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Investigating Market Behavior Correlations between Classified Tokens using the International Token Classification Framework

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Abstract

This paper explores the novel International Token Classification framework, creates a large sample set of tokens classified according to the framework, clusters the tokens into groups, and performs statistical analysis regarding the selected token's correlation. It investigates how the current token landscape looks by classifying 200 tokens. These tokens are clustered in three different groups, payment token, DeFi ecosystem token, and network utility tokens. We first investigate whether tokens tend to move in the same direction with the tokens from their group, and secondly, we use a created average portfolio return to compare the single token return with the different groups.

According to the results, we mainly found utility and payment tokens from the IT and Finance industries. Out of the three groups, tokens clustered in the payment token group showed the highest correlations within the group and with their own group portfolio average. Overall, we conclude that the classification indeed has an impact on the relationship of token pairs. However, the results show that many more factors influence the market behavior of tokens, which should also be considered.

Keywords: Blockchain; token; correlation; classification; Bitcoin.

1. Introduction

More than ten years ago, a developer named Laszlo Hanyecz ordered two large pizzas from Papa John's and made history. Hanyecz used a novel digital payment method called Bitcoin, which is now known as the first transaction using cryptocurrencies to pay for a tangible product. At this time, Hanyecz paid 10.000 BTC for two pizzas, where each Bitcoin was worth way less than a penny (McCall, 2020; Moore, 2020). However, at the time of writing and the current exchange price for Bitcoin with over 45 thousand US Dollars (USD), he would be able to buy a tenth of the whole pizza chain Papa John's for 450 million USD (CoinMarketCap, 2021b; yahoo! finance, 2021). Since 2010 the market for cryptocurrencies and mainly the growth of the world's first cryptocurrency, Bitcoin, have gained more attention (Chen, 2018). However, the technology behind Bitcoin has many more use cases than only serving as a digital currency. For example, blockchain is already of great relevance for healthcare, the supply chain sector, and many more industries (Knight, 2017). Adding assets to a blockchain is referred to as tokenization, and the blockchain representation of that asset is called token (Roth, Schär, & Schöpfer, 2019; Schär, 2020). The rising market leads to a growing need for standardization in classifying a token (Sandner & Ketz, 2019).

This paper will give insights into the basic concepts of the token economy, the classification of a token, and how this can be done using the International Classification Framework (ITC) published by the International Token Standardization Association (ITSA) (Sandner, Ketz, Tumasjan, & Lentge, 2019). Finally, we will provide insights on how classified tokens correlate in terms of price regarding their classification. Over the last year's first research papers have investigated the cross-correlation between price changes of different cryptocurrencies (Stošić, Stosic, & Ludermir, 2018). As the subject of tokenization is still at an early stage, it should be

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mentioned that a lot of research, and sources are still distributed among tweets, forums and blog posts. Only a small part of the material is of academic origin. As the world has not yet decided on a standardized token classification framework, it is also new to the academic world. This paper adds value to the topic of a unique and standardized classification framework by providing a first sample set of tokens classified according to the ITC. Afterward, we will provide a strategy to build individual clusters using the classification and group tokens to perform statistical analysis regarding the token's price behavior. The results of this paper will create one of the first use cases for the ITC. All different stakeholders taking part in the token market, reaching from private users, investment managers, and regulators to academics, can use the classification of the tokens to identify specific patterns in the token market. According to the tokens classification, private users and investors can use the correlation analysis results for diversifying their token portfolio regarding the price movement of tokens.

2. Theoretical Background and Research Gap

Prior to the main work of the paper, including a deep dive into the classification work and the following quantitative empirical analysis of token market behavior, it is essential to give a brief introduction into blockchain technology, the token market, classification frameworks, as well as the use of correlation coefficients for time series data in the financial market.

2.1. Distributed Ledger Technology, Blockchain, and Bitcoin

In 2008, someone used the pseudonym Satoshi Nakamoto to publish the first conception of the digital currency Bitcoin. With that, he introduced a digital payment infrastructure with cryptographic proof instead of trusting centralized authorities (Nakamoto, 2008). The concept of distributed ledger technology (DLT) describes a technique used to document data or transactions. While in the classical approach of a ledger, a centralized authority manages the ledger. A distributed ledger has any number of identical copies of the ledger maintained in a decentralized manner by the different participating stakeholders. Although often used as synonyms, the DLT and blockchain are not the same. Blockchain, the technology known behind Bitcoin and Ethereum, is a specific implementation of the DLT. Blockchain got its name from the process of grouping transactions or other data into blocks and attaching those blocks to a chain of already verified blocks. A cryptographic signature called hash is used to connect the blocks. Appropriate measures called consensus mechanisms are used to ensure that newly added transactions are adopted in all copies of the ledger and that there is consensus on the ledger's current status at any given time (Drescher, 2017). After the used consensus algorithm validates the transaction, the transactions are irreversible, verifiable, permanent, and secure (Chen, 2018). The first ideas to use the concept of a blockchain go even back to 1991, where Haber and Stornetta (1991) introduced a computationally practical procedure to guarantee the unalterable digital time-stamping of documents (Haber & Stornetta, 1991). However, blockchain technology's real breakthrough came with the Bitcoin whitepaper in 2008 (Cong & He, 2019).

2.2. The Concept of Smart Contracts and Possible Use-Cases of Blockchain

Bitcoin and other digital cryptocurrencies like Litecoin serve as a virtual payment method and could potentially disrupt the financial industry (Böhme, Christin, Edelman, & Moore, 2015). Beyond the use-case of the digital payment functionalities of many blockchain applications called Blockchain 1.0, it is essential to introduce two more generations of blockchain. Blockchain 2.0, which covers the concept of smart contracts, mainly focuses on decentralized finance (DeFi) and finally Blockchain 3.0, which describes in the broadest sense all those use cases of the blockchain technology beyond the finance sector.

For this paper, it is essential to introduce a key concept called smart contracts, as they are among other things used to bring assets onto the blockchain. Smart contracts should firstly fulfill the same use case as a physical contract, but in the context of the blockchain, smart contracts are programmed computer scripts stored on a blockchain. However, unlike the classic physical contract that only defines specific rules and penalties related to an individual agreement between two parties, the smart contract also automatically executes once the requirements are fulfilled to minimize the external participation and, therefore, the risk of fraud by a third party. With the smart contract, it is now possible that everything noted in the contract, even though both participants do not trust or know each other, will automatically be executed (Christidis & Devetsikiotis, 2016).

With the continuous further development of the technology over the last years, many more industries than the financial sector showed interest in the new technology. For example, entrepreneurship, digital rights management, the public sector, the energy sector, the healthcare market, and the supply chain management are highly interested in the blockchain market (Casino, Dasaklis, & Patsakis, 2019; Hughes, Park, Kietzmann, & Archer-Brown, 2019; Knight, 2017). In the healthcare sector, a common problem is that data is stored inefficiently and centralized in local systems. Different stakeholders including the doctor, healthcare provider, the patient and insurance companies each store the data locally. Blockchain technology now offers the possibility of storing data anonymously on a blockchain network (Hughes et al., 2019). A specific use case was proposed by Ekblaw, Azaria, Halamka, and Lippman (2016), who introduced a decentralized electronic health records management system to overcome the problem of centralized stored patient data. Furthermore, one of the most affected industries will be the supply chain market, where blockchain will disrupt the market by providing detailed information about cost inefficiency. Perboli, Musso, and Rosano (2018) provided a specific use case of how blockchain can overcome exactly these hidden cost-inefficient structures and optimize logistic operations.

2.3. The Growing Concept of Tokens

After introducing blockchain technology and the smart contracts' basic concepts, this paper gives an overview of the concept of tokenization. In the beginning, the concept of tokens was reserved to the crypto asset, which was native to their respective blockchain, e.g., Ether for the Ethereum Blockchain or Bitcoin for the Bitcoin blockchain. But as the interest in the concept was rising, the idea was to store an asset onto the ledger, which is not native to the blockchain. The digital asset representation on the blockchain is called token, and the process of bringing the asset to the blockchain is called tokenization (Roth et al., 2019; Schär, 2020).

The concept of tokenization can now, for example, be used to digitize a famous drawing. Imagine a famous Picasso drawing worth one million USD. The number of people who are able to buy the painting is minimal. The painting's value is defined through ownership of the physical version that cannot be divided easily. By creating a token, each worth one USD, the drawing's value and ownership can now be distributed between an infinite number of people, each owning a small piece of the expensive drawing. Adding to the advantage of transferring fractional ownership as described, more advantages come along with the concept. Global access for investments from everywhere using a smartphone into different markets is allowed, and also, it has become much simpler to trade digital valuables thanks to the high level of liquidity. As soon as certain conditions are fulfilled, the smart contract automatically executes itself almost immediately, allowing real-time transactions. Because blockchain technology allows direct trades between buyers and sellers, intermediatory participants are reduced. Two more advantages that come with tokenization are the given transparency and the immutability the blockchain technology is providing. Not only is every transaction visible, but also impossible to change or delete a transaction once it is validated and added to the blockchain, which adds a very high-security standard to the transparency factor (Sazandrishvili, 2020).

Regarding the technical implementation of those tokens, often specific standards are set using smart contract templates. A famous example is the widely used standard called ERC-20 for the Ethereum blockchain introduced by Vogelsteller and Buterin (2015), which defines specific rules and functions that every token using the ERC-20 standard should implement. These technical standards can now be used to implement protocols, for example, on top of the Ethereum blockchain, which will later be referred to as application layer protocol. Protocol is

2.4. Token Classification Frameworks

While not only the token market is having its second renaissance in terms of total market capitalization, the variety of tokens offered is also increasing. This leads to a growing need for standardization in token classification as the market is currently still lacking a standardized way to distinguish between the nature of tokens (Sandner & Ketz, 2019).

However, before heading into specific different approaches of token classification, it is essential to distinguish between the term "token" and "coin". CoinMarketCap, as one of the most common market trackers, follows the rule that the term "coin" refers to all those assets which are native to a blockchain, e.g., Bitcoin, Ethereum, XRP. In contrast, the term "token" refers to those built on top of a blockchain and governed by smart contracts (CoinMarketCap, 2021a). Previous scientific research tends to agree on this distinction between "token" and "coin" or "cryptocurrency" using technical-based differentiation aspects (Chen, 2018; Massey, Dalal, & Dakshinamoorthy, 2017).

A second approach to differentiate between different crypto assets is the purpose of creation. The German Federal Financial Supervisory Authority called BaFin divides token into three subclasses payment-token, equity- and other investment token and utility token. Payment-token usually have the exclusive function of serving as a payment method, for example, Bitcoin. In the case of equity- and other investment token, the token holder gets provided with claims under debt law with monetary content and membership rights, similar to shares and securities. The subclass utility token covers tokens that are not designed to serve with payment functionalities across different ecosystems but to be used to purchase the token provider's real economic good (Fußwinkel & Kreiterling, 2018). The private consulting company Deloitte is certifying this division into payment, investment token, and utility token and is following a similar approach (Deloitte, 2019). The Swiss Financial Market Supervisory Authority (FINMA) also tends to agree on this diversification but labels the beforehand called investment token as asset token (FINMA, 2018).

A different approach, called The Token Classification Framework (TCF), has been developed by Euler (2018), who divided the classification into five major dimensions. The first dimension covers aspects of the token's primary purpose. This is in line with a previously made distinction regarding the term's token, cryptocurrency and investment token. A token can be a cryptocurrency to serve as a digital payment method, a network token to enable a specific network and speed up its growth, or an investment token to provide the opportunity to invest in an entity or an asset. The second dimension portraits the utility of the token. Here they divide into usage tokens, which should give access to the network or service feature and work tokens, allowing the token holder actively to participate in the system. A third dimension covers the legal status, whether the token should be treated as a cryptocurrency, a utility token, or a security token. The token's underlying value is covered in the fourth dimension of the framework, where the question is covered where the token derives its value. Here is a distinction made between asset-backed tokens, where the value comes from the asset the token is backed by, share-like tokens that would most likely be regarded as securities and network value tokens, where the token is tied to the value of a network. The last dimension covers the technological implementation of the token, whether it is implemented as the blockchain's native token token, on top of a different blockchain and therefore non-native-protocol token, or on the application level as (d)App token (Euler, 2018).

2.5. The International Token Classification Framework

After reviewing some of the different existing frameworks spread across the crypto asset market for this paper, the ITC will be used. The following chapter's information is obtained from the ITC questionnaire (Sandner et al., 2019) and the documentation (ITSA, 2020). The ITC published first in 2019 by ITSA is a new approach to classify crypto tokens in a standardized way. It was created to provide a flexible tool to classify a token that different market stakeholders can use. One of the framework's explicit goals is to provide clear and transparent characteristics for tokens in multiple different dimensions. Public institutions like central banks or governments can use the ITC to gain more in-depth knowledge about the token landscape. Private investors or investment funds active in the crypto space can use the framework to run detailed market analyses or diversify their investment portfolios by knowing about the token's classification.

The framework is designed to adapt continuously and is always open for further development. For the sake of retaining an overview, the framework is vertically split into levels. Level 1 is pointing to the highest level. In version 1.0, published in October 2020, the framework covers four so-called dimension groups (level 1). Each dimension group can have an infinite number of dimensions (level 2). At the framework's current, two out of four dimension groups cover more than one dimension. Figure 1 provides an overview of the existing dimensions.

Every dimension contains then different categories (level 3), which are then further divided into subcategories (level 4), classes (level 5), subclasses (level 6), groups (level 7), and finally subgroups (level 8). The ITC uses unique ITC codes for each level. A code consists of each level's individual level segment code's composition and therefore represents a hierarchical classification path. This paper will strictly stick to the code labels used and described in the ITC and the complementary documentation. To avoid confusion every time we talk about the classification label, we will provide the ITC Code of the token and write the label in capital letters, e.g., Utility Token (EEP22).

Table 1 provides a hierarchical overview of the vertical levels and how an ITC code is assembled, using the subclass USD-Pegged Payment Token (EEP21PP01USD). The framework's design was created to leave enough space for adding further subdivisions on every hierarchical level.

As the six different dimensions on the second-highest level are the fundamental concept of the ITC, we want to provide further information for each of the dimensions. A more detailed description of all levels below level two, the dimensions can be found in the ITC framework documentation (ITSA, 2020).

Economic Purpose (EEP): The first dimension of the ITC, called Economic Purpose (EEP), uses the same distinction into three different categories as the BaFin, Deloitte, and FINMA, which has been described in the previous chapter 2.4. Comparing it to the Token Classification Framework by Euler (2018), this dimension is in line and covers aspects of the TCF's three dimensions, the purpose, the underlying value, and the utility aspects of a token. The currently used categories are Payment Tokens (EEP21), Utility Tokens (EEP22), and Investment Tokens (EEP23). Regarding the classification Payment Token (EEP21), it is important to state that the token should serve in the same way as a real-world currency in different environments. Payment Tokens (EEP21) should most likely be compared to US Dollar, Euro, the Chinese Yuan, or any other currency. A special case of payment token which is covered by the dimension are the so-called Pegged Payment Tokens (EEP21PP), often in the literature referred to as stablecoins, which try to follow a particular stable peg (e.g., USD) (Klages-Mundt & Minca, 2020). The second category of the dimensions is Utility Token (EEP22). Utility Tokens (EEP22) are designed to be used within the given environment created by the issuer. Its utility functionality can reach from serving as an access voucher to the ecosystem to a specific economic good or functionality of the issuer or distributing rewards for ecosystem participants.

Furthermore, the category Utility Token (EEP22) covers those tokens which provide the token holder with a governance functionality or a particular ownership right. The last category within the economic dimension is Investment Token (EEP23) and can be compared to equity- and other investment tokens earlier introduced by the BaFin (Fußwinkel & Kreiterling, 2018). Investment Tokens (EEP23) include those tokens "that are designed to provide institutional and/or retail investors with an instrument for investment (incl. trading, speculation, and/or hedging)" (ITSA, 2020, p. 17). As previously stated, this category is often labeled in the market as "security token". The ITC avoids using the term "security token" as the term illuminates not the token's economic purpose but on its regulatory status (Sandner & Ketz, 2019).

Issuer Industry (EIN): The second dimension, which is also part of the Economic Dimension Group (E) called Issuer Industry (EIN), covers different industries the issuer of the token is active. It is important to emphasize that the industry of the issuer of the token is the crucial point to look at and not the industry where the token finds its primary use case.

Technological Setup (TTS): The dimension Technological Setup (TTS) covers the discussion previously held about whether to call a digital asset "token" or "cryptocurrency". The ITC disagrees with the previous research presented to use the term "coin" or "cryptocurrency" as it lacks a clear definition. Regarding the technological setup, the ITC splits into two categories. On the one hand, Ledger-Native Token (TTS41), "which captures every Token that is implemented by means of a Distributed Ledger Protocol and thus forms an integral part of such software protocol (incl. the consensus mechanism defined for the Distributed Ledger)" (ITSA, 2020, p. 21). And on the other hand the category Applica-

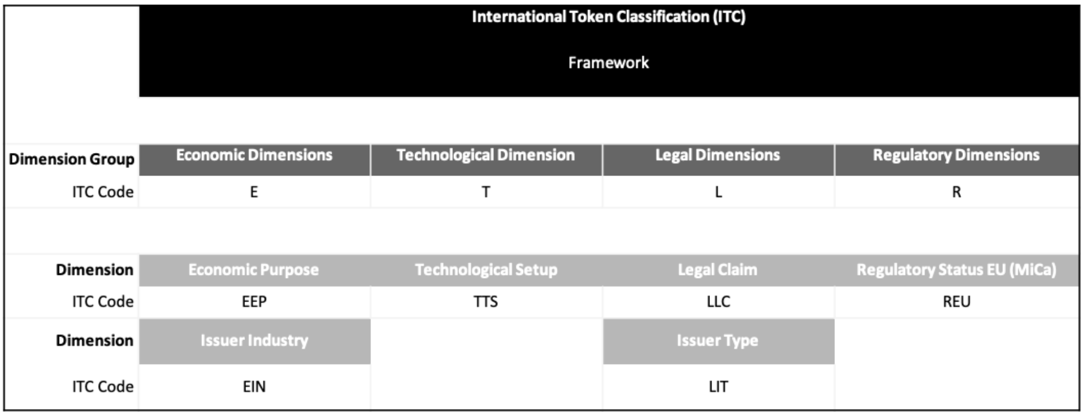

Figure 1: Dimension Overview of the ITC v1.0

Source: Own illustration based on (ITSA, 2020)

Table 1: ITC Code Composition Example for the Subclass "USD-Pegged Payment Token

Level	Level Label	Level Segment	Level Segment Code	ITC Code
1	Dimension Group	Economic Dimensions	E	E
2	Dimension	Economic Purpose	EP	EEP
3	Category	Payment Token	21	EEP21
4	Subcategory	Pegged Payment Token	PP	EEP21PP
5	Class	Fiat-Pegged Payment Token	01	EEP21PP01
6	Subclass	USD-Pegged Payment Token	USD	EEP21PP01USD
7	Group	[n/a]	[n/a]	[n/a]
8	Subgroup	[n/a]	[n/a]	[n/a]

Source: Own illustration based on (ITSA, 2020, p. 5)

tion Layer Token (TTS42), that "captures every Token that is implemented by means of an Application Layer Protocol on top of a Distributed Ledger" (ITSA, 2020, p. 22).

Legal Claim (LLC): The dimension Legal Claim (LLC) captures information on whether the token provides any legal rights to the token holder. At the current status of the ITC framework, this dimension needs to be treated with special caution. Many tokens manage their ecosystem in a decentralized nature, and often, no real third party exists where the legal claim could be raised against (Sandner & Ketz, 2019).

Issuer Type (LIT): The second dimension, Issuer Type (LIT) within the Legal Claim Dimension Group (L), covers information about the background of the token issuer. The dimension splits itself into two categories, one covering those where a legal entity behind the token can be found called Legal Entity (LIT61), and those types of issuers without a legal entity called Entity without Legal Personality (LIT62). A Legal Entity (LIT61) can be either be a Private Sector Legal Entity (LIT61PV), which covers companies or foundations issuing a token, or a Public Sector Legal Entity (LIT61PC) which refers to governments, central banks, or ministries. Token issuers, which are not clearly defined or stated in the official token documents, would fall under the category Entity without Legal Personality (LIT62). A further distinction here is whether the token is either issued by a distributed ledger directly, subcategory Distributed Ledger Protocols (LIT62DL), or is based on the distributed ledger of another protocol, which would then result in a classification into the subcategory of Application Layer Protocols (LIT62AL).

Regulatory Status EU (REU): The last dimension is the first dimension covering aspects of a token's regulatory status. This category is entirely based on the European Commission's proposal for a Regulation on Markets in Crypto Assets (MiCA) (European Commission, Directorate-General for Financial Stability, & Financial Services and Capital Markets Union, 2020). The MiCa regulation includes a description of the largest digital assets regulation as of to date and tries to provide detailed regulation rules for the entire crypto asset market (Sandner & Blassl, 2020). As the MiCa framework is still only a proposal and has not yet entered into force, it is essential to state that the dimension does not represent any official classification made by the European Commission. The ITC aims to test the potential applicability of the MiCa proposal even before it enters into force. With the category Crypto Asset in Scope of MiCA (REU51) tokens, which are either defined as Payment Token (EEP21) or Utility Token (EEP22) in the first dimension Economic Purpose (EEP) are covered. Investment Token (EEP23) are for now out of the scope of the MiCa and therefore falls under the second category Crypto Asset out of Scope of MiCa (REU52) of the dimension Regulatory Status EU (REU).

2.6. Price Correlation in the Token Economy and Research Gap

Correlation plays a crucial role in the traditional finance market and has been studied broadly in academic literature. Analysts and investment fund managers have used correlation analysis to diversify and allocate their assets across different sectors and industries. Using cross-correlation matrices allows dividing stocks into different subsets that are similar to previously identified business sectors. Identifying sectors can be useful to find an investment that can earn a return without increasing the risk (Gopikrishnan, Rosenow, Plerou, & Stanley, 2000). Due to the early stage, the market for crypto assets is in academic research regarding token price correlation is only very limited. Stošić et al. (2018) showed several collective behaviors in the crypto asset market, which can help construct a crypto asset portfolio. The literature is mainly focused on the correlation between Bitcoin and other assets such as Gold. Klein, Pham Thu, and Walther (2018) revealed that Bitcoin in shock-like moments does not negatively correlate with the market, and the price declines whenever markets are declining. Apart from the academic literature, Binance Research (2019c) suspects that the type of consensus algorithm impacts the token's price behavior. It seems that Proof-of-Work (PoW) tokens exhibit a higher correlation with each other than with non-PoW tokens indicating the impact of the technical setup of the token on the price. Another point mentioned in two different reports from Binance Research (2019b, 2020) is that programmable blockchains such as EOS, NEO, and Ethereum often have a higher correlation with each other than with non-programmable assets. As shown in a third report by Binance Research (2019a), payment token with a particular focus on privacy such as Monero or Dash shows higher than average correlations with each other compared to other tokens.

This paper will provide a sample set of tokens classified according to the new ITC v1.0 to help establish the ITC as a standardized way on how tokens should be classified. Afterward, we will use the unique dataset to build certain groups of tokens to investigate the token's price behavior. First, we will look at the correlations between tokens that are clustered in the same group. Secondly, we will investigate whether tokens correlate more with their groups than the groups they are not part of.

3. Methodology

The following chapter describes a three-step process used for this paper. A novel dataset has been created in the first step, where tokens are classified using the ITC framework introduced in chapter 2.5. Afterward, this classification data is used to create and cluster different groups of tokens according to their classification. Finally, by adding historical data of the grouped tokens, interesting correlation aspects are investigated. Each subchapter will include how the data is obtained and processed.

3.1. Classification of Tokens

In the first step in co-creation with the Project Working Group 2 – ITC (PWG2) of ITSA, a novel dataset is created. Approximately 200 tokens are analyzed and classified according to the before described ITC v1.0. The dataset, which includes the top 200 tokens according to market capitalization, is extracted from CoinMarketCap on November 29, 2020, at 1:00 pm and is sorted by the tokens market capitalization. To come up with a specific classification for the token, every token is first classified by three different participants of the PWG2 independently. Afterward, a consensus is found during a discussion with all members of the PWG2. To identify the classification for each token only official materials are used. This includes the tokens website, the whitepaper, and medium articles published by the token entity.

To follow a clear and unified line for the classification of a token according to the ITC, this paper follows the provided questionnaire and the classification guidelines provided by ITSA, which can be found in appendix A. We found additional guidelines during our work of classifying tokens, which we want to provide in this paper while remaining in line with the questionnaire and the previously defined guidelines by ITSA (ITSA, 2020; Sandner et al., 2019).

Suppose a Transactional Utility Token (EEP22TU) only provides access to the decentralized network or application that the token is implemented on and not to any additional service, product, or functionality within that network or application. In that case it will not classify as a Settlement and Access Token (EEP22TU02). However, it shall be classified as Settlement Token (EEP22TU01) as the provision of access to the decentralized network or application that the token is implemented on is considered to be a necessary prerequisite for its transactional functionality and not a functionality of its own.

Suppose a Utility Token (EEP22) is implemented as Blockchain-Native Token (TTS41BC), and the token is designed as an integral part of a Proof-of-Stake (PoS) consensus mechanism. In that case, the token will classify as Settlement and Governance Token (EEP22TU03) since the token provides governance functionality as part of the PoS consensus mechanism, which governs the distributed ledger. If a Utility Token (EEP22) is implemented as Application Layer Token (TTS42) and the application layer protocol assigns certain governance functionality to the token (e.g., voting rights), it will classify as Settlement and Governance Token (EEP22TU03). However, the Application Layer Token's classification does not depend on the type of consensus mechanism of the underlying distributed ledger.

Regarding the regulatory status of a token according to MiCA (Regulatory Status EU (MiCA)), the following rules apply:

1. If a token is classified as Utility Token (EEP22) with respect to its Economic Purpose (EEP), it will also classify

as Utility Token (REU51UT) with respect to its regulatory status in the EU (REU).

2. If a token is classified as Unpegged Payment Token (EEP21UP) according to its Economic Purpose (EEP), it will classify as Other Crypto Asset in Scope of MiCA (REU51ZZ), as the current version of MiCA does not feature a dedication definition for this category of tokens.
3. If a token is classified as Pegged Payment Token (EEP21PP) with respect to its Economic Purpose (EEP), it will either classify as E-Money Token (REU51EM) or as Asset-Referenced Token (REU51AR). Further information on the differentiation of both categories can be found in the Classification Questionnaires and/or the ITC Code Descriptions.
4. Whenever a token is classified as Investment Token (EEP23) according to its Economic Purpose (EEP), it will most likely classify as Crypto Asset out of Scope of MiCa (REU52).

Suppose a token provides access or governance functionality and is classified accordingly in the Economic Purpose (EEP) dimension. In that case, it does not necessarily imply that the token provides such functionality (e.g., access or voting rights) in the form of real relative rights against a counterparty, and hence it does not directly imply a classification as Relative Rights Token (LLC32). Each case has to be analyzed individually, and no generalizations can be made.

Regarding the classification of a "wrapped" version of a token, this paper follows a clear rule of thumb. As a wrapped version of a token helps to overcome the problem of interoperability between blockchains, one of the primary purposes is to represent the token on other blockchains to serve with payment functionalities, e.g., Wrapped Bitcoin. As its price is pegged to the original token, the token should always be classified as Asset Pegged Payment Token (EEP21PP02).

3.2. Token Groups according to the Token Classification

After classifying the top 200 tokens according to their market capitalization, it is important to build specific clusters to investigate correlation behavior. As the market for tokens is still in its early stage and projects are rising with very high speed into top positions regarding their market capitalization, this paper focuses only on tokens, which are classified and have a market capitalization of over 100 million USD. Out of the 99 remaining tokens, token groups are built. In the following section, we want to describe each group's requirements and if and why this group is included in the further analysis. The tokens grouping mainly focuses on the classification of the tokens regarding the Economic Dimension Groups (E) and the Technological Setup Dimension (TTS).

Group 1: Payment Token: The first group we are looking at is the so-called group payment token. The first condition for a token to be considered as a payment token is that the token is not only classified on a category level as a Payment Token (EEP21) but as an Unpegged Payment Token (EEP21UP). This is done to exclude the before introduced stablecoins. As their value is pegged to a particular value, mainly USD, stablecoins are in this paper not of relevance regarding the correlation of the tokens price. Also, we exclude all the wrapped versions of tokens. For example, Wrapped Bitcoin, the ERC-20 version of Bitcoin, is almost 100% correlating with Bitcoin due to its nature. The second condition for the group payment token is the Issuer Industry (EIN) of a token. A crucial factor is that the token issuer is active in the industry of Payment Services and Infrastructure (EIN06PS) or within the industry Cyber Security, Data Privacy and Digital Identity (EIN05DA04). This is done to include payment tokens focusing on privacy, as their focus is the privacy functionality, and are therefore not classified in the industry Payment Services and Infrastructure (EIN06PS) but still exist with the primary purpose to serve as a digital currency.

Group 2: DeFi Ecosystem Token: For our second group, we focus on all tokens active in the DeFi space. The group will include all classified tokens that fall under the subcategory Decentralized Finance (EIN06DF), including tokens from all different DeFi classes. We decided to look at the DeFi tokens as an aggregated group and not as further divided single groups to get a sufficiently large enough sample set.

Group 3: Network Utility Token: With the third group network utility token, we want to introduce a group of tokens serving as the native asset for their blockchain to power their own ecosystem. Regarding the classification in the Issuer Industry (EIN) dimension, we have to make sure that the token is classified as Cloud Computing, Distributed Systems, and Decentralized Applications (EIN05DA03). This class covers all tokens which are created to power a decentralized ecosystem such as Ethereum or Polkadot. All of these tokens are created to power their ecosystem created around their blockchain. The token has to be classified as some kind of Utility Token (EEP22) as the token should provide a specific type of utility within the defined environment. As the third criteria, the token has to be classified as Blockchain-Native Token (TTS41BC) regarding the Technological Setup (TTS) to make sure we only include tokens native to their own blockchain. An overview of the requirements and examples for the groups can be found in figure 2.

3.3. Correlation between Classified Tokens

The underlying dataset contains the token's historical price and is obtained from CoinGecko (2021), which is "a leading source of information on cryptocurrencies" (S. Wang & Vergne, 2017, p. 5) on January 27, 2021. For each token assigned to one of the before defined groups, we downloaded the token's price data for the last 90 days and calculated the token's daily arithmetic return. We used a short-term period of 90 days to ensure that we have the same data for each token. Some of the projects included in this analysis are very new to the market, e.g., Uniswap had its token launch only in September 2020. It is hard to compare with tokens such as Bitcoin that provide multiple years of price data. Furthermore, we follow the approach of Coinbase (2021), who are also using a time period of 90 days to calculate their correlation coefficients.

Group 1: Payment Token	***Group 2: DeFi Ecosystem Token***	***Group 3: Network Utility Token***
Requirements: Economic Purpose: Unpegged Payment Token (EEP21UP) Issuer Industry: Payment Services and Infrastructure (EIN06PS) / Cyber Security, Data Privacy and Digital Identity (EIN05DA04) Technological Setup: -	***Requirements:*** Economic Purpose: - Issuer Industry: Decentralized Finance (EIN06DF) Technological Setup: -	***Requirements:*** Economic Purpose (EEP): Utility Token (EEP22) Issuer Industry (EIN): Cloud Computing, Distributed Systems, and Decentralized Applications (EIN05DA03) Technological Setup (TTS): Blockchain - Native Token (TTS41BC)
Examples: Bitcoin, Litecoin, Bitcoin Cash	***Examples:*** Link, Uniswap, Aave	***Examples:*** Ethereum, Cardano, Polkadot

Figure 2: Requirements and Examples for the Token Groups

Source: Own illustration

As prices heavily differ in their total number, ranging from more than thousands of dollars to cents per token, it is vital to use returns instead of prices (Birch, Pantelous, & Soramäki, 2016; Meucci, 2010). We start by defining a return: r_i at the time *i*, where p_i is the price at the time *i* and $j = (i - 1)$:

$$r_i = \frac{p_i - p_j}{p_j}, \tag{1}$$

Using returns instead of raw price data comes with the benefit of normalization and is ubiquitous in finance. Due to the high differences in the absolute price of a token, it is unavoidable to normalize them to measure the price variable in a comparable metric. Besides, it is widespread in finance to use logarithmic returns instead of arithmetic returns, this paper sticks to arithmetic returns. This is possible as the considered timeframe is very short, and therefore, the logarithmic return does not significantly differ from the arithmetic return (Meucci, 2010).

3.3.1. Price Correlation within a Token Group

In a first step, we look at each previously defined group individually and compare each token within its own group. To do so, we use the pair-wise Pearson correlation coefficient between all pairs of daily returns. The Pearson correlation coefficient C_{ij} between the token *i* and *j* is defined:

$$C_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left\langle {r_i}^2 - \langle r_i \rangle^2 \right\rangle \left\langle {r_j}^2 - \langle r_j \rangle^2 \right\rangle}}, \tag{2}$$

where r_i and r_j are the token return vectors for token *i* and *j* respectively, and $\langle . \rangle$ is an average over the period investigated. For *n* tokens, the Pearson correlation matrix C is

$$C = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} \end{bmatrix}, \tag{3}$$

with all entries ranging from [-1,1], where -1 indicates a total negative linear correlation, 0 no linear correlation at all, and +1 total positive linear correlation. Correlation coefficients between 0 and 0.3 (0 and -0.3), can be interpreted as a weak positive (negative) linear relationship. If a coefficient has its value between 0.3 and 0.7 (-0.3 and -0.7) we talk about a moderate positive (negative) linear relationship and about a strong positive (negative) linear correlation for values between 0.7 and 1.0 (-0.7 and -1.0) (Ratner, 2009). As a correlation is symmetric, we will only show the lower triangular of the correlation matrix C (Birch et al., 2016; Orac, 2017; G. J. Wang, Xie, & Stanley, 2018).

3.3.2. Price Correlation between Token Groups

In a second step, this paper aims to compare correlation coefficients between the different groups. Therefore, we need to provide a way on how we can compare correlation coefficients. For each of our groups, we created a naive portfolio according to DeMiguel, Garlappi, and Uppal (2009), where each of the assets is weighted the same using a weight of *1/n*. We follow this simple approach of asset-allocation for the following reasons. Due to the ease of its implementations, we do not have to consider any optimization of the weighting process. Secondly, it is still widespread across investors to use simple allocation rules to diversify their portfolios (Benartzi & Thaler, 2001; DeMiguel et al., 2009). Compared to an approach where we would have used market capitalization as a weighting factor, we avoid that single assets like Bitcoin or Ethereum with an enormous market capitalization are dominating a whole group portfolio. As of January

11, 2021, Bitcoin and Ethereum together makeup 81.15% of the whole crypto market (CoinMarketCap, 2021a). The average return *gr* of a group portfolio *k* including *n* tokens with their return r_i is now defined as:

$$gr_k = \frac{1}{n}\sum_{1}^{n} r_i, \tag{4}$$

For this part of the analysis, we modify Equation (2), where the Pearson correlation coefficient C_{ik} now indicates the correlation between token *i* and group *k*.

$$C_{ik} = \frac{\left\langle r_i gr_k \right\rangle - \langle r_i \rangle \left\langle gr_k \right\rangle}{\sqrt{\left\langle {r_i}^2 - \langle r_i \rangle^2 \right\rangle \left\langle {gr_k}^2 - \left\langle gr_k \right\rangle^2 \right\rangle}}, \tag{5}$$

where r_i is the token return vector and gr_k is the average group portfolio return vector for token *i* and group portfolio *k*, respectively, and $\langle . \rangle$ is an average over the period investigated.

As each token we compare is included in one of the three groups, the token would automatically correlate with the group more than with other groups, only because the token itself is included in the group. Therefore, we always do not include the return of the considered token to calculate the average group of the tokens group. For example, looking at Bitcoin, we calculate the Payment Token portfolio's average group return while not including Bitcoin in the calculations. The group portfolio returns for Network Utility Tokens and DeFi Ecosystem Tokens remain untouched. The analysis will give us a matrix with three correlation coefficients C_{ik} per token for each of the defined groups. For all calculations, we used the python packages pandas and SciPy (The Pandas Development Team, 2020; Virtanen et al., 2020). The python script can be found in appendix B.

4. Results and Discussion

The following chapter will describe the obtained results in the same structure as the previous chapter regarding the paper's methodology. We will start with descriptive statistics on the top 200 tokens classified, followed by presenting the token groups and the statistical investigations' results of the statistical investigations regarding the token's price behavior.

4.1. Classification of the Top 200 Tokens

The full dataset including, the classification data of each token included in the top 200 list that was created in joint work with the project working group 2 of ITSA, can be found in appendix C. We only need the two economic dimensions and the technological setup dimension for the further grouping of tokens. Therefore, we only provide descriptive statistics about the Economic Purpose (EEP), the Issuer Industry (EIN), and the Technological Setup (TTS) in the appendix. Highlights are stated in the following sections. The results are sorted according to the ITC framework and only include the lowest level applicable if at least one token has been classified.

Economic Purpose: Looking only into the level of categories out of 200 classified tokens, 170 are Utility Tokens (EEP22), which makes a utility token dominance of 85%. 28 and correspondingly 14,0% are Payment Token (EEP21), and only 2 out of 200 tokens are classified as Investment Token (EEP23). While looking closer into the observed Payment Token (EEP21), we found mainly Unpegged Payment Tokens (EEP21UP) such as Bitcoin or Litecoin and USD-Pegged Payment Token (EEP21PP01USD) such as Tether or USD Coin. Payment tokens pegged to a different fiat currency have only rarely been found, with one token classified as EUR-Pegged Payment Token (EEP21PP01EUR).

Those tokens that fall under the category Utility Token (EEP22) do most likely serve with a mean of transaction settlement within the defined environment by the token's issuer and are therefore classified as Transactional Utility Token (EEP22TU) on a category level. The subcategory is divided into three classes. Those tokens that serve within the defined environment only with the means of transaction settlement (Settlement Token (EEP22TU01), 35 token). Or the transaction settlement functionality combined with access to a particular service, good or functionality (Settlement and Access Token (EEP22TU02), 37 token). The third option, Settlement and Governance Token (EEP22TU03), 90 tokens, combines not only the transaction settlement and access functionality but adds also a governance functionality. To cover the Non-Transactional Utility Token (EEP22NT), we find three tokens classified as Access Token (EEP22NT01) and nine tokens classified as Governance Token (EEP22NT02). A detailed breakdown of the classification can be found in appendix D.

Issuer Industry: Regarding the Issuer Industry (EIN), the dataset is dominated by two Categories. 46% of the tokens can be classified in the category Information, Communication and IT (EIN05) and 46% in the category Finance and Insurance (EIN06). Considering the subcategory level, mainly three subcategories are containing a significant amount of all tokens, Software, Data Storage and Processing (EIN05DA) with 41.5% of all 200 tokens, Payment Services and Infrastructure (EIN06PS), with 17.5% and the Decentralized Finance (EIN06DF) with 18.5%. A detailed breakdown of the classification numbers can be found in appendix E.

Technological Setup: While analyzing the technological setup of the top 200 tokens, the first thing we notice is that the total number of tokens is 209 instead of 200. This is due to the technological implementation of the following seven tokens, Tether, UNUS SED LEO, Binance USD, TrueUSD, Chiliz, Serum, and ShareToken, that exist on more than one blockchain. For example, the token Tether is implemented on four different blockchains. Tether has parallel running versions of the token on the four different blockchains Ethereum, Omni, EOS, and Tron. Regarding the distribution of the tokens, mainly two classifications are dominant. 46,41% of the tokens under consideration are Blockchain-Native Tokens (TTS41BC), and 42,58% are Ethereum ERC-20 Standard

Tokens. A detailed breakdown of the classification numbers can be found in appendix F.

Regarding the three additional dimensions, we want to provide some insights without going into further detail. In the Legal Claim Dimension (LLC), we only find two different classifications. One hundred ninety-three tokens do not provide any legal claim, while only seven tokens provide some relative rights and are, therefore, classified as Relative Rights Token (LLC32). Regarding the Issuer Type (LIT) Dimension out of the top 200 tokens, 156 are classified as Private Sector Legal Entity (LIT61PC), 29 as Distributed Ledger Protocol (LIT62DL), and 15 as Application Layer Protocol (LIT62AL). In the last dimension, Regulatory Status EU (MiCa) of the ITC, tokens are classified according to the MiCa. Eight tokens are classified as Non-Authorized Significant E-Money Token (REU51EM12), 169 as Utility Token (REU51UT), 22 as Other In-Scope Crypto Assets (REU51ZZ), and one as Crypto Asset out of Scope of MiCa (REU52)

4.2. Correlation between Classified Tokens

For the following chapter, we look at each of the beforehand defined groups individually. We first present the groups, followed by the correlation coefficients between each token and those clustered in the same group. In the last step, we compare each token with the beforehand created group portfolio returns. We repeat the process for each of the groups. A whole list of the three groups with the tokens they contain and their corresponding tickers, which we will use, can be found in the in table 2.

Group 1: payment token: The first group covers all privacy focuses, and non-privacy focused tokens, which are created to serve as a digital payment method. The group covers a total number of 13 tokens, including the most popular token, Bitcoin, Litecoin, or Monero. As previously mentioned in this paper's methodology part, so-called stablecoins are not included in the category as they are not relevant for this correlation analysis. Regarding the correlation within this group, we find that Bitcoin only shows a strong positive linear relationship with Litecoin. The highest observed correlation coefficient is between Bitcoin Cash and Bitcoin SV with 0.851. Bitcoin Cash also is the only token showing four strong positive linear relationships, followed by Zcash and Bitcoin Diamond with three. Especially low correlation coefficients are found for Dogecoin with eight weak, four moderate, and no strong positive linear relationships within the token group. A detailed list of all correlation coefficients between each of the token pairs can be found in table 3.

We observe that five of the 13 tokens show a strong positive linear relationship with their own group portfolio. Bitcoin Cash shows the highest correlation with 0.839 and Dogecoin the lowest with 0.345, which supports our findings from before. The eight remaining tokens all show a moderate positive linear relationship. For twelve of the 13 payment tokens, we find a moderate positive linear relationship with the DeFi ecosystem token portfolio. Only Dogecoin with a coefficient of 0.2380 shows a weak positive linear relationship. Looking at the correlation between the single tokens and the third group, network utility tokens, we observe two tokens, Litecoin and Zcash showing a strong positive linear relationship with the group portfolio. The remaining tokens are indicating a moderate positive linear relationship. Furthermore, we can see that eleven out of 13 correlate the most with the payment token portfolio. Only Litecoin and Decred correlate more with group 3: network utility tokens while showing a minimal difference in the coefficient. Table 4 shows the correlation coefficients between each of the payment tokens and the three portfolios.

It is also notable that we only see positive linear relationships between all the single token pairs and the correlations between the payment tokens and all of the portfolios.

Group 2: DeFi Ecosystem Token: Our second group includes all tokens active in the DeFi space. A total number of 17 out of the 99 tokens which we considered are from the DeFi ecosystem. This group includes six tokens classified as Decentralized Exchanges, Markets and Market Making (EIN06DF01) such as Uniswap, five tokens in the space of Decentralized Lending, Saving and Asset Management (EIN06DF02), e.g., AAVE. Two tokens are classified as Decentralized Derivatives, Synthetic Assets and Insurance (EIN06DF03), three tokens as Decentralized Data, Oracles and Infrastructure (EIN06DF04), and one token as Other Decentralized Finance (DeFi) (EIN06DF05). Regarding the Technological Setup (TTS), this group mainly consists of tokens implemented on top of the Ethereum blockchain. Looking into the correlation coefficients between the single token pairs within this group, we only find five strong positive linear relationships between the following pairs: Link and 0x, Link and Band Protocol, Aave and Uniswap, SNX and Aave and 0x and Ravencoin. All other relationships between the single token pairs are mainly moderate positive or sometimes weak positive. The token CEL, which powers Celsius's asset management platform, shows mainly weak positive linear relationships with the other tokens. CEL has eight correlation coefficients within the group are below 0.300, and the highest being 0.513. A detailed listing of the correlation coefficients is provided in table 5.

Regarding the correlation between the groups, eight out of 17 DeFi ecosystem tokens show the highest correlation with their own group compared to the other portfolio groups. In contrast, eight show the highest correlation with the portfolio of group 3 network utility tokens. Only Maker shows the highest correlation with group 1 payment tokens portfolio. While six DeFi ecosystem tokens show a strong, eleven show a moderate positive linear relationship with the own portfolio. We find mostly moderate positive linear relationships between the single DeFi ecosystem tokens and the payment token portfolio. Only the token of Ravencoin shows a strong positive relationship, while the tokens of SushiSwap and AAVE show only weak positive linear relationships with the payment token portfolio. We find six strong and eleven moderate positive linear relationships looking into the correlations between the DeFi ecosystem tokens and the network utility token portfolio. Again, we only see positive linear relationships between all single token pairs and the correlations

Table 2: Token Groups according to the Classification

Token Group	Name	Ticker
Group 1: Payment Token	Bitcoin	BTC
	Bitcoin Cash	BCH
	Litecoin	LTC
	Bitcoin SV	BSV
	Monero	XMR
	Dash	DASH
	Zcash	ZEC
	Dogecoin	DOGE
	Decred	DCR
	Bitcoin Gold	BTG
	Nano	NANO
	Verge	XVG
	Bitcoin Diamond	BCD
Group 2: DeFi Ecosystem Token	Chainlink	LINK
	Uniswap	UNI
	Aave	AAVE
	yearn.finance	YFI
	Celsius	CEL
	Maker	MKR
	Synthetix Network Token	SNX
	UMA	UMA
	Compound	COMP
	0x	ZRX
	Loopring	LRC
	SushiSwap	SUSHI
	Kyber Network	KNC
	Augur	REP
	THORChain	RUNE
	Band Protocol	BAND
	Ravencoin	RVN
Group 3: Network Utility Tokens	Ethereum	ETH
	Cardano	ADA
	Polkadot	DOT
	EOS	EOS
	TRON	TRX
	Tezos	XTZ
	NEM	XEM
	NEO	NEO
	Cosmos	ATOM
	Ethereum Classic	ETC
	Waves	WAVES
	Kusama	KSM
	Algorand	ALGO
	DigiByte	DGB
	Zilliqa	ZIL
	Ren	REN
	Qtum	QTUM
	ICON	ICX
	Hedera Hashgraph	HBAR
	NEAR Protocol	NEAR
	Lisk	LSK
	Blockstack	STX
	Horizen	ZEN

Source: Own illustration.

Table 3: Return Correlation between Payment Tokens

Platform	BTC	BCH	LTC	BSV	XMR	DASH	ZEC	DOGE	DCR	BTG	NANO	XVG	BCD
BTC	1.000												
BCH	0.535	1.000											
LTC	0.745	0.681	1.000										
BSV	0.373	0.851	0.475	1.000									
XMR	0.474	0.510	0.462	0.323	1.000								
DASH	0.414	0.647	0.493	0.458	0.761	1.000							
ZEC	0.453	0.707	0.575	0.553	0.713	0.842	1.000						
DOGE	0.428	0.352	0.371	0.251	0.220	0.205	0.249	1.000					
DCR	0.569	0.327	0.491	0.222	0.247	0.215	0.313	0.326	1.000				
BTG	0.539	0.743	0.539	0.679	0.505	0.650	0.671	0.222	0.323	1.000			
NANO	0.393	0.378	0.407	0.178	0.170	0.289	0.413	0.095	0.304	0.389	1.000		
XVG	0.486	0.540	0.463	0.380	0.310	0.524	0.527	0.261	0.380	0.441	0.710	1.000	
BCD	0.247	0.705	0.303	0.757	0.483	0.605	0.562	0.196	0.114	0.721	0.071	0.280	1.000

Source: Own illustration.

Table 4: Correlation between single Payment Token Returns and Group Portfolio Returns

Token	Payment Token Portfolio	DeFi Ecosystem Token Portfolio	Network Utility Token Portfolio
Bitcoin	0.6725***	0.5790***	0.5054***
Bitcoin Cash	0.8391***	0.7578***	0.6515***
Litecoin	0.7025***	0.7027***	0.6674***
Bitcoin SV	0.6335***	0.5822***	0.5274***
Monero	0.5763***	0.5238***	0.4214***
Dash	0,7042***	0.5822***	0.4294***
Zcash	0.7786***	0.7272***	0.6110***
Dogecoin	0.3449***	0.3072**	0.2380*
Decred	0.4461***	0.4826***	0.4258***
Bitcoin Gold	0.7596***	0.6334***	0.5453***
Nano	0.4517***	0.4437***	0.3946***
Verge	0.6697***	0.5985***	0.4658***
Bitcoin Diamond	0.5561***	0,4565***	0.4209***

Source: Own illustration. Note: Pearson correlation coefficients with significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$.

between the DeFi ecosystem tokens and the portfolios. The detailed correlation coefficients can be found in table 6.

Group 3: Network Utility Tokens: Our last group covers the largest set of tokens. A total number of 23 tokens have been assigned to the network utility token group, including tokens like Ethereum, Cardano, and Polkadot. Throughout this group, we mostly find correlation coefficients that indicate a moderate positive linear relationship. However, two tokens show almost only weak positive linear relationships throughout the whole group, Blockstack, and Hedera Hashgraph. Also, it is notable that the correlation coefficient between Blockstack and Hedera Hashgraph is the only one that is negative and shows a weak negative linear relationship between the two tokens. The tokens with the most correlation coefficients indicating a strong positive linear relationship are Lisk and Tezos, with nine correlation coefficients over 0.700. In table 7, we can find the detailed correlation coefficients.

Looking into the correlation between the single network utility tokens and the different portfolio returns in table 8, we observe that 16 out of the 23 tokens correlate the most with their own portfolio. Thirteen of the tokens show a strong while 10 show a moderate positive linear relationship. The correlations between the single tokens with the payment and the DeFi ecosystem token portfolio show mainly moderate positive linear relationships. For the native asset of the Ethereum blockchain ETH, we discover that it shows the

Table 5: Return Correlation between DeFi Ecosystem Token

Platform	LINK	UNI	AAVE	YFI	CEL	MKR	SNX	UMA	COMP	ZRX	LRC	SUSHI	KNC	REP	RUNE	BAND	RVN
LINK	1.000																
UNI	0.527	1.000															
AAVE	0.484	0.732	1.000														
YFI	0.377	0.536	0.655	1.000													
CEL	0.361	0.390	0.243	0.288	1.000												
MKR	0.600	0.417	0.308	0.297	0.275	1.000											
SNX	0.465	0.578	0.751	0.458	0.352	0.436	1.000										
UMA	0.408	0.382	0.259	0.352	0.297	0.262	0.270	1.000									
COMP	0.507	0.613	0.556	0.339	0.375	0.502	0.506	0.350	1.000								
ZRX	0.802	0.584	0.521	0.433	0.344	0.638	0.551	0.445	0.581	1.000							
LRC	0.447	0.418	0.495	0.364	0.224	0.316	0.531	0.324	0.398	0.574	1.000						
SUSHI	0.435	0.637	0.616	0.515	0.237	0.266	0.480	0.280	0.399	0.472	0.275	1.000					
KNC	0.664	0.478	0.387	0.328	0.221	0.524	0.379	0.419	0.502	0.625	0.306	0.365	1.000				
REP	0.564	0.392	0.345	0.441	0.379	0.521	0.422	0.484	0.432	0.645	0.338	0.315	0.517	1.000			
RUNE	0.614	0.617	0.669	0.483	0.513	0.428	0.609	0.432	0.571	0.670	0.531	0.582	0.450	0.482	1.000		
BAND	0.717	0.494	0.498	0.479	0.280	0.379	0.444	0.404	0.507	0.626	0.413	0.445	0.685	0.476	0.534	1.000	
RVN	0.667	0.475	0.361	0.390	0.406	0.569	0.452	0.439	0.568	0.790	0.466	0.365	0.655	0.668	0.568	0.612	1.000

Source: Own illustration.

Table 6: Correlation between single DeFi Ecosystem Token Returns and Group Portfolio Returns

Token	Payment Token Portfolio	DeFi Ecosystem Token Portfolio	Network Utility Token Portfolio
Chainlink	0.6364***	0.7544***	0.7795***
Uniswap	0.4283***	0.7506***	0.6057***
Aave	0.2843**	0.7337***	0.5049***
yearn.finance	0.4514***	0.6055***	0.4947***
Celsius	0.4269***	0.4443***	0.4580***
Maker	0.6842***	0.5688***	0.5773***
Synthetix Network Token	0.3945***	0.6986***	0.5324***
UMA	0.4695***	0.4964***	0.5299***
Compound	0.5443***	0.6781***	0.6077***
0x	0.6737***	0.8195***	0.8305***
Loopring	0.3627***	0.5625***	0.5057***
SushiSwap	0.2621*	0.6023***	0.4418***
Kyber Network	0.5820***	0.6431***	0.7513***
Augur	0.6782***	0.6319***	0.7413***
THORChain	0.4641***	0.7875***	0.6476***
Band Protocol	0.5393***	0.6975***	0.7386***
Ravencoin	0.7324***	0.7300***	0.7929***

Source: Own illustration. Note: Pearson correlation coefficients with significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$

highest correlation with our DeFi ecosystem group portfolio.

Looking at the results of the different groups, we also find more general results. First, it is worth mentioning that we only see positive linear relationships between the single token pairs besides one exception. Another finding was that network utility tokens that are indicating a strong positive linear relationship between the token return and the portfolio return of its own group often also show a high correlation coefficient with the other group portfolio returns, e.g., Ethereum, EOS, and Lisk. This also holds true for the other two groups, DeFi ecosystem token group, e.g., Link, and the payment token group, e.g., Ravencoin, Bitcoin Cash.

4.3. Discussion

During the classification efforts of the top 200 tokens according to market capitalization, we have mainly seen tokens classified as Utility Token (EEP22) and Payment Token (EEP21) regarding the Economic Purpose (EEP) dimension. An explanation for this could be that tokens that fall under the category Payment Token (EEP21) were the first tokens issued, followed by the tremendous rise of utility token initial coin offerings in 2017 and early 2018 (Howell & Niessner, 2020). Regarding the Issuer Industry (EIN) dimension, we found mainly token issuers in the industries of Information, Communication and IT (EIN05) and Finance and Insurance (EIN06). As the concept of tokenization is still very new and we looked at the largest projects in terms of market capitalization, we expect to find more projects from different industries in the future while looking at projects with lower market capitalization. As a lot of the tokens in our list are the native assets to run their blockchain, we found many Blockchain-Native Token (TTS41BC). The second dominating group was the widespread Ethereum ERC-20 Standard Token (TTS42ET01), which is not only the most spread token standard of the most prominent blockchain but also most of the tokens from our large DeFi ecosystem token group are implemented as an Ethereum ERC-20 Standard Token (TTS42ET01). During the screening of the token market, we also made an interesting finding regarding the tokens that are active in the DeFi space. The project behind the token describes itself often decentralized many of the tokens are classified as Private Sector Legal Entity (LIT61PV) regarding the Issuer Type (LIT). For example, the token Link, Uniswap, or SushiSwap are issued by a registered company and are therefore not entirely decentralized.

The group of payment tokens showed the highest correlations between the single tokens and between the tokens and the group portfolio returns. As previously described, we have found almost only positive linear relationships. A potential reason for that could be the rise of the total market during the time period we used. Another interesting finding was that tokens like Dogecoin, Hedera Hashgraph, or Blockstack that show mainly weak positive linear relationships within the group also show weak positive linear relationships with the three portfolio groups. We also found that the density of positive linear relationships was higher within the payment token group than in the other two groups.

Table 7: Return Correlation between Network Utility Tokens

Platform	ETH	ADA	DOT	EOS	TRX	XTZ	XEM	NEO	ATOM	ETC	WAVES	KSM	ALGO	DGB	ZIL	REN	QTUM	ICX	HBAR	NEAR	LSK	STX	ZEN
ETH	1.000																						
ADA	0.720	1.000																					
DOT	0.505	0.524	1.000																				
EOS	0.660	0.721	0.424	1.000																			
TRX	0.679	0.631	0.384	0.880	1.000																		
XTZ	0.682	0.703	0.492	0.776	0.782	1.000																	
XEM	0.404	0.479	0.223	0.556	0.532	0.515	1.000																
NEO	0.644	0.604	0.322	0.701	0.751	0.802	0.537	1.000															
ATOM	0.507	0.604	0.599	0.617	0.597	0.765	0.424	0.616	1.000														
ETC	0.720	0.615	0.420	0.741	0.818	0.775	0.480	0.787	0.563	1.000													
WAVES	0.455	0.525	0.296	0.445	0.424	0.513	0.271	0.493	0.417	0.462	1.000												
KSM	0.442	0.496	0.728	0.418	0.439	0.482	0.297	0.427	0.570	0.430	0.328	1.000											
ALGO	0.558	0.647	0.433	0.681	0.623	0.764	0.543	0.605	0.586	0.597	0.459	0.498	1.000										
DGB	0.578	0.445	0.325	0.584	0.603	0.516	0.401	0.574	0.390	0.596	0.270	0.328	0.513	1.000									
ZIL	0.327	0.406	0.355	0.329	0.340	0.386	0.374	0.308	0.422	0.327	0.227	0.332	0.434	0.522	1.000								
REN	0.654	0.649	0.561	0.612	0.577	0.675	0.435	0.527	0.608	0.556	0.474	0.476	0.682	0.401	0.397	1.000							
QTUM	0.570	0.620	0.445	0.760	0.741	0.810	0.491	0.766	0.595	0.736	0.460	0.472	0.695	0.513	0.342	0.544	1.000						
ICX	0.604	0.721	0.442	0.706	0.673	0.641	0.507	0.634	0.613	0.600	0.365	0.459	0.669	0.474	0.482	0.578	0.631	1.000					
HBAR	0.224	0.294	0.258	0.218	0.173	0.222	0.143	0.164	0.134	0.188	0.134	0.256	0.297	0.184	0.132	0.385	0.239	0.447	1.000				
NEAR	0.431	0.455	0.457	0.554	0.509	0.554	0.297	0.437	0.542	0.448	0.300	0.488	0.571	0.394	0.281	0.551	0.487	0.461	0.422	1.000			
LSK	0.661	0.711	0.479	0.793	0.821	0.764	0.614	0.742	0.612	0.780	0.509	0.542	0.702	0.638	0.423	0.653	0.752	0.719	0.337	0.540	1.000		
STX	0.256	0.125	0.067	0.223	0.189	0.221	0.168	0.218	0.135	0.141	0.105	0.194	0.275	0.232	0.024	0.248	0.127	0.181	-0.083	0.116	0.171	1.000	
ZEN	0.321	0.415	0.148	0.432	0.500	0.511	0.405	0.585	0.308	0.507	0.267	0.151	0.387	0.353	0.233	0.276	0.429	0.493	0.152	0.351	0.457	0.160	1.000

Source: Own illustration.

Table 8: Correlation between single Network Utility Token Returns and Group Portfolio Returns

Token	Payment Token Portfolio	DeFi Ecosystem Token Portfolio	Network Utility Token Portfolio
Ethereum	0.7326***	0.7555***	0.7444***
Cardano	0.6569***	0.6985***	0.7846***
Polkadot	0.4210***	0.5058***	0.5753***
EOS	0.7899***	0.7165***	0.8228***
TRON	0.8418***	0.6786***	0.8105***
Tezos	0.7143***	0.7933***	0.8652***
NEM	0.4914***	0.4729***	0.5768***
NEO	0.8031***	0.6897***	0.7849***
Cosmos	0.4961***	0.6703***	0.7268***
Ethereum Classic	0.8278***	0.6906***	0.7849***
Waves	0.4591***	0.5697***	0.5188***
Kusama	0.4507***	0.5569***	0.6030***
Algorand	0.5471***	0.7920***	0.7962***
DigiByte	0.6854***	0.5240***	0.6269***
Zilliqa	0.3480***	0.4109***	0.4724***
Ren	0.5478***	0.7412***	0.7509***
Qtum	0.7072***	0.6720***	0.7828***
ICON	0.6018***	0.6641***	0.7916***
Hedera	0.1852**	0.2750**	0.3175
NEAR Protocol	0.4748***	0.6221***	0.6298***
Lisk	0.8271***	0.7585***	0.8704***
Blockstack	0.2102*	0.2748**	0.2127*
Horizen	0.4612***	0.3593***	0.4894***

Source: Own illustration. Note: Pearson correlation coefficients with significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$

5. Conclusion

The last chapter of the thesis summarizes the classification work, the results on the investigated tokens price correlations, highlights the theoretical and practical implications, points out the limitations, and discusses future research opportunities for this topic.

5.1. Summary

This paper intends to provide a large sample set of classified tokens according to the ITC and how dependencies in the market can be identified. We created a dataset containing the top 200 tokens according to market capitalization using the introduced additional classification guidelines. Looking into the top 200 tokens according to market capitalization, we mainly find Utility Tokens (EEP22). Secondly, we find that most of the token issuers are from the industries of Information, Communication and IT (EIN05) and Finance and Insurance (EIN06). We created token groups only according to the obtained classification data and used a simple approach to create our own group portfolio returns. Using the classification dataset and the obtained groups, we found exciting dependencies between tokens while taking the classification of the token into account. We computed the correlation coefficients between the single token pairs within those groups and between the groups using the group portfolio returns. To some extent, we found that the token's classification indeed can explain some of the correlation between tokens, as the tokens show very high correlation within the groups and with the introduced average of their own portfolio.

5.2. Theoretical and Practical Implications

This paper expands the current state of research regarding the classification of a token and introduces a practical use case for the classification framework. We have reviewed different classification approaches and highlighted that the ITC covers most of the aspects that the other classification approaches are describing. The introduced additional guidelines can help further research to classify tokens according to the ITC and should be considered. The created dataset can be used by further research to investigate the token market more in detail. Also, literature can use the sample set as an indicator of how tokens should be classified. Regulators or governments can use the approach of ITSA and the dataset to differentiate between the tokens while introducing laws for the token market. Investors can use the dataset and the correlation computations results to construct new analysis and investment strategies while knowing which assets tend to move in the same direction. Due to the wide range of information the dataset provides, people interested in a specific field such as DeFi space can now use the information to gather information, whether the project behind the token is entirely decentralized or if there is a hidden company behind the project. As the token market is very new to most traditional investors, they can use the dataset to overview the current token landscape and find their potential investment target. Every person interested in the token economy can now search for a specific kind of token and compare it to a completely different one. For example, using the dataset, it is now possible to compare an Utility Token (EEP22), issued by a Private Sector Legal (LIT61PV) active in Decentralized Finance (EIN06DF) and implemented as an Ethereum ERC-20 Standard Token (TTS42ET01) to the native asset of the Ethereum blockchain ETH.

5.3. Limitations and Further Research

Due to the limited length of the paper, some aspects are not covered in more detail, such as the results of the three more applied dimensions or the correlation between single tokens and market-dominating tokens like Bitcoin or Ethereum. As this paper is one of the first scientific papers using the ITC, we covered fundamental statistical analysis instead of using more advanced methods. Furthermore, it is essential to note that we only have used 90 days of price data to calculate the correlation coefficients. As the market is currently volatile, it is not predictable what the correlation will be in a year, a month, or even a week while looking only at a short-term data set. Even during this paper's working time, some tokens dropped out of the top 200 tokens according to market capitalization, while many new tokens entered. The positive correlation we have observed in this paper may also have occurred by chance but should be analyzed again after the market provides consistent data for a longer time frame. A second limitation that should be mentioned is the equally weighted portfolio we have applied to compare single assets with a whole group. This was done to avoid a portfolio constructed, for example, by market capitalization, which would be entirely dominated by single assets such as Bitcoin for our first Group payment token or Ethereum for the second group Network Utility Token. However, a more advanced strategy to construct a real index for a group should be considered and applied. The third limitation we want to mention is the current bull market in which we currently are. The analysis should be repeated in a somehow different market, such as a bear or a stable market. Therefore, more research is necessary to evaluate whether the classification impacts the price behavior of a token. As we have seen in this paper's results, ETH shows the strongest linear relationship with the DeFi ecosystem token group portfolio. At the same time, we have discovered that the DeFi ecosystem token group portfolio mainly consists of Ethereum based tokens. Therefore, an exciting research topic could be to see whether tokens implemented on top of a blockchain tend to move together with the native asset.

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