Crypto Economy Complexity

Percy Venegas[1]

[1]Economy Monitor

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Abstract

We demonstrate that attention flows manifest knowledge, and the distance (similarity) between crypto economies has predictive power to understand whether a fork or fierce competition within the same token space will be a destructive force or not. When dealing with hundreds of currencies and thousands of tokens investors have to face a very practical constraint: attention quickly becomes a scarce resource. To understand the role of attention in trustless markets we use Coase's theorem. For the theorem to hold, the conditions that the crypto communities that will split should meet are: (i)Well defined property rights: the crypto investor owns his attention; (ii) Information symmetry: it is reasonable to assume that up to the moment of the hard fork market participants are at a level ground in terms of shared knowledge. Specialization (who becomes the expert on each new digital asset) will come later; (iii) Low transaction costs: Just before the chains split there is no significant cost in switching attention. Other factors (such as mining profitability) will play a role after the fact, and any previous conditions (e.g. options sold on the future new assets) are mainly speculative. The condition of symmetry refers to the "common knowledge" available at t-1 where all that people know is the existing asset. Information asymmetries do exist at the micro level -we cannot assume full efficiency because transaction costs are really never zero. Say's Law states that at the macro level, aggregate production inevitably creates an equal aggregate demand. Since a fork is really an event at the macroeconomic level (in this case, the economy of bitcoin cash vs the economy of bitcoin), the aggregate demand for output is determined by the aggregate supply of output — there is a supply of attention before there was demand for attention. The Economic Complexity Index (ECI) introduced by Hidalgo and Hausmann allows to predicting future economic growth by looking at the production characteristics of the economy as a whole, rather than as the sum of its parts i.e. the present information content of the economy is a predictor of future growth. Say's Law and the ECI approach are about aggregation of dispersed resources, and that's what makes those relevant to the study of decentralized systems. While economic complexity is measured by the mix of products that countries are able to make, crypto economy complexity depends on the remixing of activities. Some services are complex because few crypto economies consume them, and the crypto economies that consume those tend to be more diversified. We should differentiate between the structure of output (off-chain events) vs aggregated output (on-chain, strictly transactional events). It can be demonstrated that crypto economies tend to converge to the level of economic output that can be supported by the know-how that is embedded in their economy — and is manifested by attention flows. Therefore, it is likely that a crypto economy complexity is a driver of prosperity when complexity is greater than what we would expect, at a given level of investment return. As members of the community specialize in different aspects of the economy, the structure of the network itself becomes an expression of the composition of attention output. We use genetic programming to find drivers — in other words, to learn the rankings. Such a ranking score function has the form, returns_tokenA > returns_tokenB = f (sources_tokenA > sources_tokenB). Ultimately, the degree of complexity is an issue of trust or lack thereof, and that is what the flow of attention and its conversion into transactional events reveal.

Keywords: blockchain, cryptocurrencies, ICO, behavioral finance, complexity economics, complex networks, trading signals, market microstructure, market design, trust economics, fields finance.

JEL Classification: G02, L14, E03, D85, C53

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“men err in their productions, there is no deficiency of demand” -David Ricardo

Introduction

All parties involved in an ICO (Initial Coin Offering) have a strong incentive to trust in the success of the venture. Technologists care about innovation and long-term value, organizers care about maximizing visibility while minimizing regulatory exposure, and retail investors usually favor to get rich quickly and then move to a different venture. Sometimes the real motivation for large investors to get involved is to move money across borders through the path of lowest friction (compared to the alternatives of venture capital, private banking or over-the-counter trading), but even them will have more confidence if they can trust that the founding team has a roadmap to value that is validated by the market.

Algorithm traders of coins and tokens can profit from the volatility premium in a sustained basis only if they are good at pricing risk, and for this, they need to quantify the relative strength among tokens and the changing prospects for reserve currency status of forked coins. But crypto economies are a novel phenomena — there is little clarity on how competition really works and when value is at risk. In the words of an industry observer: How can something divide, and both parts become greater than the whole, especially when network effects are in play? Shouldn’t all non-Bitcoin altcoins that compete for the same use case go to zero? (Sokolin, 2018)

I present here a behavioral finance view on crypto economic markets, based on first principles.

The motivation for this approach is two-fold. Quantitative behavioral finance deals with finding factors that can tell us something about the fear, greed, or expectations of economic actors engaging in financial activities. And economic complexity helps explain differences in the level of income of whole economies, and more importantly, it predicts future economic growth.

We demonstrate that attention flows manifest knowledge, and the distance (similarity) between crypto economies has predictive power to understand whether a fork or fierce competition within the same space will be a destructive force or not.

Literature

The micro view: Coase’s Theorem

When dealing with hundreds of currencies and thousands of tokens investors have to face a very practical constraint: attention quickly becomes a scarce resource. To understand the role of attention in trust-less markets we should turn to the work of Ronald Coase, the Nobel laureate, who demonstrated how it is possible to trade on an externality or “social cost” (Coase). For the theorem to hold, the conditions that the crypto communities that will split should meet are:

Well defined property rights: the crypto investor owns his attention.

Information symmetry: it is reasonable to assume that up to the moment of the hard fork market participants are at a level ground in terms of shared knowledge. Specialization (who becomes the expert on each new coin or token) will come later.

Low transaction costs: Just before the chains split there is no significant cost in switching attention. Other factors (such as mining profitability) will play a role after the fact, and any previous conditions (e.g. options sold on the future new digital assets) are mainly speculative.

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The condition of symmetry refers to the common knowledge available at *t-1* where all that people know is the existing digital asset. Information asymmetries do exist but can be appreciated only by "zooming-in"– as one would do by applying gradient descent to take ever smaller steps to reach a goal. This counterintuitive insight was actually Coase's own frustration with policymakers – we cannot assume full efficiency because transaction costs are really never zero. To elaborate on the point, we can consider the dynamics of a "phase change", which can be explained using also complexity science and statistical physics but hold in social systems, as Harmon et al. demonstrated in the work on prediction of collective panic in stock markets (Harmon et al., 2011). From this perspective, we would be zooming-in into a latent state.

The macro view: Say's Law

Say's Law (also known as the Law of Markets) which has been considered the most fundamental law in classical economic theory (Jonsson and Kates, 1999), states that at the macro level, aggregate production inevitably creates an equal aggregate demand. Since a fork is really an event at the macroeconomic level (for instance, the economy of bitcoin cash vs the economy of bitcoin), the aggregate demand for output is determined by the aggregate supply of output — there is a supply of attention *before* there was demand for attention.

This view is much in the spirit of the use of the Equation of Exchange ($MV{=}PQ$) that is commonly applied in the valuation of crypto economies, where each protocol is analyzed as its own separate economy –only that in this case, is not the monetary base and velocity of money which is balanced-out with quantity of crypto and the price of a basket of digital goods, but rather attention flows. When a fork occurs, or a token is issued targeting the same audience and use case, there is a competition for attention that has to be resolved at the macro level because the larger crypto economy cannot produce enough informed investors rapidly enough.

Economic complexity

The Economic Complexity Index (ECI) introduced by Cesar Hidalgo (MIT Media Lab) and Ricardo Hausmann (Harvard) provides the ability to predict future economic growth by looking at the production characteristics of the economy as a whole, rather than as the sum of its parts (Hidalgo and Hausmann, 2009).

Formally, the mathematical definitions are as shown in Figure 1.

And the relationships (the product space of a country) can be visualized either in a matrix form or as a network graph, as in Figure 2.

Note how the proximity between productive clusters encodes production capability: low tech industries are far apart from high tech industries, similar products within an industry share the same color and are clustered together, and enablers are closer (i.e machinery and chemicals should be present to allow for an electronics manufacturing industry to flourish). The key insight from Hidalgo's and Hausmann's work is that "the complexity of a (country) economy is related to the multiplicity of useful knowledge embedded in it, and that hard to transfer, tacit knowledge is what constrains the process of growth and development". In other words, the present information content of the economy is a predictor of future growth. We have to make adaptions to apply this concept to crypto economies, but since international trade flows and information flows are abstractions with universal properties, the key principles hold well.

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If we define M_{cp}, as a matrix that is I if country c produces product p, and 0 otherwise, we can measure diversity and ubiquity simply by summing over the rows or columns of that matrix. Formally, we define:

$$Diversity = k_{c,0} = \sum_{p} M_{cp} \tag{1}$$

$$Ubiquity = k_{p,0} = \sum_{c} M_{cp} \tag{2}$$

To generate a more accurate measure of the number of capabilities available in a country, or required by a product, we need to correct the information that diversity and ubiquity carry by using each one to correct the other. For countries, this requires us to calculate the average ubiquity of the products that it exports, the average diversity of the countries that make those products and so forth. For products, this requires us to calculate the average diversity of the countries that make them and the average ubiquity of the other products that these countries make. This can be expressed by the recursion:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \cdot k_{p,N-1} \tag{3}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{cp} \cdot k_{c,N-1} \tag{4}$$

We then insert (4) into (3) to obtain

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \frac{1}{k_{p,0}} \sum_{c'} M_{c'p} \cdot k_{c',N-2} \tag{5}$$

$$k_{c,N} = \sum_{c'} k_{c',N-2} \sum \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \tag{6}$$

and rewrite this as :

$$k_{c,N} = \sum_{c'} \widetilde{M}_{cc'} k_{c',N-2} \tag{7}$$

where

$$\widetilde{M}_{cc'} = \sum_{p} \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \tag{8}$$

We note (7) is satisfied when $k_{c,N} = k_{c,N-2} = 1$.This is the eigenvector of $\widetilde{M}_{cc'}$ which is associated with the largest eigenvalue. Since this eigenvector is a vector of ones, it is not informative. We look, instead, for the eigenvector associated with the second largest eigenvalue. This is the eigenvector that captures the largest amount of variance in the system and is our measure of economic complexity. Hence, we define the Economic Complexity Index (ECI) as:

$$ECI = \frac{\vec{K} - < \vec{K} >}{\text{stdev}\,(\vec{K})} \tag{9}$$

where < > represents an average, stdev stands for the standard deviation and

$$\vec{K} = Eigenvector\ of\ \widetilde{M}_{cc'}\ associated\ with\ second\ largest\ eigenvalue. \tag{10}$$

Analogously, we define a Product Complexity Index (PCI). Because of the symmetry of the problem, this can be done simply by exchanging the index of countries (c) with that for products (p) in the definitions above. Hence, we define PCI as:

$$PCI = \frac{\vec{Q} - < \vec{Q} >}{\text{stdev}\,(\vec{Q})} \tag{11}$$

where

$$\vec{Q} = Eigenvector\ of\ \widetilde{M}_{pp'}\ associated\ with\ second\ largest\ eigenvalue. \tag{12}$$

Figure 1: Formulation of of the network model of ECI

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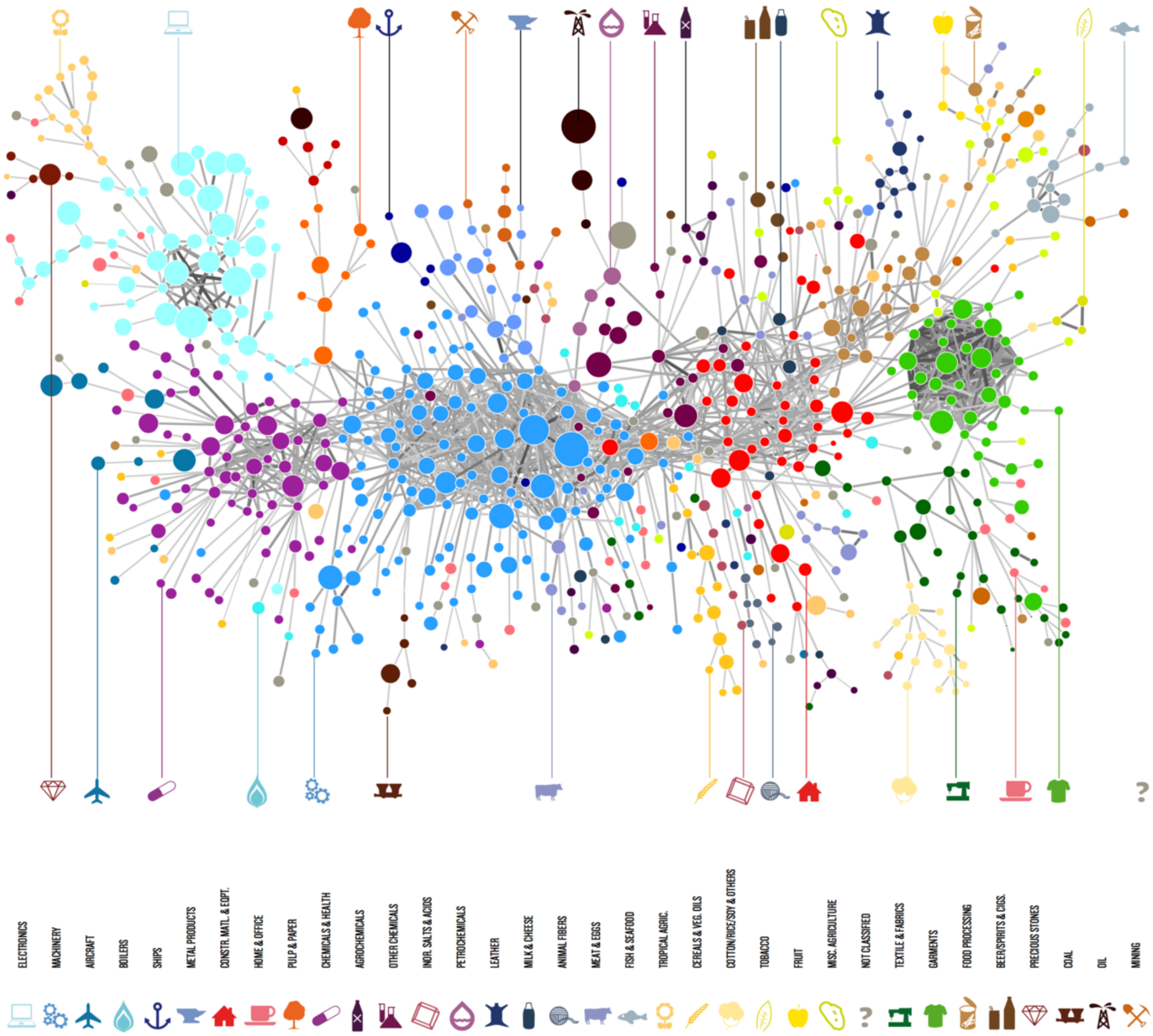

Figure 2: Network visualization of the product space

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Methods and discussion

Data for this section includes digital assets historical monthly returns (Coincheckup.com), on-chain metrics such as fees and transaction volume (Coinmetrics.com), and off-chain web and social analytics (Economy-Monitor.com). We refer to the digital asset of the bitcoin network as ticker BTC, and that one of the bitcoincash blockchain as BCH.

Micro case

Application of Coase's Theorem using empirical data

The graph in Figure 3 maps the attention flows from services used by the bitcoin cash and bitcoin communities in the period from 1 month before the hard fork to 1 month after the hard fork (July to August 2017). The network shows how audiences interests are sufficiently different, which likely offers an opportunity to support both currencies. The shared space includes common interests (such as wallets that supported both coins). The strength of the links encodes *proximity*, a measure of affinity between each service and the community — each particular cryptocurrency network is a sink, a consumer of attention of the users of a service.

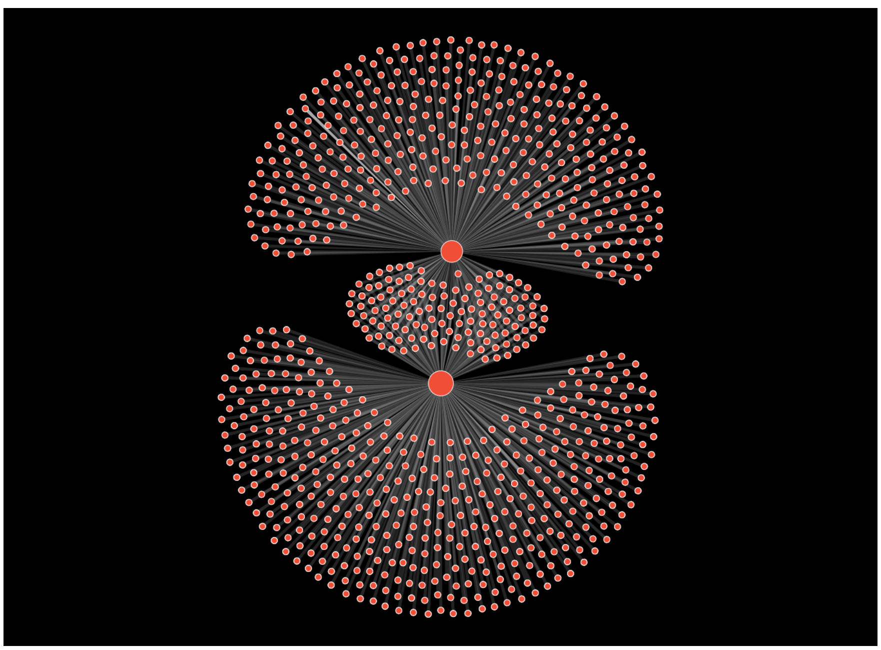

Figure 3: BCH & BTC ecosystems, top 2000 services by traffic countribution

The nodes are vertices of attention, the small ones function as sources and the large ones as sinks. In this example, the focus is on the "off-chain" economy, but the same treatment can be applied to on-chain signals. We could also slice the network views into temporal states (e.g. monthly, weekly or daily) to better appreciate the progression of the relationships between the services and their associated crypto-economy.

Proximity is a distance metric included in the original dataset from the click-stream data provider. A number of parameters are considered, including estimated geographical origin and various demographic factors, traffic volume, semantics, and, expressed interests. Therefore, all these relationships are quantifiable: even while BCH's ecosystem is smaller, the maximum proximity of the sources of attention is 5.56%, larger than BCT's 0.99% — *fitness* can make a new coin competitive even when facing a formidable incumbent. In the matrix of Figure 4, which is a sample from the network, darker color means higher proximity. The sources are services and the targets the bitcoin cash and bitcoin economies.

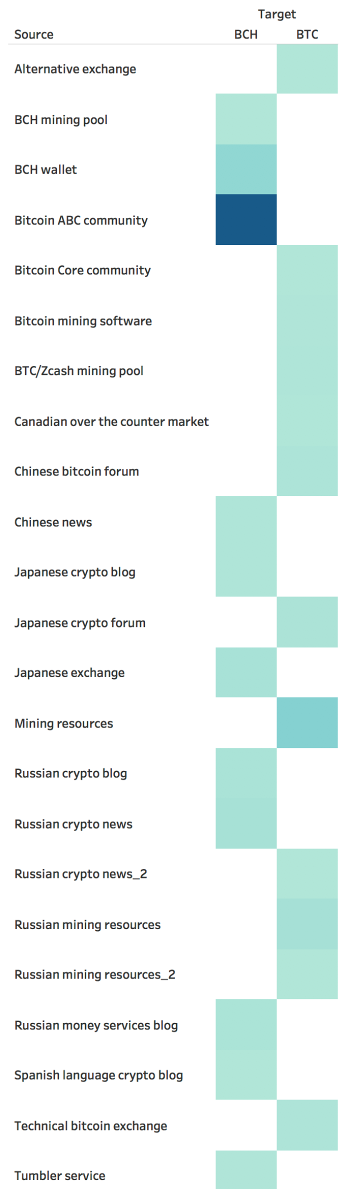

Figure 4: Matrix form from a 24-services sample of the BCH & BTC ecosystem

In Figure 3 the nodes (online communities, commercial services, etc) are in practice connected between each other, but since the objective of the visualization is to highlight the overlap between the economies, for simplicity intra-node links are not shown. For the same reason, proximity is depicted with link tone rather

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than length. Adding all links will bear a resemblance to Figure 2.

Note how bitcoin has a more diverse economy (it generates attention output from more services), and how most services are not ubiquitous across networks – each economy tends to be specialized on a certain type of attention product/service, at least during a period of time. While some of the relationships might be trivial (e.g. current users of a forked version of BTC such as Bitcoin ABC should gravitate easily to a new fork), others may encode useful investment information, such as crypto geo-political factors: users of Australian exchanges were more inclined towards BCH, over-the-counter investors in Canada remained mostly focused on BCT, Russians divided their attention.

Macro case

The fluid nature of attention

While hoarding for capital formation is a well-known fact in crypto economies, in terms of attention flows there can never be oversupply because at some attention price point there always will be a consumer. That is, the technologies of the old and new coins are close enough to ensure that users do not have to over-invest time and energy to take advantage of the opportunity — holders may even have access to "free money" if their wallets support both coins. But at the same time, the *stock of interests* from each community is unbalanced and separated enough so that there are points of attraction, where attention can flow *by gravity.*

That flux may also help explain why some minor altcoins that serve communities in which common interest is shared, resist dying: as long as there is attention flowing, some sort of passive or active transactional activity takes place. This activity may appear to obey mainly profit-seeking behavior (such as the miners' capacity rebalancing towards a dominant chain right after a hard fork), but this is also just an expression of where the stream of attention first flowed.

Figure 5 shows attention inflows from one thousand services to the economies of bitcoin, bitcoincash, bitcoinxt, bitcoinunlimited and bitcoinclassic, and the flows in between those economies. Inflows are measured by incoming visits.

The detail in Figure 6 shows a sample with the streams towards bitcoin classic: the main contributor (21.44%), is a market data service of systemic importance (contributes 44.93% and 51.74% to the attention economy of the two largest coins, BTC and BCH, and 3.33% to another of the smaller forks).

The links in Figure 5 are pair-wise relationships (when a flow of attention exist) and the streams in the Sankey diagram are the share of attention, in this case using ISP and web panel data.

Attention is a valid proxy for economic activity when choosing signals with predictive power — strong variable sensitivity, in machine learning terms. As a matter of fact, besides the "on-chain" economy that usually makes the headlines, there is an "off-chain" crypto economy where economic formation happens when groups explicitly commit resources. For instance, there are thousands of professional traders that pay hundreds of dollars each quarter for access to private chats where they discuss calls on entry/exit points. Attention pricing (Cizinska, 2018) in those trading signals services can be quantified using a similar network-view approach, and it has a direct impact on the larger "on-chain" transactional economy. And there are multiple examples of such micro-economies.

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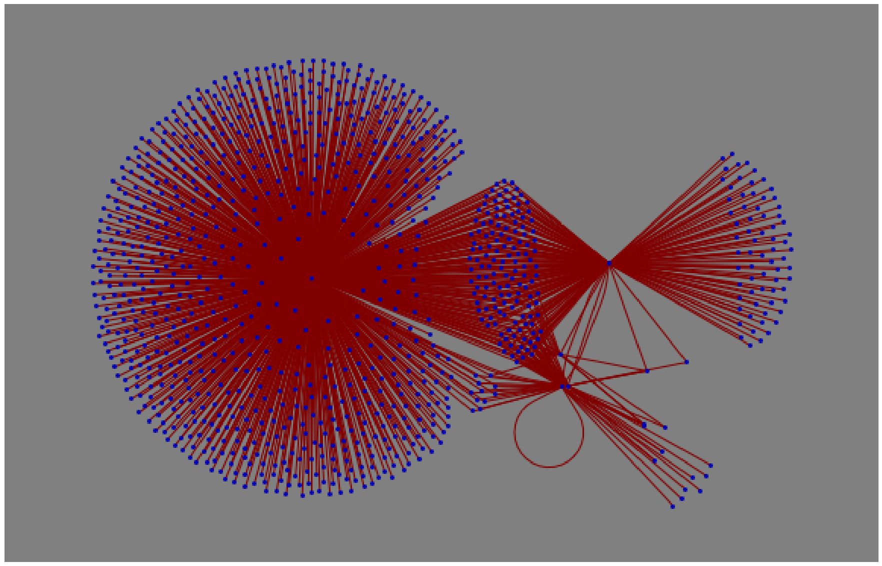

Figure 5: Full network, bitcoin forks

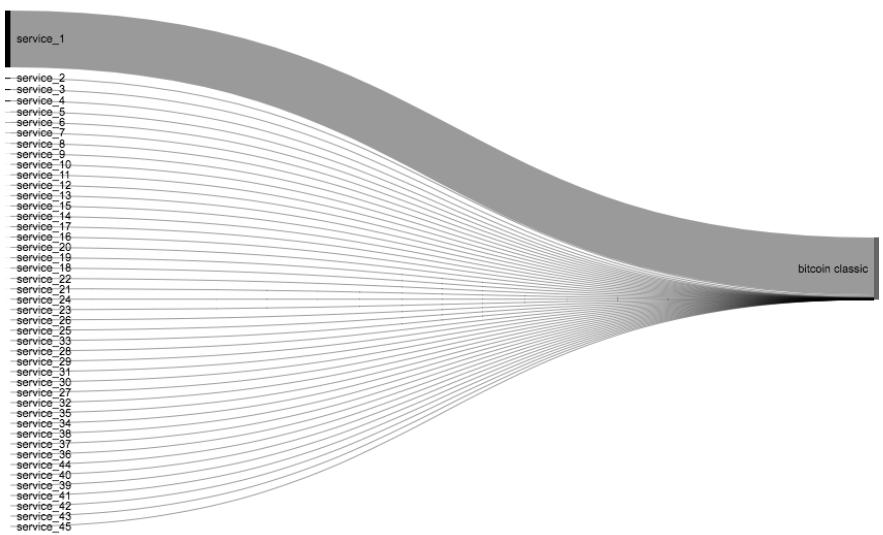

Figure 6: Sankey diagram view, Bitcoin classic detail

Crypto Economy Complexity

While economic complexity is measured by the mix of products that countries are able to make, crypto economy complexity depends on the remixing of activities. In this sense, *specialization* is a kind of division of labor — do investors become simultaneously experts in ICO valuation, crypto hedge fund operations, cryptocurrency contracts for difference betting, smart contract programming, and so on, or do they seek for social validation from the experts on each of these fields before making a decision? If we inspect the network of bitcoin forks we find that competitive coins not only are supported by hashing capacity and other characteristics that can be considered as economic fundamentals, but they rely on attention flows from a diverse pool of difficult-to-transfer knowledge. One should know those *who* know.

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We can also distinguish between on-chain events, which are usually related to the operation of the protocol and tangible transactional activity, and off-chain events, which can be any relevant signal — for instance, requests for web services or API calls. Instead of making products, these economies produce sources of attention (from/to a service). And this productive knowledge is embedded in the governance and market structures of the society — this is why a great many of the services that drive economic activity in crypto economies are essentially "social fabric", such as forums, engaging news bots, and over-the-counter exchange brokers. You should know *where* the required knowledge of those interacting agents (either people or machine) is aggregated.

A r*evealed comparative advantage* is present when the economy captures attention above its fair share — as we saw in the case of BCH, in the matrix view of Figure 4. Traffic revealed stronger knowledge intensity in BTC mining software (as you would expect from a more mature currency), but interest in BCH mining pools was of a similar quality (same color tone, similar proximity) as BTC's. Poor attention in such a critical part of the economy should doom a forked coin — this is not about vanity indicators (in this context, metrics such as social network "likes"), but an actual economic activity-enabling knowledge. Only if the agents in the economy get smarter, the competing blockchain or token can prosper.

This is, in principle, the information content of the crypto economy. But the definition of an economic agent not only applies to human activities: automated interactions, such as demand signals generated by bots operating in exchanges, reveal the preferences of their optimization-seeking users. And it only makes sense for a crypto economy to develop strength in services that are affine: this is why a clear path of attention is drawn from BCH wallets to the BCH economy, and not to BTC's (i.e. it will make little sense for users not interested in claiming BCH to try to accumulate knowledge about BCH wallets).

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Time evolution of the network

According to Hausmann, Hidalgo et al, increased economic complexity is necessary for a society to be able to hold and use a larger amount of productive knowledge (201, 2014).

It is important to understand the dynamics of crypto networks' productive structures for two reasons: structure changes over time, and, knowledge dies if it is not transmitted. It is possible to simulate those changes because the social structures behind crypto communities follow well-known models. Let us analyze the particular case of the social network producing attention towards the Bitcoin SegWit2X hard fork.

We looked at a sample of 4 431 social media mentions that covered the topic of B2X (the new forked coin) in the period of October 17–24, 2017. Most of those came from users on Twitter, Reddit, and Bitcointalk, and discussed topics such as mining of the new coin and futures contracts. The user that generated the most volume was actually a bot, which generated 4% of the volume and had 65 followers. Let us assume that those followers are mostly human and reasonably well connected, as it will be expected in small tribes such as crypto communities. We can use the Watts–Strogatz model to generate a random graph with "small world" properties, such as a social network, as shown in Figure 7.

What the resulting graph depicts is the information diffusion using density heat maps to analyze connectivity and nearness. A highly clustered version of this social network (red) is more robust and will allow the information to spread similarly. In other words, as members of the community specialize in different aspects of the economy, the structure of the network itself becomes an expression of the composition of attention output.

The example pertains mainly to the progression of social structure formation, how it is a fact of nature that participants tend to cluster together and that this kind of division of labor is a necessary condition for economies to prosper. To map the conversation dynamics we would need to create a series of directed graphs (i.e. adding arrows between nodes) and from there we could solve the minimum-cost flow problem (find the

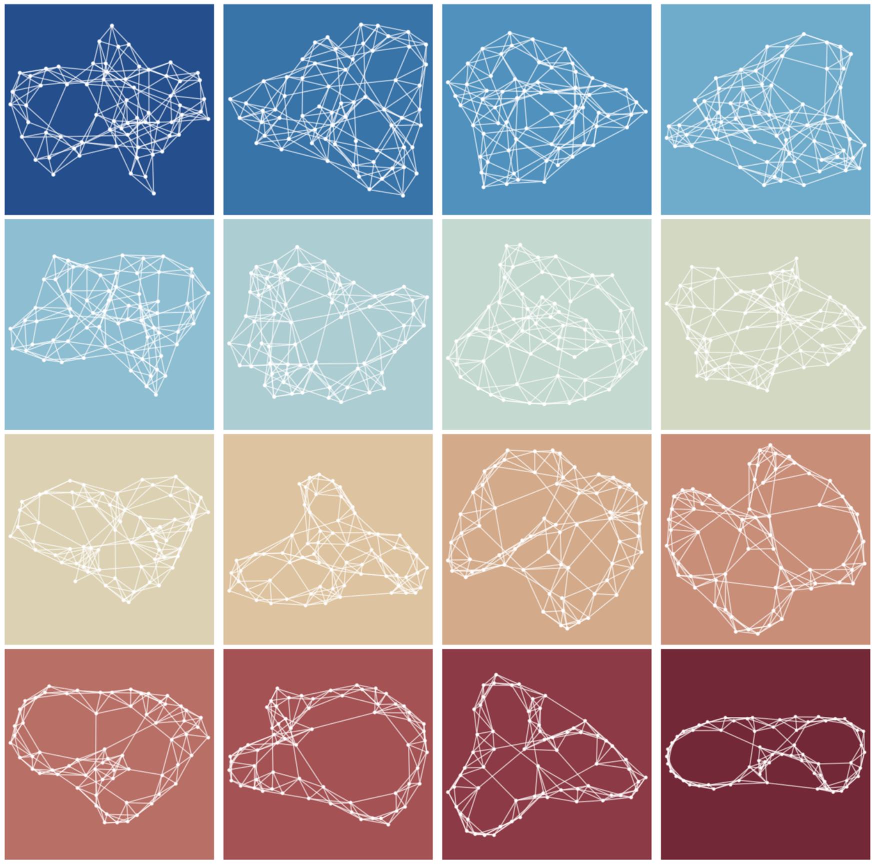

Figure 7: Clustering, sample from the Bitcoin B2X social network

cheapest possible way/the best delivery route for sending a certain amount of flow across the network); we would then find that since each cluster is a specialized group, there is no need to broadcast all information to everybody all the time – a significant gain in efficiency.

We can also superpose multiple layers (i.e. create a multiplex network) to obtain an approximate portrait of the expected evolution of knowledge-containing structures within a crypto economy. And, by comparing those meta-structures across economies it is possible to project the strength of the social cohesion – that in turns is transformed into economic activity.

There is another interesting phenomenon that is quite common in crypto economies. Often agents with perverse intentions (e.g. ICO scammers) compete for attention and disseminate information/misinformation in order to exploit trust. This also takes advantage of the information diffusion characteristics of networks, and can be analyzed using epidemic diffusion models (Lawyer, 2015) (as one can imagine, the recovery rate of a node might be low because trust is not only scarce but fragile) , or using game theory-based models (Aymanns et al., 2017).

Rankings

Ultimately, quantifying economic complexity is about ranking economies. The problem is that the ECI approach attempts to find the answer recursively based on a set of well defined products that are more or less unchanged, while in a crypto economy the sources of attention change constantly due to the swift pace

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of innovation — so there is no standardized classification of products as in international trade, and the result could not converge. Also, in the case of countries the relationships are binary (either a country produces a product or not, that is, a link exists in the network or not), while in a crypto economy the strength of the attention signal matters — this is why the boxes in the matrix on Figure 4 are colored with different intensities.

If we borrow a metaphor from mainstream finance, where the flow is the net of all cash inflows and outflows in and out of various financial assets, an alternative comes into view. Figure 8 shows the progression on the intensity of the outflows emerging from the bitcoin cash economy over three months, where size is the share from each service, and color intensity encodes the comparative scale of each service, and the most recent period is stacked at the bottom. The treemap depicts usage of various services that support the BCH economy, and the intra-economy flows between BCH and other coins.

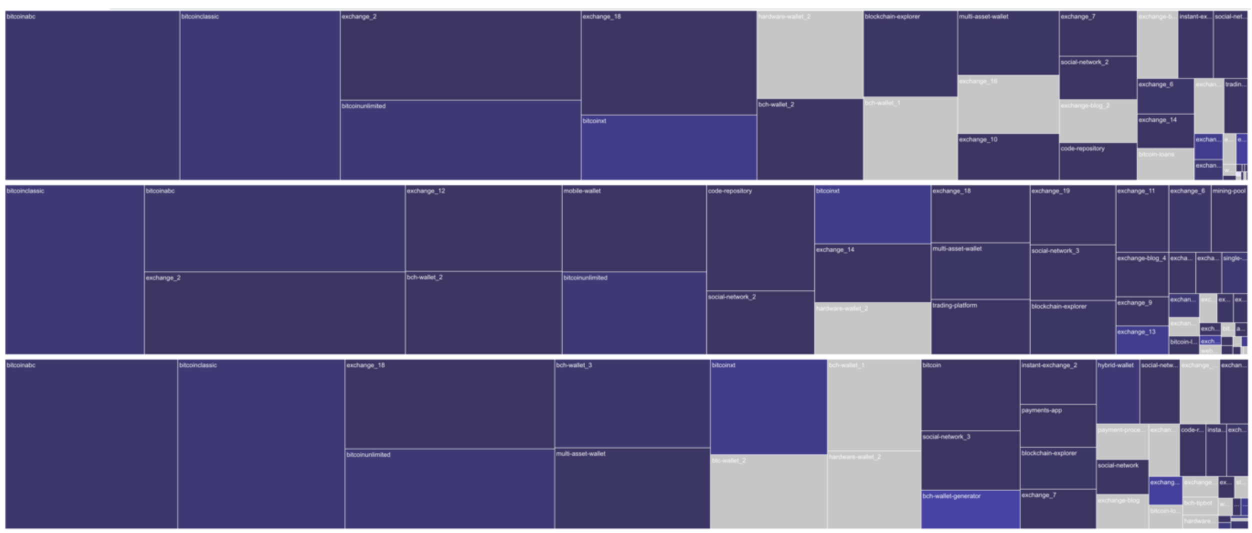

Figure 8: BCH attention outflows, July to September 2017

As we can see, this is a dynamic system: the sources *from* the BCH economy evolve from informational services (e.g blogs) to economic activity enablers (such as payment apps, supporting exchanges, and so on) and new services (e.g different types of wallets), that become more or less relevant as competition for attention increases.

If the net of inflows and outflows encode the complexity of the economy, in essence, we are talking about an information theoretical problem. We could, for instance, use a Hidden Markov model to infer an unobserved sequence of events from the observed outputs (outflows). Although the Markov method is formally considered memory-less (i.e. only the present state matters), in practice, it can be implemented with the memory of a number of previous events.

Modeling aside, there exists a sort of "value by memory" that can be derived from empirical data. Being the larger crypto economy essentially a closed system (i.e. there are still limits to the rate on the absorption of knowledge, so in small windows of time, churn in one community more or less equals gains in others), memory decay and re-wiring of links are quite common.

Another interesting observation is that it is very difficult to sustain attention after an extraordinary event; for instance, there was a spike in services interest and usage across the board during the crypto rally of June 2017, but despite overall growing business, those exact same levels of activity were not observed until

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November and December 2017.

Ranking tokens. So far we have discussed comparative measurements among coins, but we should consider other possible approaches to ranking alternative crypto economies. Let us suppose that we need to rank two economies that appear close to identical in terms of knowledge intensity (e.g tokens with very similar use case and public visibility). For such a pair of crypto economies: if a service is not ubiquitous, that will signal higher specialization in one of them; if the economy is more diverse, that is a sign of strength.

As a case in point, we look at Augur and Gnosis, the prediction markets. Let us begin by plotting *returns* (Figure 9), defined as the current dollar value of a $1 investment at the time of token sale. We identify peaks at 59.27x (Augur) and 12.16x (Gnosis), so from an investment perspective, both tokens show different performance. But what are the sources of such dissimilarity?

Figure 10 plots the ranges of contribution from the largest sources of attention *to* the economies of both tokens (Augur on top), during the same period. The box plot diagram shows relative traffic share to the websites of both projects.

First, we note the binary nature in the share of sources: often one token captures all of the attention of an important service, in detriment of the other which gets nothing. Or, there is a combination of smaller contributing services, as in the case of 100% of attention from a popular newsletter that went to the economy of one token. And, shared sources tend to be the usual suspects: news outlets, ICO trackers, and the like.

But there are also moments when a lagger can show increased strength. For instance, in July, Stox (another prediction market that just held an ICO on August) captured a larger share of attention than its peers: monopolized Facebook (97.52%), Twitter (54.67%), Bitcointalk (83.95%), Steemit (64%) and VKontakte (83.93%). Even when considering a basic proxy for attention, such as web activity, there is a temporary monopoly in terms of direct visits (47.9%). However, in September after the ICO had concluded, the attention finally converged to the same level of Augur and Gnosis. Figure 11 shows how there is clearly a dominant attention economy (Augur's) despite the transient bursts of activity from other smaller players.

This "bursting" pattern in the signal hints at the possibility of applying methods inspired by biology. For instance, we could use genetic programming (Schmidt and Lipson, 2009) to find drivers — in other words, learn the rankings. Such a ranking score function has a form as in Equation 1,

$$returns_{tokenA} > returns_{tokenB} = f(sources_{tokenA} > sources_{tokenB})$$

Where each source is weighted according to the total contribution to the group of tokens.

The scoring function may also include delayed effects, to reflect on the time-dependent nature of the relationship between financial returns and attention flows (i.e. current performance as a function of previous visibility & demand). The Spearman's Rank Correlation is the error measure of choice for the machine learning model, since it is agnostic to the exact values and simply measures the correlation of putting tokens in the same order – the only assumption is the ability to sort the objects (crypto economies) according to each given attribute (sources of attention).

There is no one-size-fits-all attention metric because one needs to be aware of the context and optimize for different objectives and risk appetites. What matters is that attention is one of the key elements of a trust decision system, being the others the probability of gain, the expected gain, and the fraction of capital that the investor is willing to risk (Jøsang and Presti, 2004). And that trust is built when visibility increases, while trust is resolved when an investment is realized (Krabec, 2017).

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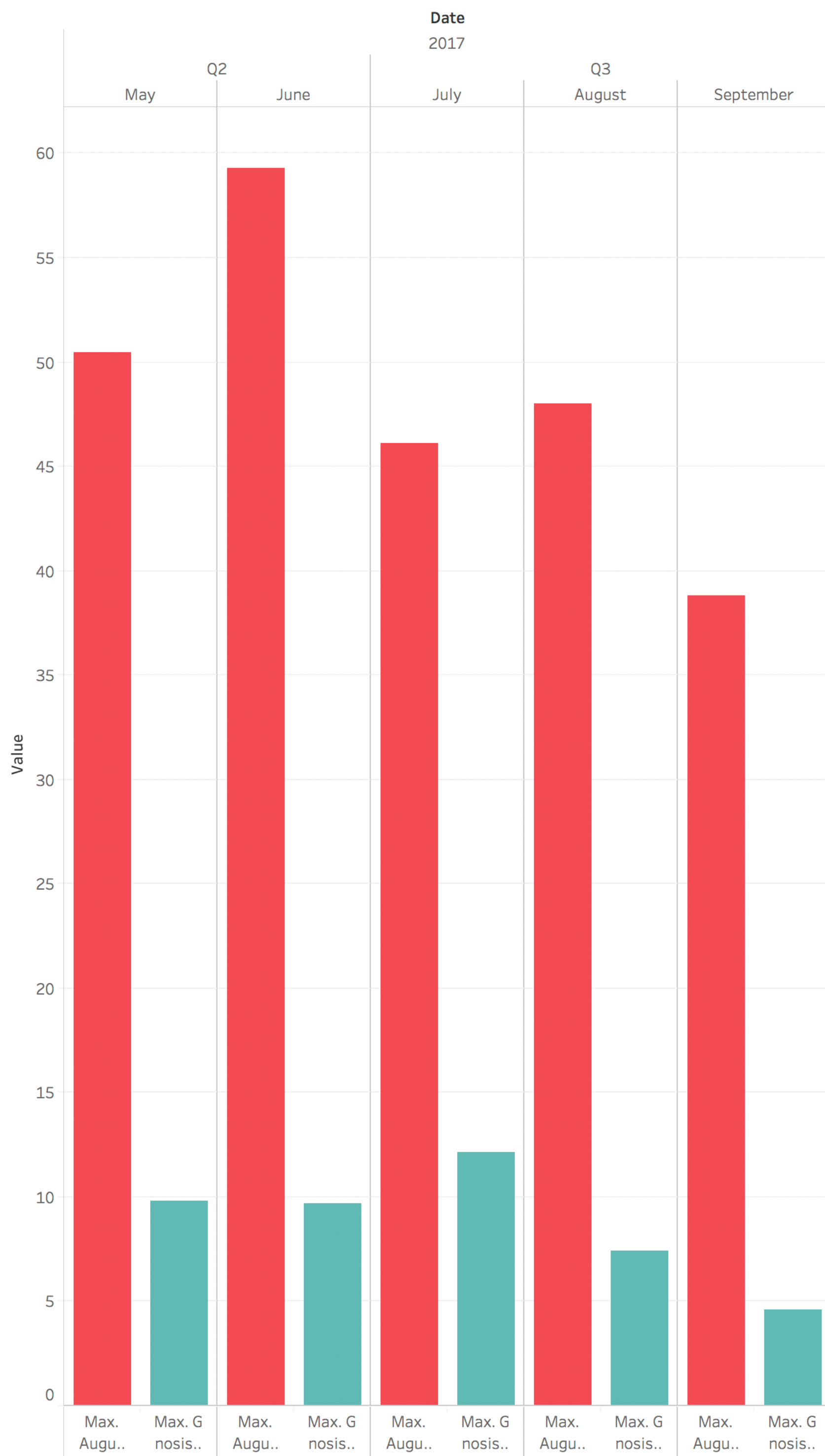

Figure 9: Peak returns. Source: TokenData

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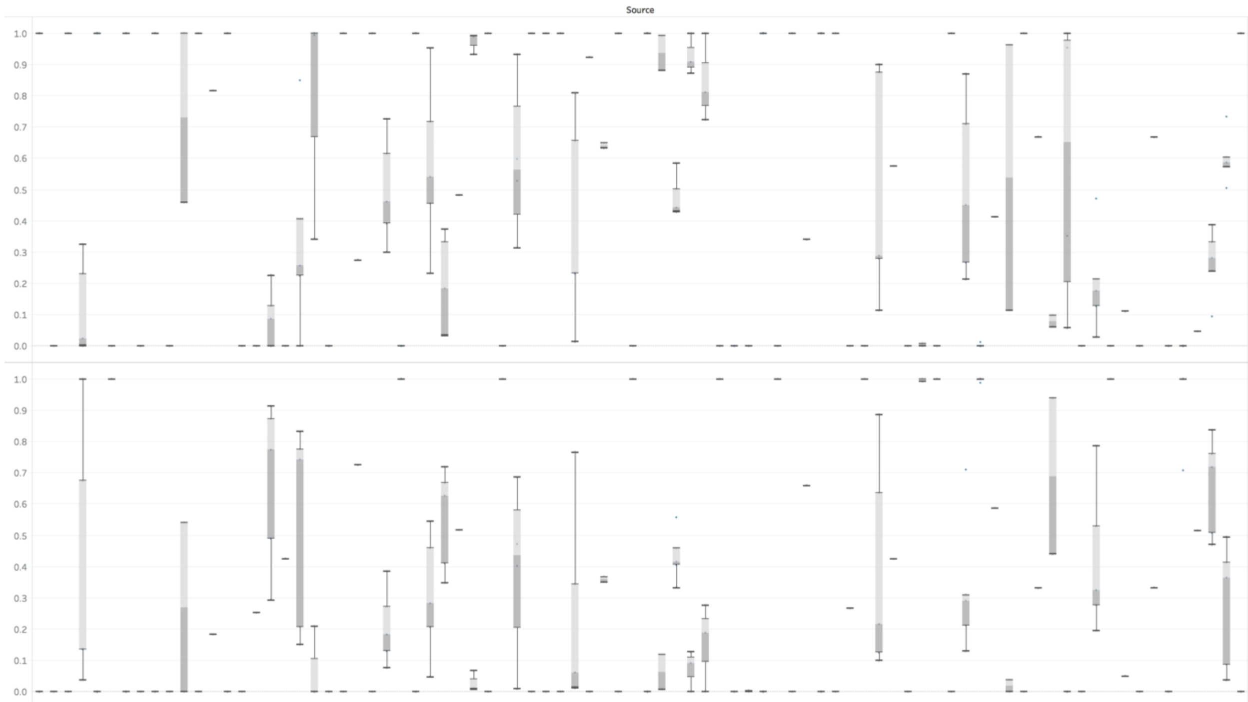

Figure 10: Top 22 attention sources

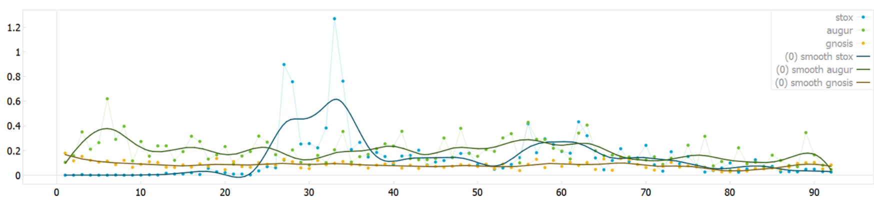

Figure 11: Prediction markets normalized attention inflows, Jul-Sept 2017

Rankings heuristics

The machine learning-genetic programming approach is applicable to both tokens and coins. Let us demonstrate step by step how it is applied to the BCT-BCH case.

Traffic share. We sample the top 1000 sources that are shared by both bitcoin and bitcoincash over a period of 6 months, from August 2017 to January 2018. To make the sources of attention representative, we select bitcoin.org and bitcoincash.org as the attention sinks. Figure 12 shows how the distributions are different: bitcoin captures the larger share of traffic from most sources (80% or higher), while bitcoincash has more sources that are small contributors (20% or lower).

Contribution. However, the “market share” of each attention economy has to be modulated by the contribution of each source — as we saw before, some sources have a disproportionately large weight. Here we look at the aggregate contribution from all sources towards both Bitcoin and BitcoinCash, across 6 months. We see how the dominance of 3 sources is clear, while there are hundreds of smaller contributors.

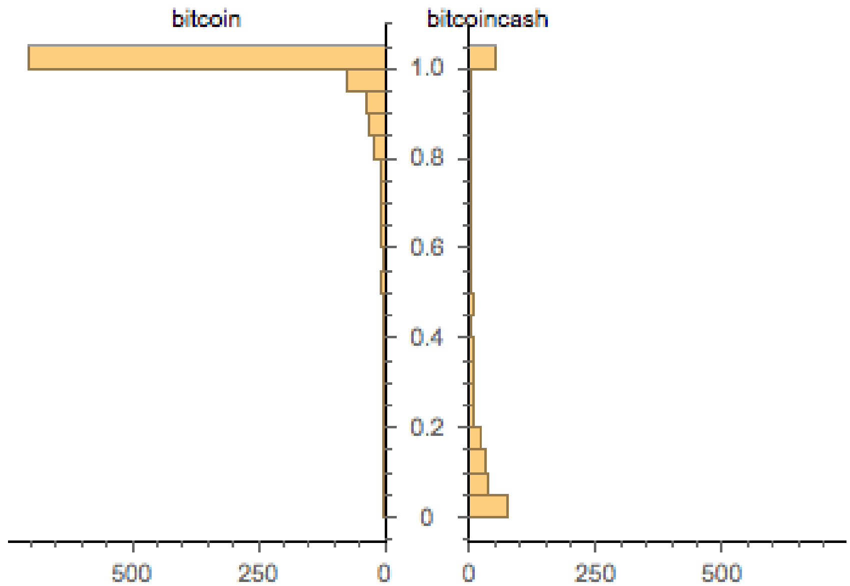

Figure 12: Paired histogram, traffic sources

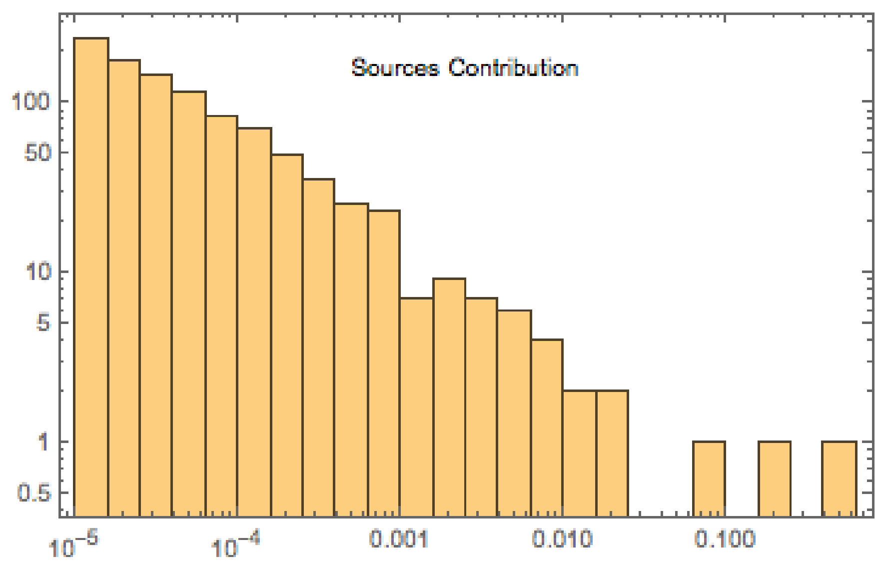

Figure 13: Contribution. Log, LogCounts

Share over time. To better understand the shape of the data we construct an array, in which the vertical axis represents the passage of time (from August at the top, to January at the bottom), the cells in the horizontal from left to right are each one of the first 200 sources (we take this smaller sample from the top contributors from the 1000 sources, for simplicity of analysis and visualization), and the colors encode the traffic intensity (yellow is high, blue is low, red is no data).

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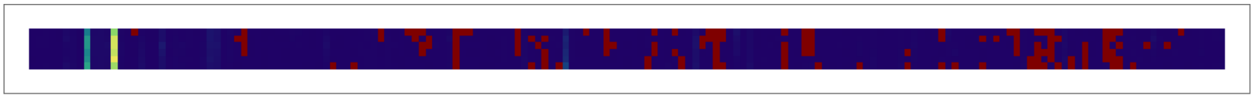

Figure 14: bitcoin, array of variables

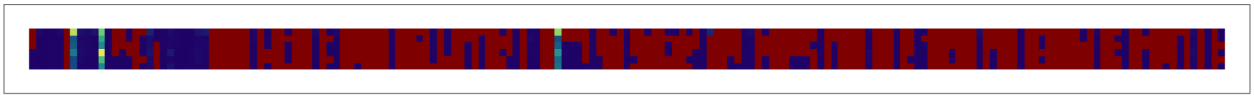

Figure 15: bitcoincash, array of variables

We can verify that bitcoin has a virtual monopoly on attention (there is very little red on its chart). There is also no apparent overlap in the top sources for each crypto-economy — this is a sign of specialization. For instance, some forums clearly chose the bitcoincash camp, and some statistics services adopted BCH as their niche specialty (or became favorites of the bitcoincash community). Over there, bitcoincash wins the contest for attention — but since the contribution of those sources to the overall bitcoin-bitcoincash economy is small, their positive impact on the creation of value is not certain.

One thing that is striking to see is that time did not make things better for bitcoincash: there is some creative destruction in the form of services that bitcoincash came to dominate later, but there are not really many. And few more that did not exist at the beginning came online later as developers started building tools specifically for this economy. But in general, the ones that were strong at the beginning remained so across the whole period of time.

Predictive model. The first thing that we should note is that these are fat arrays — that is, they have too many variables and very few observations. This is by itself a challenge for most machine learning techniques unless an evolutionary algorithm is used.

When we start learning ranking models, we interpret *returns* as an indication of value, and the demand signals from traffic sources (e.g. average page visits) as the *drivers* of that value. Since we are constructing a ranking system, we are interested in the demand relationships that optimize $BTC\_returns > BCH\_returns$.

The first formula that we discover may appear as a trivial model: the returns of BCH are larger when the influential site Bitcoin.com, an advocate of BCH that also operates a wallet service, throws its weight to support BCH. Model 1 is shown (variable names are shortened for readability).

$$(BTC_{returns}) \ > \ (BCH_{returns}) = (-BTCbitcoincom) \ > (-BCHbitcoincom)$$

We keep running new generations of our evolutionary search (an example, see two more models in the Table of Figure 16), and more informative relationships emerge; non-mainstream search engines where demand signals begin to pop-up, also mining pools, and even informational sites. Several iterations can be run, and if we do it over larger sample sizes (instead of the 200 sources, we use the original 1000, or even 10.000) and more time periods (temporal steps measured in weekly or daily returns, instead of months), likely many other interesting relationships will appear.

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greater((BTC returns), (BCH returns)) = greater(average_bitcoin_w_cryptocurrencyfacts_com - average_bitcoin_w_bitcoin_com, average_bitcoincash_w_cryptocurrencyfacts_com - average_bitcoincash_w_bitcoin_com)

Variable	Sensitivity	% Positive	Positive Magnitude	% Negative	Negative Magnitude
average_bitcoin_w_cryptocurrencyfacts_com	1.5022	100%	1.5022	0%	0
average_bitcoincash_w_bitcoin_com	0.59128	100%	0.59128	0%	0
average_bitcoin_w_bitcoin_com	0.33582	0%	0	100%	0.33582
average_bitcoincash_w_cryptocurrencyfacts_com	0	0%	0	0%	0

greater((BTC returns), (BCH returns)) = greater(average_bitcoin_w_p2pool_in - average_bitcoin_w_Ask_Search, average_bitcoincash_w_p2pool_in - average_bitcoincash_w_Ask_Search)

Variable	Sensitivity	% Positive	Positive Magnitude	% Negative	Negative Magnitude
average_bitcoin_w_Ask_Search	1.2894	0%	0	100%	1.2894
average_bitcoin_w_p2pool_in	0.66338	100%	0.66338	0%	0
average_bitcoincash_w_Ask_Search	0	0%	0	0%	0
average_bitcoincash_w_p2pool_in	0	0%	0	0%	0

greater((BTC returns), (BCH returns)) = greater(-average_bitcoin_w_bitcoin_com, -average_bitcoincash_w_bitcoin_com)

Variable	Sensitivity	% Positive	Positive Magnitude	% Negative	Negative Magnitude
average_bitcoincash_w_bitcoin_com	1.0216	100%	1.0216	0%	0
average_bitcoin_w_bitcoin_com	0.51346	0%	0	100%	0.51346

Figure 16: Model 3, 2, 1 variable sensitivity

Explanation of terms

Sensitivity: The relative impact within this model that a variable has on the target variable.

% Positive: The likelihood that increasing this variable will increase the target variable. If % positive = 70%, then 70% of the time increases in this variable lead to increases in the target variable (but the remaining 30% of the time it either decreases it or has no impact). If % positive = 0%, increases in this variable will not increase the target variable.

Positive Magnitude: When increases in this variable lead to increases in the target variable, this is generally how big the positive impact is.

% Negative: The likelihood that increasing this variable will decrease the target variable. If % negative = 60%, then 60% of the time increases in this variable lead to decreases in the target variable (but the remaining 40% of the time it either increases it or has no impact). If % negative = 0%, increases in this variable will not decrease the target variable.

Negative Magnitude: When increases in this variable lead to decreases in the target variable, this is generally how big the negative impact is.

Details: Given a model equation of the form `z = f(x,y....)`, the influence metrics of `x` on `z` are defined as follows:

Sensitivity: $\overline{\left|\frac{\partial z}{\partial x}\right| \cdot \frac{\sigma(x)}{\sigma(z)}}$, evaluated at all input data points.

% Positive: The percent of data points where $\frac{\partial z}{\partial x} > 0$

% Negative: The number of data points where $\frac{\partial z}{\partial x} < 0$

Positive magnitude: $\overline{\left|\frac{\partial z}{\partial x}\right| \cdot \frac{\sigma(x)}{\sigma(z)}}$, at all points where $\frac{\partial z}{\partial x} > 0$

Negative magnitude: $\overline{\left|\frac{\partial z}{\partial x}\right| \cdot \frac{\sigma(x)}{\sigma(z)}}$, at all points where $\frac{\partial z}{\partial x} < 0$

where:

$\frac{\partial z}{\partial x}$ is the partial derivative of *z* with respect to *x*,

$\sigma(x)$ is the standard deviation of *x* in the input data,

$\sigma(z)$ is the standard deviation of *z*,

$|x|$ denotes the absolute value of *x* and

$\overline{x}$ denotes the mean of *x*.

Figure 17: Variable sensitivity definition

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This diversity points to an interesting fact: we should perhaps deploy *model ensembles (Kotanchek et al.)*, rather than standalone models. And this makes sense: while in classical Economic Complexity theory one deals with relatively unchanged basket of products that are produced by the same countries, in a crypto economy new sources of attention are born and die constantly, and the sinks of that attention (the economies of each network) also are created at any time that a fork occurs and a community rallies behind the new coin.

A final observation is that standalone models are fragile themselves – they are either incomplete or lack sufficient explanatory power, as shown in Figure 16-17. In that regard, our preferred anti-fragile ranking system should be one that is flexible and robust — as the crypto-economies that are being analyzed themselves.

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Conclusions

In essence, both Say's and the ECI approach are about aggregation of dispersed resources, and that's what makes those so relevant to the study of decentralized systems (even when not using only blockchain data, but rather off-chain data points).

Some services are complex because few crypto economies consume them, and the crypto economies that consume those tend to be more diversified.

We should differentiate between the *structure of output* (off-chain events) vs *aggregated output* (on-chain, strictly transactional events). Until now most valuation proposals have focused on the second, leaving the first in the realm of non-scientific due diligence — applying various degrees of rigorosity, but still leaving open too many questions.

But it can be demonstrated that crypto economies tend to converge to the level of economic output that can be supported by the know-how that is embedded in their economy — and is manifested by attention flows. Therefore, it is likely that a crypto economy's complexity is a driver of prosperity when complexity is greater than what we would expect, at a given level of investment return.

Practical implications of this research

It may appear strange, but the transition to a trust-less financial system is all but frictionless.

In regards to predictive power, this research suggests that one can estimate the probability of certain events occurring on a certain timeframe based on known constraints of the blockchain financial system, because although attention can switch instantly, there are physical limitations in the capacity of the current system and its connection to the mainstream financial system.

For instance, one may think about off-ramps from exchanges. If getting close to the date of a fork it becomes evident that the event will create a major market disruption, even a three days lead time will not be enough to run to safety because most wire transfers will take longer than that. There are private banking services that hold the equivalent to nostro-and-vostro accounts with exchanges to facilitate the operation of arbitrage traders, and those should benefit from this situation (and that can be measured using the flows approach). But even those fiat banking platforms have limitations in the amount of business that they can handle when a catastrophic, fat-tailed event occurs. And if some are located in jurisdictions that happen to have banking holidays days before the fork, that stresses the system even more.

Would such an scenario be a definitive strike to a nascent "crypto organism"? Perhaps not, but without having a comprehensive understanding of the relevant parts of the system and how they interact it is impossible to meaningfully forecast emerging behavior.

Ultimately, the degree of complexity is an issue of *trust* or lack thereof, and that's what the flow of attention and its conversion into transactional events reveal.

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