

GREY FLOWLESS, OR PREDICTING CAPITAL OUTFLOWS IN CRYPTOCURRENCY

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Abstract: *Globalization and irrational capital distribution have fuelled global financial crises. Illicit transactions on a global scale worsen financial challenges, limiting government spending on public services. Amid these challenges, blockchain technology and cryptocurrencies have emerged as potential solutions. Due to anonymity public identification through “keys”, some scholars argue that cryptocurrencies create an opportunity for misuse as an easy tool for money laundering, tax evasion and illegal activities. This study investigates the relationship between illicit finance flows and cryptocurrency markets, utilizing grey systems theory and grey relational analysis. Drawing samples from 41 states with the highest cryptocurrency trade volumes, the research reveals nuanced dynamics within the cryptocurrency market, shedding light on the connections between cryptocurrencies, shadow activities, and capital outflows. The findings contribute valuable insights to the ongoing discourse on the impact of cryptocurrencies on global financial stability. The intricate exploration of these interconnections underscores the need for a comprehensive understanding of the role cryptocurrencies play in shaping the contemporary financial landscape.*

Keywords: *Globalization, Illicit finance flows, Cryptocurrency markets, Grey systems theory, Financial stability*

INTRODUCTION

Even though relevant national policies and international regulation are in place, lack of transparency and corruption, especially in developing countries, reduce effectiveness of these practices in stimulating financial stability, resulting in tax evasion and growth of criminal activities (Fanusie & Robinson, 2018). This means, that centralized financial systems and state power have proven insufficiency in combating illicit activities. Therefore, the need in searching for new systems and tools which could better deal with existing challenges greatly increases. One of such innovative systems was brought to economic world through invention of blockchain systems and its application in trade transactions through cryptocurrencies, offering higher efficiency and transparency for financial transactions. According to European Commission, cryptocurrencies contribute to the establishment of ‘trust between two mutually unknown and unrelated parties to such extent that sensitive and secure transactions can be performed with full confidence over an open environment, such as the Internet’. This solution has introduced a new economy, namely ‘crypto economy’.

In the early 1990s physicists Stuart Haber and W Scott Stornetta published the first paper to outline the use of a chain of cryptographically secured blocks to preserve the integrity of past information to protect it. This paper was followed by the subsequent seminal whitepaper “Bitcoin: A Peer-To-Peer Electronic Cash System” in 2008 by Satoshi Nakamoto (a group of people), where the scholars described the financial transactions that can be made through the use of blockchain systems, adding practical value to previous research in this area.

Cryptocurrency is the largest primary application of blockchain technology and is recently experiencing an unprecedented rise with market capitalization surpassing in 2018 \$335b (Bright, Koskinen, & Malm, 2019).

In academic literature, opinions on the long-term existence of cryptocurrencies are separated, however several key applications have been identified by several sources. For instance, report of the UK Government (Lerner, 2003) states that blockchains have the capacity to 'reform our financial markets, supply chains, consumer and business-to-business services, and publicly-held registers'.

One of the key scientific opinions in this area is the analysis of Babbitt and Dietz (Babbitt and Dietz, 2014), which define cryptoeconomy regardless of 'geographic location, political structure or legal system, but using cryptographic techniques to constrain behavior in place of using trusted third parties'. Foundational principles of the blockchain technology are cryptography, smart contracts, distributed consensus and system architectures.

As a novel financial concept cryptocurrency is anticipated to remove inefficiencies identified in the financial industry, such as overcentralisation, too many intermediaries, unwillingness to delete or change historic records, tracking issues and others, adding more practical value of the current research due to the need to get a more informed perspective of how well cryptocurrency is performing with regard to transparency of financial transactions.

Cryptocurrency has demonstrated tremendous growth over last years, and the volume of trade transactions in cryptocurrencies multiplies every quarter (Broséus et al., 2016). The key advantages of cryptocurrency comparing to its precedents is its decentralized, or distributed nature. Unlike other forms of money, crypto money is not a promissory note issued by states or their central banks, rather it is a speculative code issued by individual miners (Brown, 2016; Glaser et al., 2014). Use of cryptographic signatures and smart contracts and peer-to-peer networks, which form the heart of cryptocurrency distributed consensus systems allows from the one hand, confidentiality for the financial transactions, while on the other hand, transparency and credibility in financial interactions and operations.

Cryptocurrency is a revolutionary form of money, and by its functions and nature significantly differ from all other forms of money ever existed. Cryptocurrency deliver key monetary functions deriving from its nature as described by the main relevant theories of commodity, debt (credit) and fiat theories of money.

Cryptocurrencies proved successfully delivering store of value function of money, ensuring transparency of transactions made in this currency and parties of these transactions accountable for their content. However, on the other hand, even though trade transaction both on national and international level continue to expand by means of cryptocurrencies which can be used for provisioning trade supply, the integrated distributed ledger still fails with carrying mean of exchange function, compared to its alternatives, namely national fiat currencies.

Although, crypto market continues to grow and saturate both from technical and economic viewpoints with progressively increasing number of currencies mined over the world (Mukhopadhyay et al., 2016; Corbet et al., 2020), number of arguments and misinterpretations around the concept of cryptocurrencies also boosts in the academic literature (Lee et al., 2019; Farrugia et al., 2020; Alvarez, 2018). Majority of debates around the impact of cryptocurrency are possessed on the state of shadow and illegal activities and capital outflows from one country to another. Further development and expansion of trade transactions using cryptocurrency creates the concerns around the nature and governance issues associated with this currency.

Existing debates among economists on governance and regulation of cryptocurrency can be resolved by describing the technical nature of this phenomenon (Irwin & Turner, 2018; (Yermack, 2013; Brière, Oosterlinck, & Szafarz, 2013; Brito, Shadab, & Castillo, 2014; Buchholz et al., 2012). Unlike the centralized or decentralized systems, shared and distributed data structures or ledgers, or blockchains, can securely store digital transactions without using a central point of authority, blockchain platforms instead of a single trusted center management, allow each individual network member within a distributed network of digital users to hold a copy of the records' chain and partner on the valid state of the ledger with consensus, safeguarding integrity of the ledger. New transactions are linked to previous transactions by cryptography which makes blockchain networks resilient and secure.

Despite overarching interest of international agencies towards revealing and measuring trade using cryptocurrencies, assessment of cryptomarket maturity by states remains challenging task for global cryptocurrency researchers and scholars (Lee et al., 2019, Farrugia et al., 2020; Alvarez, 2018; Hileman & Rauchs, 2017). Very few methodologies consider cryptocurrency markets maturity in a complex context, paying attention to mainly volume and number of transactions made in these endogenous currencies. However, while internet users continue safely to transact on the internet, international organizations should ensure crime finance, including three-dimensional rendering (source of funds, ways of transferring the funds and use of funds) is not flowing through this channel (Jacquez, 2016).

According to existing views on cryptocurrencies (Brezo and Bringas, 2012), due to anonymity public identification through "keys", cryptocurrencies create an opportunity for misuse as an easy tool for money laundering, tax evasion and illegal activities. In the broadest form, illicit financial flow cover illicit activities, in particular the provision of services or the production, sale, possession or use of goods forbidden by law, including the illicit production and trafficking of drugs, the illicit manufacturing of and trafficking in firearms, trafficking in persons, and money laundering, as defined in the relevant international treaties. (C.Williams, 2018). Many researchers (Farrugia et al., 2020; Brown, 2016; Bichler, Malm, & Cooper, 2017) define international financial flows in four main categories in accordance with the activities, generating these transactions, and point out inefficiencies of current financial systems and need of decentralized systems. According to analysis of Decker et al, financial institutions establish trust through audit process (Möser & Narayanan, 2019), proposing a software-based audit of bitcoin exchanges. This way financial institutions eliminate state and private intermediary actors, such as auditors, replacing latter with software relying on trusted computing.

There are studies that have been already carried out about illicit financial flows within crypto market (Liu & Tsyvinski, 2018; Liu, Tsyvinski, & Wu, 2019; Brezo & Bringas, 2012), however, majority of them are based on application of mathematical and statistic techniques to estimate cryptocurrency market maturity. Furthermore, the empirical results of research carried up to date lacks consideration of many supplementary factors, impacting market maturity and development. Therefore, the purpose of the research is to provide scientifically based and empirically proven evidence to hypothesis on existence of relation between the two concepts, one of which reflects an economic power (Liu & Tsyvinski, 2018), while another one impedes international equality and sustainability.

The current research is grounded on two fundamental theories. First, quantity theory of money defines the key factors, impacting scale and maturity of cryptocurrency as a broad term, introduced as money and successfully delivering key money functions, such as store of value,

and ideally medium of exchange. Quantity theory of money describes the value of money using its key parts, namely money supply, its velocity and demand for money. According to the quantity theory of money, cryptocurrency market maturity was identified based on the cryptocurrency market cap (money supply), cryptocurrency velocity (transaction volume divided by cryptocurrency market cap) and demand for cryptocurrency.

To analyse cryptocurrency components in the most inclusive way, we used a grey system theory approach, which is broadly applied to decentralized systems' research (Broséus et al., 2016; Bichler & Malm, 2013; Farrell, 2015), such as cryptocurrency. Being interdisciplinary, grey system approach can explain the complex relationships between the elements of cryptocurrency as a multifaceted system of different elements, since decentralized systems need "a whole systems perspective, including levels, spheres, sectors and functions and seeing the community level as the entry point at which holistic definitions of development goals are from the people themselves and where it is most practical to support them. It involves seeing multi-level frameworks and continuous, synergistic processes of interaction and iteration of cycles as critical for achieving wholeness in a decentralized system and for sustaining its development" (UNDP, 2021).

As major part of grey system theory, grey relational analysis was applied during the research since the cryptocurrency system is comprised from the elements with novel features and limited information available. Application of grey relational analysis is driven by several reasons. First, the current research deals with huge amount of uncertain information, especially the one, related to illicit capital flows (Kuo, Yang, & Huang, 2008). Second, being very complex and uncertain, illicit finance flows require examination of its elements before making assessment and predictions of the system as a whole. Through application of grey relational analysis, a complex umbrella series with observable and latent variables in face of cryptocurrency was produced and analysed and further examined to have a link with the level of illicit financial flows (Holz et al., 2020), constructed by GFI (GFI, 2018). After grey relational research is completed and grades are obtained, we are comparing the grey coefficients against globally applied illicit finance flow estimations in order to reveal the possible correlation between these two concepts.

Finally, we conducted relational analysis of different social, political and economic exposure and development criteria of sustainable development of nations in order to answer the fundamental question of the research and examine the relationship between cryptomarket maturity of the countries and the state of their illicit finance flows.

RESEARCH METHODOLOGY

The current study, based on grey systems theory application, aims to scientifically reveal the grey relational coefficients of different criteria, which describe the maturity of the cryptocurrency, and examine impact of cryptocurrencies on the state of illicit trade with the existing information gaps. Selection of criteria of cryptocurrency system is grounded on the key components of currency system in accordance with the quantitative theory of money.

The theory of grey relational analysis is nowadays broadly used in many different areas, including finance markets performance analysis, money markets and economic analysis. It was first introduced (Deng, 1982; Deng, 1989) as a response to gaps and incompleteness of research data related to the studies of actual problems, including illicit and illegal economic activities. The scholar introduced grey elements and relations to express the level of trust to the source of

research information in any area and explained the behavior of mechanisms using grey clustering. Linking social and natural science through framing mathematical models for quantitative analysis with uncertain and incomplete information, grey relational analysis aims to help with decision making using multiple variables and factors. Unlike the other methodologies, applied to measure and estimate cryptomarket maturity, our methodology involves grey system theory and grey system analysis, which is not a statistical method. The reason for using grey system is a significant complexity of statistical methods and quite a large number of causes of illicit financial flows, which obscures the calculations and at high risk of creating chaotic datasets with huge discrepancies.

To successfully implement the proposed research, we used the following methodological approach:

1. Based on quantity theory of money we defined the key components of cryptocurrency and developed a list of key criteria, that contribute to market maturity and saturation: cryptocurrency market cap (money supply), cryptocurrency velocity (transaction volume divided by cryptocurrency market cap) and demand for cryptocurrency. Our data was constructed upon eight key features, which broadly reflect key currency market indicators, applied to crypto type of money. Based on the criteria, the cryptocurrency dataset was created for 41 countries with the largest number of cryptocurrency traders in the world.
2. Using grey system theory approach, which is broadly applied to decentralized systems' research (Broséus et al., 2016; Bichler, Malm, & Cooper, 2017; Farrell, 2015), such as cryptocurrency, we adopted grey relational analysis, since the cryptocurrency system embraces elements with novel features and limited information available, e.g. this is a system with grey parts. Interdisciplinary grey system methodology successfully explains complex relationships between the elements of multidimensional decentralized cryptomoney system. We adopted the grey relational analysis to our cryptocurrency dataset with multiple variables describing cryptocurrency market environment in order to identify the maturity of cryptocurrency markets. Within this framework we construct the decision matrix, grey relational coefficients and identify the ranking of the countries by cryptomoney market maturity.
3. We have completed multiple regression analysis in order to answer the fundamental question of the research and examine the relationship between cryptomarket maturity of the countries and the state of their illicit finance flows in a more sophisticated way using latent variables, such as level of political and economic exposure. Therefore, after grey relational research is completed and grades are obtained, relational analysis was conducted by comparing the grey coefficients against globally applied illicit finance flow estimations in order to reveal the possible correlation between these two concepts. We then matched the result of grey relational coefficients to the list of countries with the level of illicit finance flows to reveal the correlation possible. To study the relationship between crypto market capitalization and illicit financial flows data collection approach is based on data points obtained from Global Finance Institution, World Bank, UN Comtrade, CoinMarketCap and DataWorld databases. We selected countries and ranked them by following criteria:
 - i. Crypto market maturity identified for the country X
 - ii. Illicit Financial Flow of the country X identified as per the UN data using trade misinvoicing tools and techniques
 - iii. Social, political and economic exposure and development criteria of sustainable development of nations.

The following steps were conducted during the grey relational analysis:

- I. The evaluation matrix was produced based on the information collected on the key criteria, describing the maturity of cryptomarkets.
- II. We then develop our standard series with the target values of selection criteria in our decision making model. This series will identify our reference points in the decision making problem.
- III. After creating our matrix with 41 countries and 8 attributes of crypto markets we perform grey normalization in order to be able to compare the country series for each attribute. The values in the normalized series will be in the interval from 0 to 1. We apply three traditional methods of normalization to our data. For attributes, where higher is better for a selection criterion, or attribute, we apply the following calculation:

$$x_{i^*}(k) = \frac{x_i(k) - \min_k x_{i^*}(k)}{\max_k x_{i^*}(k) - \min_k x_{i^*}(k)}$$

where, $\min_k x_{i^*}(k)$ is a minimum value as per selection criteria I in the decision matrix,

$\max_k x_{i^*}(k)$ is a maximum value as per selection criteria I in the decision matrix

For attributes, where lower value is more desired for selection criteria, we used the following procedure:

$$x_{i^*}(k) = \frac{\max_k x_{i^*}(k) - x_i(k)}{\max_k x_{i^*}(k) - \min_k x_{i^*}(k)}$$

For selection criteria with a given desired value within the evaluation matrix, we perform the following method:

$$x_{i^*}(k) = 1 - \frac{|x_i(k) - x_0(k)|}{\max \{ \max_k x_i(k) - x_0(k); x_0(k) - \min_k x_i(k) \}}$$

where $x_0(k)$ is a desired value of alternative (country) k

- IV. Once the normalized sequence is ready, we calculate the deviation sequence as an absolute difference between reference sequence and comparable sequences. This action is performed for further obtainment of Grey Relational coefficient.

So, we subtract normalized decision matrix values and standard series values and get an absolute value of this subtraction equation, as indicated below:

$$\Delta_{0i}(k) = |x_{i^*}(k) - x_{0^*}(k)|$$

$$\begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \Delta_{01}(5) \\ \Delta_{02}(1) & \Delta_{02}(2) \cdots & \Delta_{02}(5) \\ \vdots & \vdots & \vdots \\ \Delta_{12}(1) & \cdots & \Delta_{12}(5) \end{bmatrix}$$

- V. Once the concluding matrix is ready, we identify grey relational coefficients of attribute k for alternative I (country)

$$y(x_0(k), x_i(k)) = \frac{\Delta_{min} + \zeta * \Delta_{max}}{\Delta_{0j} - \zeta * \Delta_{max}}$$

Where Δ_{max} refers to the highest value in the deviation sequence, Δ_{min} represents the lowest value in the difference sequence

y is the grey relational coefficient, and ζ is an adjustment coefficient between Δ_{0j} and Δ_{max} , which belongs to an interval from 0 to 1.

For the purposes of the current research we used ζ equal to 0.5.

VI. Based on grey relational coefficients we construct the grey factor matrix:

$$\begin{bmatrix} y_{01}(1) & y_{01}(2) & y_{01}(5) \\ y_{02}(1) & y_{02}(2) \cdots & y_{02}(5) \\ \vdots & \vdots & \vdots \\ y_{12}(1) & \cdots & y_{12}(5) \end{bmatrix}$$

VII. and finally, we identify our grey relational grades. Grey relational grade displays the similarity between the normalized decision matrix and the standard series. Similarity increases as the grey relational grade increases, and therefore the highest similarity gives the best alternative in the decision making challenge. If the importance levels of the selection criteria in the decision making problem are equal, the grey relational grade is calculated as

$$\tau(X_0, X_i) = \frac{1}{m} + \sum_{k=1}^{12} y(X_0(k), X_i(k))$$

However, with different importance levels of attributes in the decision making problem, a different equation is used:

$$\tau(X_0, X_i) = \sum_{k=1}^{12} y(X_0(k), X_i(k)) * W_i(k)$$

where $W_i(k)$ is a weighted value of the selection criteria i .

For the purposes of the current research, we have proportionally distributed the value among all the criteria.

RESULTS

As mentioned above, traditional grey relational analysis procedure was adopted to assess the level of cryptocurrency market maturity. Within this framework we construct the decision matrix.

First, using grey relational analysis we evaluate maturity and performance of cryptocurrencies in the countries and then compare this to the state of IFF. Selection criteria of our evaluation matrix is built upon a set of attributes for selected countries with the largest share of cryptotraders in the total amount across the globe. As a result, 41 economies were selected, namely China, United_States, Japan, United_Kingdom, India, Canada, Hong_Kong, Australia, Brazil, Switzerland, Russia, Mexico, Saudi_Arabia, Singapore, Sweden, Poland, Malaysia, United_Arab_Emirates, Vietnam, Turkey, Chile, Norway, Philippines, South_Africa, Denmark, Czech_Republic, New_Zealand, Pakistan, Morocco, Colombia, Romania, Hungary, Nigeria, Argentina, Peru, Ukraine, Kazakhstan, Kenya, Dominican_Republic, Croatia, Tanzania.

The following criteria was selected for alternatives (scenarios):

- ❖ Cryptocurrency trading volume in 2020, mln USD
- ❖ Share of trading volume in M2 broad money supply
- ❖ Average trading value per user

- ❖ Number of cryptoowners
- ❖ Share of cryptoowners in total population
- ❖ Legal Status of Cryptocurrencies
- ❖ Regulatory Framework for Cryptocurrencies: (Application of Tax Laws, Anti-Money Laundering/Anti-Terrorism Financing Laws, or Both)
- ❖ Countries that have or are in the process of issuing their own national or regional cryptocurrency

We then develop our standard series with the target values of selection criteria in our decision making model. This series will identify our reference points in the decision making problem. We have applied normalization to our data due to measurement differences of the criteria selected.

Since there is no standard of what should be the value of our preferred reference $x_0(k)$, when creating a normalized comparable sequences, the reference sequence was chosen from given original values of comparable sequences. Since all criteria have “the higher – the better” characteristic, target values for each of our criteria/sub criteria is selected as max values among all countries observed.

Since as mentioned the values in the evaluation matrix had “the higher – the better” characteristic, the normalized values were calculated using the following formula from Part 2. Research Data and Methodology:

$$x_{i^*}(k) = \frac{x_i(k) - \min_k x_{i^*}(k)}{\max_k x_{i^*}(k) - \min_k x_{i^*}(k)}$$

For example, the attribute “Cryptousers_Share_Of_Population” for United_States was obtained as follows:

$$0.489429 = (6,46 - \text{MIN}(\text{RANGE} \text{” Cryptousers_Share_Of_Population”}))/(\text{MAX RANGE} \text{” Cryptousers_Share_Of_Population”} - \text{MIN RANGE} \text{” Cryptousers_Share_Of_Population”})$$

The other values have also been calculated in the similar way.

After normalized table is ready, deviation sequence can be calculated as a difference between reference (target) value and comparable sequence.

To calculate the absolute value of the difference between the target, or reference, value and comparable sequence, we applied the following formula

$$\Delta_{0i}(k) = |x_{i^*}(k) - x_{0^*}(k)|$$

For example, “legal status of cryptocurrencies” for Japan was calculated as follows:

$$\Delta_{03}(3) = |x_{3^*}(3) - x_{0^*}(3)| = |1 - 0.06104752| = 0.93895248$$

We applied the similar calculation for all countries and for each criterion to produce the table shown above. This formula shows how far the values of comparable sequences are from the values of target sequences. If the difference values are close to 0, it means that the comparable sequence values are close to the reference sequences, or target values. And vice versa, if the difference values near to 1, it means that the comparable values are far from the desired target value.

After difference sequences are ready, we used these values to calculate grey relational coefficients. Our adjustment coefficient ζ between Δ_{0j} and Δ_{max} was chosen as 0.5.

$$y(x_0(k), x_i(k)) = \frac{\Delta_{min} + \zeta * \Delta_{max}}{\Delta_{0j} - \zeta * \Delta_{max}}$$

For instance, to calculate the grey relational coefficient average transaction value per user for Vietnam, we applied the following formula:

$$y(x_0(5), x_{12}(5)) = \frac{\Delta_{min} + 0.5 * \Delta_{max}}{\Delta_{0\ 12} - 0.5 * \Delta_{max}}$$

To obtain the respective grey relational coefficient, we need to obtain first the highest and the lowest deviation values in the range of country values for criteria average transaction value per user:

$$\begin{aligned} \Delta_{min} &= 0 \\ \Delta_{max} &= 1 \end{aligned}$$

Once the minimum and maximum deviation values are known, grey relational coefficient average transaction value per user for Vietnam is calculated as follows:

$$y(x_0(5), x_{12}(5)) = (0+0.5*1)/(0.989898+0.5*1) = 0.335593$$

Similarly, we obtain the other grey relational coefficients.

After grey relational coefficients are calculated, we can obtain grey relational grades by using the following equation:

$$\tau(X_0, X_i) = \sum_{k=1}^{12} y(X_0(k), X_i(k)) * W_i(k)$$

For the purposes of the current research, the importance of each criteria was selected equal. Grey relational grades represent the correlation between target sequence and comparable sequence and are equal to weighted sum of the values in Table 4. Therefore, the best performance of cryptomarket is selected for the alternative (country) with the highest correlation.

For instance, grey relational grade for the United Kingdom is calculated as follows:

$$\tau(X_0, X_4) = \sum_{k=1}^5 y(X_0(5), X_4(5)) * 0.2$$

As explained above, the weighted share was selected equal for each alternative, therefore it is equal to 0.2.

We have further ranked the grey relational grades of the countries from the greatest to the lowest cryptomarket performance comparison.

The next part of the data analysis includes comparison of grey relational grades against illicit finance flows, obtained from GFI database (GFI, 2018).

Country	Grey Relational Grade	Grey Grade Ranking	IFF	IFF Ranking
China	0.448831432	19	19.63	9
United_States	0.686291986	1	11.4	28
Japan	0.505328468	9	9.8	29
United_Kingdom	0.477219137	15	8.5	30
India	0.397895939	35	19.5	10
Brazil	0.443099532	23	16.5	23
Russia	0.541745724	3	19.3	11
Mexico	0.426950805	29	14.46	25
Saudi_Arabia	0.35338034	39	22.44	5

Poland	0.44396952	22	17.21	21
Malaysia	0.42871459	28	23.63	3
United_Arab_Emirates	0.351959316	40	25.16	1
Vietnam	0.440385873	25	16.68	22
Turkey	0.425403132	30	20.85	6
Chile	0.438397895	26	12.12	27
Philippines	0.433298612	27	24.24	2
Pakistan	0.354855142	38	17.65	17
Morocco	0.341208134	41	19.26	12
Colombia	0.392753582	36	16.4	24
Romania	0.444768525	21	19.94	8
Hungary	0.418705121	34	18.13	15
Nigeria	0.503408115	10	17.88	16
Argentina	0.459646585	17	13.61	26
Peru	0.44188191	24	18.87	14
Ukraine	0.489868532	13	19.96	7
Kazakhstan	0.423399111	31	17.35	19
Kenya	0.494064616	12	22.62	4
Dominican_Republic	0.4448156	20	17.37	18
Croatia	0.419351586	33	17.3	20
Tanzania	0.373909933	37	19.11	13

We have applied color coding to the rankings of the respective alternative both in grey relation grades and IFF ranking to visualize the results of the correlation analysis.

The first part of the research is completed successfully by obtaining the grey relational coefficients, however, when comparing to the IFF level in the selected states, direct neither positive nor negative relationship between maturity of cryptocurrency market and illicit financial trade can be concluded.

For this reason, we have included analysis of latent variables, such as political and economic exposure and culture index into our research. We have selected political freedom scores issued on annual basis by the Freedom House agency (Freedom House, 2021), which is an updated and most comprehensive dataset from all researched broken down by countries. Another advantage of freedom scores dataset of Freedom House Inc. is that this index includes not only political but also social integration of the states, based on its methodology (Freedom House, 2021). At the same time, appreciating cultural differences of the selected states, we have chosen a culture index dimensions, namely, power distance, individualism, masculinity and uncertainty avoidance indexes into our research. Cultural dimensions are based on 6D Model of national culture (Hofstede, 1984; (Hofstede Insights, 2020) introduced in Hofstede's Cultural Dimensions Theory by Hofstede G. et al in 1980. Subsequently, Gross Domestic Product (GDP) per capita was chosen to demonstrate economic development of the states. The data was obtained from World Bank on the latest year available in the World Bank Databank (The World Bank, 2019).

We further applied the multiple linear regression analysis to our dataset to identify the relationship between illicit financial flows and set of independent variables, including crypto grey relational grades and selected above freedom scores, national cultural dimensions and GDP per capita. Our independent variables include observed variable of grey relational grades as well as latent variables of GDP per capita, political and social integration level and selected cultural dimensions, namely power distance index, masculinity index, uncertainty avoidance index and individualism index. Mentioned cultural dimensions are considered to be the most powerful when choosing the mechanisms of financial management by economic agents.

The summary output of our research returned the following statistical results.

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<i>Regression Statistics</i>	
Multiple R	0.802753
R Square	0.644412
Adjusted R Square	0.531271
Standard Error	2.740324
Observations	30

The result of the research shows statistical significance as per the 30 values for 7 variables observed:

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	19.87653	5.785131	3.435797	0.002361	7.878906	31.87416	7.878906	31.87416
Grey Coefficient, CryptoMaturity	-13.5859	9.022759	-1.50573	0.146359	-32.2979	5.126177	-32.2979	5.126177
Freedom Score	-0.04505	0.023592	-1.90965	0.069304	-0.09398	0.003874	-0.09398	0.003874
GDP per capita	4.77E-06	3.97E-05	0.120137	0.905465	-7.8E-05	8.72E-05	-7.8E-05	8.72E-05
IDV (INDIVIDUALISM)	0.009488	0.048773	0.194534	0.847543	-0.09166	0.110637	-0.09166	0.110637
PDI (POWER DISTANCE INDEX)	0.119966	0.040255	2.980165	0.006905	0.036483	0.203449	0.036483	0.203449
MAS (Masculinity)	-0.02005	0.038262	-0.52407	0.605469	-0.0994	0.059298	-0.0994	0.059298
UAI (Uncertainty Avoidance Index)	-0.02014	0.026632	-0.75631	0.457484	-0.07537	0.035089	-0.07537	0.035089

Our data fits the model by 81%. The regression model result of our ANOVA test is given below:

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	7	299.3942	42.7706	5.695625	0.000749
Residual	22	165.2063	7.509378		
Total	29	464.6005			

As shown above, our regression model returns strong F significance score, proving the relevance of our hypothesis on the correlation between illicit finance flows and cryptomarket maturity. As stated in the beginning of our research, we also used our proxy indicators, which strengthened our research.

DISCUSSIONS

The current study was conducted to determine if development of novel endogenous cryptocurrencies can influence countries' likelihood to impact capital outflows. According to existing views on cryptocurrencies (Brezo and Bringas, 2012), due to anonymity public identification through "keys", cryptocurrencies create an opportunity for misuse as an easy tool for money laundering, tax evasion and illegal activities.

It was hypothesized that anonymity of public identification keys creates a space for violence, increasing scale of money laundering, tax evasion and illegal activities, predicting high level of capital outflows.

To test the hypothesis, research methodology including grey relational and multiple regression analysis was used. We first applied grey relational analysis to evaluate maturity of cryptotrader at 41 states with the highest number of cryptotraders and returned their grey relational coefficients in cryptocurrency maturity. Based on the grey relational coefficients obtained for cryptocurrency maturity, we developed a new dataset comprising cryptocurrency, socio-economic and illicit trade factors across the 30 states, with available data on research

criteria. Multiple regression analysis was adopted to determine the relationship between these factors. Our data fit the multiple regression model by 81%, which is quite strong evidence of the relationship between mentioned factors. Result shows that 53.12% of the variance in illicit finance flows can be accounted by the set of cryptocurrency maturity and socio-economic predictors, collectively, $F(7,22) = 5.6956$ $p < 0.001$.

Looking at the unique individual contributions of predictors, the result shows that economic indicator, such as GDP per capita, and cultural indexes, namely Individualism and Power Distance Index, positively predict illicit financial flow level.

Furthermore, result also reveals that those countries which have high rate of transactions in cryptocurrency, freedom scope, masculinity and uncertainty avoidance are more likely to report low level of illicit finance flows.

This suggests that use of blockchain systems in monetary transactions can be considered a more transparent system, adding value to the state of global trade relationships not only by less bureaucracy and intermediaries involved, but also higher transparency and simplicity.

Having central idea of decentralization, these distributed systems however provide total security and confidentiality, being transparent. Without a central authority within this network, blockchains establish trust through consensus and cryptography. Cryptography is used to shift the burden of trust from intermediaries (such as banks, financial and govern institutions) to cryptographic algorithms, and constructing and analyzing protocols that prevent third parties or the public from reading private messages. Cryptography provides techniques for keeping information secret, for determining that information has not been tampered with, and for defining who authored process of information. It is based on techniques related to aspects of information security such as confidentiality, data integrity, entity authentication, and data origin authentication. Cryptography is not the only means of providing information security, but rather one set of techniques. From the other hand, cryptocurrency development can positively impact the quality of international financial transactions, reducing not only transaction costs, but also reducing the illicit financial flows, as revealed by the research results. However, use of AML/KYC and other regulations relevant to transactions with cryptocurrency has an important role to bridge the gaps within trade operations with cryptocurrency that might potentially cause illicit financial outflows.

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