Influencers and their relevance for bitcoin adoption

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Summary. The aim of this paper is to analyse the motives behind the demand for bitcoin. In order to achieve this, an overlapping generations model is constructed including influential and followers´ actors. The conjecture is that bitcoin demand is associated with an influence parameter that responds to the behaviour of these actors. For the empirical evaluation, data sets estimating the behaviour of influencers and followers are constructed. The results support the proposed conjecture.

Keywords. Money, bitcoin, beliefs, influencers, followers.

JEL codes. E40, E42, D83, D85, G32, E52.

1 Introduction

Bitcoin's demand motives are associated with its supply characteristics. Bitcoin has no intrinsic value, so, given its predetermined supply, its value depends on opinions that it can function as currency technology[1].

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[1]The importance of opinions on the demand for bitcoin can be seen, on the one hand, in the greater than fifteen percent rise after Elon Musk tagged his account with *hashtag* Bitcoin in his Twitter bio on January 28, 2021. On the other hand, significant declines in bitcoin's value have been observed in response to regulators' warnings about its risks. In August 2021, the SEC chairman's considerations of potential cryptoasset regulations generated a drop in price of close to ten percent. The same effect generated the IMF's warnings about the use of bitcoin as a national

In this context, the research seeks to answer the question of whether it is possible that the demand for bitcoin is associated with the opinions of one group of influencers and regulators and the behaviour of other groups of followers.

An overlapping generations model is constructed with two monetary assets (fiat money and bitcoin) and two actors (influencers and followers). The influential actors operate as opinion leaders regarding the utility of each asset and their opinions are replicated by the group of followers. For the empirical evaluation, a set of indicators is constructed in order to measure the expectations of a group of influential actors and a group of followers based on messages on the social network Twitter. In order to identify the influential actors, a network analysis is performed to group the central nodes.

The chapter is organised as follows. The second section refers to the associated literature. Third section develops the framework, defining and characterising the demand motives for bitcoin. Fourth section builds the overlapping generations model incorporating the influence of market actors and regulators on bitcoin demand. Fifth section empirically evaluates the model through the construction of an index. Finally, results are presented.

2 Literature

Conceptual references

A group of papers associated with the demand motives for bitcoin introduce digital assets into a framework of overlapping generations and assume that the demand for such assets is determined by expectations that these assets will have value in the future. Garratt and Wallace, 2018 analyse the reasons why bitcoin could have a positive value. The authors show that this positive value depends on agents' expectations that bitcoin will be accepted as a means of payment and store of value: 'people give up other things to get bitcoin only because they think that others in the future will do the same'. Similarly, Biais et al., 2020 use an overlapping generations model to assess the value of bitcoin arriving at the same considerations. Like this research considers that the demand for digital assets is linked to the expectation of their future value. However, the research proposes that this expectation is linked to the opinion of a special group of agents: the influencers. The research proposes that this group of influencers is further divided into two groups. On the one hand, market actors promoting digital assets and, on the other hand, regulators of the current financial system. The proposal of influential market actors is linked to the ideas introduced by Menger, 1892, section VI, who distinguishes influencers in the liquid asset market: 'nothing may have been so favourable to the genesis of a medium of exchange as the acceptance,

currency (Tobias & Weeks, 2021). For a detailed analysis of the consequences of regulatory announcements on the price of bitcoin see, for example, Auer and Claessens, 2018.

on the part of the most discerning and capable economic subjects, for their own economic gain, and over a considerable period, of eminently saleable goods in preference to all others'. The idea of the regulator as the one who determines the value of a monetary asset is influenced by the proposals of the referents of the German historical school Knapp, 1924. In addition, the present research suggests the existence of another particular group of agents: the followers. This group of agents has the function of amplifying the message generated by the influencers. The existence of this group of actors is associated with Keynes ideas set out in Section V of Chapter 12 of the General Theory: 'Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally'[2]. Part of the theoretical literature links these motives to the traditional functions of money. According to Yermack, 2013, digital assets would not fulfil the function of a store of value or unit of account because their price is highly volatile[3] It would also not fulfil the role of a medium of exchange since few transactions take place and that it is used for speculation. For these reasons, digital assets would have a low level of demand.

2.1 Empirical references—

Regarding empirical work, a group of papers estimate the demand for digital assets based on information generated in social networks. This literature uses market sentiment analysis as a tool to assess movements in the price of currencies (Matta et al., 2015; Stenqvist & Lönnö, 2017). In contrast to this paper, the present research only evaluates the opinion of a group of influential actors and not of all users of the social network. In this sense, some works such as the one by Hamza, 2020 study the behaviour of a particular group of influencers based on market sentiment analysis. The authors intend to test the conjecture that opinion leaders' sentiment about cryptoassets can be used to predict prices. Like this paper, this research analyses´s opinion restricted to a group of influencers on the Twitter social network Twitternote[4]. However, the selection of this group of influencers in this research is done through network techniques.

Auer and Claessens, 2018 indicate that, although cryptocurrencies are often thought to operate outside the reach of national regulation, in reality their valuations, trading volumes and user bases react strongly to news about regulatory initiatives. The authors conclude that news about possible general bans on cryptocurrencies or their subjection to securities legislation have the strongest negative effect on valuations, followed by news about anti-money laundering and counter-terrorist financing and news about restrictions on the interoperability of cryptocurrencies with regulated markets. This research agrees that regulators' actions are one of the determining factors in the level of adoption of digital assets. However, this paper suggests that there are two groups of influential

[2]Keynes, 2014

[3]Yermack indicates that the exchange rate volatility between Bitcoin and dollars in 2013 was 142 per cent, an order of magnitude higher than the exchange rate volatilities of other currencies against the dollar. Gold, a plausible alternative to these currencies as a store of value, had a volatility of 22 per cent in 2013.

[4]Data collection is performed using the same tool coded in Python: Get Old Tweets

actors. On the one hand, regulators and, on the other hand, market actors. In addition, this paper performs data analysis on the basis of information from social networks rather than news.

Other empirical studies, such as that of Kallinterakis and Wang, 2019 , show that cryptocurrency herding behaviour is significant, with greater intensity during bull markets, low volatility and high volume days. Another empirical study, Hotar, 2020, also seeks to demonstrate the existence of herding behaviour in interactions between agents.

A set of studies seek to relate the demand for cryptoassets to structural factors such as inflation, remittances, capital controls, advancement of technologies (Hileman, 2014; Yechen et al., 2016). A group of structural empirical studies assumes that they are a special group of financial assets and relates them to other assets in search of correlations (Brière et al., 2015; Eisl et al., 2015).. The present research recognises the contributions of the structural approach, but associates itself with the market sentiment analysis literature.

Other papers construct an estimate of costs and benefits of digital assets from events in the ecosystem (Biais et al., 2020). In contrast to that paper, this project generates an approximate profit index for bitcoin demand based on information obtained from social networks from a network analysis of Twitter.

3 Reasons for bitcoin demand

This paper considers that the demand for digital assets is associated with the expectation that the functions of money will be fulfilled in the future. In addition, it is proposed that this expectation is interconnected with the opinion of a group of influencers and the behaviour of a group of followers.

3.1 Beliefs

Demand for an asset as a monetary asset depends on expectations that such assets may perform the functions of a means of payment, a store of value and a unit of account in the future. In term of Garratt and Wallace, 2018, 'beliefs are important; if the young at a date give up some of the good for money, it are important; if the young at a date give up some of the good for money, it is because they think the next generation will also do that´.

Beliefs and demand for bitcoin. In this framework, the demand for bitcoin depends on the belief that it will function as money in the future. As Garratt and Wallace, 2018 suggests, 'people give up other things to get bitcoin only because they think that others in the future will do the same´. These authors consider that 'the best theory of the value of bitcoin is that it rests on what are called self-fulfilling beliefs and that the set of beliefs that can be self-fulfilling is huge.´

3.2 Influencers

Menger, 1892, in section VI, On the genesis of media of exchange, indicates that 'nothing can have been so favourable to the genesis of a medium of exchange as the acceptance, by the *most shrewd and able economic subjects*[5], for their own economic benefit, and for a considerable period of time, of goods eminently saleable in preference to all others'. Within the framework of Menger's considerations, one can recognise an original idea about influencers. Belief in the fulfilment of the functions of money in the future is associated with the considerations of a group of individuals. This situation could be associated with the concept of smart money. The concept of smart money refers to investments by people who have more information, knowledge, and analytical power, thus they can detect and foresee trends in advance. In traditional markets, these actors typically include large institutional investors. These actors could be divided into two groups: market participants (investors, developers, journalists) and regulators. In a first stage, it is expected that market influencers will have the greatest impact on the system. While the influence of regulators is expected in a second stage, as the system can take on a certain volume of relevance.

Definición 3.1 (Bitcoin influencers) *Actors who have more information and better analytical skills than the rest of the market participants. They are the ones who determine the price trend in the long term.*

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3.3 Followers

Keynes points out at the end of section V of chapter 12 of the General Theory that 'Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally´. If everyone makes the same mistake it is unlikely to receive any reproach for it. However, if an individual errs by taking a view contrary to that of the majority, then he or she is likely to receive recrimination from the rest. Followers are the actors who mimic the behaviour of influential actors. With their behaviour they can amplify the actions of the influencers and can exacerbate price changes. Their actions may be associated with herd behaviour or imitation behaviour. Herd behaviour is common in finance, because emotions often play a determining role and people consider that there are others who have more information and a better ability to analyse it. In the case of currencies, this situation becomes more intense because individuals generally recognise that they do not understand the nature of money, nor the forces that give money its value[6].

Definición 3.2 (Bitcoin followers) Followers are those agents that mimic the behaviour of in-

[5] Italics are my own.

[6] The most famous historical example is the Dutch tulips.

fluencers. Follower behaviour is associated with short-term price behaviour. In terms of expectations and information, followers have expectations with incomplete information.

4 Demand model with introduction of influencers

4.1 Economy with a fiat monetary asset

There is a standard overlapping-generations economy with a fiat currency, $fiat$. In the traditional framework of the overlapping generations model, assets cannot be carried across periods and there is no ability to work when old. Therefore, the demand for the monetary asset responds to the need of the young to consume in the next period. That is, the demand motive for fiat currency responds to the need for a store of value between t and $t+1$ and a means of payment in $t+1$. The standard overlapping generations model assumes that there is a hypothetical market between generations and assumes that the monetary asset will have value in the next period. In this hypothetical market the young consume part of the goods received and exchange the rest for money with the old. Money functions as a system of records between the two generations. Therefore, the demand for the fiat asset will be the number of young people in the period as a function of the amount of unconsumed income, $N_t(y_t - c_t)$.

Beliefs A fundamental feature of the OLG model is that it is necessary for individuals the desire to keep monetary assets from one period to the next. The monetary asset has no intrinsic value. That is, no utility can be derived from its consumption. Therefore, its value derives from its utility in order to facilitate exchange. The model assumes that people of different generations believe that the asset will have a positive value in the next period. That is, the value a person places on a unit of money at time t, v_t, depends on what a person believes the value of a unit of fiat money will be at time $t + 1$,v_{t+1}. By a similar logic, the value of a unit of fiat money at $t + 1$, depends on a person's beliefs about the value of money in period $t + 2$. And so on. Thus, the value of a monetary asset at any point in time depends on an infinite chain of expectations about its future values (Champ & Freeman, 2004).

In this economy with a single monetary asset, the value of money is determined by the equilibrium condition of the money market.

$$v_t^{fiat} M_t^{fiat} = N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$

4.2 Creating a new digital currency

A group of the country's citizens attempt to create a new currency, btc. At this early stage, the new currency is only accepted by the small group of enthusiasts who created it.

The value of assets is determined independently in each of their money markets. Like the demand for fiat money, the demand for digital money responds to the possibility of maintaining a system of records over time.

$$v_t^{fiat} M_t^{fiat} = N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$
$$v_t^{btc} M_t^{btc} = N_t^{btc} \left(y^{btc} - c_{1,t}^{btc} \right)$$

Actors demand monetary assets in order to be able to consume in the next period (means of payment function). For this, actors need monetary assets to maintain a time-invariant record. It is assumed that both fiat and digital assets allow the recording of transactions under the same conditions[7].

In a next stage, a group of the country's citizens decide to abandon the use of the fiat asset and start using the digital asset. This asset substitution responds to the expectations of this group of citizens regarding the ability of each asset to function as a means of payment in the following periods. While a change in the belief regarding the future fulfilment of the functions of money is sufficient to explain the changes in the demand for money in the model, one could consider that the group of citizens who switch find relative advantages in registering the digital asset. We define λ_t as the fraction of citizens who choose to hold bitcoin balances.

$$v_t^{fiat} M_t^{fiat} = (1 - \lambda_t) N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$
$$v_t^{btc} M_t^{btc} = N_t^{btc} \left(y^{btc} - c_{1,t}^{btc} \right) + \lambda_t N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$

4.3 Introduction of controls on asset holdings

The more citizens who want to hold balances in the digital asset (i.e. the higher the value of λ_t), the higher the value of the digital asset and the lower the value of the fiat asset. In the event that the fraction of citizens who choose to hold bitcoin balances is too high, the local government could restrict bitcoin holdings. We define I_t as the fraction of citizens reached by bitcoin holding controls.

Therefore, the determination of the value of each asset will have to take into account the controls imposed by the government on the holding of the digital asset.

[7]This idea is associated with Kocherlakota's concept of money as a social memory process.

$$v_t^{fiat} M_t^{fiat} = I_t N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right) + (1 - I_t)(1 - \lambda_t) N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$
$$v_t^{btc} M_t^{btc} = N_t^{btc} \left(y^{btc} - c_{1,t}^{btc} \right) + (1 - I_t)\lambda_t N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$

In the case of widespread government control of digital asset ownership (i.e. a higher value of I_t), the fraction of citizens who will be able to choose freely between assets decreases.

4.4 Introduction of influencers and followers

Of the citizens who are free to choose, the fraction of citizens who choose the digital asset, and thus the fiat asset, will be associated with the behaviour of a group of influencers and a group of followers[8].

In this context, it is defined the following parameter of influence:

$$\lambda_t = S(\mu_t)$$

where μ_t is a parameter indicating the interest of the influencers and S is a function indicating the imitation behaviour of the followers. The parameter S in turn depends on the interest of market influencers and the regulator. The function S amplifies the reflected interest of the influencers.

If influencers have a positive opinion of the digital asset, followers will mimic that interest, reinforcing the general interest in the asset. In this way, the behaviour of the imitators can generate increases in the volatility of the asset[9]. By definition, the values of λ can be between zero and one. This implies that, for relatively moderate values of the influencers, a high value of s will generate values of λ close to their extremes. In this way, we seek to capture the sudden changes in the valuation of the asset in the face of changes in the direction of the influencers' valuation and its subsequent amplification by the followers.

In summary, information is generated by one group of actors and amplified by another group of actors[10]. The equations of the model are synthesised below.

$$v_t^{fiat} M_t^{fiat} = I_t N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right) + (1 - I_t)(1 - \lambda_t) N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$
$$v_t^{btc} M_t^{btc} = N_t^{btc} \left(y^{btc} - c_{1,t}^{btc} \right) + (1 - I_t)\lambda_t N_t^{fiat} \left(y^{fiat} - c_{1,t}^{fiat} \right)$$

[8] This idea can be modelled from game theory through the interdependent strategies of the influencers.

[9] This behaviour of the followers could be useful to generate a conceptual framework for bank runs or, more generally, sudden substitution between assets.

[10] Policy measures aimed at moderating the run should take into account the distinction between these two groups of actors. On the one hand, it could seek to avoid the negative message by influencers (a small group in number but of great relative weight in terms of their opinions) or it could seek to avoid the massive amplification of that message by followers (a large group in number of agents but of lesser relative weight in terms of their opinions).

$$\lambda_t = S(\mu_t)$$

The conceptual evaluation corroborates the conjecture by introducing into the OLG model the parameter of influence, the value of which is a function of the behaviour of influencers and followers. If the influencers have a positive opinion of the digital asset in relation to its potential monetary functions, the followers will mimic that interest by reinforcing the general interest in the digital asset. In this way, the behaviour of imitators can generate increases in the asset's volatility.

5 Measuring the opinions of influencers and followers

For the empirical evaluation, a set of indicators is constructed in order to measure the expectations of a group of influential actors and a group of followers based on messages on the social network Twitter. In order to identify the influential actors, a network analysis is performed to group the central nodes.

The empirical conjecture indicates that there is an association between the value of λ and the value of the digital asset. Higher levels of λ are expected to be associated with increases in the value of the digital asset. To empirically evaluate the λ function, its two components must be estimated. On the one hand, the interest of the influencers, μ_t and, on the other, the amplification generated by the followers, S[11].

5.1 Methodology

The universe under study is the total global demand for bitcoin from its inception in January 2009 to the present, January 2022. Intentionally and by subjective criteria, the total number of tweets from the start of the bitcoin system in January 2009 to April 2013 is selected as a sample. This selection responds, on the one hand, to the technical feasibility of the availability of information and the possibilities of processing the data with traditional computational tools. And, on the other hand, to the possibility of analysing the initial moments of bitcoin as a possible monetary asset.

The proposed model indicates that the demand for bitcoin is associated with a group of influencers and a group of followers. These variables are not observable. To approximate the influence of a group of actors, the opinions of influencers on the social network Twitter will be estimated. To approximate the behaviour of followers, estimates will be made of the network topology of messages on the Twitter network.

The value of bitcoin will be determined based on price data from the Coinmetrics site. The

[11] As the model assumes the existence of two monetary assets, the estimation of the relative interest for one assumes that, by difference, the relative interest of the other is being found. The assumption is that the individual always chooses some monetary asset because it is the only way to be able to consume in the next period.

collection of tweet data is done using the same Python-coded tool, GetOldTweets. The following data fields are included for each tweet: `tweet id`, `user id`, `id users mentioned` and `tweet text`.

To analyse data, first, there is a description of data. Second, it performs correlations between the bitcoin price and the estimated variables for the influencers' opinions and for the group of followers. Third, it is proposed a variance decomposition. Fourth, it will perform a Grenger Causality analysis.

5.2 Findings

To estimate the opinions of the influencers and the followers, a database is generated with the messages that mention the word bitcoin. As a sample, it is selected the total number of tweets since the first record of bitcoin price, in July 2010, until April 2013. During the period analysed, a total of 516,532 tweets containing the word bitcoin were surveyed.

5.2.1 Estimation of the influencers opinions.

In order to estimate the opinion of the influencers, messages posted by a group of influencers on the social network Twitter are selected. Networking techniques are used to determine who is part of the group of influencers. An actor is defined as an influencer if he or she is frequently mentioned by the rest of the users of the social network. This consideration is associated with the PageRank algorithm, which measures the importance of each node within the graph, based on the number of incoming relationships and the importance of the corresponding source nodes. The underlying assumption is that an actor is only as important as the actors it connects to.

To illustrate this approach, it is proposed to analyse the tweets mentioning the word bitcoin during 2009. Table 1 lists the messages mentioning the word bitcoin during 2009. Table 1 also indicates the users who generated the tweet, username (column 2), and, where applicable, the mention of other users of the social network, mentions (column 3). The data can be represented visually through a network graph (see Figure 1). In the graph, users (nodes) are included by circles and mentions of each other (links) by arrows. The level of influence of each user is indicated by the size of each node's circle. Due to the small number of tweets that occurred in the initial stage of bitcoin during its year of creation, it can be directly observed that the user bitcoin, Innotribe and Target receives the most mentions from the rest of the users in the network[12]. The process ends by counting the number of tweets generated by the influencers.

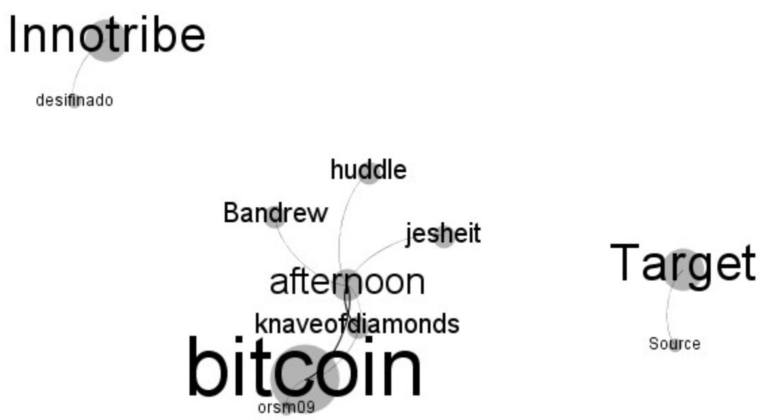
[12]For the following periods, the ranking of influencers will be obtained by programming in the R language.

Table 1: 2009 tweets mentioning the word bitcoin

date	username	mentions	text
19 Jun 09	afternoon	@jesheit @bitcoin @Bandrew @huddle	Very pleasant day cycling around London and coworking with
24 Sep 09	hxn		this is really interesting: bitcoin , the p2p cryptocurrenc
27 Jan 09	halfin		Thinking about how to reduce CO2 emissions from a widesprea
11 Jan 09	halfin		Running bitcoin
13 Dec 09	desifinado	@Innotribe	RT @Innotribe : Bitcoin : encrypted P2P currency without ba
04 Dec 09	LuceroDiehard		RPF Bitcoin - possible revolution of money?: http://bit.ly/
23 Jul 09	orsm09	@bitcoin	Note: AppExchange - Install Hundreds of Cloud Computing App
21 Jan 09	halfin		Looking at ways to add more anonymity to bitcoin
18 Feb 09	mbauwens		Just wrote: Bitcoin : new open source P2P e-cash system: Sa
19 Jun 09	knaveofdiamonds	@bitcoin @afternoon	Hmm, @bitcoin looks interesting: any idea when there will b
29 Jan 09	fafcffacfff		From: Satoshi Nakamoto - 2009-01-11 22:32 Bitcoin v0.1.2 is
13 Dec 09	petervan		Bitcoin : encrypted P2P currency without banks http://bit.l
13 Dec 09	Innotribe		Bitcoin : encrypted P2P currency without banks http://bit.l
04 Dec 09	RonPaulForums		Bitcoin - possible revolution of money?: http://bit.ly/8GUS
19 Jun 09	afternoon	@knaveofdiamonds @bitcoin	@knaveofdiamonds We're getting ready to go into beta pretty
20 Jun 09	knaveofdiamonds	@afternoon	@afternoon not yet: am building an app during http://railsr
09 Jun 09	NOWevent		#bde bitcoin demoing too!
09 Jun 09	simongrice		#bde 3 demo companies next up - then lunch - Bitcoin , Idea
18 Feb 09	beAtorrent		#2 P2P Foundation Â≫ Blog Archive Â≫ Bitcoin : new open sou

Source: own construction based on Twitter API.

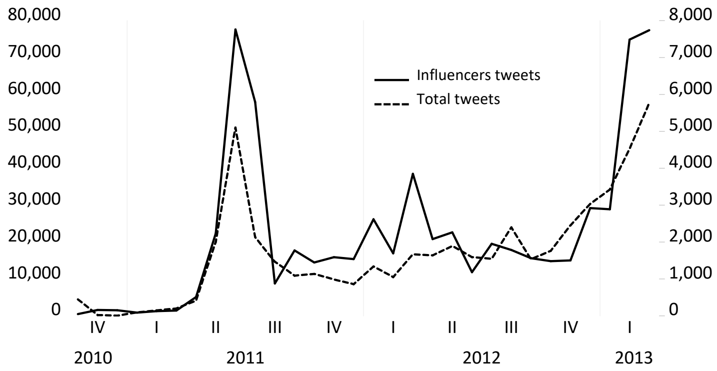
Figure 1: Network graph of 2009 tweets mentioning the word bitcoin



Notes. The size of the node indicates the degree of importance according to the PageRank algorithm: bitcoin (0.1662), Target and Innotribe (0.1161), afternoon (0.0964), knaveofdiamonds, jesheit, huddle and Bandrew (0.0791), Source, desifinado and orsm09 (0.0627). Source: own construction based on Twitter API and Gephi processing.

The approach illustrated for the 2009 sample is applied for the total sample in monthly periods, from July 2010 to April 2013. July 2010 is taken as the first month because it is the first month for which bitcoin price data is available. With the proposed method, the influencers for each month are selected and then the posts of these influencers are counted. It is proposed to consider the top 10 per cent of influencers according to the PageRank algorithm. In this way, a time series is constructed with the number of posts of the influencers. The estimated series has a total of 67,213 tweets. The new series has an association level with the total tweet series of 0.89, reflecting the relevance of the influential tweets in capturing the central tendency of the data.

Figure 2: Influencer tweets and total tweets



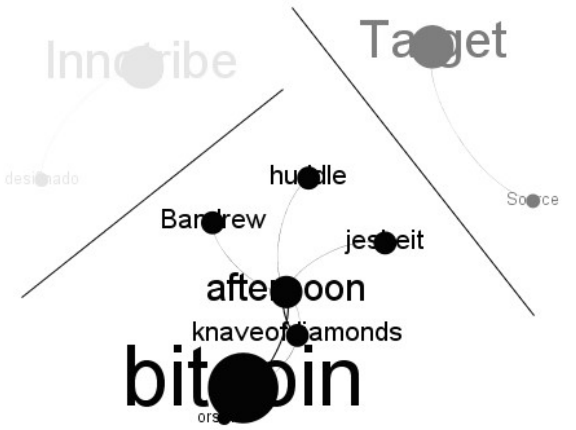
Notes. An association is observed between the dynamics of the series of total tweets and influencer tweets. The new series has an association level with the total tweet series of 0.89, reflecting the relevance of the influential tweets in capturing the central tendency of the data. Both series are in absolute values. Source: own construction based on Twitter API

5.2.2 Estimating the behaviour of the followers group

In order to empirically approximate the behaviour of the follower, the same network of Twitter messages containing the word bitcoin will be studied. However, unlike the estimation of influencers, the network actors (nodes) will not be evaluated. Instead, metrics that account for the structure of the network will be analysed. In network theory, there are numerous metrics that account for network structure. For this study we will estimate the number of nodes (the total number of actors in the network), the number of links (the number of interactions of the nodes with each other), the average degree (the average number of links of each actor), the diameter and clustering coefficient (as a measure of cross-interactions between actors) and the number of communities (clusters between actors).

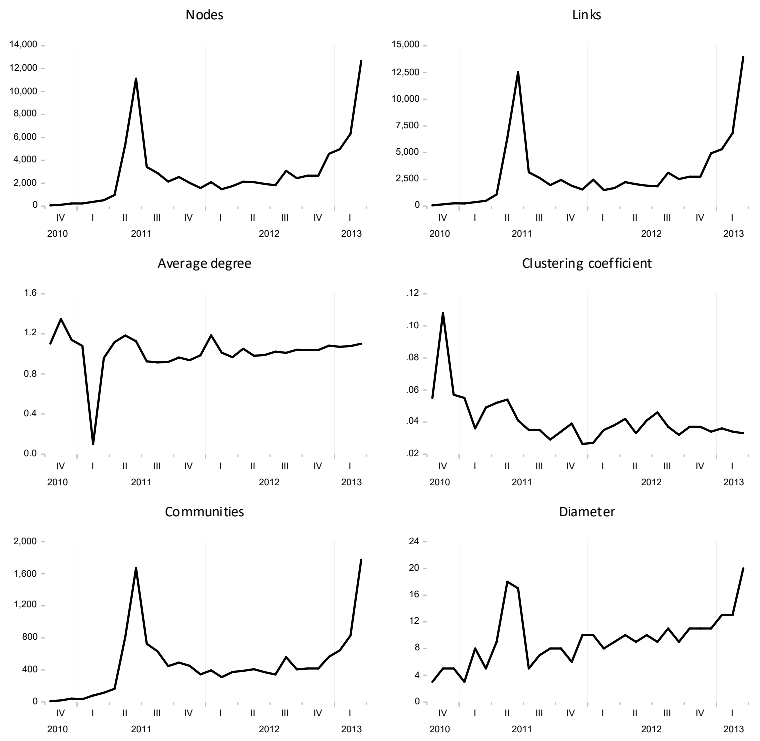
To illustrate the proposal for estimating follower behaviour, it is suggested to consider the number of communities observed during 2009, in the same data set as the one used to exemplify the case of influencers. Communities are one of the possible metrics to describe the dynamics of a network. Figure 3 shows the same message network for 2009 as the one indicated for the estimation of influencers. From this network, it can be observed that there are three distinct groups. In other words, there are three communities. This network metric and others will be counted for the rest of the sample monthly (see Figure 4).

Figure 3: Network graph of 2009 tweets mentioning the word bitcoin identifying communities



Notes. Source: own construction based on Twitter API and Gephi processing.

Figure 4: Network metrics that account for network structure

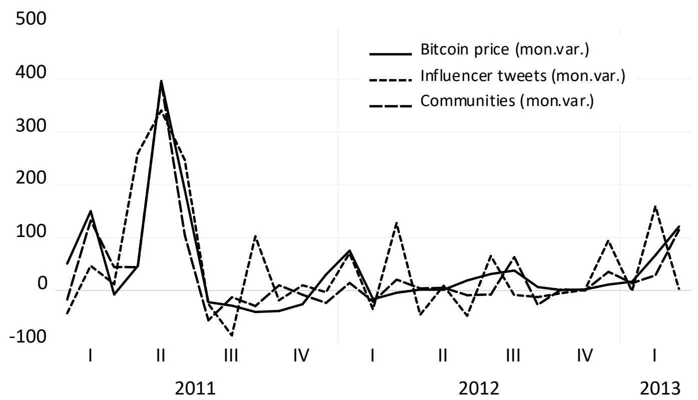


Notes. Source: own construction based on Twitter API and Gephi processing.

5.2.3 Association between variables estimating influencer opinion, follower behaviour and the price of bitcoin

After having estimated influencers opinions using the PageRank and estimated the behaviour of the group of followers using network metrics, the aim is to evaluate the association between these estimations and the price of bitcoin. For this part of the analysis, monthly variations of the variables will be considered (see Figure 5).

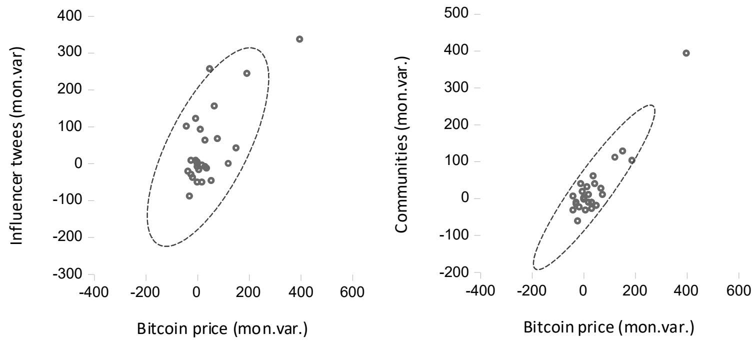
Figure 5: Bitcoin price, influencer tweets and number of communities
(in monthly changes)



Source: own construction based on Twitter API and Eviews processing.

Correlation analysis confirms the high degree of association between the study variables. The correlation between the monthly change in bitcoin price and the monthly change in influencers tweets is 0.7 and the correlation between the change in bitcoin price and the change in number of communities is 0.92 (see Figure 6)

Figure 6: Correlation analysis between bitcoin price, influencer tweets and network metrics as a proxy for followers (in monthly changes)



Source: own construction based on Twitter API and Eviews processing.

The existence of correlation is an important finding. However, the research conjecture is that the degree of influence generated by influencers and followers has an impact on the price of bitcoin. Therefore, the behaviour of influencers should be expected to anticipate the price dynamics. In this sense, a Grenger Causality analysis is performed to assess temporal anticipation (see Table 2). The results indicate that influencer tweets cause in the Grenger sense the price of bitcoin and the number of communities with a significance level of 5 percent. In turn, it is observed that the number of communities causes in the Grenger sense the price of bitcoin. This corroborates the conjecture that the behaviour of the influencers followed by the behaviour of the followers could have an impact on the price of bitcoin.

Table 2: Grenger causality between influencer tweets, communities and bitcoin price.

Pairwise Granger Causality Tests
Date: 08/31/22 Time: 13:50
Sample: 2011M01 2013M03
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
COMMUNITIES does not Granger Cause INFLUENCERS_TWEETS	27	0.68867	0.5127
INFLUENCERS_TWEETS does not Granger Cause COMMUNITIES		4.66689	0.0204
BITCOIN_PRICE does not Granger Cause INFLUENCERS_TWEETS	27	0.68744	0.5133
INFLUENCERS_TWEETS does not Granger Cause BITCOIN_PRICE		3.50372	0.0478
BITCOIN_PRICE does not Granger Cause COMMUNITIES	27	2.87706	0.0776
COMMUNITIES does not Granger Cause BITCOIN_PRICE		3.58192	0.0450

Source: own construction based on Twitter API and Eviews processing.

6 Chapter conclusions

The main finding is that the demand for bitcoin is associated with the behaviour of influencers and followers. The conjecture is confirmed.

The conceptual evaluation corroborates the conjecture by introducing into the OLG model the parameter of influence, the value of which is a function of the behaviour of influencers and followers. If the influencers have a positive opinion of the digital asset in relation to its potential monetary functions, the followers will mimic that interest by reinforcing the general interest in the digital asset. In this way, the behaviour of imitators can generate increases in the asset's volatility.

The empirical evaluation also supports the conjecture. First, bitcoin's price is explained by the evolution in the number of tweets generated by influencers. Second, the price is explained by the evolution in the dynamics of the network of twitter messages containing the word bitcoin.

The main contribution is to link the bitcoin demand to the behaviour of a group of influencers and a group of followers. This result is compatible with the literature that associates the demand for bitcoin to the belief that it can function as a means of payment, a store of value and a unit of account. On the empirical side, the main contribution is the proposal to identify influencers and followers using network analysis techniques.

The limitations of the model include the lack of inclusion of uncertainty and the lack of articulation with explanations from game theory. The limitations of the empirical evaluation are associated with the lack of evaluation of market sentiment.

These limitations are expected to be included in future studies

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