-release/2019/04/08/record-high-remittances-sent-globally-in-2018. Last accessed on November 1, 2019.

Figure 3: **Average Daily Transaction Fees on the Bitcoin Network**

The figure shows the average daily transaction fees (in %) on the Bitcoin blockchain. The sample period is from January 1, 2014 to January 1, 2019.



indexes for real estate as this asset category is very different in terms of investment horizon and liquidity compared to all assets mentioned above. In unreported results, however, I also include the MSCI real estate index and verify that my results are unaffected.

All in all, I investigate the volatility spillovers between 19 assets. If were to follow the approach of Diebold and Yilmaz (2009) this would imply a total of $19! \simeq 1.21 \times 10^{17}$ possible identification strategies. The parsimonious nature of the approach developed in this paper reduces this number to 120. As mentioned above, I will compute the spillover measures for all 120 possible identification strategies, hence obtaining a range for each of the estimates. As we will see in the next section, the obtained intervals are fairly narrow.

5 Results

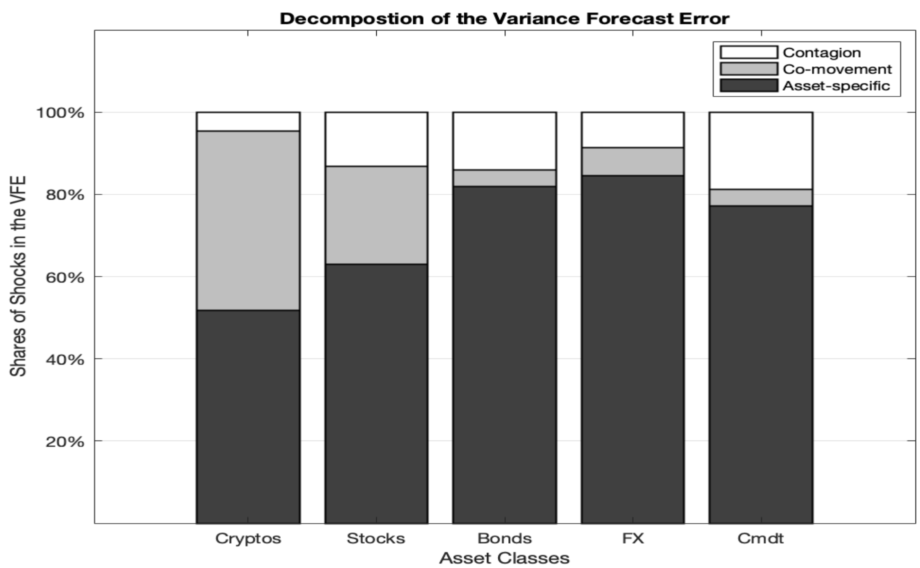
I present the results in three steps. *First*, I present the average composition for the VFE for each asset class. The aim is to highlight the characteristics which determine to which extend a given asset category is prone to contagion from other asset classes. *Second*, for each asset class, I establish the composition of the received contagion, i.e. I identify the origin of the volatility contagion received by each asset class. I will focus in particular on the average impact that crypto-assets have on traditional asset classes. These insights help to narrow the focus of the analysis on the impact crypto-assets have on the bond and the FX markets. *Third*, I go more into detail by discussing the impact that individual crypto-assets have on individual assets of the bond and FX asset classes. This part of the analysis demonstrates the benefits of using sectoral shocks to capture volatility contagion across asset classes. As mentioned above, sectoral shocks allow me to represent each asset class with several assets, hence, capturing the heterogeneity within an asset class. If each asset class was only represented by single asset, I would not be able to identify the *wealth* channel (i.e., impact of service crypto-assets and apps on the corporate bond market) and the *remittance channel* (i.e., impact of payment crypto-assets on the fiat-currencies of lower middle income countries), as these effects might cancelled out (or be absorbed) when regrouping/representing an asset class into single index.

5.1 Sensitivity to Volatility Contagion

Figure 4 shows the different compositions of the average VFE for different asset classes.

Figure 4: Composition of the Variance Forecast Error

This graph captures the average composition of the VFE for each asset category. The white (grey) portion represent the average contagion (co-movement) share of the VFE. The black portion illustrates to which extent the VFE is on average driven by asset specific shocks.



The distinction between idiosyncratic, co-movement, and contagion shocks highlights how crypto-assets differ from traditional asset classes. I make two noteworthy observations; (i) The VFE of crypto-assets is almost completely due to shocks that are specific to crypto-assets. Indeed, as captured by the white area only 4.66% of the VFE is due to contagion (i.e. shocks coming from other asset classes). In case of traditional asset classes, an average of 13.70% of the VFE is explained by contagion.

That is, the average VFE of crypto-assets is primarily driven by shocks specific to that category as the contagion from other asset classes is small. Hence, the volatility of crypto-assets is to some extent independent of shocks from other asset classes. (ii) Computing the feedback share as captured in equation (8) shows that 45.74% of the variance of crypto-assets, steaming from crypto-assets them selves (sum of black and gray portion) is due to co-movement. In other words, almost 50% of the variance that is due to shocks of crypto-assets is simply due to co-movement of assets, i.e., the volatility of crypto-assets is driven to a large extent by feedback among those assets. A shock occurring to one crypto-asset quickly reverberates across the asset class. In case of the traditional asset classes, such feedback only accounts on average for 11.15% of the variance.

Taking a closer look at the traditional asset classes we notice that the FX markets also appear to only mildely be affected be volatility contagion. As pointed out by Baruník et al. (2017) volatility of exchange rates is generally controlled by central bank interventions which often successfully impact the level and, hence, is less prone to volatility contagion from other asset classes. We would therefore think that the bond market should also be rather resistant to volatility contagion. However, in the present paper, bonds are primarily represented by corporate bonds. Hence, this asset category is more prone to shocks of the real economy, comparable to stock and commodity markets.

This intuition is confirmed in the next part, where I identify the origin of the volatility conation received by each asset class.

5.2 The Impact of Crypto-assets

As mentioned above I do not select a single identification strategy, but rather compute the spillover measures for all possible identification strategies. This yields a range of estimates for the linkages. Table 4 shows the average composition of the contagion part of VFE for all asset classes.

Table 4: Contagion Shares

This table decomposes the average total contagion received by each class. The contagion shares capture to which extent the volatility-contagion is driven by a given asset class. The contagion shares are average across all 120 possible identification strategies. The corresponding standard errors are denoted in brackets.

		From				
		Cryptos	Stocks	Bonds	FX	Cmdt
To	Crypto-Assets	·	28.91 (0.41)	21.71 (0.23)	19.51 (0.20)	29.86 (0.29)
	Stocks	11.40 (0.78)	·	25.04 (1.64)	20.53 (1.21)	43.03 (2.88)
	Bonds	16.57 (0.23)	37.87 (0.84)	·	20.31 (0.34)	25.25 (0.66)
	Foreign Exchange	15.93 (0.13)	28.46 (0.96)	28.23 (0.88)	·	27.38 (0.99)
	Commodities	12.65 (0.64)	53.26 (2.02)	25.27 (1.30)	8.82 (0.47)	·
Total To Others		56.55	148.49	100.25	69.18	125.53
Share To Others		11.31	29.70	20.05	13.84	25.11

Given that I am considering 5 asset classes, and, hence an asset class can receive contagion from up to four asset classes, the average impact of an asset class on another one should on average be around 25%. It turns out, as captured by the first row of Table 4, that stocks and commodity markets each drive around 30% of the volatility contagion received by crypto-assets, whereas bond and FX markets only account for roughly 20% each. This tighter link between crypto-assets and stock as well as commodity markets does not come as a surprise, as all three asset categories are know to attract speculative investors.

The first column of Table (4) indicates how much of the volatility contagion received by traditional asset classes is driven by shocks occurring to crypto-assets. We notice that on average crypto-assets accounts for roughly 15% of the contagion received by traditional asset classes. The last row of Table 4 captures how much of the total contagion across asset classes can be attributed to a given asset classes. We notice that crypto-assets only account for 11.31% of the total contagion. Given that crypto-assets are constitute an emerging asset class, we would expect a small relevance in terms of the overall contagion across markets (Corbet et al., 2018).

While the main focus of the paper is to understand the volatility contagion from crypto-assets to the traditional asset classes, it is important to highlight that the new methodology developed in this paper, yields results that are consistent with the literature focusing on the volatility contagion among traditional asset classes. That is, I notice that the volatility contagion between stock and commodity markets are particularly strong, i.e. stock (commodity) markets account for 53.26% (43.03%) of the volatility contagion received be commodity (stock) markets. These linkages were studied by e.g. Awartani and Maghyereh (2013) who investigate the spillovers between oil and equities in the Gulf Cooperation Council countries, and Maghyereh et al. (2016) who study the linkages between oil and eleven major stock exchanges. Further, we notice that the bond markets also play a significant role in the volatility contagion across asset classes, as it accounts for 20.05% of all volatility contagion in the present setting. The linkages between stock, bond, and commodity markets are studied by Yang and Zhou (2016). Lastly, we notice that FX markets accounts only for 13.84% of the volatility contagion. This is in line with Diebold and Yilmaz (2012) who show that volatility spillovers from FX markets had little impact on the volatility of other markets.

The number indicated in brackets in Table 4 represent the standard errors of the contagion shares. I notice that the contagion shares from and to crypto-assets present smaller standard errors than the contagions across traditional assets classes. This illustrates that the impact crypto-asset have on traditional assets, does not vary much across identification strategies. Table (5) gives more detail on the range of contagion shares for different identification strategies.

Table 5: **Range of Contagion for different identification strategies**

The variable μ and σ correspond to the cross sectional mean and standard deviation of the obtain volatility contagion estimates. The variable $Id.St.$ denotes the number of identification strategies. The last part of table represents the smallest (min) volatility contagion estimate, the largest (max) volatility contagion estimate as well as serval quantiles.

	μ	σ	$Id.St.$	min	0.1	0.25	0.50	0.75	0.9	max
Stocks	11.40%	8.50	120	3.12	3.53	3.96	7.29	21.56	23.36	27.01
Bonds	16.57%	2.54	120	11.94	13.56	14.54	16.29	18.15	20.09	23.08
FX	15.93%	1.38	120	13.00	14.01	15.09	15.82	16.67	17.94	18.99
Cmdt	12.65%	7.03	120	4.62	4.97	7.40	9.13	18.28	19.86	28.30

While the average impact that crypto-assets have on traditional asset classes is roughly 15% in each case, I notice that the range of contagion shares that crypto-assets have on the bond and FX markets are narrow as indicated by the small standard deviation. This means that the impacts are robust and, in particular for those to linkages do not depend much on the identification strategy. Hence, I will now determine through which channel crypto assets impact bond and FX markets. That is, while average impacts are around 15%, I show next that the impact of crypto-assets on individual assets of other asset classes can go as high as 30%.

5.3 Asset by Asset Contagion

The impact crypto-assets have on bond and FX markets, captures the *wealth* channel and the *remittance* channel, respectively. Table (6) represents the contagion share that individual crypto-assets have on individual assets representing the bond an FX markets.

5.3.1 Crypto-asset and Bond Markets: The Wealth Channel

As seen in the previous section, crypto-asset account for 16.57% of the volatility contagion received by the bond market on average. However, the methodology developed in this paper allows to represent each asset class with several variable. This is why 16.57% represents the average impact that all crypto asset have on all assets of the bond market on average. I can also quantify the impact that crypto-assets have on each of the individual assets representing the bond market (see Table 6, Panel A). I notice that, 27.51% of the total volatility contagion received from U.S.

Table 6: Volatility Contagion of Individual Assets

Panel A contains the volatility contagion of individual crypto-asset categories on subcategories of bonds. Panel B depicts the corresponding impulse response functions.

			PANEL A: Contagion Shares						PANEL B: Impulse Responses				
			From						From				
			Crypto-assets						Crypto-assets				
			Bitcoin	Pay	Ser	SMC	dapp	all	Bitcoin	Pay	Ser	SMC	dapp
To	Bonds	MOVE	2.04 (0.07)	6.46 (0.29)	2.58 (0.11)	4.92 (0.22)	2.77 (0.10)	13.01 (0.00)	-0.24 (0.00)	-0.30 (0.00)	-0.23 (0.00)	-0.36 (0.00)	-0.67 (0.65)
		US	1.15 (0.05)	5.21 (0.19)	12.72 (0.19)	3.67 (0.12)	13.24 (0.21)	27.51 (0.00)	-0.05 (0.00)	-0.08 (0.00)	-0.18 (0.00)	0.04 (0.01)	-0.47 (0.44)
		EU	3.26 (0.14)	5.76 (0.30)	1.25 (0.06)	3.97 (0.23)	1.05 (0.02)	11.54 (0.00)	-0.07 (0.00)	-0.08 (0.00)	-0.04 (0.00)	0.09 (0.00)	0.02 (0.27)
		China	3.39 (0.06)	3.74 (0.07)	8.40 (0.07)	1.04 (0.02)	2.56 (0.03)	14.22 (0.01)	0.41 (0.00)	0.39 (0.00)	-0.47 (0.01)	0.03 (0.02)	-0.47 (0.14)
	FX	High	1.13 (0.05)	1.33 (0.05)	1.03 (0.05)	5.07 (0.13)	0.86 (0.02)	6.77 (0.00)	0.01 (0.00)	0.00 (0.00)	-0.02 (0.00)	-0.07 (0.00)	-0.03 (0.14)
		Up. Mi.	3.98 (0.10)	1.08 (0.02)	4.91 (0.08)	1.70 (0.02)	7.00 (0.07)	13.06 (0.00)	0.27 (0.00)	-0.02 (0.00)	0.28 (0.00)	-0.14 (0.00)	0.98 (0.21)
		Low Mi.	3.92 (0.09)	17.02 (0.32)	8.49 (0.12)	1.69 (0.07)	3.04 (0.18)	27.66 (0.00)	-0.21 (0.00)	-0.38 (0.00)	-0.28 (0.00)	-0.13 (0.03)	-0.35 (0.28)
		Low	9.09 (0.04)	1.55 (0.03)	3.50 (0.10)	6.21 (0.08)	4.27 (0.02)	16.23 (0.01)	-0.03 (0.00)	-0.12 (0.01)	0.30 (0.01)	-0.40 (0.00)	-0.17 (0.21)

corporate bonds stems from crypto-assets. This number drops to 14.22% (11.54%) for the Chinese (European) corporate bond indices. In the following, I will take a closer look at the link of crypto-assets and the U.S. corporate bond market.

In general, the volatility linkages between assets can either be described as complementary or substitutive.

A complementary volatility linkage captures the idea that higher uncertainty in one market yields higher uncertainty in other market. This mechanism is often studied in the context of the greek sovereign debt crisis. In this branch of the literature, authors often highlight the role of credit providers, and how they may contribute to the reverberation of volatility within and across financial markets. This channel can be briefly summarized in four steps; (i) banks buy sovereign greek bonds, (ii) Greek presents strong financial troubles in the wake of the financial crises of 2007, (iii) the probability of default increases (or more generally the aptitude of Greece to reimburse its debt decreases), (iv) banks which hold greek debt have reduced collateral (yielding less wholesale funding and potentially margin calls). Hence, as pointed out by De Bruyckere et al. (2013) negative shocks in one market can directly affect collateral values and cash flows associated with securities in other markets. This mechanism of reverberation is referred to as *collateral* channel.

A substitutive volatility channel captures the 'flight to safety' dynamics. That is, high uncertainty in one market corresponds to a higher probability of a decline market, therefore investors reallocate their wealth to other markets where we observe a lower volatility which captures the probability of a rising market. This channel can be described as the *wealth* channel since it captures that investors reallocate their financial wealth from markets with high uncertainty to markets with lower uncertainty.

Taking a closer look at Table 6, reveals that crypto-assets and U.S. corporate bonds are linked in a substitutive manner. That is, in Panel A of Table (6), I notice that, the sub-categories of crypto-assets named service crypto-assets and decentralized applications (dapps) explain, respectively, 12.72% and 13.24% of the volatility contagion received by the U.S. corporate bonds. Looking at the impulse responses indicated in Panel B of Table 6, I notice that a 1% increase in the volatility of service crypto-assets (dapps) decreases the volatility of the corporate bond index spread by 18 (47) basis points. In other words, high volatility of crypto-assets corresponds to a higher probability of a decline market, therefore investors reallocate their wealth to the traditional markets where we observe a lower volatility which captures the probability of a rising market. This decrease in volatility of the U.S. corporate bond index captures that investors reallocate their financial wealth from the crypto-asset ecosystem back to the traditional asset classes.

I can think of two types of investors, who this reasoning applies to; individual and institution investors.

Regarding individual investors, as explained in section 2, it is important to remember that both service crypto-assets and dapps provide services such as cloud storage and other services that are provided by established industries. Hence, to some extend they might attract similar investors (and consumers). When this market displays higher uncertainty, investors reallocate their wealth to a related market, yet, presenting less uncertainty.

Institutional investors capture the dynamics of large scale investment. In this case I follow the idea of indirect investments. That is rather than investing directly in crypto-assets, some investors might provide loans to crypto-asset trading platforms (or crypto-exchanges). As pointed out by Makarov and Schoar (2019), most crypto-asset trading platforms allow for margin trading. In some cases individual investors can leverage their position up to a factor of 100 (e.g. Bitmex, Bybit, Primexbt, Xena).[11] Due to the market's opaque and unregulated nature it is unclear, however, how large the total resulting debt is and who holds it (Financial Stability Board, 2018). Leveraged trading provides a tool to benefit from the volatility of the underlying. Such trading strategies do not come without risk. This is especially true in the case of crypto-asset which display very high volatility; it can yield high gains but at the same time it can quickly yield large loses. This buildup of leverage can give rise to financial vulnerabilities (Adrian et al., 2019). Together with the unregulated nature of the crypto-asset ecosystem, the built-up leverage can imply that sudden changes in the market sentiment can increase the probability of default of the exchange which offers margin trading. That is, as opposed to regulated markets with clearing houses and other safety mechanisms, crypto-exchanges bear the entire debt in case investors default or refuse to pay.[12] Limited risk bearing capacity of crypto-exchanges implies a higher probability of default in case of economic downturns for crypto-assets. Hence, even though crypto-asset price movements appear to be uncorrelated with traditional assets, in case the crypto-asset ecosystem faces high uncertainty, investors reallocate their financial resources to markets with less uncertainty.

To better understand the dynamics of volatility contagion between service crypto-assets and U.S. corporate bonds, I conduct a rolling window analysis. That is, I use a 250 day rolling window to compute a time series of measures for volatility contagion. Further, I compute the net volatility contagion between those two assets.

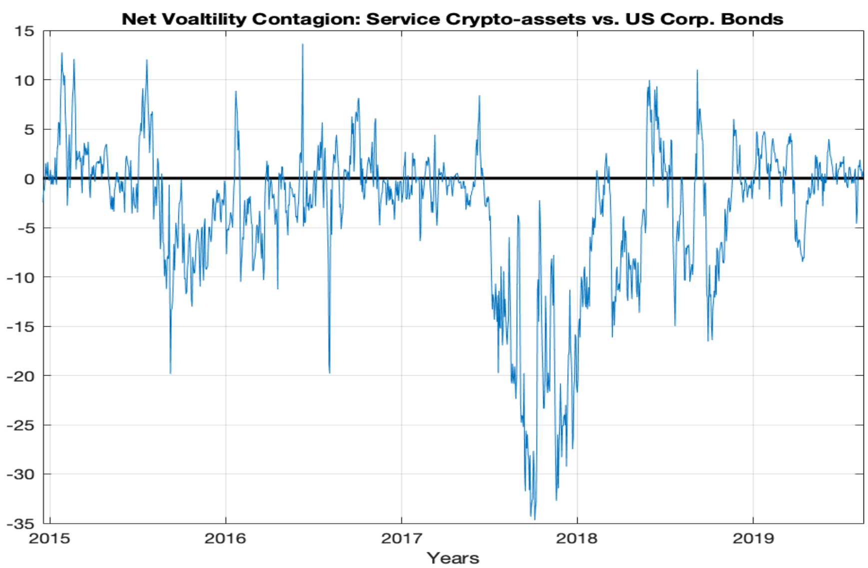
[11] More detailed information is available on the respective websites of those crypto-exchanges

[12] The international nature of crypto trading can make it difficult for exchange to claim the margins they are owed.

The net volatility contagion is defined as the difference of the volatility contagion from service crypto-assets to U.S. corporate bonds and the volatility contagion from U.S. corporate bonds to service crypto-assets. Hence, a positive net conation means that service crypto-assets have a larger impact on U.S. corporate bonds, than U.S. corporate bonds have on service crypto-assets. The dynamics are plotted in Figure 5.

Figure 5: Net Volatility Contagion

The net volatility contagion is defined as the difference of the volatility contagion from service crypto-assets to U.S. corporate bonds and the volatility contagion from U.S. corporate bonds to service crypto-assets. Hence, a positive net conation means that service crypto-assets have a larger impact on U.S. corporate bonds, than U.S. coporate bonds have on service crypto-assets.



First, I notice that there are some peaks where the net contagion is strongly positive (more than 10%), i.e. service crypto-assets have a stronger impact on U.S. corporate bond than U.S. corporate bonds have on service crypto-assets. These events generally correspond to hacks of crypto-exchanges, i.e. higher probability of default translates into higher volatility, hence setting in motion the capital flow towards the traditional markets.

Second, I also notice that from mid 2017 up to early 2018 the net contagion is negative, i.e. service crypto-assets are on the receiving end of the volatility contagion. It is important to note that this period corresponds to the the the largest "crypto-bubble" to date. It seems as if U.S. corporate bonds represent a driving factor of the volatility of service crypto-assets during that period. While this observation constitutes some intriguing motivation to further study the determinants of the crypto-bubble in late 2017, I leave this to further research as the focus of the present paper is to determine and quantify the impact crypto-assets have on the traditional asset classes (and not vice versa).

5.3.2 Crypto-asset and FX Markets: The remittance channel

The literature of volatility spillovers in FX markets dates back to Baillie and Bollerslev (1991) and Ito et al. (1992). While this literature overall is rich, I notice that most papers only focus on a subcategory of fiat-currencies. That is, Kanas (2000), Hong (2001), Melvin and Melvin (2003), Kitamura (2010), Cai et al. (2008), Baruník et al. (2017) study the volatility spillover between major exchange rates such as U.S. dollar against the British Pound, the Japanese Yen, the Deutsche Mark, the French Franc, (and later the Euro), the Swiss Franc, the Canadian Dollar, etc. Another branch of the literature address regional spillovers among emerging countries, see e.g. Tai (2004) for East Asian countries, Bubák et al. (2011) for Eastern European countries, and Carsamer (2016) for Sub-Saharan countries. To the best of my knowledge, this is the first paper to consider all fiat-currencies in the context of volatility spillovers.

In general the dynamics of FX volatility spillovers are traced back to monetary policy and interventions. Indeed, as pointed out Taylor (2001), Devereux and Engel (2003), and Dick et al. (2015) a change in a differential between two central bank policies yields an adjustment in the currency pair of those two countries. However, in light of the emergence of crypto-assets, and their ability to transfer wealth on global scale, it seems reasonable to take a different approach. That is, while fiat-currencies used to be the only means to transfer wealth, the European Central Bank (2019) points out that crypto-assets play an increasingly important role in international remittance payments. This is why volatility in the payment crypto-assets account for as much as 17.02% of the contagion received by currencies of the lower middle income countries.

Looking at Table (6), I notice that volatility of payment crypto-assets reverberates particularly to the lower income countries. Hence, the contagion between crypto-assets and FX markets capture the *remittance* channel. As pointed out by the world bank[13] in the recent years the amount of remittances sent towards low and lower middle income countries has steady grown and reached an all time high in 2018.

From the perspective of an individual who is sending remittances, crypto-assets or via the traditional banking system constitute two substitutive ways. When there is volatility in the exchange rates, banks (or other financial institutions) take higher

[13]see https://www.worldbank.org/en/news/press-release/2019/04/08/record-high-remittances-sent-globally-in-2018. Last accessed on November 1, 2019.

margins on the exchange rate in order to cover potential losses due to fluctuations in the exchange rate. Accordingly, using crypto-assets to transfer money becomes relatively more interesting. Conversely, if crypto-assets are very volatile, people rather rely on the traditional system. This substitutive linkage is captured by a negative IR. More precisely, a 1% increase in the volatility of payment-crypto-assets yields a 38 basis point decrease in the volatility of the currencies of the lower middle income countries. The net contagion between payment crypto-assets and lower middle income currencies (defined as the different of the impact of payment crypto-assets on lower middle income currencies and the impact of lower middle income currencies on payment crypto-assets) is positive (see Table 7 in the appendix). In other words, volatility in the crypto-space pushes more customers to the traditional system, than volatility in the traditional system pushes customers to the crypto-space.

6 Robustness

I conduct a series of robustness checks to verify the results hold true in various conditions; subsample of identification strategies, different lags both P and H.

I only consider a subset of the possible 120 identification strategy. More precisely I only consider the identification strategies where crypto-asset are in the first position of the linear projections. This reduces the number of identification strategies to 24 as I only permute the ordering of the LP of the residuals from the traditional asset classes. Intuitively, this means that all correlations that cryptos may have with any of the remaining asset class are removed from crypto-assets and attributed to the traditional asset classes. This yields more conservatives measure of the potential impact that crypto-assets might have on traditional asset classes. My results persist in this subset of identification strategies. This was to be expected as the range of the contagion shears was narrow to begin with.

Next, I verify that my results all hold true for different lags P in the VAR and different number of aggregation period H for the VFE. In unreported results I show that the results are similar for $P \in [\ 10\ 15\ 20\ 30\ 40\ ]$ and $H \in [\ 10\ 15\ 20\ ]$ I notice that with increasing values of H the results actually improve in the sense that the contagion shares increase. As the forward aggregation period H increases, the spillovers measures better capture the feedback loop between asset classes. Consequently, while shocks specific to an asset category are relatively constant over time, with an increasing aggregation period the linkages between assets loop back, hence increasing the contagion between asset classes.

7 Conclusion

This paper analyzes the impact volatility of crypto-assets has on the volatility of traditional asset classes. Understanding the linkages across assets raises the issue of properly distinguishing between contagion and co-movement of assets. This paper defines contagion as the impact of a shock of one asset on another asset. Conversely, co-movement simply captures interdependence across assets without being able to attribute the origin of the shock to a given asset. Using *systemic* shocks to study spillovers implies an interpretation in terms of co-movements as all shocks are correlated. Conversely, the reverberation of *reduced* shocks captures *contagion* across assets. Reduced shocks only contain idiosyncratic variation and have no correlation with other shocks. Obtaining reduced shocks, however, requires an identification strategy which is implemented with the Cholesky decomposition. Such approach bears two drawbacks: (i) a strongly increasing number of possible identification strategies with the number of assets under consideration, and (ii) the Cholesky decomposition is not able to accommodate tighter interaction between asset of a same asset class.

This paper overcomes both of these drawbacks by introducing a new type of shocks coined as *sectoral* shocks. These shocks are obtained by a series of linear projections of the systemic shocks. As opposed to the Cholesky decomposition, which requires identification strategies between individual assets, the identification strategies implemented with the LPs are able to accommodate sectoral linkages within an asset class. That is, while the Cholesky decomposition removes the correlation between individual asset, my approach only removes the correlation between asset classes, however, I allow for correlation within an asset class. By neutralizing the correlation of shocks across asset classes, the resulting spillover measures capture the impact (net of correlation) that one asset class has on another, i.e. it quantifies contagion across asset classes.

This approach allows to show the existence of a *wealth* and *remittance* channel. The former captures how volatility of the subcategories of crypto-assets best described as start-ups, i.e. service crypto-assets and decentralized applications (that are in direct competition with traditional service providers) impacts the volatility of U.S. corporate bond index. The latter captures how the subcategory of payment crypto-assets, impacts the volatility of fiat-currencies of lower middle income countries.

This paper is only able to uncover those channels because each asset class is represented with several assets. If crypto-assets would only be represented with a single asset, e.g. Bitcoin, none of these channels would have been revealed. At the same time, not making any identification strategy within an asset class, implies that each asset is properly attributed its own shocks (even in case of co-movements with other assets). If we would have implemented an asset by asset identification strategy within asset class, shocks would have been either diluted or wrongly attributed to first asset within that asset class.

By considering an extensive list of variables for each class and all possible identification strategies across asset classes, together with a parsimonious model that empirically establishes contagion, this paper is able to quantify the impact that crypto-assets have on traditional asset classes.

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Appendix

A Linear Projection of residuals

To compute the inverse of block matrix I use the approach as discussed by Ben-Israel and Greville (2003)

$$\Sigma = \begin{bmatrix} \Sigma_{k_1k_1} & \Sigma_{k_1k_2} & \Sigma_{k_1k_3} \\ \Sigma_{k_2k_1} & \Sigma_{k_2k_2} & \Sigma_{k_2k_3} \\ \Sigma_{k_3k_1} & \Sigma_{k_3k_2} & \Sigma_{k_3k_3} \end{bmatrix} \tag{A.1}$$

$$\begin{aligned}\bar{z}_{t,k_1} =& \epsilon_{t,k_1} - \begin{bmatrix}\Sigma_{k_1k_2} & \Sigma_{k_1k_3}\end{bmatrix}\begin{bmatrix}\Sigma_{k_2k_2} & \Sigma_{k_2k_3}\\ \Sigma_{k_3k_2} & \Sigma_{k_3k_3}\end{bmatrix}^{-1}\begin{bmatrix}\epsilon_{t,k_2}\\ \epsilon_{t,k_3}\end{bmatrix}\\ =& \epsilon_{t,k_1} - \begin{bmatrix}\Sigma_{k_1k_2} & \Sigma_{k_1k_3}\end{bmatrix}\begin{bmatrix}\Sigma^{k_2k_2} & \Sigma^{k_2k_3}\\ \Sigma^{k_3k_2} & \Sigma^{k_3k_3}\end{bmatrix}\begin{bmatrix}\epsilon_{t,k_2}\\ \epsilon_{t,k_3}\end{bmatrix}\end{aligned}$$

where

$$\begin{bmatrix}\Sigma^{k_2k_2} & \Sigma^{k_2k_3}\\ \Sigma^{k_3k_2} & \Sigma^{k_3k_3}\end{bmatrix} = \begin{bmatrix}\Sigma^{-1}_{k_2k_2} + \Sigma^{-1}_{k_2k_2}\Sigma_{k_2k_3}K\Sigma_{k_3k_2}\Sigma^{-1}_{k_2k_2} & -\Sigma^{-1}_{k_2k_2}\Sigma_{k_2k_3}K\\ -K\Sigma_{k_3k_2}\Sigma^{-1}_{k_2k_2} & K\end{bmatrix} \tag{A.2}$$

with $K = (\Sigma_{k_3k_3} - \Sigma_{k_3k_2}\Sigma^{-1}_{k_2k_2}\Sigma_{k_2k_3})^{-1}$

$$\begin{aligned}\bar{z}_{t,k_2} =& \epsilon_{t,k_2} - \Sigma_{k_2k_3}\Sigma^{-1}_{k_3k_3}\epsilon_{t,k_3}\\ \bar{z}_{t,k_3} =& \epsilon_{t,k_3}\end{aligned}$$

$$\begin{aligned}\begin{bmatrix}\bar{z}_{t,k_1}\\ \bar{z}_{t,k_2}\\ \bar{z}_{t,k_3}\end{bmatrix} &= \begin{bmatrix}\epsilon_{t,k_1}\\ \epsilon_{t,k_2}\\ \epsilon_{t,k_3}\end{bmatrix} - \begin{bmatrix}0 & \Sigma_{k_1k_2}\Sigma^{k_2k_2} + \Sigma_{k_1k_3}\Sigma^{k_3k_2} & \Sigma_{k_1k_2}\Sigma^{k_2k_3} + \Sigma_{k_1k_3}\Sigma^{k_3k_3}\\ 0 & 0 & \Sigma_{k_2k_3}\Sigma^{-1}_{k_3k_3}\\ 0 & 0 & 0\end{bmatrix}\begin{bmatrix}\epsilon_{t,k_1}\\ \epsilon_{t,k_2}\\ \epsilon_{t,k_3}\end{bmatrix}\\ &= \begin{bmatrix}I_{n(k_1)} & -\Sigma_{k_1k_2}\Sigma^{k_2k_2} - \Sigma_{k_1k_3}\Sigma^{k_3k_2} & -\Sigma_{k_1k_2}\Sigma^{k_2k_3} - \Sigma_{k_1k_3}\Sigma^{k_3k_3}\\ 0 & I_{n(k_2)} & -\Sigma_{k_2k_3}\Sigma^{-1}_{k_3k_3}\\ 0 & 0 & I_{n(k_3)}\end{bmatrix}\begin{bmatrix}\epsilon_{t,k_1}\\ \epsilon_{t,k_2}\\ \epsilon_{t,k_3}\end{bmatrix}\end{aligned}$$

$$=\bar{C}\epsilon_t$$

B VFE Shares

Table 7: Contagion and co-movement shares across and within asset classes

		Crypto-Assets					Stocks				Bonds				Foreign Exchange				Commodities	
		Bitcoin	Payment	Service	Platoform	dapps	VIX	US	EU	China	MOVE	Short-Term Corp	EU	China	High	Up. Mi.	Low Mi.	Low	OilVIX	GoldVIX
Cryptos	Bitcoin	52.63	10.53	9.59	14.96	7.93	0.86	0.93	0.06	0.33	0.30	0.17	0.14	0.05	0.33	0.19	0.11	0.06	0.76	0.08
	Payment	14.97	50.67	9.96	13.35	5.16	0.30	1.29	0.21	0.67	0.12	0.28	0.09	0.21	0.24	0.06	0.22	0.04	1.13	1.04
	Service	12.51	10.21	49.13	14.43	9.06	0.48	0.42	0.34	0.09	0.12	0.44	0.46	0.51	0.46	0.69	0.17	0.13	0.09	0.24
	Platoform	13.05	10.41	12.91	52.47	7.41	0.46	0.25	0.41	0.14	0.14	0.22	0.23	0.31	0.43	0.14	0.41	0.03	0.25	0.33
	dapps	8.93	9.43	9.50	13.77	53.75	0.20	0.03	0.09	0.60	0.10	0.94	0.34	0.47	0.35	0.06	0.77	0.06	0.50	0.13
Stocks	VIX	0.16	0.29	0.06	0.45	0.32	77.64	0.48	1.56	0.29	3.57	0.44	0.96	0.33	0.41	0.36	0.97	0.22	6.34	5.15
	US	0.44	0.35	0.54	0.30	0.16	26.54	60.92	1.23	1.54	1.77	0.73	0.63	0.23	0.46	0.22	0.34	0.34	1.85	1.41
	EU	0.17	0.73	0.15	0.47	0.34	29.92	0.26	54.30	2.55	1.36	0.15	0.13	0.05	0.82	0.26	0.53	1.14	3.97	2.71
	China	0.07	0.07	0.14	0.17	0.05	21.50	1.03	8.23	58.93	1.61	0.63	0.15	0.23	2.47	0.55	0.39	0.04	1.71	2.03
Bonds	MOVE	0.61	1.83	0.73	1.39	0.80	15.33	0.34	0.98	0.14	63.60	0.26	2.56	0.10	0.13	0.26	0.37	0.25	4.71	5.60
	Short-Term Corp	0.11	0.50	1.20	0.33	1.25	0.44	0.99	0.35	0.24	5.25	84.54	0.50	0.37	0.51	0.13	0.76	1.41	0.87	0.26
	EU	0.16	0.29	0.06	0.20	0.05	0.64	0.39	0.69	0.70	4.91	1.02	88.58	0.32	0.18	0.18	0.39	0.74	0.31	0.16
	China	0.28	0.31	0.69	0.09	0.21	0.40	0.32	0.61	2.56	0.18	0.13	0.27	91.10	0.30	0.55	0.47	0.58	0.71	0.23
FX	High	0.06	0.07	0.06	0.28	0.05	1.40	0.23	0.23	0.49	1.11	0.31	0.78	0.04	85.33	4.56	3.86	0.46	0.20	0.48
	Up. Mi.	0.47	0.13	0.58	0.20	0.83	2.81	0.36	0.13	0.43	2.12	0.92	0.36	0.33	3.72	83.60	0.53	0.13	2.02	0.30
	Low Mi.	0.43	1.88	0.93	0.18	0.32	2.77	0.17	0.15	0.71	1.61	0.15	1.11	0.06	8.48	1.87	78.03	0.51	0.20	0.42
	Low	0.52	0.09	0.20	0.35	0.24	0.23	0.08	0.19	0.52	1.19	0.20	0.09	0.23	0.12	0.50	2.72	90.97	0.21	1.34
Cmdt	OilVIX	0.12	0.09	0.09	1.41	0.11	10.66	0.32	0.23	0.38	0.82	0.32	0.44	0.25	0.06	0.46	0.14	0.89	80.36	2.84
	GoldVIX	0.27	0.28	0.11	1.54	0.22	9.22	0.78	1.18	0.29	3.40	0.40	2.46	0.12	0.20	0.10	0.09	0.13	5.37	73.86