Social signals and algorithmic trading of Bitcoin

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Abstract

The availability of data on digital traces is growing to unprecedented sizes, but inferring actionable knowledge from large-scale data is far from being trivial. This is especially important for computational finance, where digital traces of human behavior offer a great potential to drive trading strategies. We contribute to this by providing a consistent approach that integrates various data-sources in the design of algorithmic traders. This allows us to derive insights into the principles behind the profitability of our trading strategies. We illustrate our approach through the analysis of Bitcoin, a cryptocurrency known for its large price fluctuations. In our analysis, we include economic signals of volume and price of exchange for USD, adoption of the Bitcoin technology, and transaction volume of Bitcoin. We add social signals related to information search, word of mouth volume, emotional valence, and opinion polarization as expressed in tweets related to Bitcoin for more than 3 years. Our analysis reveals that increases in opinion polarization and exchange volume precede rising Bitcoin prices, and that emotional valence precedes opinion polarization and rising exchange volumes. We apply these insights to design algorithmic trading strategies for Bitcoin, reaching profits of more than 200% in less than a year. We verify this high profitability with robust statistical methods that take into account risk and trading costs, confirming the long-standing hypothesis that trading based social media sentiment can yield positive returns on investment.

Introduction

Our online society generates data on the digital traces of human behavior at unprecedented scales and resolutions. This produces a *data deluge*, in which researchers are confronted with a vast amount of observational data that is not the product of carefully designed experiments [30]. One of the main challenges of the scientific community is to develop methods to extract meaningful knowledge from that data beyond mere descriptive analyses [43]. This is particularly important in financial trading: Data can be available to all financial agents, but it is the analysis and its applications what makes a difference. Within computational finance, the field of algorithmic trading [47] deals with the implementation and evaluation of automatic trading strategies, which are often kept in private companies and away from publicly accessible research. The most common kind of algorithmic trading is based on the principles of *technical analysis* [36], using the time series of prices to formulate predictions about returns. Technical analysis is often insufficient to derive satisfactory returns [4], motivating the inclusion of large-scale social signals and the evaluation through data-driven simulations on historical data, called *backtesting* [15]. In this article, we present a set of methods to derive stylized facts from the analysis of multidimensional economic and social signals, and to apply that knowledge in the design and evaluation of algorithmic trading strategies.

We illustrate an application of our approach to algorithmic trading of the Bitcoin cryptocurrency, using a wide variety of digital traces about economic and social aspects of the Bitcoin ecosystem.

Bitcoin (BTC) is a digital currency designed to operate in a distributed system without any central authority, based on a cryptographic protocol that does not require a trusted third party [16]. Introduced in a 2008 paper written under the pseudonym of Satoshi Nakamoto [34], Bitcoin serves as a technology to transfer money quickly for negligible fees [49]. One of the first markets to adopt Bitcoin was the *Silk Road*, a website where illegal commerce became possible thanks to the relative anonymity of Bitcoin [13]. Since then, the use of Bitcoin has widely expanded beyond criminal activities: At the time of writing, Bitcoin is accepted by many legal merchants and charities [6], including large businesses like Dell [18]. Bitcoin-accepting businesses, exchange markets, and wallet services compose the *Bitcoin ecosystem* [16], where different kinds of agents interact, trade, and communicate through digital channels. The increasing adoption of Bitcoin and its online nature allow us to simultaneously monitor its social and economic aspects. Every purchase of goods or services in Bitcoin leaves a trace in a public ledger called the *Block Chain*, creating a publicly accessible economic network [42]. Bitcoin's delocalized technology aligns with the online interaction of its users through social networks and forums, motivating its adoption by new users through word-of-mouth [24].

Contributions of this article. Based on established principles of time series analysis and financial trading, we present a framework to derive general knowledge from multidimensional data on social and economic aspects of a market. We apply a general statistical model to detect temporal patterns in the co-movement of price and other signals. Those patterns are tested through a method robust to the empirical properties of the analyzed data, formulating concise principles on which signals precede market movements. We combine those principles to produce tractable trading strategies, which we evaluate over a leave-out sample of the data, quantifying their profitability. Our approach, rather than focusing on improving a particular method, takes a multidisciplinary stance in which we combine principles from social psychology and economics with methods from information retrieval, time series analysis, and computational finance.

We apply our framework to the Bitcoin ecosystem, monitoring the digital traces of Bitcoin users with daily resolution. We combine *economic signals* related to market growth, trading volume, and use of Bitcoin as means of exchange, with *social signals* including search volumes, word-of-mouth levels, emotional valence, and opinion polarization about Bitcoin. Our results reveal which signals precede changes of Bitcoin prices, a knowledge that we use to design algorithmic trading strategies. We evaluate the power of our strategies through backtesting data-driven simulations, comparing returns with technical analysis strategies. As a consequence, we test the hypothesis that social media sentiment predicts financial returns in the Bitcoin ecosystem.

Social signals in finance. Understanding the role of social signals in finance not only has the potential to generate significant profits, but also has scientific relevance as a research question [41]. Two different research approaches give insights to this question: One is the *statistical analysis* of social and financial signals in order to test the existence of temporal correlations that lead financial markets. The second one applies these signals in *prediction scenarios*, measuring their accuracy as a validation of the underlying behavior of the system, but not necessarily of their profitability. The statistical analysis of search engine

data reveals that search trends can predict trading volumes of individual stocks [8]. In addition, stock prices in S&P 500 are correlated with tweet volumes [33], but the applicability of these patterns into trading strategies is yet to be evaluated.

Sentiment in social media is closely related to socio-economic phenomena, including public opinion [26]. This motivates the application of sentiment indicators in the statistical analysis of financial data. Early works on the sentiment in specialized forums gave negative results about their their impact on returns [48]. Further research showed that emotions in private instant messaging between workers of a trading company precede stages of market volatility [40]. The expression of anxiety in publicly accessible data from general blogs precedes trading peaks and price drops in the S&P 500 [25], and sentiment in Twitter can be used to predict movements in large-scale stock indices [7]. It is important to note that, to date, there is no evidence that such sentiment-based predictions produce significant returns on investment [41].

Online Polarization. While most of previous works on sentiment in financial markets focus on dimensions of valence or mood, the collective phenomenon of polarization of opinions is often overlooked. The emergence of polarization in a society gives early warnings on political and economic phenomena: Polarization in social networks of Swiss politicians precedes controversial elections [21], and polarization patterns in the Eurovision Song Contest appear before states of distrust in the European economy [23]. With respect to financial markets, speculation theories point to the role of diverse beliefs in financial transactions [28], leading to the hypothesis that polarization and disagreement influence trading volumes and prices [27]. In this line, the empirical analysis of polarization in stock message boards shows that states of disagreement lead to increased volatility [3].

The missing link. To date, there is a significant knowledge gap between the analysis and application of social signals to trading scenarios. Findings from statistical analyses alone are not guaranteed to lead to profitable strategies at all [25]. For example, movements of the Dow Jones Industrial Average (DJIA) can be predicted with mass media sentiment [46] and Twitter mood [7], but to date no research has shown that such prediction methods can be profitable in trading scenarios. Similarly, the analysis of discussion patterns in specialized blogs predict returns of some technology companies [17], but it is still open to evaluate the potential returns of such a predictor. The application of methods that process arbitrarily large datasets lead to results difficult to apply, for example the predicting power of search volumes of the query *"moon patrol"* [11] in backtesting over the DJIA [15]. Furthermore, analyses of Twitter discussions about companies can be applied in a portfolio strategy, yet its evaluation through backtesting leads to very moderate returns and their statistical significance is not assessed [38]. In addition, no previous research has proposed a prediction technique that derives significant returns on investment from online sentiment data [41]. Our research aims at closing the gap between these lines of research. To do so, we unify the statistical analysis and its application to design and evaluate trading strategies, based on tractable principles with potential impact in the finance community.

Trading strategy framework

To design and evaluate trading strategies, we present a framework that uses a set of economic and social signals related to the agents of the market under scrutiny. Among those signals, the only required one is an economic signal of prices of an asset, namely a stock, currency, or tradable index. To understand profitability, we convert the price time series $P(t)$ into a return time series:

$$Ret(t) = \frac{P(t) - P(t-1)}{P(t-1)} \tag{1}$$

which quantifies proportional changes in the price at every time step. The data on these signals is divided in an analysis period and a leave-out period, as depicted in Figure 1. The division in these periods needs to allocate enough data in the leave-out sample to provide the testing power to assess the statistical significance of strategy profits. For daily trading, a leave-out period of about one year is usually sufficient, but this ultimately depends on the expected profitability and variance of the trading strategies.
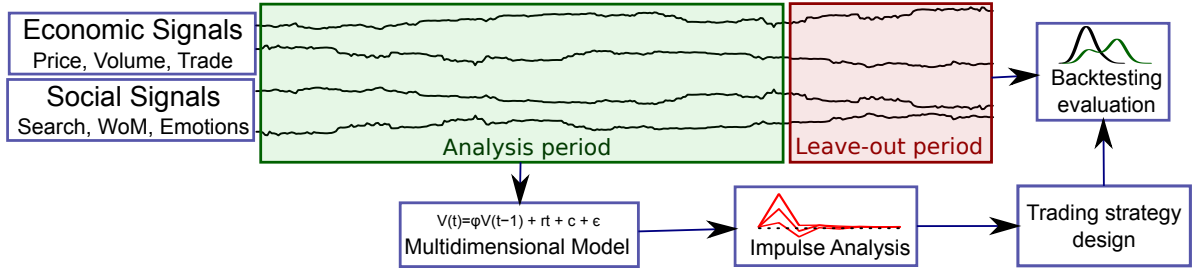

Figure 1: **Framework for analysis of social and economic signals and trading strategy design and evaluation.**

Multidimensional analysis.   The first step in our framework focuses on the analysis period, applying a multidimensional model of Vector Auto-Regression (VAR) [51], which is commonly used in the analysis of multidimensional time series in finance [48, 1, 24]. A VAR models multidimensional linear relations with given lags, which in our analysis we set to one day. Thus, given the vector of signals $V(t)$ we fit the equation

$$V(t) = \phi V(t-1) + r * t + c + \epsilon \tag{2}$$

where ϕ is a matrix of weights of the linear relations between variables, r is a deterministic trend vector, c is the vector of constant intercepts, and ϵ is a vector of uncorrelated errors. While more advanced models can be considered, including longer lags and non-linear terms, we choose the VAR model of lag 1 for its general character and its proved power to reveal patterns in finance [48, 24]. More complex models might have higher power to reveal nuance patterns, but at the expense of a loss of generality due to the focus on particular systems.

We include all the time series in a single model to avoid the false positives associated with pairwise Granger tests. To ensure the correct application of the VAR model, we need to verify that our analysis is consistent with its fundamental assumptions: i) that the elements of $V(t)$ are stationary and their variances do not

greatly differ, and ii) that the error term ϵ has no temporal nor structural correlations. We verify the first set of assumptions on the properties of $V(t)$ by applying a set of tests and transformations prior to the application of the VAR model. We ensure that our conclusions are robust to the second set of assumptions by correcting for correlations in the noise term, as explained in the Materials and methods section.

Impulse analysis. The VAR weights ϕ are only informative when there are no correlations in the error term ϵ of equation 2, which is usually not the case in practice. To extract stylized facts that can be used in the design of trading strategies, we perform an impulse analysis by measuring Impulse Response Functions (IRF) [32] while correcting for correlations in the empirical error. This method simulates the system dynamics when it receives a shock in one of the variables, applying the VAR dynamics of Equation 2 to reproduce the changes in the rest of the variables through time. By recording the changes in each variable, we can estimate the total size and the timespan of the perturbation produced by the shock. In essence, the IRF method creates a computational equivalent of the system under scrutiny, to test its reaction to exogenous impulses in each of its elements.

Trading strategy design and evaluation. The output of the impulse analysis step, shown in Figure 1, is a set of patterns of Granger-type "causation", i.e. it tests the null hypothesis of the absence of temporal correlations among the variables. We use these patterns as stylized facts that indicate which variables precede changes in price returns. For example, if variable $Y(t)$ has a significant impact on $Ret(t)$ in the impulse analysis, we will include $Y(t)$ in our trading strategy design with sign s_Y, which takes the value 1 if the response of $Ret(t)$ to $Y(t)$ was positive, and -1 otherwise. Thus, a predictor based on $Y(t)$ would be

$$sign(Ret(t+1)) = sign(s_Y * (Y(t) - Y(t-1))) \tag{3}$$

This way, we predict increases (decreases) in price between time t and $t+1$ if signals with positive responses increase (decrease) between time $t-1$ and t, and vice versa for signals with negative responses. Since our multidimensional analysis is robust to confounds between multiple time series, the findings of impulse analysis can be integrated in a *Combined* strategy based on a voting mechanism. The *Combined* strategy applies the other predictors and formulates a prediction corresponding to the sign of the sum of their outputs, i.e. the majority vote.

We evaluate the profitability of the designed strategies in comparison to the benchmark of standard strategies, based on the backtesting over the leave-out sample as indicated in Figure 1. For each strategy, we make a data-driven simulation of a trader following that strategy, and we record the profits of that trader on a daily basis. Details on the computational simulation of financial traders can be found in the Materials and methods section.

Bitcoin social economic and signals We apply our approach to the case of trading Bitcoin based on social and economic signals of the Bitcoin ecosystem. We set up a system that monitors different data sources, retrieving data in real time in combination with historical time series. The data volumes recorded during our study period of almost four years is shown in Figure 2, and can be interactively browsed in

our online visualization[1]. The signals we measure, explained more in detail in the Materials and methods section include economic signals of price $P(t)$ and returns $Ret(t)$, trading volume in a wide range of Bitcoin exchange markets $FX_{Vol}(t)$. Furthermore, we measure the economic signal of transaction volume in the Block Chain $BC_{Tra}(t)$, which measures the volume of usage of Bitcoin as a currency, and the amount of downloads of the most important Bitcoin client $Dwn(t)$ as a measure of growth in adoption of the Bitcoin technology. The social signals we measure are the level of search volume in Google for the term "bitcoin" $S(t)$, the word-of-mouth level as measured by the amount of *tweets* containing Bitcoin-related terms $T_N(t)$, and the emotional valence $T_{Val}(t)$ and opinion polarization $T_{Pol}(t)$ expressed in those tweets using lexicon-based approaches from psycholinguistics [37, 50] (more details in Materials and methods). All these signals are shown in Figure 2, illustrating the large oscillations of price and other signals related to Bitcoin.
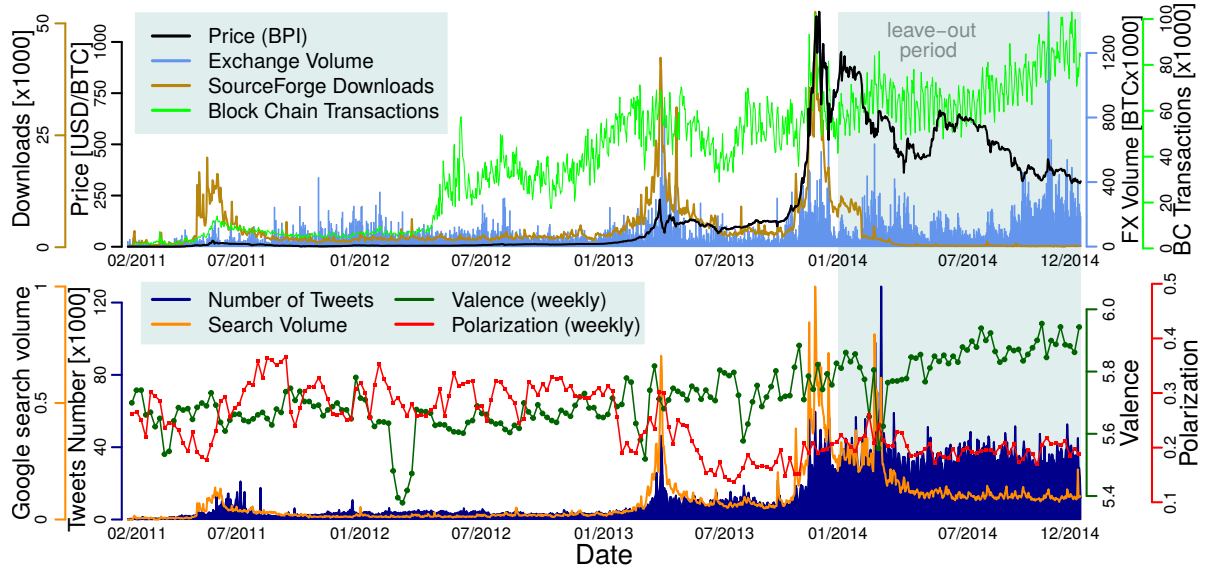

Figure 2: **Time series of data volumes in the Bitcoin ecosystem.** Interactive version: `www.sg.ethz.ch/btc`

Results

Data-driven Bitcoin trading strategy design

For our statistical analysis, we include all the data up to January 1st, 2014, covering almost 3 years. After applying stationarity tests, we conclude that the time series of price returns $Ret(t)$ can be assumed to be stationary, as well as the first differences of the other seven signals (details on the stationarity test results can be browsed in `www.sg.ethz.ch/btc` and in the SI). As a consequence, we define our variable
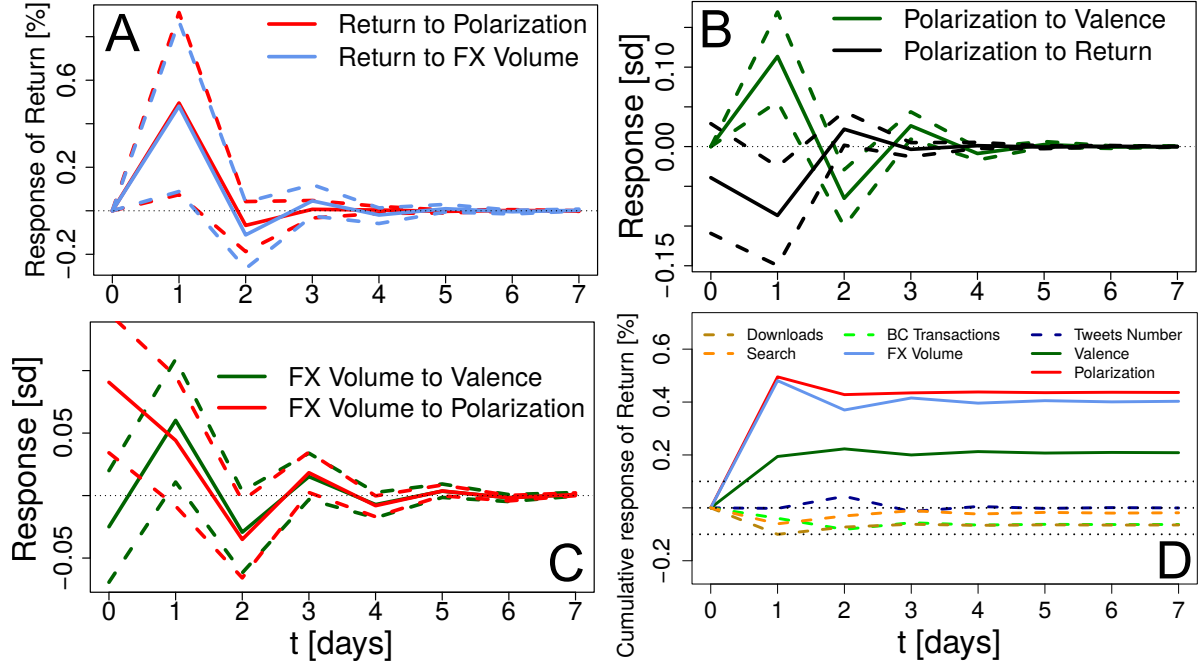
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[1]`www.sg.ethz.ch/btc`

Figure 3: **Results of Impulse Response Function analysis.** (A) Impulse Response Functions of return to shocks in Twitter polarization and exchange volume, (B) of Twitter polarization to shocks in return and Twitter valence, and (C) of exchange volume to shocks in Twitter valence and polarization (right). Solid lines show responses, dashed lines show 95% confidence intervals. (D) Cumulative Impulse Response Functions of price return to changes in the other signals. Dashed lines indicate responses below the 0.1% level.

vector as:

$$V(t) = [Ret(t), \Delta FX_{Vol}(t), \Delta BC_{Tra}(t), \Delta Dwn(t),$$
$$\Delta S(t), \Delta T_N(t), \Delta T_{Val}(t), \Delta T_{Pol}(t)]$$

composing the input to the multivariate analysis of our framework. We fit a VAR as explained in Materials and methods over the analysis period. We compute IRF for all pairs of variables, all results including VAR estimates and IRF values can be browsed in `www.sg.ethz.ch/btc` and in the SI. Here, we comment on the most relevant results, which serve as input for our trading strategy design.

Figure 3 A shows the IRF of returns to shocks in polarization and volume in exchange markets, where the response is measured in return percentages. Both polarization and exchange volume have significantly positive influences in price returns one day after the shock, decreasing rapidly afterwards. The increase of returns with polarization is consistent with the hypothesis that disagreement fuels trading in speculative scenarios [27, 3], where information asymmetries fuel price bubbles. Exchange volume also increases with polarization, as shown in Figure 3 C, but the the relationship is instantaneous rather than lagged as in the case of returns.

Figure 3 B shows the response of polarization in Twitter to shocks in returns and valence. The negative effect of polarization shows that price drops lead to increases in polarization, signaling the disagreement in the Bitcoin community due to price crashes. The pattern linking valence to polarization is relevant, revealing that periods with increasing positivity in expresion precede stages of higher polarization. The role of valence can further be observed in the IRF of exchange volumes in Figure 3 C, in which valence has a significant effect. The combination of patterns of increasing polarization and exchange volume following stages of increasing valence show the relevance of valence in price returns, in addition to the effects of polarization and exchange volume.

We further validated these results in two ways. First, we fit a VAR with lags longer than a day, selecting the optimal lag that optimizes the Bayesian Information Criterion. We found that a lag of 2 is optimal, but the results of the fits and IRF analysis did not qualitatively change (see SI). Second, we performed a Monte Carlo test, computing the impulse response functions for time series with randomized permutations of the values. The results of these permutation tests show are consistent with the above results, as reported in the SI, showing the robustness of our approach.

Turning analysis into strategy   We summarize the above findings as stylized facts that can drive the decisions of an algorithmic trader. We focus closer on the role of each signal into returns, by computing the cumulative changes given by the IRF analysis. This way, we can identify which signals show a sizable pattern that precedes changes in returns, and filter out those that are not significant or can be explained as confounds of the others. Figure 3 D shows the results, measuring the cumulative change in return percentage when each one of the other signals receives a shock of size one standard deviation. The three signals with effects above the 0.1% level are polarization, valence, and exchange volume, reaching effects up to 0.5% in one day that prevail through time. Note that this is a relatively large value, because trading results in geometric returns. Such effect sizes have strong potential impact on the profitability of trading strategies over long time periods. This allows us to discard the rest of the signals, feeding into our trading strategy design by producing four strategies: three strategies of positive sign, *Valence*, *Polarization*, and *FXVolume*, and a fourth *Combined* strategy determined by a voting mechanism as explained in the Trading strategy framework section.

Bitcoin strategy evaluation

To evaluate the profitability of our four strategies, we set up a benchmark against random strategies and technical strategies. Random strategies sample a random number with 0 mean at every time t, and formulate a prediction based on the sign of the random number. Among technical strategies, the simplest is *Buy and Hold*, which simply buys BTC with the initial capital at time $t = 1$, selling it only once at the time when profits are evaluated. The technical strategies we use are a benchmark of simple standard predictions [4]: i) the *Momentum* strategy, which predicts that price changes at time $t + 1$ will be the same as at time t, ii) the Up and Down Persistency strategy *UPD*, which predicts that price increases at time t are followed by decreases at time $t + 1$, and vice versa, and iii) the Relative Strength Index strategy *RSI*, which computes an additional time series of ratios of return sign frequencies over a rolling window of five days, and predicts price changes based on reversals of this time series (more details in [4]).
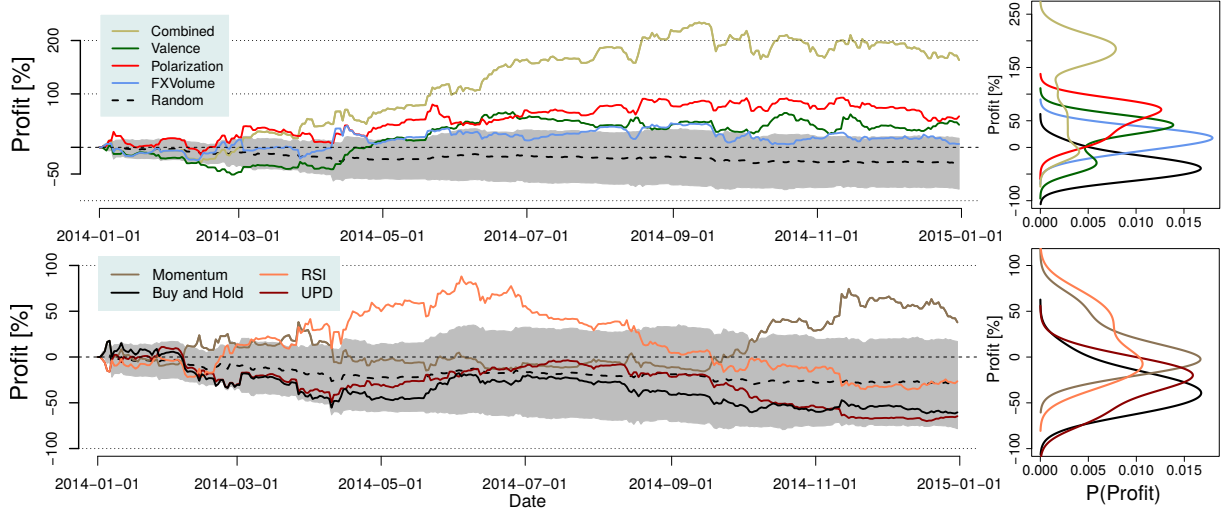
Figure 4: **Profits of trading strategies.** Left: Time series of profit for our strategies (top), and technical strategies (bottom). Shaded areas show one standard deviation of the random strategy. Interactive version: `www.sg.ethz.ch/btc` Right: Kernel density plots of the profit of each strategy (bandwidth=15%).

The simulation of each strategy produces a time series of profits

$$\text{Profit}(t) = \frac{C(t) - C(0)}{C(0)} * 100 \tag{4}$$

where $C(t)$ is the capital of the trader at time t and $C(0)$ is the initial investment capital. Figure 4 shows the time series of profits for our four strategies and the technical strategies. In addition, we compute the profit of *Buy and Hold*, and the results of the simulation of 10000 random traders. The *Valence*, *Polarization* and *Combined* strategies clearly perform better than a random trader, while the *FXVolume* is not very far from the result of random traders. Among the technical strategies, only *RSI* and *Momentum* are able to eventually reach beyond the outcome of random traders, but are still clearly outperformed by the *Polarization* and *Combined* strategies.

The stopping time of the simulation of a trading strategy is given by our data, but a variety of factors might trigger a trader to stop trading earlier in a real scenario [47]. For that reason, we explore the distribution of profits of each strategy, assuming that the trading stops at any arbitrary point of our backtesting period. Thus, for each strategy we have a set of profit values, one for each possible trading end date. The left panel of Figure 4 shows the Kernel Density Plots of the distributions of profits for each strategy. It can be appreciated that the most profitable strategy is *Combined*, followed by *Polarization* and then *Valence* and *RSI*. We quantitatively assessed this result, through Wilcoxon tests [52] over the distributions of profits (more details in SI), confirming the observation that the most profitable strategies are *Combined*, and *Polarization*. More precisely, the *Combined* strategy gives profits beyond 100% for most of the time during the trading period. The profitability of these strategies lends strong support to the hypothesis that social media sentiment has the power to produce positive returns on investment, especially when including polarization measures beyond the trivial quantification of valence or mood.

Costs and risks of the Combined strategy

To understand better the possible weaknesses of the Combined strategy, we run a series of tests to evaluate the role of transaction costs and additional risks. Trading Bitcoin in an online market usually comes at a cost, which often depends on the activity and the traded capital. Trading costs can potentially erode the profitability of trading strategies, especially if they require many movements. We simulated the same backtests for costs increasing from 0 to 0.3% of the exchanged capital, a value well above the maximum costs of major trading platforms [5]. As a simplification, we assume that buying, selling, and borrowing costs are the same, yet their values might depend on the trading volume of a strategy [5]. Figure 5 shows the final profits of the Combined strategy, which decreases monotonically with trading costs. The strategy is still highly profitable for low costs, but for costs above 0.25%, the stategy is not profitable any more.
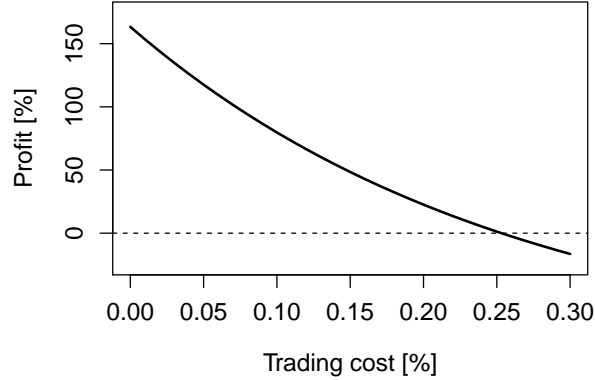

Figure 5: **Final profit of the Combined strategy versus trading cost.**

We additionally evaluate the robustness of the Combined strategy to risk factors stemming from the volatility of Bitcoin prices. While the upwards trend of profit in Figure 4 shows that the Combined strategy is profitable, the abrupt changes in its value might induce risks depending on when trading starts and ends. To correct for such risk, we applied the Sharpe test [45], which computes risk-corrected profit called Sharpe Ratio as: $SR = \frac{\mu_R - R_f}{\sigma_R}$, where μ_R and σ_R are the mean and standard deviation of the daily rate of return of a strategy $R(t) = (C(t) - C(t-1))/C(t-1)$. R_f is the "risk- free" return rate of a theoretical investment that would give certain profit under no risk at all, which is often estimated as the interest rate of high-quality sovereign bonds. At the time of writing, some European sovereign bonds are giving interest rates close to zero or even negative [19], which motivates our conservative choice of $R_f = 0$. The value of SR is calculated in annualized units, taking into account that Bitcoin can be traded 365 days a year.

The Combined strategy gives high profit without excessive additional risk, with $SR = 1.823$ at a significant level ($p = 0.03456$). This is specially relevant in comparison to low-risk traditional investments, for example the DJIA has an annualized Sharpe Ratio of 0.8 over the same period. Additionally, the distribution of daily returns of the Combined strategy follows a lognormal distribution, as tested through maximum lihelihood fits and Kolmogorov-Smirnov tests, and the time series of returns is not autocorrelated and can be considered stationary (see SI). This additional analysis shows that the high profitability of the Combined strategy is not due to risky correlations in the behavior of the trading strategy.

Concluding remarks

Our work applies established methods of time series analysis and computational finance to integrate the analysis, design, and evaluation of trading strategies and social and economic signals. We have shown that our approach successfully reveals temporal patterns in the Bicoin ecosystem, in particular the relation between price returns and the signals of exchange volume and Twitter valence and polarization. Our statistical analysis is robust to noise correlations and the finite nature of time series, providing a consistent set of results that we can apply to strategy design. We evaluated the profitability of our strategies through data-driven simulations of a computational model of a trader, showing that a strategy that combines valence, polarization, and exchange volume can reach profits around 200% in less than a year. The added value of including polarization in our analysis constitutes evidence that collective factors of emotions and opinions predict financial returns, beyond trivial macroscopic aggregates like average valence.

Our framework can be applied to other trading scenarios[2] in which social signals are available, like in the case of company stock trading driven by sales data, news information, and social media sentiment towards a company. The general nature of our methods are of special relevance for real trading scenarios, as the stylized facts we use to design strategies provide a tractable explanation for their mechanisms. This allows traders to understand and evaluate the principles of the algorithmic trading strategies designed in our framework. Such tractability is an advantage in comparison to more complex, non-linear, or subsymbolic models that do not have straightforward interpretations. Furthermore, the rules that drive our trading strategies do not require retraining or calibration during trading, and the social and economic signals we employ can be quantified during a day in order to have an instant trading decision ready at the beginning of the next day. Our application to Bitcoin trading is thus realistic, making use of shorting options and performing well under the typical trading costs of Bitcoin markets [5].

The application of our results should be taken with caution. Historical profit through backtesting do not necessarily predict future ones, and the information sources analyzed here could be adopted by Bitcoin traders. Financial markets are known to quickly absorb knowledge, as it happened with the inclusion of search trends data in stock trading [15]. It is also difficult to estimate the scalability of automatic trading strategies, as financial markets are complex adaptive systems that react to trades of large volume. Furthermore, systemic risk emerges from algorithmic trading, creating *flash crashes* due to algorithmic resonance [16]. In addition, structural changes might happen when exchange markets close or governments regulate Bitcoin, changing the rules of the game in a way such that our trading strategies might not work any more.

With our study, we have shown how social signals can be turned into profit. This extends the range of typical business applications for social media data like viral marketing or user engagement. Specifically, our combination of statistical analysis and backtesting serves as a framework for future applications of social media data in algorithmic trading. It allows a robust validation of strategy profits and a clear understanding of the system dynamics behind these profits. The application of our framework to Bitcoin trading illustrates that (asymmetric) information and profit are two manifestations of the same thing, and how traders can apply these macroscopic information sources to derive large profits. We foresee that the applications of social signals to finance will reach far beyond Bitcoin, not only to make private profit but also to understand the dynamics of individual and collective decisions and emotions.

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[2]Our data and methods will be public for replication.

Materials and methods

Stationarity tests.   Before fitting the VAR model, we test the stationarity of each time series through two alternative tests: i) the Augmented Dickey Fuller (ADF) test [20], which has the null hypothesis that the tested time series is *non-stationary*, and ii) the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [29], with the null hypothesis that the time series is *stationary*. Under these two tests, it can be considered safe that a time series is stationary if it passes the ADF test with a p-value below 0.05 and does not pass the KPSS test, giving a p-value above 0.1 [32, 24]. We first analyze the time series of levels of each signal $X(t)$, applying the differentiation operator $\Delta X(t) = X(t) - X(t-1)$ until each time series is stationary. This step is inspired in the Box-Jenkins method of ARIMA time series analysis [2], and for financial it is usual to reach stationarity after first differences [32, 24]. The stationary properties of these time series imply that their means and standard deviations are bound, allowing us to renormalize them through the Z-transformation $Z(t) = (X(t) - \mu_X)/\sigma_X$, where μ_X and σ_X are the mean and standard deviation of each time series. This way, all time series have the same scale and variance, and their effects in statistical analysis can be compared.

Impulse response function analysis.   In the impulse analysis, we correct for the correlations in ϵ in two ways. First, we apply orthogonalized impulses of unit covariance, creating a shock of one standard deviation in a variable under the error correlations of the VAR [53]. Second, we apply bootstrapping on the resulting responses by producing surrogate time series from resampling the residuals [32]. This way, we numerically compute confidence intervals of the responses in a very strict way, avoiding false positives and taking into account the finite size of the analysis period. In our case, we create $10,000$ bootstrap samples to estimate 95% confidence intervals of the responses. As a result, we simultaneously measure the dynamics of the system and test their statistical significance.

Trading based on predictions.   During each timestep, the prediction function makes a forecast either based on Equation 3, or based on the price time series for technical strategies. Positive predictions translate into *buy* decisions when the trader does not own the asset, and *hold* if it does. Negative predictions translate into *sell* positions when the trader owns the asset or *short* when it does not own it. Shorting works as follows: Traders can make profit from correct predictions of price drops even if they do not own the asset predicted to drop in price. This is implemented by borrowing the asset, selling it first and buying it later for a lower price. The limitation for borrowing is usually imposed on the amount of capital already held by the trader, and often incurs in additional transaction costs and legal regulations [12]. The simulation of each strategy produces a time series of profits, allowing us to measure their profitability based on historical data.

Economic signals from financial data   The establishment and bankruptcy of various Bitcoin exchange markets motivated the creation of the Bitcoin Price Index (BPI) [14]. The BPI combines a set of price indices from well-performing exchange marketplaces to provide a reference for BTC/USD exchange rates, and is accepted as a standard measure of Bitcoin price in economics [10, 44]. We use the daily closing prices of each day t at 23:59 GMT from `coindesk.com`, composing the time series of price $P(t)$ from February 1st, 2011 to December 31th, 2014, shown in the top panel of Figure 2. For the same

period, we retrieved the daily volume of BTC exchanged in 80 online markets for other currencies from `Bitcoincharts.com`. Aggregating all these data sources, we compose an Internet-wide measurement of Foreign eXchange (FX) volume of BTC traded every day $FX_{Vol}(t)$, including more than 152 Million BTC in exchange trades.

Every purchase of products and services in BTC leaves a trace in the *Block Chain*, the distributed ledger that records all transactions in the Bitcoin network. We construct a time series with the daily amount of Block Chain transactions $BC_{Tra}(t)$, including more than 55 million transactions in the studied period. This measures the overall activity of the system when using Bitcoin as means of exchange. In addition, we measure the growth of the Bitcoin market through its amount of adopters, using the operationalization of measuring the amount of downloads of the most popular Bitcoin client[3] [24]. The resulting time series of downloads $Dwn(t)$ is shown in the top panel of Figure 2.

Social signals   We record the overall interest towards Bitcoin through information search, as quantified by the Google trends volume for the term "bitcoin", $S(t)$, shown in the bottom panel of Figure 2. We track the attention of social media about Bitcoin in Twitter via the Topsy data service. From the full track of data accessible by Topsy, we focus on tweets that contain Bitcoin terms as in previous research [24], finding a total of $19,578,671$ Bitcoin-related tweets. The first social signal we extract from Twitter is the daily amount of unique tweets about Bitcoin $T_N(t)$, measuring the level of word-of-mouth and attention towards Bitcoin and shown in the bottom panel of Figure 2.

We continue by measuring the collective emotional valence with respect to Bitcoin, as expressed through the text of Bitcoin-related tweets. Valence is considered the most important dimension of affect, quantifying the degree of pleasure or displeasure of an emotional experience [39]. The expression of valence through text is a common practice in psychological research, in which lexicon techniques are used to empirically measure emotions [9, 22]. We measure the average daily valence of Bitcoin-related tweets through a state-of-the-art lexicon technique [50], which improves the previous ANEW lexicon method [9] with more than 13000 valence-coded words. We compute the daily average Twitter valence about Bitcoin during day t in two steps: First we measure the frequency of each term in the lexicon during that day, and second we compute the average valence weighting each word by its frequency. This measurement matches more than 50 million valence-carrying tokens, and produces the time series of Twitter valence $T_{Val}(t)$.

Our last social signal is opinion polarization, which builds up on measuring the semantic orientation of words into positive and negative evaluation terms [35]. We apply the LIWC psycholinguistics lexicon-based method [37], and expand its lexicon of stems into words by matching them against the most frequent English words of the Google Books dataset [31]. As a result, we consider 3463 positive and 4061 negative terms that appear as more than 8 million Twitter tokens. We compute the daily polarization of opinions in Twitter around the Bitcoin topic $T_{Pol}(t)$, calculating the geometric mean of the daily ratios of positive and negative words per Bitcoin-related tweet. Note that, instead of repeating a measurement of valence through two different lexica, we quantify polarization as a complementary dimension to emotional valence. This way, opinion polarization measures the simultaneous coexistence of positive and negative subjective content, rather than its overall orientation [35, 48].

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[3]http://sourceforge.net/projects/bitcoin

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