Trust Asymmetry

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Abstract

In the traditional financial sector, players profit from information asymmetries. In the crypto world, information asymmetries are the main driver for transactions. Transactions are a flow, trust is a stock. Even if the information asymmetries across the medium of exchange are close to zero (as is expected in a decentralized financial system), there exists a “trust imbalance” in the perimeter. The final production firms in the medium of exchange where we find trust asymmetries is close to zero — in shared distributed ledgers and digital commerce. In the context of the traditional financial sector, information asymmetries might be viewed as a particular case of information asymmetries — albeit one in which hidden information can be accessed, of the sort that neither price nor on-chain data can provide. The key discovery is the existence of a “trust imbalance” in the medium of exchange, the original fundamental source of intrinsic value in digital assets. This research is relevant to policymakers in every country, to all economic agents — who are looking to understand the structure and dynamics of digital asset-based financial systems. In contributions, we also apply to any socio-technical system of “value-based attention flows.”

Keywords: Trust economics, Computational trust, Cryptocurrencies, Bitcoin, Behavioral finance, Web Analytics, Blockchain Analytics, Machine learning, Genetic programming, Markets disintermediation, Topological Data Analysis, Applied Quantitative Analysis, Field Finance.

JEL Classification: G02, F63, B17, C53, C58

Introduction

The are various reasons why bitcoin (and to a lesser extent, other algorithmic currencies) are quickly capturing an increasing share of international flows, the US and the EU printed large amounts of money after the financial crisis, and because of nationalistic sentiment, now international flows: the US and the EU printed large amounts of money, whereas China and Japan did not. The rise of the South and Asia Pacific; programmatic money is a superior other asset; vault (cold storage), or similar.

1.2 Digital commerce

Cross-border payments are an inconvenience for the majority of human-

It is easy if one lives within the walled gardens of the internet. Amazon takes your money if you live in the US/EU, Alibaba if you live in China. But as the teams at the MIT’s Collective Learning group and the Harvard’s Growth Lab point out, growth will not come from the West or even China, but from India and everywhere else. Nonetheless, consumers in the emerging world face great difficulties getting access to affordable credit cards that can work without problems all the time, everywhere — not even bitcoin debit cards are readily available because the banks are largely issued to European and North Americans, and also, issuers, are constantly limiting their use to purchase cryptocurrency. Meanwhile, a large share of freelancers (many of whom are bitcoin earners) live in the developing world, and the current KYC policies that traditional banks enforce really do not apply to them — it is unrealistic to understand the financial reality of emerging economies from an office in Basel, where the know-your-customer standards are issued.

International commerce runs a large deficit of trust. Merchants are wary of prospect customers, buyers have no confidence in sellers, and local regulations have no power over foreign merchants. However, demand for new payment methods (including cryptocurrencies) is growing across multiple markets. Figure 2 shows that search engine queries for “where can I spend bitcoins” and “ ” quadrupled from April to May 2017.

When even a weak signal shows strengthening demand (Russia’s top search engine is Yandex, India’s first language is Hindi) merchants know that something Interesting is going on, and they begin supporting new payment methods such as digital currencies. The way it works is that users accumulate or buy cryptocurrencies to use them in exchange for services, goods, and entertainment. Deposits are handled by a payments processor and are put in custody in an exchange (for instance, engage in trading activities), vault (cold storage), or similar.

Despite the decentralized nature of the medium of exchange, there are winners and losers. The demand for new payment methods is increasing, and trust asymmetries are growing.

If the payment mechanism takes care of processing and fraud simulta- neously, then the decision is straightforward.

1.3 Trust asymmetries

Note that in none of those two cases were there any “real banks” in- volved. And these are not fictional scenarios: today there is trading between Africa and Asia denominated in bitcoin (mainly via over-the-counter markets) [22], and digital currency denominated e-commerce grows [4] while brick and mortar retail shrinks. Money is already flow- ing for legitimate international commerce, largely without the banks. Figure 3 shows the intuition behind the concept.

Even if the information asymmetries across the medium of exchange are close to zero (as it is expected in a decentralized financial system), there exists a trust imbalance. And there are different levels of trust among trustful parties: naturally, a merchant will trust a local banker more than its foreign counterpart. In the middle, there is no need to trust a bank, a correspondent bank, or even a government. You just need to trust that people will pursue their own self-interest: miners will verify transactions while it is profitable to do so, and over-the-counter exchanges will maintain order books as long as there is demand. There is only the issue of on-ramping and off-ramping to fiat, but one could argue that this lies at the boundaries of the medium of exchange — it is a trust coupling problem. Therefore, whoever can scale up trust provides a valuable financial intermediation service — at least until the system becomes mature.

2 Literature

In their book “Beyond Smart Beta: Index Investment Strategies for Active Portfolio Management” Kyla, Kamil, and Stulman define Total Return as the amount of value an investor earns from a security over a specific period when all distributions are reinvested [16]. While it is still early in the development of crypto assets to account for all distributions (dividends, coupons, capital gains), it is customary to use at least the price increase to measure the investment’s performance. Typically, these historical returns would be the “goal” in a predictive model, or “learn” (in an interactive fashion) what demand signals are also signs of value appreciation. However, in crypto economies prices are not taken as a measurement of market sentiment, and related quantities such as on-chain transaction volume are difficult or impos- sible to assess in a trustworthy manner [6]. Therefore we may begin to characterize off-chain flows in terms of returns (a common success measure for investors), but soon we should move beyond prices, exchange volumes and transaction counts, and include hard metrics such as fees into our analysis.

An ideal scenario to study trust asymmetry is the case of a cryptoeconomic system with two chains of trust (one chain of trust in each case) that are supported by the know-how that is embedded in their economy — and
is manifested by attention flows. And, since a fork is really an event at the macroeconomic level (for instance, the economy of BitcoinCash vs the economy of Bitcoin), the aggregate demand for output is deter-
mained by the aggregate supply of output — there is a supply of atten-
tion before there is a demand for output. We also discussed the prac-
ticities of quantifying economic complexity by ranking economies, focusing on the specific case of cryptocurrencies and tokens. Here we will demonstrate how to develop the heuristics of such an approach, from the perspectives of structure and dynamics of the combined sys-

2.1 Trust equations
The socio-technical modeling of mass and information flow has usually been accomplished in econometrics, industrial, and, policy planning circles, using Jay Forrester’s System Dynamics methodology [10]. The further development that continuous systems contain differential equations is hidden from the user by talking about levels, i.e., quantities that can accumu-
late (state variables), and rates, i.e., quantities that influence the accu-
accumulation and/or depletion of levels (state derivatives) [8]. A typical model for the traditional financial system is shown in Figure 4. How-
However, real-life systems modeling in the context of a digital economy involves a different set of variables, notably, the inclusion of online ac-
tivity and distributed ledger related records (either online or offline, if the architecture is based on mesh networks).

In the example, the level’s rate equations have the form of the deriva-
tive of the level with respect to time, which equals the summation of inflows minus the summation of outflows. In the case of the decentral-
ized financial system, the levels of trust are computed from the rates of information flows (attention and transactions); although the forma-

tion is similar Forrester’s, deriving the equations requires either analy-

tical or machine learning modeling. In the Methods and Analysis sections, we provide additional literature covering such methodologies.

3 Methods
Data for this section includes digital assets historical monthly re-

turns (Coincheckup.com), on-chain metrics (Coinmetrics.com), and off-chain web and social analytics (EconomyMonitor.com and click-
stream data providers). The period of study is August 2017 to January 2018.

3.1 The characterization of flows
When a blockchain split event occurs, a race (competition) for atten-
tion begins between at least three actors: search engines, price tickers, faucets, wallets, educational sites, and the many services that support a crypto economy. One such event occurred on August 1st 2017, when the Bitcoin blockchain forked, creating two competing digital assets, BTC and BCH [3]. We obtained monthly data for 177 of those web-

returns as a function of inflows when compared to the more mature 

returns are driven by inflows into the BitcoinCash economy (2).

In Bitcoin, the model with complexity equal to 22 becomes infor-
mation. It contains a metavariable (lateral online * m) (Kondratie) that ap-

pears in 6.6% of the models, and one of the variables from that specific metavariable construct (lateral online) appears in some form in 4 of the 6 models. These variables are those aside from the two other variable com-

quences of the model are a proxy for demand (the largest social network

and search engines in Russia), usage of离子在线 actually has invest-

ment implications – that service was a famous bitcoin scam and Punzi

scheme, where BTC holders actually invested and lost funds [5]. The p-

value for the metavariables considered in the analysis is under 0.03, as

shown in Figure 9 and Figure 10.

In the BitcoinCash economy, the drivers are notably different, and the complexity of the models tends to be higher. The fact that the indepen-
dent variables are different than those that drive BTC returns speaks for

the structurally different constitution of both economies: users of dif-

ferent services both consume information and have a preference
to trade in different exchanges, such as Korea-based Bithumb.

Some are even different people, as demonstrated by the fact that they

seek information in Yahoo and social validation in Facebook, not in

Yaoyou or Komodo. It seems that 67% of variable combinations of higher com-

plexity models may also induce over-fitting in the presence of noise.

2.2 Bitcoin
In total, 532 models were generated, with the majority of those (55.15)
containing at least three variables. The modeling process explores the

trade-off between model complexity and model error (1- R^2). This is

illustrated in the ParetoFrontLogPlot which displays each of the re-

turned models’ quality metrics, complexity, and accuracy. The models
denoted by red dots are all optimal in the sense that for a given level of
difficulty there is no lower complexity of that model, or no more accurate model [15]. Notably, there are 3 models at an order of magnitude materially better than the rest (error on a scale under 10^3), and one of those is an optimal model.

2.3 BitcoinCash
In the BitcoinCash case it is more difficult to determine what the dom-
inant best models are, this is confirmed by the number of models with

relatively high error, and the higher dimension and larger number of possible variable combinations (50 models use 5 variables, whereas

the Bitcoin case no model had more than 4 variables).

4 Analysis
The first thing that we need to understand is the meaning of the models

obtained. A trivial observation would be of the kind that one could find in

the financial economy. There might be a large number of elements (L), where the length of each edge, (l1, . . . , lN) are elements of L. The edges mirror complex-

ity values, giving rise to a complexity space (in our case, a trust space, where the subset contains a variable that is a direct expression of investor’s financial commitment – such as the use of a cryptocurrency exchange).

Figure 12 shows a tangible representation of the trust imbalance con-
cept represented in Figure 3. By comparing the edge lengths (Eu-
clidean distance) and complexity values using a ratio of the form dis-
tance/complexity, we find that the median distance is 0.00235542 for

Bitcoin and 0.00080608 for BitcoinCash. The counterintuitive find-
ing is that although the Bitcoin economy is more complex in macroe-

conomic complexity terms (diversity, and absence of services), dur-

ing the stage of the formation of the competing BitcoinCash economy the complexity of models required to describe it is higher, given a similar

level of complexity. The reasons are structures of trade, the older economy is in a relatively steady state in relation to the new entity.

4.1 Dynamics
To model the dynamics we make use of Forrester’s System Dynam-

ics approach, a tool familiar to econometricians and policymakers. If we simply to obtain the form of a two-sided system (what one econ-

omy loses the other gains) and focus on the flows in one direction, the

schematic is as shown in Figure 13. The “goal” is an implicit input to the system, for instance, the attention (a gauge that im-

plies a variable rate of action) is an input to the stock component at the

behavioral feedback loop represents information about the state of the

level of trust.

In analytical form, the general equation that describes the stock com-

ponent is (t):

\[ M = \left( \frac{1}{2} \sum_{(\text{inflows})} - \sum_{(\text{outflows})} \right) \]

Where, n, m denote the complexity boundaries; we integrate over
time, since we are measuring usage per month. The outflows are im-

plied, and not shown in the graph, but we assume that whatever at-
tention BitcoinCash is losing, Bitcoin is gaining — although in practice there might be as well leakages towards other competing forks.

So, at complexity level 11 (the worst error is what matters) BCH re-

turns are driven by inflows into the BitcoinCash economy (2).

\[ \text{BitcoinCash} = (-0.011 + 4.67 \times 10^{-3}) \cdot n \]

And outflows can be described by the Bitcoin economy gains (3).

\[ \text{Bitcoin} = (4.89 + 0.000107) \cdot m \]

At the same level of complexity the error measure associated to the

Bitcoin model (0.04) is lower than for the BitcoinCash model (0.283); again, the result demonstrates the behavioral traits of the economic agents, with the Bitcoin model yielding significant markers in the code repository (GitHub) become a factor for the newer coin, while the more established coin has higher visibility in organic channels (in this case, duckDuckGo, a search engine popular among developers).

This formulation encapsulates tacit knowledge since the model in-
cludes information in people’s heads (e.g search patterns are revealed preferences, but are private to the user until the data is mined). It also contains explicit knowledge: blockchain unprecedented advantage is the public availability of transactional data. But from an investment
perspective, the reason why modeling the level of trust is important is because the shape of the trust surface has a relationship with the probability of gain or loss [14]; this extends as well to the domain of computational trust [12] a discipline in information security that deals with the analysis of trust structures such as those of a PKI (Public-Key Infrastructure).

**Fields finance.** Another way to analyze the condition of asymmetry is by looking at trust imbalances among the same set of variables. In this way, we force the evolutionary algorithm to choose the best model that simultaneously contains both variables, and that allows for the flow to be visualized on a higher dimensional space (e.g. a vector field). To make the streams fully descriptive of the path to material economic activity (not simply market sentiment) we use blockchain fees rather than returns, and time series of daily usage data rather than share of inflows; the off-chain data expressively includes variables related to transactional activity (e.g. cryptocurrency exchanges, cryptocurrency payment platform for merchants). This allows for a better description of the causal relationship, and facilitates additional verification using forecasting methods such as bivariate Granger causality [20].

The resulting inflow equations are arranged into a field of the form given by (4).

$$\{\text{Fees}_{\text{BTC}}, \text{Fees}_{\text{BCH}}\} = \{f(X_1, X_2), g(X_1, X_2)\}.$$  

Where $X_1$ refers to huobi.pro, a Chinese exchange; $X_2$ refers to coinpayments.net, a payments platform.

We slice the data by month (from September to November), to focus on the periods of analysis that are of interest — where we want to study the persistence or the break of trust symmetry. We obtain 6 equations in total. 2 for each month (each one describes how usage of the services under study may predict the movements in BTC or BCH fees). To obtain the rate of change of inflows levels (rather than levels themselves) we use the expression (1) applying a derivative at both sides and with-out other modification than assuming outflows equal 0; this requires that we compute the gradient of the field. The results are plotted in Figure 14, where $X_2$ is the component in the horizontal axis.

The flows give rise to a field. The $f$ term (blue) and the $g$ term (brown), each is expressed by vectors with components $X_1$ and $X_2$. We see how in September the vectors almost cancel out each other; however, the effect of consumption on BTC is leading — in fact, that month neither the exchange or the shopping cart solution show flows that are meaningfully correlated to the BitcoinCash economy. The economy of BitcoinCash actually becomes relevant to these services in October; as for Bitcoin, fees behavior is better described by the rate of exchange usage in October and by the rate of merchant service usage in November. The flows are mapping the belief consensus of the users of each coin.

The transition from September to October marks the phase change in trust dynamics (when the new coin adoption actually kicks off among the general public).

These observations are confirmed by the sensitivity metrics of the models (Figure 15). We see how in October, and especially in November, the relative impact that variables have on the target variable becomes material. We calculate sensitivity as the product of the mean of the absolute value of the partial derivative of $X_2$ with respect to $X_1$, and the ratio of the standard deviation of $X_2$ and the standard deviation of $X_2$. The % positive or negative represents the likelihood that increasing this variable will increase the target variable.

5 Conclusions

Digital assets detractors usually say that there is no proven demand for cryptocurrencies, but it has been demonstrated that demand not only can be measured but that crypto-economies and their driving variables can be ranked as demand evolves [7]. Perhaps the exercise of comparing Bitcoin and BitcoinCash is not entirely fair (after all BTC had the first mover advantage, by several years), but the heuristics that we have learned from the data have relevant implications nonetheless. For instance, one could identify what are the sources of systemic importance, or what traffic is overpriced or underpriced. And since in blockchains transaction count and exchange volume can be manipulated by batch- ing transactions and other artifacts, one of the viable measures of value might be actual supply and demand of attention.

Furthermore, if crypto assets defy the "Efficient Market Hypothesis" and the idea that all available information is encoded in prices, something more profound may be going on here: beyond any of the traditional definitions of utility, disintermediation of trust by itself might entail a premium. In that case, the value of the chain may reside on the chain itself: the nodes running the software are simply an expression of people’s beliefs — being that the belief that the market can be manipulated for personal gain; that it is about time to challenge the government monopoly on money; that algorithmic money might be the more convenient utilitarian artifact to conduct transactions if you have already digitized a large part of your day-to-day activities, or else. This belief consensus is a human-machine construct, and perhaps this is why economists who are not trained as technologists have a hard time grasping the implications of a blockchain financial system.

But what is more intriguing is that what the quantitative analysis reveals is not conflicting at all with the definition of intrinsic value — value is, after all, a matter of perception. So the argument that cryptocurrencies have no intrinsic value is without merit, and as we have demonstrated, not backed by data. Furthermore, even regulators stances are evolving; according to FinCEN, a digital currency can represent a “value” that “substitutes for currency” [1] – this value representation is what is encoded in the off-chain network flows that we have quantified as trust metrics builders. And a more fundamental question about value arises: as the trust asymmetries between crypto economies reveal a structural divergence in value perception, could this paradigm provide incontestable proof of value in digital assets, including those with enhanced privacy features which by default make key transactional data opaque or unavailable?

Immediate applications of this research include Discreet Log Contracts [9], which have the potential to enhance the use cases of cryptocurrencies and other cryptographic currency networks by allowing users to discretely enter into futures contracts for a wide variety of assets, trusting oracles only to sign the correct price. Possible next steps include the formalization of evaluation frameworks for the trust metrics and trust models. For instance, the share of flows is in principle a probability, therefore it could also be analyzed using formalisms from logic. Subjective logic [13] is a type of probabilistic logic that explicitly takes uncertainty and source trust into account, and could be used for this purpose. Also, topology concepts such as persistent homology could be implemented to study the robustness of the trust metrics obtained [7]. Finally, one may argue that in essence, trust asymmetries are a particular case of information asymmetries. In this view, we could use the rich literature of information theory, signal processing, complex networks, and, econophysics to develop on the methods here described.
References


