Heterogeneity and Volatility Regimes of Cryptoassets

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Abstract

Crypto-assets attract more and more investors due to their potential returns and diversification benefits. Contrary to popular believe, only a minority of crypto-assets are cryptocurrencies. Thus in our study, we distinguish between payment crypto-assets (i.e. crypto-currencies), platform crypto-assets and protocol crypto-assets. In light of the heterogeneity of crypto-asset, we show that they present different regime dynamics. More precisely, the different subgroups of crypto-assets tend to regroup in three separate clusters. That is, the analysis yields four regimes with different levels of variance: ranging from extremely low through 'neutral' and high volatility regimes up to 'explosive' volatility. The clusters of crypto-assets distinguish themselves by the time they spend in the 'explosive' and 'neutral' volatility regime.

Keywords: Bitcoin, Cryptoassets, Regime Switching Models, Heterogeneity, Coins and Tokens.

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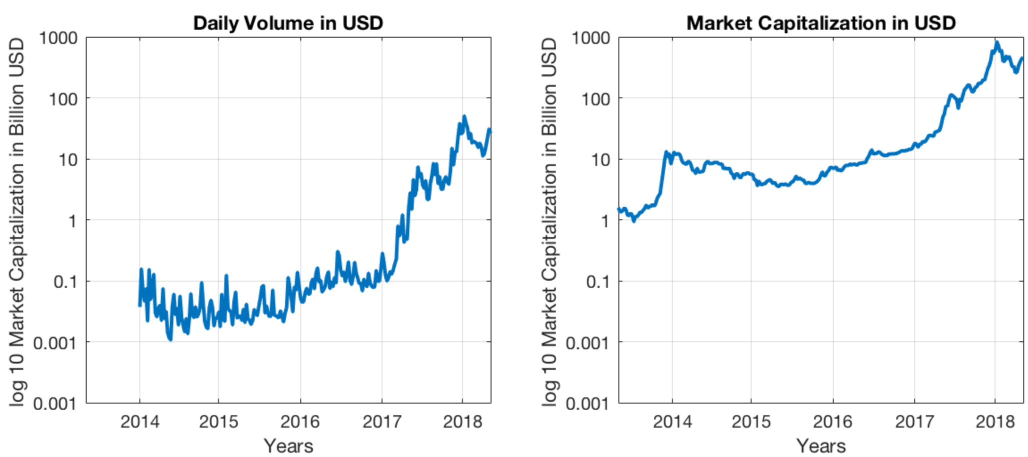
1 Introduction

In the recent years the crypto-asset ecosystem has gathered more and more attention. Investors are attracted by the large returns and the potential for diversification benefits.[1] Indeed, the previous financial crises and the resulting depressed financial markets provide few attractive investment opportunities. In comparison, the expansion and growth opportunities of the crypto-asset market are very favorable, to say the least. Figure 1 illustrates the evolution of the crypto-asset space over the past five years.

Figure 1: **Daily Volume and Market Capitalization of Crypto-assets**

The left (right) graph represents the aggregated daily trading volume (market capitalization) of all crypto-assets. The data is downloaded from coinmarketcap.com. The sample period is from April 28, 2013 to May 12, 2018.



As of May 2018 we observe over 1,500 actively traded crypto-assets with a market

[1]We would like to note that the crypto-asset space is also a potential source of scams. Given the lack of knowledge on the assets and technological features and the hype created, many investors invest without being well informed.

capitalization of \$ 420 Billion and daily trading volume above \$ 30 Billion (see Figure 1). Given that the first crypto-asset was created less than eleven years ago, these numbers appear quite impressive.

People mistakenly assume that all crypto-assets serve the purpose of a currency. This is most likely due to the fact that the first and most prominent crypto-asset, Bitcoin, is a crypto-currency (more precisely a payment crypto-asset). That is, in his seminal paper, Nakamoto (2008) introduces Bitcoin as the first digital *currency* based on a *distributed* peer-to-peer payment system. The underlying technology is referred to as the blockchain. Recent reviews on the mechanics of blockchains and crypto-assets include, but are not limited to Böhme et al. (2015), Nanda et al. (2017), Weiss and Corsi (2017), Smith and Kumar (2018) and Buchwalter (2018). In a nutshell, the blockchain is a chain of blocks containing information. In case of payment crypto-assets this information consists of transactions. However, storing a record of transaction between individuals is not the only possible use of the blockchain. The community of crypto-enthusiasts has developed other uses for the blockchain technology. That is, rather than storing a record of transactions like the blockchain of payment crypto-assets, the blockchain of platform crypto-assets allows for decentralized cloud storage (e.g., Filecoin), or decentralized cloud computing (e.g. Ethereum). The later gave rise to another category of crypto-asset called the protocol crypto-assets. As opposed to payment and platform crypto-assets, protocol crypto-assets do not have their own blockchain but rather live on the blockchain of other platform crypto-assets. Hence, in the present analysis we distinguish between a total of three types crypto-assets; payment crypto-assets, platform crypto-assets and decentralized applications (dapps).[2] Each crypto-asset has its own native currency. As pointed out by (Huberman et al., 2017) the issuance of a native currency constitutes the extrinsic motivation for the participation in its maintenance, while, at the same time, it is also constitutes a means of payment for those who want to use the service (cloud storage, etc.).

It is those native currencies that have been subject to wild speculations in the recent years. That is, investors have shown interest in crypto-assets because of their diversification potential and expected returns. Low correlation with traditional markets and high average returns make this market interesting for both individuals and institutional investors. Initial studies focus on the benefits of Bitcoin in the context of portfolio diversification (Briere et al., 2015). However, little has been done with respect to the time series structure of a cross section of crypto-assets.

In this research we propose to analyze the regime dynamics of crypto-assets and see their differences in their regime dynamics. Regimes are a common feature of financial assets. The incorporation of market regimes has shown to be a feature of financial assets or commodities, as typically returns, volatilities and correlations tend to behave pro-cyclically. Although prior work has analyzed statistical features and hedging properties, they have overlooked the dynamics and the synchronization of market regimes of crypto-assets.

We use an Heterogeneous Regime Switching Model (HRSM) to capture, both the

[2]Protocol crypto-assets are divided into two subcategories: backed and unbacked crypto-assets. Backed crypto-assets represent a claim on another asset and hence do not capture any new information. Therefore, these assets are excluded from the analysis. Unbacked crypto-assets, however, constitute an independent asset whose value is not dependent on another asset. Unbacked crypto-assets are also referred to as decentralized applications or dapps.

regime switching behavior and the heterogeneity of crypto-assets. We analyze two different datasets. In the first one we cover a long time series (4 years) but only a small cross-section (64 assets). Conversely, the second dataset covers a shorter period (2 years), but it captures a larger cross-section (202 assets). The analysis yields four regimes for crypto-assets for both samples: a regime that we call 'neutral', because volatility is close to zero; a regime with 'moderate', 'high' and one with 'explosive' volatility. The'explosive' volatility regime can be driven by both very high or negative returns depending on the sample period. Having two different datasets confirms that the regime switching behavior is neither affected by the presence/absence of other of other assets, nor is it impacted by the sample period under investigation. Further, some crypto-assets display higher volatility in the beginning of their existence. To check whether this might affect the clustering, we analyzed the clustering behavior of the small cross section in a shorter time horizon (2 years), and find that clustering is overall not affected by higher volatility in the beginning of the sample.

In the sample of 64 assets, the results show the existence of two clusters of crypto-assets: (i) one group spends most of the time in the moderate and high volatility regime (ii) while the other group spends most of the time in the high and neutral volatility regime. These two clusters correspond overall to to payment and platform crypto-assets, respectively. We note that protocol crypto-assets do not regroup in their own cluster. This is probably due to the fact that they are underrepresented in the long time series sample, since their existence requires an already established platform crypto-asset.

Hence, we study a second sample with a shorter time series (2 years), but a larger cross-section (202 assets), such that all three asset classes are represented in large enough numbers. In this case, the analysis yields three different clusters: (i) one of the groups is the most stable. It just switches between the moderate and high volatility regime, and it hardly goes to the neutral and super explosive regimes, (ii) the second group spends more time in extreme regimes than the first group. It switches frequently between the extreme regimes, that is said, it goes directly from explosive volatility to almost zero volatility, while the previous cluster has a more smooth switching between adjacent regimes, (iii) and the third cluster has even a more volatile behavior. It is most of the time in the high or explosive volatility regime. It is a group of assets that have had a strong increase in valuation in the last subperiod. These three clusters correspond overall to the payment, platform and protocol crypto-assets, respectively.

Our paper makes two contributions to the burgeoning literature on crypto-assets. *First*, it sheds light on the heterogeneous cross-section of crypto-assets, and hence nullifies the idea of a homogeneous asset class. *Second*, it complements the literature of crypto-assets by describing the cyclical behavior of returns, a key ingredient in dynamic portfolio optimization. By shedding light on the cyclicality of crypto-asset we provide valuable information to investors: the cyclicality of crypto-assets can be tied to fundamental technological characteristics of crypto-assets. Hence, by analyzing the dynamics of regimes, our work has implications for diversification benefits; the costs of ignoring market regimes can be high, particularly for highly risk-averse investors.

The remainder of the paper is structured as follows. In section 2 we make a brief presentation of literature. In section 3 we discuss the methodology used to analyze the cyclicality of crypto-assets. In section 4 we discuss the classification of crypto-assets and present the data. Section 5 contains the results. Section 6 offers some concluding remarks.

2 Literature Review

Our paper relates with the burgeoning financial literature on crypto-assets. The introduction of Bitcoin was a landmark and the early literature has followed the public interest in Bitcoin and analyse its investment properties: its diversification benefits (Briere et al., 2015) and its safe haven properties (Dyhrberg, 2016; Selmi et al., 2018).

A related strand analyzes how crypto-assets compare with other classes of assets. Baur, Hong, and Lee (2017) show that Bitcoin is primarily used as speculative asset rather than a currency. Wilson-Nunn and Zenil (2014) highlight the similarities of Bitcoin and precious metals such as gold and silver. Hence, Bitcoin is generally is described as a commodity serving the purpose of portfolio diversification. Baur, Dimpfl, and Kuck (2018) conclude that Bitcoin return, volatility and correlation characteristics are distinctively different compared to gold and the US dollar. Ji, Bouri, Gupta, and Roubaud (2018) find that Bitcoin is isolated from other assets, stock, bonds, commodities and currencies. and none of the selected assets seems to influence the Bitcoin market. However, the paper reports the existence of lagged relationships between Bitcoin and other assets during the bear market. Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) use the spillover index approach and its variants for examining relations among three popular crypto-assets (Bitcoin, Ripple and Litecoin) and other traditional financial assets (the foreign exchange, stock, VIX, gold and bond). Their empirical results show that the three popular crypto-assets are relatively isolated from other financial assets and thus crypto-assets constitute a risk diversification for investors.

Given the evidence on the idiosyncratic nature of Bitcoin, it is not surprising that studies do not find common drivers with traditional financial assets. Liu and Tsyvinski (2018) conclude that crypto-assets have no exposure to most common stock market and macroeconomic factors and also have no exposure to the returns of currencies and commodities. Aalborg et al. (2018) find that Bitcoin returns are not driven by VIX and other variables. Panagiotidis et al. (2018) find a significant interaction between Bitcoin and traditional stock markets, but a weaker interaction with FX markets and the macroeconomy and with internet search queries indicators. Giudici and Abu-Hashish (2019) use correlation network vector autoregression process to models the interconnections between different crypto and classic asset prices. Their results also confirm that bitcoin prices are typically unrelated with classical market prices, thus bringing further support to the "diversification benefit" property of crypto assets. Ciaian et al. (2018) analyse the relationship between the prices of Bitcoin and sixteen other crypto-assets, and found that they are indeed interdependent, but independent from exogenous factors.

Works have also addressed the existence of regimes and structural breaks. That is, Thies and Molnár (2018) use break points to study regimes of Bitcoin. They find that structural breaks in average returns and volatility of Bitcoin are very frequent. Several regimes with positive average returns and one regime with negative average returns are captured. Across regimes, higher volatility is associated with higher average returns, with exception of the most volatile regime, which is the only regime with negative average returns.[3] Bouri et al. (2018) analyzed price explosivity of seven largest crypto-assets by market capitalisation (Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar) using daily data. Price explositivity is defined as the exponential price growth of an asset. The results show that all crypto-assets in the sample experienced explosive behaviours in multiple periods. Furthermore, the study provides evidence of a multidirectional co-explosivity behaviour, i.e. explosivity in one crypto-asset can lead to explosivity in other crypto-assets, while this effect does not necessarily depend on the size of each crypto-asset.

More recently, papers have started to analyse the cross-section of crypto-assets and their inter-relation. Koutmos (2018) measures interdependencies among 18 major crypto-assets and shows that Bitcoin is the dominant contributor of return and volatility spillovers among all the sampled crypto-assets; he also finds that volatility spillovers have risen steadily over time and that there are 'spikes' in spillovers during major news events regarding crypto-assets. These findings suggest growing interdependence among crypto-assets and, by extension, a higher degree of contagion risk. To sum up, previous papers generally only focus on Bitcoin or a handful of crypto-assets. This paper brings the analysis to a cross-section of 202 crypto-assets and fills the gap in literature by looking at the dynamics of the time series of a large cross

[3]Their sample is from September 2011 to August 2017 (2,170 daily observations.)

section of crypto-assets.

3 Methodology

The HRSM, which is used for our empirical research, is a parametric method. It extends the RSM first introduced by Hamilton (1989), which has been widely used to model economic and financial time series. This extension captures the unobserved heterogeneity between the different time series and therefore we can distinguish between different regime-switching dynamics. This model has been used and thoroughly described by Dias and Ramos (2013); Pereira et al. (2017); Ramos et al. (2011) in the investigation of regimes and heterogeneity in stock markets. In this work, we follow the same approach but apply it to crypto-assets.

The proposed model contains three types of variables: a time-varying response variable, a time-constant discrete latent variable, and a time-varying discrete latent variable. Let y_{it} represent the response of observation i at time point t, where $i \in 1, \ldots, n$, $t \in 1, \ldots, T$, and $y_{it} \in \Re$. The time-constant and time-varying discrete latent variables are denoted by w and z_t, respectively, where $w \in 1, \ldots, S$ and $z_t \in 1, \ldots, K$. The latter implies that the number of categories of the two types of latent variables equal S and K, respectively. We distinguish between the two types of latent variables. We refer to w as a latent class and to z_t as a latent state or regime. The time-constant latent classes (w) can be seen as clusters for which the process under study differs. The time-varying latent variable with Markovian transition structure (z_t) is used model the distribution of the time-specific responses as well as to capture changes that occur across adjacent time points.

The Mixture Gaussian Hidden Markov Model (MGHMM) is hence defined as:

$$f(\mathbf{y}_i;\boldsymbol{\varphi}) = \sum_{w=1}^{S}\sum_{z_1=1}^{K}\sum_{z_2=1}^{K}\cdots\sum_{z_T=1}^{K} f(w,z_1,\ldots,z_T)f(\mathbf{y}_i|w,z_1,\ldots,x_T) \tag{1}$$

with

$$f(w,z_1,\ldots,z_T) = f(w)f(z_1|w)\prod_{t=2}^{T} f(z_t|z_{t-1},w) \tag{2}$$

and

$$f(\mathbf{y}_i|w,z_1,\ldots,z_T) = \prod_{t=1}^{T} f(y_{it};z_t). \tag{3}$$

Equation (1) describes $f(\mathbf{y}_i;\boldsymbol{\varphi})$, the (probability) density function associated with index return rates for stock market i. The right-hand side of this equation shows that we are dealing with a mixture model containing one time-constant latent variable and T time-varying latent variables. The total number of mixture components (or latent classes) equals SK^T, which is the product of the number of categories of w and z_t for $t = 1, 2, ..., T$. As in any mixture model, $f(\mathbf{y}_i;\boldsymbol{\varphi})$, results from the marginalization over the latent variables that being discrete is the summation of weighted average of class-specific probability densities – here $f(\mathbf{y}_i|w,z_1,\ldots,z_T)$ – where the (prior) class membership probabilities or mixture proportions (McLachlan and Peel, 2000).

Equations (2) and (3) show the conditional independence assumption implied by the MGHMM that simplify the form of the mixture proportion $f(w,z_1,\ldots,z_T)$ and the class-specific densities $f(\mathbf{y}_i|w,z_1,\ldots,z_T)$, respectively. More specifically, the equation for $f(w,z_1,\ldots,z_T)$ shows that within latent classes w, z_t is associated only with z_{t-1} and z_{t+1} and thus not with the latent states occupied at the other time points – the well-known first-order Markov assumption. The equation for $f(\mathbf{y}_i|w, z_1, ..., z_T)$ shows that conditionally on z_t, the response at occasion t (y_{it}) is independent of responses at other time points – usually referred to as the local independence assumption – and independent of the latent classes and the latent states at the other time points.

Unobserved heterogeneity is captured by the time-constant latent variable w, autocorrelations are captured by the first-order Markov transition process in which the state at time point t may depend on the state at time point $t-1$, and flexible distributions of the returns are possible because of the time-specific mixture distribution for the response variable.

As can be seen from Equations (2) and (3), the model of interest is characterized by four sets of probability functions:

- $f(w)$ is the probability of belonging to a particular latent class w and $\pi_w = P(W = w)$;
- $f(z_1|w)$ is an initial-state probability; that is, the probability of having a particular latent initial state conditional on belonging to latent class w: $\lambda_{kw} = P(Z_1 = k|W = w)$;
- $f(z_t|z_{t-1}, w)$ is a latent transition probability; that is, the probability of being in a particular latent state at time point t conditional on the latent state at time point $t-1$ and class membership; assuming a time-homogeneous transition process, we have $a_{jkw} = P(Z_t = k|Z_{t-1} = j, W = w)$;

- $f(y_{it}|z_t)$ is the Gaussian density function for the observed response, which is the probability density of having a particular observed stock return in index i at time point t conditional on the latent state occupied at time point t. This distribution is characterized by the vector $\theta_k = (\mu_k, \sigma_k^2)$ containing the means (μ_k) and variances (σ_k^2) for latent state k (and invariant across latent classes). Since the marginal distribution is a mixture of densities it defines a flexible model that takes into account skewness and kurtosis.

The $K(SK + 2) - 1$ free parameters of the MGHMM ($\boldsymbol{\varphi}$) include the $S - 1$ class sizes, the $S(K - 1)$ initial-state and $SK(K - 1)$ transition probabilities and the $2K$ conditional means and variances of the observed variables ($2K$). We conduct the parameter estimation by Maximum Likelihood (ML) estimation. The ML estimation of the parameters of the HRSM-S involves maximizing the log-likelihood function $\ell(\varphi; \mathbf{y}) = \sum_{i=1}^{n} \log f(\mathbf{y}_i; \varphi)$, a problem that can in theory be solved using the expectation-maximization (EM) algorithm (Dempster et al., 1977). As the EM algorithm needs to compute and store the $S{\cdot}2^T$ entries of $f(w, z_1, \ldots, z_T|\mathbf{y}_i)$ for each stock market, its complexity increases exponentially with T, which makes it impractical or even impossible to apply for large values of T. The Baum-Welch algorithm (Baum et al., 1970) circumvents the computation of this joint posterior distribution and makes use of the conditional independencies implied by the model.

To decide on the number of latent classes and latent states we do the following. The selection of the dimension of the model in mixture modeling, the number of latent classes (S), is typically based on information statistics such as the Bayesian information criterion (BIC) of Schwarz (1978) and the Akaike information criterion

(AIC) of Akaike (1974). Because simulation studies have shown that in mixture modeling the AIC tends to overestimate the number of latent classes (see, for example, Dias (2007)), in our application we select the S that minimizes the BIC value. This measure is defined as follows:

$$BIC_S = -2\ell_S(\hat{\varphi}; \mathbf{y}) + N_S \log n, \tag{4}$$

where N_S is the number of free parameters of the model concerned, and n is the sample size.

4 A Heterogeneity of Crypto-assets

In this section we first give a brief introduction to crypto-assets. This allows us to shed light on the heterogeneity of crypto-assets. We further present the summary statistics of our samples.

4.1 Crypto-assets and Distributed Networks

In order to fully understand the heterogeneity among crypto-assets we need to understand their underlying mechanism. The foundation of any crypto-asset is the blockchain. In its simplest form, the blockchain is defined as a platform where information is stored and/or processed. The particularity of this platform is that once the information is stored, it can not be deleted or modified, i.e. it is *immutable*. This immutability is insured via cryptography which chains blocks of information chronologically together. Trying to change information in one of the previous blocks would break the chain apart.

4.1.1 Blockchain

People mistakenly assume that a currency is the only application of the blockchain technology. This is most likely due to the fact that the first and most prominent crypto-asset, Bitcoin, is a crypto-currency (more precisely a payment crypto-asset). That is, in his seminal paper, Nakamoto (2008) introduces Bitcoin as the first digital *currency* based on a *distributed* peer-to-peer payment system. It is important to understand that a blockchain neither needs to be distributed, nor is it limited to provide a payment system. Let us address these two points in turn.

First, Blockchains do not need to be distributed across a network. This is well illustrated by the example of Casey and Vigna (2018) who highlight the usage of the blockchain technology in the Azraq refugee camp in Jordan. The World Food Program is using blockchain technology to overcome administrative challenges. That is, in order to avoid mismanagement of resources and possible corruption in the camp, the World Food Program stores each refugees' food entitlements in a blockchain. Storing this information in a blockchain makes the database completely immutable. This not only streamlines the administrative burden but also avoids possible human mismanagement of the resources. This centralized application of the blockchain is very far from the Bitcoin example which is generally associated to the blockchain technology.

Hence, when talking about blockchain it is important to be aware of the distinction between *distributed* blockchains (e.g. Bitcoin) and *centralized* blockchains (e.g.

food entitlements database). In the later case, the blockchain technology simply provides an immutable way of storing information. However, the information platform is still controlled by a single centralized entity, e.g. the World Food Program. Conversely, crypto-assets are based on a network of distributed blockchains in which each node has equal authority in terms of making decisions and interacting with the database. Hence, the information is not controlled by a single entity. Instead, each node of the network has a complete copy of the database and all nodes together maintain (and update) the database. As such, in a distributed network decision making power and assignment of accountability is transferred from a trusted third party (or centralized authority) to a network of small independent entities.

4.1.2 Networks as Intermediaries

To understand this delegation of rights and duties we need to understand the concept behind centralized authorities and the functions they traditionally fulfill. A centralized authority is organized around a single decision node which stores and updates the database. This structure allows centralized authorities to facilitate interactions between two parties who both trust the third party. The relying parties use this trust to secure their own interactions.

A typical example in that context is the role of bank in the purchase of good with a credit card. Despite the fact that the seller does not receive the money instantly, the interaction (between the buyer and the seller) is made possible by relying on a trusted intermediary, i.e. bank. That is, both the buyer and the seller trust that the bank will transfer the correct amount of the money. In other words, the bank facilitates the interaction. As such third parties can be seen as necessary intuitions that allow for interaction on a large scale by providing trust and maintaining a the platform where information is stored. Hence, distributed networks need to find new answers to trust and maintenance, which so far, are only dealt with in a centralized setting.

Crypto-assets are generally described as allowing for peer-to-peer interaction without the need to rely on a third party. To be more precise crypto-assets do not rely on *centralized* network. However, crypto-assets still rely on *distributed* network. That is, there is no single node that makes a decision but rather a network of individual nodes which reach consensus. Distributed networks are also referred to as permissionless networks. The gist is that everybody is allowed to join the network. To establish trust in a decentralized setting we need two elements. First we need a reliable database that cannot be tampered with. The immutability feature of the blockchain makes it the perfect platform to store information. Second, we need a consensus mechanism which insures that only the correct information is added to the database. Hence, the immutability of the blockchain together with a consensus mechanism constitutes a platform which cannot be modified by single entity alone, i.e. a platform that can be trusted.

At the same time, the network is also in charge of storing the database. In a centralized setting, the database is usually only stored by the single decision node. In a decentralized network, however, the database is distributed among all the nodes of the network. That is, each node of the network has a full copy of the complete database. In other words, to be a node of the network, one needs to download to complete database and update it through time. Since participating in the network requires an effort, an *incentive system* is required in order to allow for the existence of a distributed information platform. This incentive system shall insure that the platform is maintained and updated in trustworthy and transparent way, but yet without the need to rely on a centralized authority.

4.1.3 Classification

To call upon the extrinsic motivation of the participants, distributed networks need to reward the actors who participate in the maintenance of it. Concretely, each distributed blockchain has a native currency which is used to compensate individuals for their participation in the maintenance of that blockchain. As such, the native currency of each blockchain primarily constitutes the necessary incentive for participation in the maintenance of it. It is important not to jump to conclusions. Despite the fact that each decentralized blockchain contains a native currency, it does not mean that all decentralized blockchains serve the purpose of a payment crypto-asset (or crypto-currency). This relates to the second point mentioned above; distributed blockchains are not necessarily crypto-currencies.

In case of Bitcoin, the compensation mechanism for those who maintain the platform and the the provided service are identical, i.e. a system of money. However, there is another category of blockchains which is referred to as *platform* crypto-asset. In the case of a platform crypto-assets the compensation mechanism (system of money) is different from the provided service. There are numerous peer-to-peer services that can be provided by a distributed network. For instance, Filecoin, allows for cloud storage in a peer-to-peer fashion. People who would like to use the service provided by a Filecoin need to pay for it with that currency. Hence, as opposed to Bitcoin, Filecoin has no intention of becoming an universally accepted currency. Instead, Filecoin, simply constitutes the currency in which the service is paid for. It is important that independently of the kind of blockchain, the issuance of a native currency constitutes the extrinsic motivation for the participation in its maintenance, while, at the same time also a means of payment for those who want to use the service (Huberman et al., 2017).

Payment and platform crypto-assets belong to the category of blockchain crypto-assets. There is another category called protocol crypto-asset. They further widen the space of possible peer-to-peer interactions by using the blockchain infrastructure of platform crypto-assets. Protocol crypto-assets do not have their own blockchain. Instead they 'live' on the blockchain of other crypto-assets. This carries the benefit that protocol assets can simply rely on the already existing network of its host blockchain, rather than creating a new network. This allows for a quicker adoption.[4] Protocol crypto-assets can be split into two groups: backed and unbacked crypto-assets. Backed crypto-assets represent a claim on another asset. The most prominent example is Tether, a 'stable-coin' which represents a claim on the USD. As backed crypto-assets contain no new information, these assets are excluded from the analysis.[5] An unbacked crypto-asset is referred to as a decentralized application

[4]A comparison would be a smart phone 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 spread a simple game.

[5]It is also worth noticing that out of more than 3,000 crypto-assets, less than 20 qualify as backed crypto-assets.

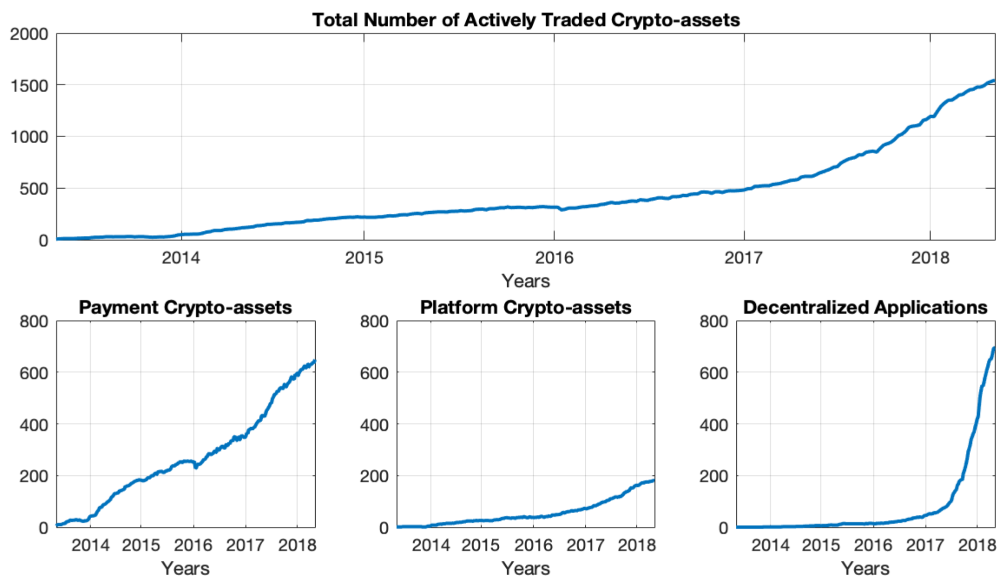
or dapp. A dapp consists of one or more smart contracts. As such, a dapp can fulfill various functions such as a database or a small program, and provide a broad range of service. It is important to notice that, in contrast to blockchain crypto-assets (that issue new money with each new block), the issuance of the native currency of protocol assets is controlled by the developing team of a given dapp. Hence, we observed large price variation in response to ad-hoc releases of new amounts of native currencies.

4.2 Overview

Figure 2 provides an overview of the number of assets in the different categories over time. We see that payment crypto-assets are the first category to exist and until recently also the largest one in terms of numbers of assets. The reason for this is straightforward. When Bitcoin was first introduced the source code which describes the workings of the blockchain was made publicly available for each and everyone (who has the knowledge) to verify the validity of the system. The aim is build trust and transparency in the system given the absence of third parties. As such, this transparency has allowed to easily innovate on the existing technology, and create numerous other crypto-currencies. Hence, most payment crypto-assets are mere improvements to Bitcoin. The next level of crypto-assets was introduced with the creation of platform crypto-assets. Unsurprisingly the number of platform crypto-assets remains relatively small. Not only is more challenging from a technical perspective to create such a platform, but also each platform should have some characteristics that make it unique. Copying and improving the source code as it is done for payment crypto-asset is not enough in this case. At the same time, platform crypto-asset allow for the creation of protocol crypto-assets which are easier to code. Further protocol crypto-assets conveniently avoid the need to create a network as they live on the blockchain of other assets (which already have their network). This explains the drastic increase of the number of protocol crypto-assets (see figure 2).

Figure 2: **Number of Crypto-assets through Time**

The upper (lower) graphs represents the aggregated (individual) number of all crypto-assets in each category. The data is downloaded from coinmarketcap.com. The sample period is from April 28, 2013 to May 12, 2018.



As of May 12, 2018, coinmarketcap.com lists 1544 actively traded crypto-assets. That is, we count 649 payment crypto-assets, 160 platform crypto-assets and 694 dapps. The cross section of crypto-assets is actually even richer but not all of the crypto-assets are still actively traded. As illustrated in upper panel of figure 2 there is clear trade-off between the number of crypto-assets and length of time series data. We hence have to forfeit looking at a large cross section, denoted N order to have a sufficiently long time series data, denoted T.

4.3 Dataset

As opposed to traditional assets which only trade on weekdays, it is important to note that crypto-assets are traded all days of the week. We estimate our model in two time periods.

- Dataset 1: from 2014, April 28 to 2018, May 12, i.e. 1476 daily observations for 64 assets
- Dataset 2: from 2016, May 1 to 2018, May 12, i.e. 741 daily observations for 202 assets

For the days with missing price data, we have set the price equal to the previous close price. However if more than 1% of missing values then it is removed from the sample. We have not removed outliers, otherwise we would be removing heterogeneity. Similarly, we have not removed penny cryptos, i.e. cryptoasset that trade a small unit price. Daniele and Dickerson (2019) remove those assets due to concerns of price manipulation. However, we believe that if the market capitalization of a crypto-asset is sufficiently large, independently of the unit price, it is unlikely that the crypto-asset is subject to price manipulation. To verify our intuition we control for market capitalization in the robustness checks.

Table 1: **Summary Statistics**

This table contains the summary statistics for our two samples. The summary statistics are computed from daily log returns. Further $\mathbb{E}[\,\cdot\,]$, $\mathbb{V}[\,\cdot\,]$, $\mathbb{S}[\,\cdot\,]$, and $\mathbb{K}[\,\cdot\,]$ correspond to the first, second, third and fourth moment, respectively and $\alpha_1[\,\cdot\,]$ captures the autocorrelation of order 1. The mean and standard deviation are expressed in percent.

Cryptoasset	N	$\mathbb{E}[\,\cdot\,]$	$\mathbb{V}[\,\cdot\,]$	$\mathbb{S}[\,\cdot\,]$	$\mathbb{K}[\,\cdot\,]$	$\alpha_1[\,\cdot\,]$
Model 1: April 28, 2014 to May 12, 2018						
All	64	0.15	4.75	-0.46	7.16	-0.02
Payment	50	0.14	4.71	-0.40	7.26	-0.01
Platform	11	0.18	8.55	-0.07	4.35	-0.23
dapp	3	0.19	9.53	0.34	11.60	-0.21
Model 2: May 1, 2016 to May 12, 2018						
All	202	0.40	5.02	-0.72	6.96	0.02
Payment	148	0.41	5.07	-0.64	6.65	0.01
Platform	37	0.46	6.05	-0.51	5.40	-0.02
dapp	17	0.15	6.22	-0.95	11.63	-0.10

All assets reject the normality test of Jarque and Bera (1980) at the 1% significance level. As such, we can not use a mean variance analysis to comment on the risk return trade-off of the different asset classes.

4.4 Hypotheses and Covariates

4.4.1 Type Dummy

As described before crypto-assets have inherently technical differences and can be distinguished among themselves. Thus our first hypothesis is that the intrinsic features of crypto-assets might be important for the regime dynamics. We take as the base payment crypto-asset and identify with dummy variables if a crypto-asset qualifies as platform or protocol crypto-asset.

4.4.2 Covariates

Demand The behavior of returns can be determined by the irrational behavior of investors such as popularity and enthusiasm. Thus, we test the hypothesis that regime dynamics can be driven by sentiment on the crypto-asset market. Following Buchholz et al. (2012) and Horra et al. (2019), we use the price of bitcoin a proxy for its demand.

Volume We first analyse the hypothesis that volume conveys information. So we analyze changes in volume as amain determinant in the regime dynamics.

$$vol_{i,t} = \ln(Vol_{i,t}/Vol_{i,t-1})$$

Then we also analyze if speculative trading affect regime dynamics. We can use abnormal volume (abn_vol) as defined in Barber and Odean (2007):

$$abn\_vol_{i,t} = \frac{\ln(Vol_{i,t})}{\frac{\sum_{j=1}^{52} \ln(Vol_{i,t-j})}{52}}. \tag{5}$$

High market capitalization The overall crypto-asset market presents a high degree of concentration. We also consider the hypothesis that high market capitalization crypto-assets have a different regime dynamics than those with low market capitalization. We use a dummy to identify all crypto-assets that do not belong to G10 in terms of market capitalization. We follow Swinkels and Yi et al. (2018) results show that in most cases, crypto-assets with high market capitalization (e.g., Bitcoin, Litecoin and Dogecoin) propagate large volatility shocks, while small-cap crypto-assets are more likely to receive volatility shocks from others.

5 Results

In this section we present the results of the estimation of the results with two different datasets.

5.1 Estimation of Model 1

Our first estimation favours a longer time sample, and it only includes a relatively small cross-section of 64 assets. The sample period goes from 2014, April 28 to 2018, May 12.

We estimate models using different values for S(S = 1,. . . ,8), with 1000 different sets of starting values to minimize the effect of local maxima. A solution with two latent classes (S = 2) yields the lowest BIC value log-likelihood = -345540.54, number of free parameters = 39; and BIC = 691243.3). This means that the best solution incorporates two types of regime dynamics. Regimes are described in Table 2 and they distinguished by the level of volatility

- Regime 1 is a regime with explosive volatility and negative returns;
- Regime 2 is a regime with moderate volatility and negative returns;
- Regime 3 is a neutral regime, with very low volatility and very low returns;
- Regime 4 is a high volatility and positive returns;

The high levels of volatility of crypto-assets have already been referred in the literature, see e.g., Katsiampa (2017). We note that the very high price jumps induce very high levels of volatility as we find here, the combination of explosive volatility and negative returns indicate a period of strong drops in crypto-assets prices. Regime 3 is also interesting to mention because it reflects a state where there is almost no price changes and therefore low volatility. We have dubbed it 'neutral' regime.

Table 2: **Regime occupancy**

This table reports the estimated probabilities of being in a given regime $P(Z|W)$. The period goes from 2014, April 28 to 2018, May 12. The sample has 64 crypto-assets.

Regimes	1	2	3	4
P(Z)				
	0.033	0.531	0.045	0.390
	0.006	*0.021*	*0.008*	*0.010*
Return (mean)				
Intercept	-10.341	-0.371	-0.002	0.487
	2.661	*0.026*	*0.004*	*0.092*
Risk (variance)				
	21480.929	24.931	0.059	275.364
	691.567	*0.377*	*0.001*	*4.725*

Table 3 shows the estimates of the probability of the average proportion of crypto-assets of markets in each regime over time (P(Z)). Cluster 1 spends most of the time in the moderate and high volatility regime, 59.8% and 36.6% over time, respectively. Cluster 2 spends most of the time in the high and neutral volatility regime, 53.3% and 18.2% over time, respectively and also 14.6% of the time in the explosive volatility regime. Thus comparatively, the first group seems to have a more stable patter than the second one.

The next rows show the transition probabilities between the two regimes. For the first cluster, the diagonal values of the matrices are close to one for regimes 2, 3, and 4, that is the moderate, neutral and high volatility regimes, which means that there is regime persistence, i.e., once a crypto-asset enters a given regime, it is likely to remain in that regime for some period of time.

For the second cluster, the diagonal values of the matrices are close to one, for regimes 2 and 4, the moderate and high volatility regimes, which means that is regime persistence is higher only for those two regimes. It is interesting to note also that crypto-assets in this cluster switch between the explosive and the neutral regime often, very differently from the first group, that has a more smooth transition for neighbour volatility regimes, while the second group switches abruptly between extreme volatility regimes.

Table 3: **Cluster Regime Occupancy and Transition Probabilities with two Clusters**

This table reports the estimated probabilities of being in a given regime $P(Z|W)$. Remaining rows report transition probabilities between regimes. Standard errors are reported in italics. The period goes from 2014, April 28 to 2018, May 12. The sample has 64 crypto-assets.

Regimes	1	2	3	4
Cluster 1				
P(Z—W)	0.014	0.598	0.022	0.366
	0.001	*0.007*	*0.004*	*0.007*
Regime 1	0.539	0.020	0.001	0.440
	0.021	*0.010*	*0.001*	*0.023*
Regime 2	0.001	0.925	0.001	0.074
	0.000	*0.002*	*0.000*	*0.002*
Regime 3	0.000	0.033	0.967	0.000
	0.000	*0.006*	*0.006*	*0.000*
Regime 4	0.015	0.122	0.000	0.863
	0.001	*0.004*	*0.000*	*0.004*
sojourn time	2.171	13.263	30.303	7.310
Cluster 2				
P(Z—W)	0.146	0.139	0.182	0.533
	0.008	*0.012*	*0.006*	*0.012*
Regime 1	0.666	0.000	0.239	0.096
	0.013	*0.001*	*0.011*	*0.009*
Regime 2	0.000	0.879	0.000	0.121
	0.001	*0.012*	*0.002*	*0.012*
Regime 3	0.193	0.000	0.519	0.289
	0.010	*0.000*	*0.011*	*0.012*
Regime 4	0.025	0.032	0.099	0.845
	0.003	*0.004*	*0.005*	*0.007*

Table 6 in the Appendix summarizes the results for the distribution of crypto-assets across latent classes. Crypto-assets are divided into two latent classes that represent two distinct regime dynamics. The first group yon stains mainly payment crypto-assets such as Blackcoin, Goldcoin, Litecoin while the second group mainly contains platform crypto-assets. The class assignments are always with probability 1 which indicates a solid likelihood of the class assignment. Bringing this clustering back to the technological characteristics of the underlying assets, we notice that payment crypto-assets are relatively more stable than platform crypto-assets on average. This comes as no surprise as payment crypto-assets provide a service (i.e. a system of payment) whose value is relatively more constant over time. Platform crypto-assets on the other hand experience more extreme regimes as the valuation of the proposed service (and its usefulness) may vary over time.

5.2 Estimation of Model 2

In this subsection, we present the results of the estimation using data from 2016, May 1 to 2018, May 12. This is a shorter time series but the sample is contains a larger cross-section with 202 assets.

We estimate models using different values for S(S = 1,. . . ,8), with 1000 different sets of starting values to minimize the effect of local maxima. A solution with three latent classes (S = 3) yields the lowest BIC value (log-likelihood = -574439.92, number of free parameters = 55; and BIC = 1149171.8). This means that the best solution incorporates three types of regime dynamics. Regimes are described in Table

4 and they distinguished by the level of volatility.[6]

- Regime 1 is a regime of moderate volatility and negative returns;
- Regime 2 is a neutral volatility regime, with very low volatility and returns close to zero;
- Regime 3 is a regime of high volatility and positive returns
- Regime 4 is a regime of explosive volatility and positive returns.

Again the results emphasize a pattern of four regimes of volatility. There are some issues to highlight. First, in this period crypto-assets spend more in time in the explosive volatility regime and less on the moderate volatility regime. Second, the explosive volatility regime is associated with positive returns, where in the longer model with negative returns. This reflects a period of increasing valuation of crypto-assets. Again we have a state that we dubbed neutral regime, because prices hardly change and also volatility.

Table 5 shows the estimates of the probability of the average proportion of crypto.assets of markets in each regime over time (P(Z)). Cluster 1 spends most of the time in the moderate and high volatility regime, 58.4% and 38.2% over time, respectively. Cluster 2 spends most of the time in the high and moderate volatility regime, 58.2% and 26.2% over time, respectively. Then it spends 12.5% of the time in the explosive volatility regime. Cluster 3 spends most of the time in the explosive and high volatility regime, 38.7% and 37.3% over time, respectively. Then is spends 14.6% of the time in the neutral volatility regime.

[6] The sorting of regimes is done by returns.

Table 4: **Regime Occupancy**

This table reports the estimated probabilities of being in a given regime $P(Z|W)$. Remaining rows report transition probabilities between regimes. Standard errors are reported in round brackets. The sample period is from 2015, April 30 to 2018, May 12. the sample has 2014 assets.

Regimes	1	2	3	4
P(Z)				
	0.439	0.030	0.449	0.082
	0.014	*0.003*	*0.009*	*0.007*
Return (mean)				
Intercept	-0.216	-0.001	0.335	4.176
	0.025	*0.003*	*0.062*	*0.574*
Risk (variance)				
	27.427	0.038	211.125	3880.369
	0.430	*0.001*	*3.236*	*67.470*

The next rows show the transition probabilities between the four regimes. When the diagonal values of the matrices are close to one, it means that there is regime persistence, i.e., once a crypto-asset enters a given regime, it is likely to remain in the same regime for some period of time. We note that except for crypto-assets in Cluster 1, all the other crypto-assets show high persistence in the explosive volatility regime. Differently crypto-assets in Cluster 1 show higher persistence in the neutral regime. Crypto-assets in cluster 3 switch between the explosive and the neutral regime often, very differently from the first and second group. The first group has a smoother transition for neighbour volatility regimes, while the second group switches abruptly between extreme volatility regimes. Overall assets in cluster 3 have show a strong increase in valuation in the sample period and they spend more time in the high and explosive volatility regime. Crypto-assets in cluster 1 are the ones that spend less time in the explosive volatile regime and also in the neutral one.

Table 5: **Cluster Regime Occupancy and Transition Probabilities with three Clusters**

This table reports the estimated probabilities of being in a given regime $P(Z|W)$. Remaining rows report transition probabilities between regimes. Standard errors are reported in italics. The sample period is from 2015, April 30 to 2018, May 12. the sample has 2014 assets.

Regimes	1	2	3	4
Cluster 1				
P(Z—W)	0.584	0.017	0.382	0.017
	0.010	*0.003*	*0.010*	*0.001*
Regime 1	0.914	0.040	0.129	0.000
	0.003	*0.006*	*0.005*	*0.001*
Regime 2	0.001	0.961	0.000	0.000
	0.000	*0.006*	*0.000*	*0.000*
Regime 3	0.082	0.000	0.855	0.460
	0.003	*0.000*	*0.004*	*0.022*
Regime 4	0.003	0.000	0.016	0.540
	0.001	*0.000*	*0.002*	*0.022*
sojourn time	11.601	25.316	6.887	2.176
Cluster 2				
P(Z—W)	0.267	0.026	0.582	0.125
	0.012	*0.002*	*0.007*	*0.007*
Regime 1	0.819	0.282	0.070	0.000
	0.007	*0.029*	*0.005*	*0.000*
Regime 2	0.029	0.245	0.016	0.015
	0.004	*0.015*	*0.002*	*0.003*
Regime 3	0.144	0.399	0.863	0.252
	0.007	*0.032*	*0.005*	*0.010*
Regime 4	0.007	0.074	0.051	0.732
	0.003	*0.014*	*0.003*	*0.010*

Table 7 in the appendix summarizes the results for the distribution of crypto-assets across latent classes. Crypto-assets are divided into three latent classes that represent three distinct regime dynamics. The class assignments are again always with probability 1 which indicates a solid likelihood of the class assignment. A closer look at the clusters reveals: (i) payment crypto-assets tend to regroup in the first cluster (which is characterized by the moderate and high volatility regime), (ii) platform crypto-assets spend most time in second cluster (which is characterized by the high and moderate volatility regime), and (iii) decentralized applications spend tend to regroup in the third cluster (which is characterized by the explosive and high volatility regime). The regroupment of the first two clusters is similar to the one of the longer time sample with the smaller cross section. What is interesting to notice is that while platform crypto-assets and dapps provide overall similar services they tend to regroup in different classes. More precisely, dapps spend more time in explosive volatility regimes. It is no surprise that the valuation of dapps experiences more volatile regimes as the issuance of new native currency of those is more ad-hoc and not regulated by the blockrate of the blockchain.

6 Conclusion

In this paper we analyze the cyclical behavior of a large sample of crypto-assets. The application of our HRSM allow to describe the pattern of regimes as well as describe the behavior of crypto-assets. The results show four regimes for crypto-assets in both periods: a regime that we call neutral, because volatility is close to zero; a regime with medium, high and one with explosive volatility. The explosive volatility regime can be driven by both very high or negative returns depending on the time period.

In the sample of 64 assets, the results show two groups of crypto-asses, while in the sample of 202 assets we have three groups clusters that show different regime dynamics. One of the groups is the most stable of the crypto-assets. It just switches between the moderate and high volatility regime, and it hardly goes to the neutral and explosive regimes. Other group spends more time in these extreme regimes than the first group. It switches frequently between the extreme regimes, that is said, it goes directly from explosive volatility to almost zero volatility, while the previous cluster has a more smooth switching between adjacent regimes. The third cluster has even a more volatile behavior. It is most of the time in the high or explosive volatility regime. It is a group of assets that had a strong increase in valuation in the last sub-period. Our results not only highlight important differences in the behavior of crypto-assets, but also show that those patterns can be linked to the technological characteristics of the underlying assets.

Appendix

7 Model 1 Clusters

Table 6: **Modal cluster for Crypto-assets in Model 1**

This table reports the classification of cryptocurrencies by modal cluster or latent class. Columns identify cryptocurrencies. Posterior probabilities express the evidence that a given cryptocurrency belongs to a given latent class. The maximum posterior probability indicates the assignment to the modal latent class.

Asset	Posterior Probability		Modal
	Cluster 1	Cluster 2	
42	1	0	1
ANC	1	0	1
AUR	1	0	1
BTB	1	0	1
BTC	1	0	1
BITS	1	0	1
BLK	1	0	1
BLC	1	0	1
CBX	1	0	1
CCN	1	0	1
DASH	1	0	1

continued

Asset	Posterior Probability		Modal Latent class
	Cluster 1	Cluster 2	Modal
DEM	1	0	1
DMD	1	0	1
DGB	1	0	1
DGC	1	0	1
DOGE	1	0	1
EFL	1	0	1
FTC	1	0	1
GLD	1	0	1
GRS	1	0	1
NLG	1	0	1
LTC	1	0	1
MAX	1	0	1
MZC	1	0	1
MEC	1	0	1
MINT	1	0	1
XMY	0	1	2
NET	1	0	1
NOBL	1	0	1

continued

Asset	Posterior Probability		Modal Latent class
	Cluster 1	Cluster 2	Modal
NVC	0	1	2
NYAN	1	0	1
XPM	0	1	2
POT	1	0	1
PTC	1	0	1
PPC	1	0	1
PND	1	0	1
RBY	0	1	2
XRP	1	0	1
RIC	1	0	1
RDD	1	0	1
QRK	0	1	2
SLR	1	0	1
SXC	1	0	1
UNO	1	0	1
TES	1	0	1
TRC	1	0	1
ZET	1	0	1

continued

Asset	Posterior Probability		Modal Latent class
	Cluster 1	Cluster 2	Modal
ZEIT	1	0	1
WDC	0	1	2
VTC	1	0	1
XCP	1	0	1
ECC	1	0	1
EMC2	0	1	2
TIPS	1	0	1
FLO	0	1	2
HUC	1	0	1
MOON	1	0	1
NMC	0	1	2
NXT	1	0	1
OMNI	1	0	1
XWC	1	0	1
BELA	1	0	1
TAG	1	0	1
MAID	1	0	1

8 Model 2 Clusters

Table 7: **Modal cluster for Crypto-assets in Model 2**

This table reports the classification of cryptocurrencies by modal cluster or latent class. Columns identify cryptocurrencies. Posterior probabilities express the evidence that a given cryptocurrency belongs to a given latent class. The maximum posterior probability indicates the assignment to the modal latent class.

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
AIB	0.000	0.000	1.000	3
BSTY	0.000	0.000	1.000	3
CPC	0.000	0.000	1.000	3
EMC2	0.000	0.000	1.000	3
EUC	0.000	0.000	1.000	3
FLO	0.000	0.000	1.000	3
GBC	0.000	0.000	1.000	3
LOG	0.000	0.000	1.000	3
NMC	0.000	0.000	1.000	3
NXS	0.000	0.000	1.000	3
PXI	0.000	0.000	1.000	3

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
RBY	0.000	0.000	1.000	3
WDC	0.000	0.000	1.000	3
XMG	0.000	0.000	1.000	3
BURST	0.000	0.000	1.000	3
1337	0.000	1.000	0.000	2
GP	0.465	0.535	0.000	2
TX	0.001	0.999	0.000	2
ABY	0.000	1.000	0.000	2
ACP	0.000	1.000	0.000	2
ADCN	0.000	1.000	0.000	2
ANC	0.000	1.000	0.000	2
AUR	0.000	1.000	0.000	2
BCY	0.337	0.663	0.000	2
BERN	0.000	1.000	0.000	2
BITB	0.000	1.000	0.000	2
BOLI	0.000	1.000	0.000	2
BTC	0.000	1.000	0.000	2
BTCD	0.000	1.000	0.000	2

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
CCN	0.000	1.000	0.000	2
CDN	0.000	1.000	0.000	2
CON	0.000	1.000	0.000	2
COVAL	0.000	1.000	0.000	2
CRB	0.000	1.000	0.000	2
CURE	0.000	1.000	0.000	2
DASH	0.000	1.000	0.000	2
DGD	0.000	1.000	0.000	2
ERC	0.000	1.000	0.000	2
ETH	0.014	0.986	0.000	2
EVIL	0.036	0.964	0.000	2
EXCL	0.000	1.000	0.000	2
FJC	0.000	1.000	0.000	2
FLDC	0.005	0.995	0.000	2
FRN	0.000	1.000	0.000	2
GCR	0.000	1.000	0.000	2
GRC	0.000	1.000	0.000	2
HYP	0.000	1.000	0.000	2

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
LEO	0.000	1.000	0.000	2
LSK	0.000	1.000	0.000	2
MAID	0.000	1.000	0.000	2
MOIN	0.000	1.000	0.000	2
MOJO	0.000	1.000	0.000	2
MZC	0.000	1.000	0.000	2
NEVA	0.000	1.000	0.000	2
NVC	0.000	1.000	0.000	2
PAC	0.000	1.000	0.000	2
PAK	0.000	1.000	0.000	2
PINK	0.000	1.000	0.000	2
POST	0.000	1.000	0.000	2
QRK	0.000	1.000	0.000	2
QTL	0.000	1.000	0.000	2
RADS	0.000	1.000	0.000	2
SNRG	0.000	1.000	0.000	2
SYS	0.000	1.000	0.000	2
TIT	0.000	1.000	0.000	2

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
TRC	0.000	1.000	0.000	2
TRK	0.005	0.995	0.000	2
UNIT	0.000	1.000	0.000	2
USDT	0.000	1.000	0.000	2
VIA	0.080	0.920	0.000	2
XCT	0.000	1.000	0.000	2
XLM	0.000	1.000	0.000	2
XMY	0.000	0.998	0.002	2
XPM	0.000	1.000	0.000	2
XRA	0.000	1.000	0.000	2
XST	0.000	1.000	0.000	2
ZET	0.462	0.538	0.000	2
ZNY	0.000	1.000	0.000	2
LDOGE	0.000	1.000	0.000	2
OBITS	0.000	1.000	0.000	2
RBIES	0.000	1.000	0.000	2
SWING	0.020	0.980	0.000	2
TRUMP	0.000	1.000	0.000	2

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
42	1.000	0.000	0.000	1
OK	1.000	0.000	0.000	1
SC	1.000	0.000	0.000	1
8BIT	1.000	0.000	0.000	1
ADC	1.000	0.000	0.000	1
ADZ	0.642	0.358	0.000	1
AEON	1.000	0.000	0.000	1
AMP	1.000	0.000	0.000	1
APC	0.991	0.009	0.000	1
BAY	0.591	0.409	0.000	1
BCN	1.000	0.000	0.000	1
BELA	1.000	0.000	0.000	1
BITS	1.000	0.000	0.000	1
BLC	1.000	0.000	0.000	1
BLK	1.000	0.001	0.000	1
BLOCK	1.000	0.000	0.000	1
BTA	0.916	0.084	0.000	1
BTB	1.000	0.000	0.000	1

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
BTM	1.000	0.000	0.000	1
BTS	1.000	0.000	0.000	1
BUN	0.818	0.182	0.000	1
BYC	1.000	0.000	0.000	1
CANN	0.625	0.375	0.000	1
CBX	0.610	0.390	0.000	1
CLAM	1.000	0.000	0.000	1
CLUB	1.000	0.000	0.000	1
DCR	1.000	0.000	0.000	1
DEM	1.000	0.000	0.000	1
DGB	1.000	0.000	0.000	1
DGC	1.000	0.000	0.000	1
DMD	0.998	0.002	0.000	1
DOGE	1.000	0.000	0.000	1
DOT	1.000	0.000	0.000	1
DSH	1.000	0.000	0.000	1
DUO	1.000	0.000	0.000	1
ECC	1.000	0.000	0.000	1

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
EDRC	1.000	0.000	0.000	1
EFL	1.000	0.000	0.000	1
EGC	1.000	0.000	0.000	1
ENRG	1.000	0.000	0.000	1
EXP	1.000	0.000	0.000	1
FCT	1.000	0.000	0.000	1
FTC	1.000	0.000	0.000	1
FUZZ	1.000	0.000	0.000	1
GAME	1.000	0.000	0.000	1
GCN	1.000	0.000	0.000	1
GLD	1.000	0.000	0.000	1
GRS	1.000	0.000	0.000	1
GUN	1.000	0.000	0.000	1
HODL	1.000	0.000	0.000	1
HUC	1.000	0.000	0.000	1
INFX	1.000	0.000	0.000	1
IOC	1.000	0.000	0.000	1
LTC	1.000	0.000	0.000	1

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
MAX	1.000	0.000	0.000	1
MEC	1.000	0.000	0.000	1
MEME	1.000	0.000	0.000	1
MINT	1.000	0.000	0.000	1
MOON	1.000	0.000	0.000	1
MUE	1.000	0.000	0.000	1
NAV	0.996	0.004	0.000	1
NEOS	1.000	0.000	0.000	1
NET	1.000	0.000	0.000	1
NLG	1.000	0.000	0.000	1
NOBL	0.918	0.082	0.000	1
NSR	1.000	0.000	0.000	1
NTRN	1.000	0.000	0.000	1
NXT	1.000	0.000	0.000	1
NYAN	1.000	0.000	0.000	1
NYC	1.000	0.000	0.000	1
OMNI	1.000	0.000	0.000	1
PIVX	1.000	0.000	0.000	1

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
PND	1.000	0.000	0.000	1
POT	1.000	0.000	0.000	1
PPC	1.000	0.000	0.000	1
PTC	1.000	0.000	0.000	1
PURA	1.000	0.000	0.000	1
RDD	1.000	0.000	0.000	1
RIC	1.000	0.000	0.000	1
RVR	1.000	0.000	0.000	1
SDC	0.986	0.014	0.000	1
SIB	1.000	0.000	0.000	1
SLG	1.000	0.000	0.000	1
SLR	0.965	0.035	0.000	1
SLS	1.000	0.000	0.000	1
SPR	1.000	0.000	0.000	1
SXC	1.000	0.000	0.000	1
TAG	1.000	0.000	0.000	1
TEK	0.821	0.179	0.000	1
TES	1.000	0.000	0.000	1

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
TIPS	1.000	0.000	0.000	1
TRUST	1.000	0.000	0.000	1
UBQ	1.000	0.000	0.000	1
UNITY	1.000	0.000	0.000	1
UNO	1.000	0.000	0.000	1
VRC	1.000	0.000	0.000	1
VTC	1.000	0.000	0.000	1
WBB	1.000	0.000	0.000	1
XAUR	0.980	0.020	0.000	1
XCN	1.000	0.000	0.000	1
XCP	1.000	0.000	0.000	1
XDN	1.000	0.000	0.000	1
XEM	1.000	0.000	0.000	1
XMR	1.000	0.000	0.000	1
XRP	1.000	0.000	0.000	1
XVG	1.000	0.000	0.000	1
XWC	1.000	0.000	0.000	1
YOC	1.000	0.000	0.000	1

continued

Asset	Posterior Probability			Modal
	Cluster 1	Cluster 2	Cluster 3	
ZEIT	1.000	0.000	0.000	1
BLITZ	1.000	0.000	0.000	1
CLOAK	1.000	0.000	0.000	1
PIGGY	1.000	0.000	0.000	1
QWARK	1.000	0.000	0.000	1
SAFEX	1.000	0.000	0.000	1
SHIFT	1.000	0.000	0.000	1
START	0.995	0.005	0.000	1
STEEM	0.973	0.027	0.000	1
TROLL	1.000	0.000	0.000	1
USNBT	1.000	0.000	0.000	1

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