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How economic freedom reflects on the Bitcoin transaction network

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Abstract

Based on the assumption that economic freedom facilitates the growth of traditional economic sectors, this study seeks to understand the role it plays in fintech sector. For this purpose, by adopting the social network analysis methodological approach, it considers the geographical network of Bitcoin transactions as a proxy to measure the national level of fintech development and compares it with a set of economic freedom indicators related to the top 70 world economies. The analysis revealed significant relationships between the performed network centrality measures and national levels of economic freedom. In particular, as confirmed by the implemented multilevel regression models, high levels of freedom to trade internationally combined with a restrained value of inflation and low administrative requirements can be considered as determining factors for fintech development. The study also showed a large number of Bitcoin transactions conducted in those countries characterized by fewer capital controls and restrictions, a result that feeds suspicions of illegal behavior, such as money laundering or terrorism financing, carried out through the use of cryptocurrencies. Findings of this research might be strategic for fintech entrepreneurship and policymakers interested in designing policies that aim to foster innovative sectors while ensuring the legality of financial flows.

Keywords Bitcoin · Blockchain · Cryptocurrencies · Social network analysis · Fintech

JEL Classification L26 · O33

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1 Introduction

Recent technological introductions have led to the development of innovative businesses (Block et al. 2017), such as the financial technology sector (fintech), which combines finance and technology to offer new financial instruments (Bjørnskov and Foss 2013). The main tools that characterize this innovative business, such as Initial Coin Offerings (ICOs) and cryptocurrencies are based on blockchain technology (Zavolokina et al. 2017).

Prior research on fintech area mainly focuses on Bitcoin cryptocurrency (Satoshi and Nakamoto 2008). In particular, several authors in the scientific literature have analyzed statistical and technological aspects of its transaction network, such as the anonymity of users (Reid and Harrigan 2013) and the distribution of amounts among Bitcoin wallets (Ron and Shamir 2013) but it has rarely considered the existing relationships with socio-economic aspects at national level. At this early stage of fintech sector development, it is strategic to identify its main enabling factors and potential risks in order to allow policymakers to create institutional contexts able to facilitate the dissemination of fintech instruments and, at the same time, of limiting the related socio-economic risks.

The level of national economic freedom represents an enabling factor for the economic growth of a country (Cebula and Clark 2012). Based on this assumption, it is interesting to understand the role it plays in the development of fintech sector. In particular, high levels of economic freedom at national level produce positive effects on the conduct of financial activities (Gohmann et al. 2013). The research work has been mainly driven by the following questions: is it possible to identify any relationships between the degree of economic freedom associated with a specific country and the use of fintech services within it? What drives fintech sector development at the national level?

Considering that Bitcoin cryptocurrency represents the most widespread application of blockchain technology, the Bitcoin geographical transaction network has been considered as a proxy to evaluate the fintech sector development at the country level. By using social network analysis approach, this study explores how the position of each country expressed in terms of centrality measures performed on the Bitcoin geographical network responds to changes in the degree of economic freedom in the top 70 economies selected by the ranking drawn up by the *International Monetary Fund (IMF)*. The network modeling and social network analysis approach offer great explanatory power as they enable to trace of the international trend of Bitcoin flows passing through the international wallets.

The study showed that countries characterized by high levels of economic freedom, evaluated in terms of freedom to trade internationally, a restrained value of inflation and low administrative requirements can be considered suitable for fintech sector development, in fact, they present high values of social network centrality indicators performed within the geographical Bitcoin network.

With reference to potential illegal conduct arising from the use of cryptocurrencies, concerning a good percentage of the total number of Bitcoin international transactions (Foley et al. 2019), the analysis also revealed high levels of network centrality indicators by those countries characterized by low controls and restrictions on capital.

2 Data collection

In order to accomplish the research purpose, two different datasets have been collected to be part of the analysis. They are represented by a geographically enriched set of Bitcoin transactions modeled in a network and a series of economic freedom indicators provided by Fraser Institute. As specified in the Introduction, the analysis has regarded the top 70 world economies.

2.1 Bitcoin system

Bitcoin original reference implementation consists of a distributed ledger on which all the system transactions are stored securely and permanently. (Arvind et al. 2016) All the transactions are organized in blocks that are periodically generated by the miners representing system users able to perform complex cryptographic algorithms (such as *SHA256*) required for creating a new block. (Drainville 2012) Each of them is validated by a P2P network and subsequently added to the blockchain.

Bitcoin users represent entities of the network that run a software allowing the block verification in a decentralized manner without requiring the trust of a third party, such as a bank or a government institution. The Bitcoin protocol relies on a strong user consensus among all participants of the system (Mingxiao et al. 2017) based on a proof of work validation mechanism. It consists of a part of data which is difficult to produce in terms of costs and processing times and, at the same time, it complies with certain requirements that can be easily verified by other network members. It follows that, once Bitcoin transactions are collected in a specific block, they can not be manipulated without manipulating all followings blocks, activity that requires the collusion of the network majority (Ober et al. 2013).

2.2 Bitcoin dataset

The Bitcoin blockchain represents a typical example of big data. Due to a large number of daily transactions occurring in the Bitcoin system, the blockchain has reached a huge size and its analysis requires ever-increasing computational resources. In the scientific literature, different approaches have been proposed to acquire the information content of the Bitcoin blockchain according to the type of analysis to be conducted.

In particular, Reid and Harrigan in their analysis of Bitcoin network anonymity adopted a direct blockchain reading approach (Reid and Harrigan 2013), the same method used by Ron and Shamir in their statistical analysis on Bitcoin amounts distribution among wallets (Ron and Shamir 2013). This strategy is effective for studies which are limited to the transaction information stored in the blockchain, whereas to enlarge the analysis dimensions involving other transaction-related

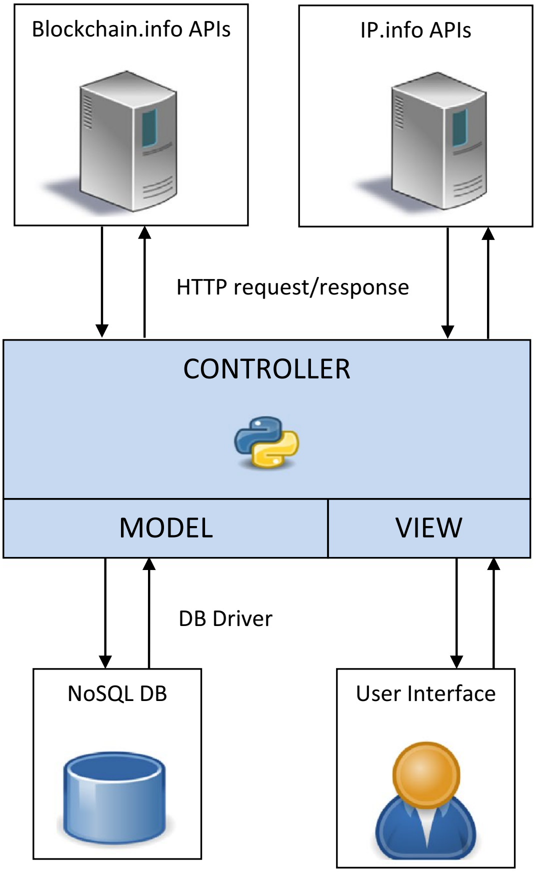

Fig. 1 Scraping system architecture

features, it is necessary to enrich the blockchain information content by integrating it with additional details provided by other information sources. Several authors in literature have adopted the blockchain enrichment approach through web scraping as in the case of bitcoin market analysis conducted by Lischke and Fabian (Lischke and Fabian 2016).

It follows that, since blockchain does not store any geographical information of recorded transactions, a direct reading of it is not enough to achieve the aims of this research, therefore an internet scraping aimed at increasing the basic blockchain dataset has been needed. It has been performed by developing a scraping system with the Python programming language and some of its specific libraries such as 'Beautifulsoup', 'Python Requests' and 'Urllib'. As shown in Fig. 1, the system architecture complies with *the Model View Controller paradigm (MVC)* and it has been able to interact with *Blockchain.info* services offering transactions' information, such as the IP addresses involved (Kaminsky 2011). Geolocation has been possible by exploiting *IPInfo.it* web services that allow identifying the country to which an input IP address belongs. Figure 1 describes the scraping system architecture and all the entities involved in the data collection process.

The selected dataset contains 2,318,585 Bitcoin transactions occurring from 2013 to 2016 that have been stored in a NoSQL database in order to be processed. Each transaction is characterized by the following attributes: transaction identifier, timestamp, origin country, destination country, sender address, receiver address and total amount. The data model with the addition of some descriptive statistics, is showed in Appendix 1.

Surely, the collected dataset might be used to address a wider range of issues beyond the analysis conducted in this study, such as the analysis of Bitcoin financial hubs over time and the identification of major market services (Chawathe 2018). Other relevant issues in the fintech landscape that require big data collection are represented by Initial Coin Offerings (ICOs) (Adhami et al. 2018) and the analysis of others cryptocurrencies (Buterin et al. 2013).

2.3 Economic freedom indicators

The economic freedom represents an important element related to an institutional environment and its degree varies significantly among states (Gohmann et al. 2008). The level of freedom associated with an economy can be measured considering different components (Carlsson and Lundström 2002), in particular, is much important take into account production and transaction costs (North 1990), the characteristics of its monetary system, the freedom to trade internationally and the level of business regulation.

The different components of national economic freedom have been evaluated considering a specific set of indicators provided by Fraser institute database, which is divided into four areas and whose values vary from 0 to 10. The first area, defined as Size of Government, measures the impact of government expenditures and tax rates on economic freedom. The overall value of this indicator is high with low levels of public expenditure as a share of the total. The indicator groups of the second area, known as Sound Money focuses on the price stability in the exchange process held by a specific money. Large values of this measure indicates a time stable money which reduces transaction costs and facilitates exchanges. Its value is determined by the government adoption of policies that maintain low rates of inflation and the freedom of use alternative currencies. The Freedom to Trade Internationally, the name used to define the third area, evaluates the level of international exchanges that might be limited by restrictions on country residents to engage voluntary exchange across national boundaries. Countries with a higher value of this indicator are characterized by low tariffs, freely convertible currency and freedom of physical and human capital movement. The Regulation indicator, representing the fourth area, considers the impact of regulations on entry into markets influencing the bureaucracy costs, the ease of undertaking business, tax compliance and licensing restrictions. Once explored the four different areas of economic freedom assessment, the components shown in Table 1 and detailed in Appendix 2, have been selected to be part of the analysis because hypothesized as suitable to achieve research objectives.

Table 1 Descriptive statistics for the selected economic freedom indicators

Economic freedom indicators	N	Min	Max	M	SD
Administrative requirements	280	0.00	7.69	3.95	1.34
Money growth	280	2.77	9.98	8.80	1.10
Standard deviation of inflation	280	0.00	9.95	8.45	2.07
Inflation	280	0.00	10.00	8.94	1.92
Tariffs	280	4.07	10.00	7.59	1.18
Compliance costs of importing and exporting	280	0.00	9.96	6.89	2.98
Foreign investment restrictions	280	0.00	9.22	6.11	1.43
Capital controls	280	0.00	9.23	3.48	2.53

3 Social network analysis

By using social network analysis (SNA) methodology it has been possible to analyze the geographical Bitcoin transaction network and to evaluate the position of each country expressed in terms of properties and transaction relationships within it. The adoption of a network perspective allows adding informative power to the individual attributes of nodes (Wasserman 1994). The analysis has been conducted by using some of the main indicators of network centrality (Freeman 1978) (Batagelj and Mrvar 2003) which are suitable for modelling various socioeconomic phenomena and they have already been used by some authors in literature in identifying financial flows attributable to money laundering activities (Fronzetti Colladon and Remondi 2017). They have been considered as strategic for the study of Bitcoins flows among international wallets and in identifying the countries representing Bitcoin transaction hubs, due to the numerous international flows passing through them. The selected social network centrality indicators are briefly described in the following subsections.

3.1 Degree centrality

This indicator considers the value of degree that represents the sum of nodes directly attached to a specific node for which is calculated. Considering directed graphs, there are two different types of degrees that can be calculated, known as indegree and outdegree. The first measure is obtained counting the number of ties directed to a node, while outdegree is given by the number of ties that the node directs to others. The all-degree is the sum of indegree and outdegree and the weighted all degree for the generic node in a directed graph can be expressed with the equation below:

$$C_D\left(n_i\right) = \sum_{j=1}^{N}(a_{i,j} + a_{j,i})$$

where $a_{i,j}$, indicates the number of incoming ties and $a_{j,i}$ is the number of outgoing ties.

Nodes with high values of degree centrality are central in the network and they tend to influence the others.

3.2 Closeness centrality

This measure represents the inverse of the distance of a node to all the others in the network. Its computation involves all the shortest paths between each couple of nodes in the graph. Considering a graph with N nodes, the Closeness Centrality equation is the following:

$$C_C\left(n_i\right) = \sum_{j=1}^{N} 1/d(n_i, n_j)$$

where $d\left(n_i, n_j\right)$ represents all the edges allocated in the shortest path linking n_i and n_j.

It is possible to normalize the value of Closeness Centrality as shown below:

$$CC\left(n_i\right) = (N - 1)C_c\left(n_i\right)$$

3.3 Betweenness centrality

This indicator is based on the shortest paths connecting each couple of nodes in the graph and is higher when a node is more often in this subset. In the case of a network with N nodes, the betweenness centrality value for a specific node can be calculated with the following formula:

$$C_b\left(n_i\right) = \sum_{j<k} g_{jk}(n_i)/g_{jk}$$

where g_{jk} is the total number of the shortest paths connecting two nodes in the graph and $g_{jk}(n_i)$ is the number of shortest path linking two nodes that go through the node n_i.

3.4 Bitcoin transaction network

Network centrality measures are considered to be crucial for this study since they can contribute to explaining how strategic is the network position of each country within the Bitcoin network. A country holds a strategic network position when it conducts transactions with a large number of foreign countries and is frequently crossed by international Bitcoins flows.

In order to perform the selected network centrality indicators, two directed graphs have been modeled based on the Bitcoin transaction dataset. The first one, defined as Generic Network contains nodes representing Bitcoin addresses belonging to users regardless of their nationality, whilst the second one, shown in Fig. 2 and identified as Geographical Network, is characterized by nodes that

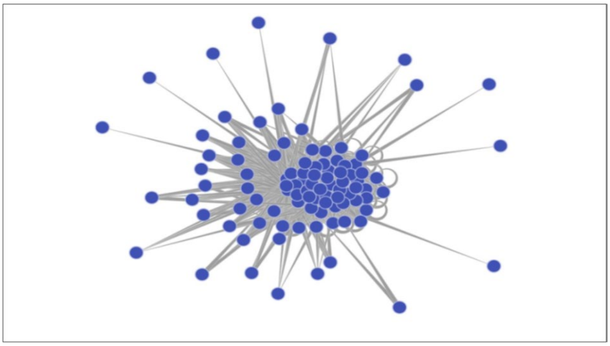

Fig. 2 Static view of the Bitcoin geographical network

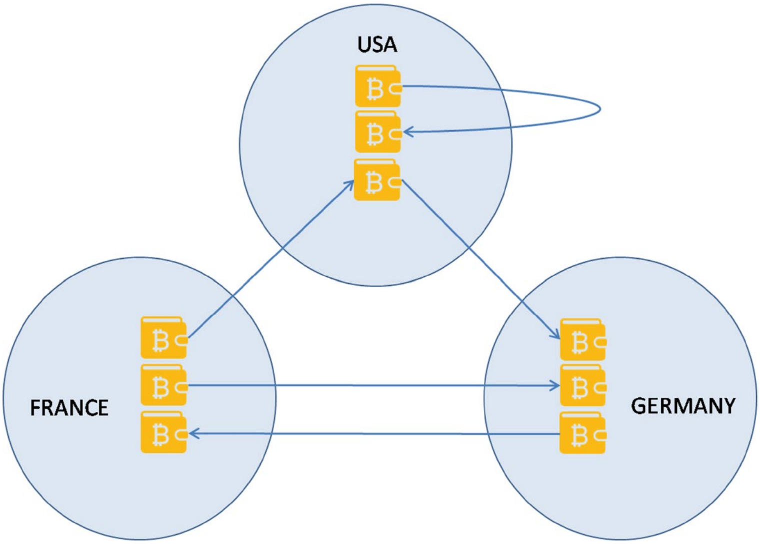

Fig. 3 An example of international Bitcoin transaction flows passing through different international wallets

symbolize countries and links representing transactions involving among them (included internal transaction visible as loops) and has been obtained by merging addresses of the Generic Network associated to user belonging to the same country.

Figure 3 shows an example of international Bitcoin flows passing through different international wallets within the Bitcoin geographical transaction network.

Once the geographical network has been modeled, the selected centrality metrics, whose values are shown in Table 2, have been performed on it. Specifically, each of them has been used as a proxy for certain economic aspects which will be described in detail in the next section related to the research hypotheses development.

Table 2 Descriptive statistics for network metrics

Network metric	N	Min	Max	M	SD
Closeness centrality	280	0	0.88	0.46	0.19
Betweenness centrality	280	0	0.79	0.42	0.20
Degree centrality	280	0	9023	5203.74	2630.43

4 Research hypotheses

On the basis of the considerations set out in the previous section concerning fintech business, economic freedom and social network analysis, the followings hypotheses are considered to be tested:

H1 The national level of freedom to trade internationally positively affects the number of foreign countries with which the country conducts international Bitcoin transactions.

Whereas the freedom to trade internationally fosters investments and international commerce (Berggren 2009) and Bitcoin cryptocurrency represents a valid alternative to traditional financial instruments to purchase goods and transfer money (Polasik et al. 2015; Scott 2016), it follows that the absence of tariffs barriers might encourage the use of Bitcoin as a means of payment in international trade and remittances.

The freedom to trade internationally represents a parameter under the institutions' control, which mostly relates to the levels of tariffs, regulatory trade barriers and import and export costs (Jansen and Nordås 2006). Considering that the closeness centrality indicator calculated on a node of the geographical Bitcoin transaction network represents the country's propensity to conduct transactions with a diversified number of other countries, it is expected that countries with a high level of freedom to trade internationally are characterized by high values of closeness centrality.

The second hypothesis is based on the relationship among inflation, real exchange rate and international trade (McKenzie 1999) by stating the following:

H2 A low national inflation rate positively influences the volume of Bitcoin flows passing through the country

Countries with a low and stable inflation value are expected to be crossed by numerous Bitcoin flows and therefore to be characterized by high values of Betweenness centrality in the Bitcoin Transaction Network.

Whereas a high level of monetary inflation leads to an unstable real exchange rate and the variability of the latter may harm international trade flows (Cushman 1983), countries with a low value of monetary inflation are preferred by Bitcoin users using cryptocurrencies as a means of payment for international commerce.

The third hypothesis is founded on the assumption that in order to facilitate the development of innovative businesses are necessary national contexts inclined to low transaction costs and a lean bureaucracy (Sørensen 2007), consequently:

H3 Countries with low levels of bureaucracy costs and where it is easy to undertake a business activity are characterized by a large number of Bitcoin domestic and cross border transactions.

Countries with a lean bureaucracy are supposed to have high values of degree centrality in the Bitcoin geographical network, which means a large volume of domestic and cross border transactions associated with the country. As in the case of freedom to trade internationally, the level of bureaucracy costs can be directly controlled by policymakers through structural reforms that might facilitate the carrying out of entrepreneurial activities (Bawn 1997).

In summary, each research hypothesis has been linked to a specific set of economic freedom indicators according to their area of interest. Specifically, the first hypothesis has been associated with the levels of tariffs and the compliance of import and export costs. In a technologically advanced and interconnected world scenario, characterized by ease of communication and low transportation costs of goods, the freedom of exchange across national boundaries represents a key component of economic freedom.

The second hypothesis is based on the link between inflation and international trade. Specifically, a stable level of monetary inflation rate facilitates international trade, since it ensures a stable real exchange rate. As explained by some authors in the scientific literature, inflation is also linked to trade openness (Lane 1997) and the growth in the rate of inflation tends to lead to an increase in its volatility and high and volatile inflation rates distort market prices, affect the fundamental terms of long-term contracts and leads to a reduction in international trade (Stockman 1985).

Lastly, the third hypothesis has been related to the administrative requirements that influence the performance of entrepreneurial activities within a specific geographical context.

With reference to network variables introduced in the hypotheses, the closeness centrality measures the number of foreign countries with which the reference country conducts cross border transactions. It follows that a country characterized by a high value of closeness centrality is affected by numerous flows of Bitcoins and a wide variety of foreign countries with which international transactions are conducted.

The betweenness centrality indicator expresses how many Bitcoin flows those cross international wallets, pass through the country for which its value is calculated. As a consequence, a country crossed by numerous flows of Bitcoins as it is characterized by low and stable inflation, therefore attractive for the exchange operations of cryptocurrencies into fiat currency, will present high value of the Betweenness centrality indicator.

Finally, the degree centrality indicator is a proxy for the number of incoming and outgoing transactions associated with the country for which it is performed.

It can be deduced that countries characterized by high degree centrality values are those that generally present favorable conditions for the development of fintech instruments within it, and, therefore, are characterized by a high number of national and international Bitcoin transactions.

5 Research methodology

Research has been conducted by using social network analysis (*SNA*) methodological approach, which has allowed to study the relationships, expressed in terms of international transactions within the Bitcoin geographical network, that are established among the various countries.

The socioeconomic network modeling has been relevant to this research in order to determine which network characteristics can help to explain the potential relationship between the national levels of economic freedom and the development of fintech sector among countries. Socioeconomic networks provide a point of view on economic and social interactions and they can be used to represent high-density statistical graphs with several actors and links (Borgatti et al. 2009).

In particular, the Bitcoin network modeling has allowed tracing Bitcoins paths among different international wallets during the execution of transactions, whereas the computation of the main network centrality indicators has enabled to establish the position of each country within these flows. Specifically, the measures of degree, closeness and betweenness centrality performed on a network node, representing a specif country, have represented proxies to evaluate respectively, its propensity to conduct Bitcoin transactions, the diversity of countries with which international transactions are carried out and finally, how many Bitcoin flows pass through its wallets and then be forwarded to others located abroad.

The analysis approach adopted, allows to focus on the relationships concerning countries, expressed in terms of Bitcoin transactions, and to identify which of them represent Bitcoins transaction hubs because they are characterized by high values of network centrality indicators within the geographical network and therefore most of Bitcoin flows go through them.

In order to test the hypotheses, the study approach initially involves the calculation of Pearson correlations coefficients among the selected centrality network and economic freedom indicators and then proceed with the implementation of multilevel regression models in order to expand the first results emerged from the correlations.

These models are widely used in socio-economic studies and they are described in detail in the works of Snijders and Bosker (1994) and in other well-known studies (Nezlek 2010). The choice to apply them derives from the nested structure of data, in fact, single-level regression models are not suitable for the analysis of data characterizing this study since their hierarchical structure is ignored. Multilevel models, also known as multilevel mixed-effects or hierarchical models, allow varying intercepts across countries, as well as to explain the level of variance which is ascribable to the differences at a country level.

The analysis includes the implementation of multilevel regression models for each of the network centrality indicators considered as the variables to be predicted using a selected set of economic freedom indicators as predictors. Each regression model is based on the calculation of the values of the intercept (β_0), the parameters estimated at each individual regressor (β_i), the variance within and between groups (represented by countries), the coefficient of intraclass correlation (ρ) and the percentage of first (within the country) and second (between countries) level variance reduction. The best model for each network centrality indicator to be predicted, characterized by all significant values of predictors and with the highest reduction in the first and second level of variance, can be considered as the one that helps explain which economic freedom indicators have more influence on the network indicator for which the model is calculated. Each regression model can be represented with the Eq. (1) where *Y* represents the network variable to predict, X_i the ith predictor characterized by a specific economic freedom indicator, and *U* the statistical error:

$$Y = \beta_0 + \beta_1 * X_1 + \cdots + \beta_n * X_n + U \tag{1}$$

6 Results

In order to conduct the analysis, as control variables have been included the *Global Innovation Index (GII)*[1] and the *Human Development Index (HDI)*[2] which are commonly used in socio-economic research (Dutta et al. 2017; Wonglimpiyarat 2010; Auty 2005) and provide guidance on the dissemination of innovation and human development within each country.

Confirming the second hypothesis (H2), a significative positive relationship has regarded the value of country inflation and the betweenness centrality in the Bitcoin network. In particular, the countries with restrained and stable inflation with the addition of a national currency affected by low volatility, show high values of betweenness centrality. This means that the majority of Bitcoin flows involve low inflation countries and this is presumably due to the trust of people on their traditional currencies in order to conduct future exchanges and preserve the purchasing power of the transferred amount.

Other important characteristics required to a country to facilitate the fintech business development are low values of importing and exporting costs and the absence of regulatory trade barriers that reflect on the indicators of closeness centrality confirming the second hypothesis (H2).

All the considered centrality measures appear to be significantly influenced by low values of administrative requirements and bureaucracy costs as well as, to

[1] The Global Innovation Index (GII) provided by the *World Intellectual Property Organization* ranks the innovation performance of 126 countries which represent 90.8% of the world's population and 96.3% of global GDP.

[2] The Human Development Index (HDI) is a tool developed by the *United Nations* to measure and rank countries' levels of social and economic development.

a lesser extent, by the ease to undertake a business in accordance with the third hypothesis (H3).

In addition to the initial assumptions, a strong positive relationship between capital controls and restrictions on foreign investment and the degree centrality has been discovered. This finding suggests a potential use of the cryptocurrency to evade restrictive measures imposed by national authorities, in particular to overcome limits on foreign investment and capital controls. Furthermore, a significant correlation between the control variables and network measures has emerged, confirming that those variables affect the position of each state within the Bitcoin transaction network.

In order to expand the interesting results emerging from the correlation coefficients, the multilevel regression models have been developed. The models built, shown in Tables 3, 4 and 5 are based on repeated observations over time (level 1) by country (level 2) and all the variables with no collinearity problems have been tested starting from an empty model with no predictors (M1) with the aim of measuring the intraclass correlation coefficient (ICC) and continuing with the execution of furthers models in order to evaluate the power of each variable (M2–M12). In addition, the attempt to introduce lagged predictors has not led to improvements in results. The last column (M12) of Tables 3, 4 and 5 is characterized by the significant variables that ensure the best reduction of the variance between groups (L2) and within the group (L1). It has been obtained by selecting the best results, in terms of L1 and L2 variance reduction, obtained from the implementation of regression models with all possible combinations of independent variables. The coefficients reported in this column are capable of explaining better than the others the values of the independent variable to predict.

The values of ICC of 59%, 51, % 58% for the degree centrality, betweenness centrality and closeness centrality respectively, in addition to legitimizing the use of multi-level analysis, expresses that much of the variability in the values of network indicators are attributable to differences in levels of economic freedom between different countries.

The model shows that some components of economic freedom can help to explain Bitcoin's geographical network centrality values better than others. In other words, each network measure can be better explained by a specific set of independent variables and their inclusion allows to improve the model compared to the empty and control variables models (M1, M2, M3). In particular, the values of indicators expressing tariffs, costs of importing and exporting and administrative requirements can help to explain both between and within the variance of closeness centrality, as shown in Table 3. The value of betweenness centrality appears to be affected by the national money growth and its inflation including changes over the years (Table 4). Lastly, Table 5 shows that the degree centrality is primarily associated with restrictions on foreign investments and capital controls. It has been found that countries with fewer capital controls and low limitations on capital moving from abroad are characterized by high values of degree centrality. This result represents a warning to the control authorities as Bitcoin might be used as an alternative instrument to traditional fund transfer channels to evade security controls and carry out money laundering and terrorist financing activities.

Table 3 Multilevel regression models of the effects of economic freedom variables on the closeness centrality

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Global Innovation Index		0.003** (− 0.001)										
Human Development index			0.493** (− 0.057)									
Tariffs				0.031*** (− 0.005)								0.014** (0.002)
Compliance costs imp/exp					0.023*** (0.001)							0.019*** (0.001)
Money growth						0.027** (0.005)						
Standard deviation of inflation							0.011* (0.003)					
Inflation								0.017** (0.003)				
Administrative requirements									0.018** (0.004)			0.015** (0.002)

Table 3 (continued)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Foreign inv. restrictions										0.032** (0.003)		
Capital controls											0.014** (0.002)	
Constant	0.360** (0.360)	0.205** (0.023)	0.031* (0.046)	0.126*** (0.041)	0.205** (0.008)	0.122* (0.049)	0.265 (0.029)	0.207** (0.029)	0.290*** (0.020)	0.164** (0.021)	0 .310*** (0.011)	0.062** (0.019)
ICC	0.58											
Variance level 2	0.00520	0.00237	0.00249	0.00214	0.00032	0.00405	0.00327	0.00273	0.00259	0.00074	0.00258	0.00036
Variance level 1	0.00366	0.00352	0.00341	0.00375	0.00253	0.00354	0.00393	0.00388	0.00375	0.00407	0.00356	0.00218
Variance reduction level 2 (%)		54.36%	52.23%	58.85%	93.92%	22.10%	37.18%	47.56%	50.14%	85.84%	50.35%	93.06%
Variance reduction level 1 (%)		3.99%	6.75%	− 2.51%	31.00%	3.36%	− 7.44%	− 5.96%	− 2.47%	− 11.01%	2.75%	40.48%
AIC	− 637.166	− 667.538	− 682.231	− 670.506	− 834.498	− 649.894	− 638.158	− 650.769	− 658.824	− 690.595	− 663.232	− 831.693
BIC	− 626.262	− 646.999	− 667.750	− 656.010	− 820.002	− 635.398	− 623.662	− 636.273	− 644.342	− 676.114	− 648.794	− 816.970

p p value, *AIC* Akaike information criterion, *BIC* Bayesian information criterion

Standard errors in parentheses. *, **, and *** = significantly different from zero at the 90%, 95%, and 99% levels

*0.05 < p ≤ 0.10; ** 0.01 < p ≤ 0.05; *** p ≤ 0.01

Table 4 Multilevel regression models of the effects of economic freedom variables on the betweenness centrality

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Global Innovation Index		0.002** (0.001)										
Human Development index			0.325** (0.076)									
Tariffs				0.018** (0.007)								
Compliance costs imp/exp					0.016** (0.002)							
Money growth						0.046** (0.005)						0.023** (0.003)
Standard deviation of inflation							0.030*** (0.002)					0.015*** (0.002)
Inflation								0.034** (0.002)				0.015** (0.002)
Administrative requirements									0.005* (0.006)			

Table 4 (continued)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Foreign inv. restrictions										0.030** (0.004)		
Capital controls											0.014*** (0.003)	
Constant	0.423** (0.009)	0.332** (0.023)	0.165** (0.061)	0.284 (0.054)	0.314*** (0.016)	0.013* (0.045)	0.169*** (0.018)	0.116*** (0.019)	0.405 (0.026)	0.240** (0.028)	0.374** (0.014)	0.048* (0.029)
ICC	0.5101											
Variance level 2	0.00542	0.00442	0.00466	0.00547	0.00415	0.00220	0.00101	0.00105	0.00450	0.00370	0.00200	0.00092
Variance level 1	0.00520	0.00525	0.00503	0.00521	0.00538	0.00525	0.00443	0.00516	0.00531	0.00530	0.00562	0.00511
Variance reduction level 2 (%)		18.35%	14.05%	23.40%	56.75%	66.95%	81.36%	80.62%	11.58%	63.16%	21.33%	83.02%
Variance reduction level 1 (%)		− 0.94%	3.30%	− 3.32%	1.00%	14.80%	0.85%	9.99%	− 1.18%	− 8.10%	1.82%	30.80%
AIC	− 556.840	− 563.931	− 562.536	− 555.736	− 593.390	− 640.190	− 684.870	− 677.658	− 550.952	− 577.630	− 557.474	− 698.693
BIC	− 545.936	− 549.392	− 548.055	− 541.240	− 578.894	− 625.694	− 650.374	− 661.162	− 536.470	− 563.148	− 543.036	− 685.970

p p value, *AIC* Akaike information criterion, *BIC* Bayesian information criterion

Standard errors in parentheses. *, **, and *** = significantly different from zero at the 90%, 95%, and 99% levels

*0.05 < p ≤ 0.10; ** 0.01 < p ≤ 0.05; *** p ≤ 0.01

Table 5 Multilevel regression models of the effects of economic freedom variables on the degree centrality

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Global Innovation Index		55.128** (9.744)										
Human Development index			7339.105** (1152.856)									
Tariffs				342.119** (108.488)								
Compliance costs imp/exp					271.517*** (30.031)							
Money growth						473.0978** (95.884)						
Standard deviation of inflation							308.236** (53.240)					
Inflation								297.348** (57.205)				
Administrative requirements									382.935* (84.801)			
Foreign inv. restrictions										860.528*** (37.240)		818.707*** (40.419)

Table 5 (continued)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Capital controls											248.790*** (49.638)	54.981*** (22.913)
Constant	5203.743** (161.848)	2847.054* (436.750)	− 613.062 (923.490)	2632.573** (836.154)	3378.835** (229.189)	1050.99*** (856.493)	2623.012** (464.465)	2563.874*** (526.874)	3762.955** (358.892)	18.469*** (233.787)	4364.563** (218.706)	83.621* (232.733)
ICC	59.20%											
Variance level 2	1,561,927	929,299.6	1,084,848	999,153.7	391,731.1	1,191,131	699,330.4	884,611.5	832,866.6	171,628.8	967,569.2	81,343.8
Variance level 1	1,086,896	1,109,904	1,005,631	1,163,735	1,175,844	1,062,347	1,218,595	1,152,781	1,111,119	780,794.9	1,089,497	766,164.4
Variance reduction level 2 (%)		40.50%	30.54%	36.03%	74.92%	23.74%	55.23%	43.36%	46.68%	89.01%	38.05%	94.79%
Variance reduction level 1 (%)		− 2.12%	7.48%	− 7.07%	− 8.18%	2.26%	− 12.12%	− 6.06%	− 2.23%	28.16%	− 0.24%	29.51%
AIC	4825.929	4803.043	4721.153	4766.378	4724.588	4755.932	4758.611	4757.935	4729.041	4495.855	4681.475	4467.272
BIC	4836.834	4817.582	4735.634	4780.874	4739.084	4770.428	4773.107	4772.431	4743.523	4510.337	4695.913	4485.301

p p value, *AIC* Akaike information criterion, *BIC* Bayesian information criterion

Standard errors in parentheses. *, **, and *** = significantly different from zero at the 90%, 95%, and 99% levels

*$0.05 < p \leq 0.10$; **$0.01 < p \leq 0.05$; ***$p \leq 0.01$

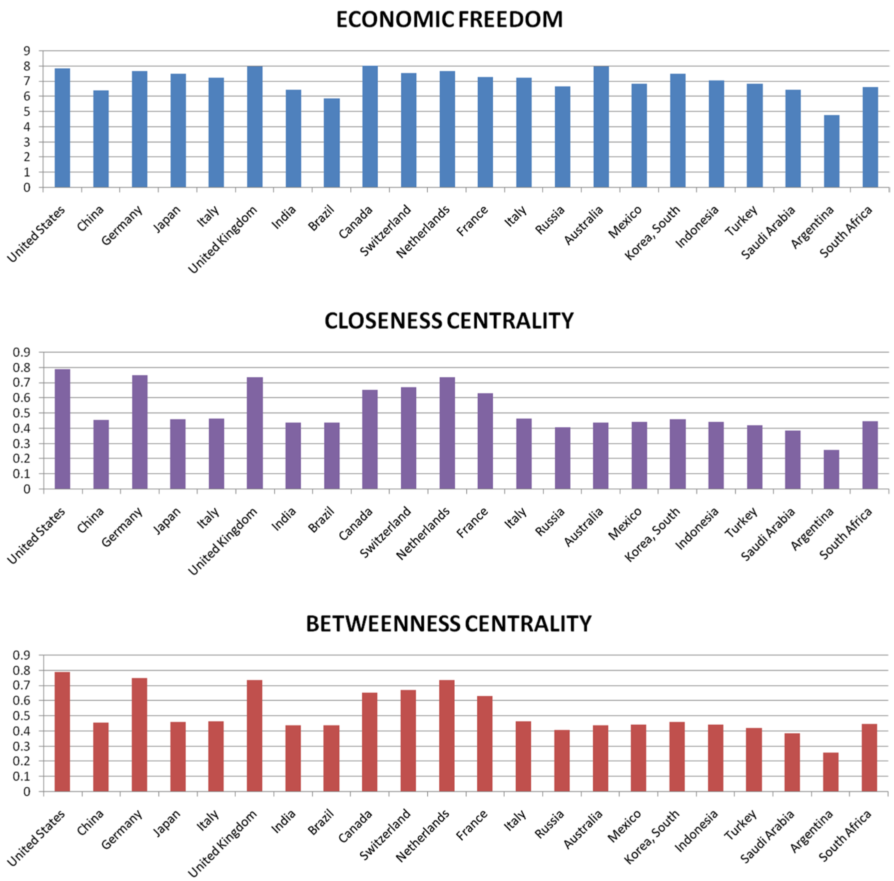

Fig. 4 Bar charts of network centrality and economic freedom measures for G20 state members with the addition of The Netherlands and Switzerland

The results of the study has shown that countries with considerable values of some components of economic freedom such as low values of importing and exporting costs, tariffs and administrative requirements with the addition of a stable fiat currency, hold a central position, mainly expressed by high values of closeness and betweenness centrality within the Bitcoin geographical network and they can be considered as the financial hubs of fintech business.

There are also other components of economic freedom, such as controls on capital and restrictions on foreign investments, which are mainly reflected in the values of degree centrality within the Bitcoin geographical network and whose deficiency might lead to the use of Bitcoin for illegal conduct such as money laundering.

Figure 4 shows the bar charts of centrality values within the Bitcoin network and economic freedom indicators in the G20 area. The network analysis shows the predominance expressed in terms of network centrality by those countries characterized by high levels of economic freedom, such as the USA, Germany and the UK.

Compared to its economic power and its geographical extension, China seems to have a peripheral position, whereas countries with low levels of capital controls and restriction on foreign investments, such as Switzerland and The Netherlands, are very central in the network confirming the specific role that the different components of economic freedom play in the development of fintech sector.

7 Conclusions

Cryptocurrencies and all the blockchain-based services are becoming increasingly popular and the interest of the public opinion and the world of research in them is growing. This study has been conducted with the aim of understanding some of the determinants of fintech sector development. The analysis has investigated the main components of economic freedom that can be considered as enabling factors for the fintech business growth in the top 70 world economies. Bitcoin transactions have been used as a proxy to evaluate the national propensity to adopt blockchain-based services and important relationships between the trend of the main network centrality indicators performed within the Bitcoin geographical transaction network and a series of national economic freedom indicators have emerged, confirming that, as in the case of general economic growth, high levels of national economic freedom leads to the fintech sector development within the country. As shown by the implemented multilevel models, not all the components of economic freedom affect the fintech growth process in the same manner, in particular high levels of freedom to trade internationally with low values of regulatory barriers and administrative requirements as well as a restrained value of inflation are considered to be strategic for fintech sector development. This study also found that low controls on capital might lead to Bitcoin use for illegal conduct such as money laundering or terrorist financing, a result that represents a warning to the supervisory authorities to adopt specific measures aimed at avoiding illegal behavior.

Based on these considerations, it follows that states which are characterized by high levels of economic freedom evaluated in terms of the enabling fintech business factors described above, such as the USA, Germany and the majority of highly developed countries, are more attractive for fintech entrepreneurship. These countries hold a central position in the Bitcoin transaction network and have seen a large spread of blockchain-based services in the last few years, the reason why they can be considered as the first international hubs in the fintech sector. Rather significant is the case of China, where in the last decades there has been a great industrial and technological development and despite this, due to the severe government restrictions on economic freedom and on the use of innovative technological tools, it is characterized by low values of centrality in the Bitcoin geographical network and fintech services are not significantly widespread within the country. An improvement in terms of economic freedom on those institutional parameters, such as the freedom to trade internationally and a lean bureaucracy on which the institutions can intervene directly, might stimulate the growth of this innovative sector in the countries where its level is low, mostly composed by emerging countries since it represents a great development opportunity for the entire world economy.

At this stage of fintech development process, there emerges a positive economic impact due to increased financial flows, but unfortunately it is not possible to affirm the same from the socio-economic point of view as these flows are frequently linked to illegal activities. Given the benefits that the development of the fintech sector can bring to global economic growth in the coming years, it is strategic to establish effective measures to protect the community against illegal activities carried out through the use of cryptocurrencies also aimed at mitigating the socioeconomic risks associated with it. Surely it is an international challenge that should be uniformly addressed by the various countries in order to avoid the emergence of parallel markets in which illegal activities might take place, as evidenced by the results of this study. The establishment of a task force aimed at preventing fraudulent conduct through the use of cryptocurrencies might help prevent negative socioeconomics impacts from their hazardous types of use and it might allow to fully appreciate the added value offered by the instruments of fintech scenario, as well as to increase the confidence of people in their adoption.

Furthermore, the social network analysis approach used in this study to identify suspicious Bitcoin flows might be combined with that proposed by Foley et al. (2019) in order to select a subset of suspect blocks to be submitted to the judicial authorities for inspection.

In addition, the provision of financial incentives to the use of cryptocurrencies might facilitate their development process. For instance, aid measures may be envisaged to facilitate economic operators accepting payments via cryptocurrencies and all service providers who are willing to use fintech instruments in offering their services by promoting its usage for legal and well-known purposes.

For sure, there are many other fintech enabling factors, such as the availability of a performing technological infrastructure and trust of people on new financial instruments that will be analyzed in future works.

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Compliance with ethical standards

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Appendix 1

In this appendix are reported further descriptive statistics of the Bitcoin dataset on different dimensions of analysis.

General statistics of Bitcoin dataset

Attribute	Value
Time interval	2013–2016
Number of blocks	1460
Number of transactions	2,318,585
Average number of transactions per block	1588
Number of countries involved	113
Cross border transactions (%)	2,156,396 (93%)
Internal transactions (%)	162,189 (7%)
Country with most transactions	USA

Incoming transaction statistics

Country of origin	Number of transactions
USA	562,487 (24.26%)
Germany	435,714 (18.79%)
The Netherlands	106,397 (4.59%)
UK	80,761 (3.48%)
Others	1,133,226 (48.88%)

Outgoing transaction statistics

Country of destination	Number of Transactions
USA	428,974 (18.50%)
Germany	347,814 (15%)
The Netherlands	137,251 (5.91%)
UK	80,592 (3.47%)
Others	1,323,954 (57.10%)

Data model description

Data field	Type
Transaction identifier	String
Timestamp	Date
Origin country	String
Sender address	String
Destination country	String
Receiver address	String
Amount	Float

Appendix 2

This appendix describes the economic freedom indicators provided by the Fraser Institute. Further information available at https://www.fraserinstitute.org/Economic freedom indicators description

Economic freedom indicators	Area	Description
Money growth	3—Access to sound money	This component measures the growth of the money supply in the last 5 years minus the annual growth of real GDP in the last 10 years
Standard deviation of inflation	3—Access to sound money	The component measures the standard deviation of the inflation rate over the last 5 years. Generally, the GDP deflator was used as the measure of inflation for this component. When these data were unavailable, the Consumer Price Index was used.
Inflation	3—Access to sound money	Generally, the CPI was used as the measure of inflation for this component as it is often available before the GDP deflator is available. When these data were unavailable, the GDP deflator inflation rate was used
Tariffs	4—Freedom to trade internationally	This sub-component measures the amount of taxes on international trade as a share of exports and imports.
Compliance costs of importing and exporting	4—Freedom to trade internationally	This sub-component is based on the World Bank's Doing Business data on the time (i.e., non-money) cost of procedures required to import a full 20-foot container of dry goods that contains no hazardous or military items
Regulatory trade barriers	4—Freedom to trade internationally	This sub-component is based on the Logistics Performance Index survey question: "1) Efficiency of the clearance process (i.e., speed, simplicity and predictability of formalities) by border control agencies, including customs
Foreign investment restrictions	4—Freedom to trade internationally	This sub-component is based on the following two questions from the Global Competitiveness Report: (1) "How prevalent is foreign ownership of companies in your country?
Capital controls	4—Freedom to trade internationally	This component measures restrictions on capital transactions, looking at 13 types of international capital controls reported by the International Monetary Fund
Administrative requirements	5—Regulation	This sub-component is based on the Global Competitiveness Report question: "Complying with administrative requirements (permits, regulations, reporting) issued by the government in your country?"

Economic freedom indicators	Area	Description
Bureaucracy costs	5—Regulation	This sub-component is based on the Global Competitiveness Report question: "Standards on product/service quality, energy and other regulations (outside environmental regulations) in your country.
Starting a business	5—Regulation	This sub-component measures how easy it is to start a business. It looks at the number of procedures, the time it takes to go through these procedures, the costs (such as fees) of starting a business, and minimum capital requirement needed to formally start a business
Tax compliance	5—Regulation	This sub-component is based on the World Bank's Doing Business data on the time required per year for a business to prepare, file, and pay taxes on corporate income, value-added or sales taxes, and taxes on labor
Business regulations	5—Regulation	This component identifies the extent to which regulations and bureaucratic procedures restrain entry and reduce competition
Licensing restrictions	5—Regulation	This sub-component is based on the World Bank's Doing Business data on the time in days and monetary costs required to obtain a license to construct a standard warehouse

Appendix 3

The correlation coefficients for each of the selected variables showing significative positive correlations among them, supporting the idea that Social Network Analysis can help to evaluate national fintech sector development and its relationships with the levels of economic freedom at the country level.

Correlation coefficients of the selected network and economic freedom variables

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Closeness centrality	1	1																		
Betweenness centrality	2	0.74***	1																	
Degree centrality	3	0.85***	0.76***	1																
Global innovation index	4	0.55***	0.51***	0.58***	1															
Human development index	5	0.58***	0.66***	0.69***	0.70***	1														
Tariffs	6	0.78***	0.58***	0.36**	0.28***	0.42**	1													
Compliance cost import export	7	0.91***	0.52***	0.59***	0.65***	0.68***	0.40*	1												
Regulatory trade barriers	8	0.80***	0.53***	0.67***	0.66***	0.70***	0.48**	0.96***	1											
Money growth	9	0.38**	0.68***	0.37*	0.26***	0.05	0.08	0.28**	0.30***	1										
Standard deviation inflation	10	0.40**	0.76***	0.51**	0.27***	0.34*	0.20**	0.52***	0.54**	0.36**	1									
Inflation	11	0.47***	0.89***	0.47**	0.22***	0.37**	0.36**	0.49***	0.54***	0.53***	0.67***	1								
Administrative requirements	12	0.73***	0.54**	0.39***	0.30***	0.22**	0.45**	0.20**	0.32*	0.28	0.09	0.32*	1							

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Bureaucracy costs	13	0.67***	0.50**	0.63***	0.61***	0.72***	0.48**	0.76***	0.80***	0.26*	0.54**	0.54**	0.36*	1						
Starting a business	14	0.46***	0.38*	0.39**	0.45**	0.44**	0.15	0.49**	0.55***	0.47**	0.45**	0.51**	0.42**	0.59***	1					
Tax compliance	15	0.25	0.24	0.31	0.44***	0.47***	0.26*	0.43**	0.50**	0.32*	0.17	0.41**	0.54**	0.50**	0.62**	1				
Business regulations	16	0.67***	0.44	0.59***	0.59***	0.66***	0.38**	0.62***	0.71***	0.37**	0.39**	0.58**	0.74***	0.81***	0.72***	0.79***	1			
Licensing restrictions	17	0.29	0.22	0.18	0.19	0.14	0.11	0.17	0.24	0.32**	0.13	0.41**	0.52**	0.31**	0.44**	0.41**	0.61**	1		
Foreign investment restrictions	18	0.59**	0.61**	0.87***	0.53***	0.47***	0.46***	0.61***	0.73***	0.32*	0.58***	0.54***	0.48**	0.72***	0.47**	0.40**	0.68***	0.27	1	
Capital controls	19	0.64**	0.52***	0.81***	0.41**	0.45**	0.38*	0.47**	0.50**	0.22	0.29*	0.32*	0.12	0.48**	0.34*	0.28	0.41*	0.05	0.40**	1

*, **, and *** = significantly different from zero at the 90%, 95%, and 99% levels

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