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ABSTRACT
Cryptocurrency such as Bitcoin is a rapidly developing phenomenon in financial technology with considerable research interest but is understudied. In this research article, we use a Design Science Research paradigm to create a high-frequency trading strategy at the minute level for Bitcoin using six exchanges as our Information Technology artifact. We created financial indicators and utilized a machine learning (ML) algorithm to create our strategy. We provided two sets of evaluation. First, we evaluated this strategy against another popular ML algorithm and found our algorithm performed better on the average. Second, we analyzed the economic benefits using the strategy against out-of-sample trading in foreign exchange currency. We presented both descriptive and prescriptive contributions to Design Science Research via the development and testing of our artifacts.

KEYWORDS
Cryptocurrency; bitcoin; high-frequency trading strategy; design science

Introduction

With the recent development of financial technology, known as FinTech, cryptocurrency is, by far, the most innovative virtual currency that has been created. Built upon decentralized and distributed financial ledger concepts and a peer-to-peer network protocol, cryptocurrency is thought to revolutionize the way financial transactions are done on the Internet.[1] Started by Nakamoto,[2] Bitcoin is the first cryptocurrency offered. Since Bitcoin's inception however, there are a myriad of cryptocurrencies, namely Ethereum, Ripple, and Litecoin. The list of cryptocurrencies continues to grow.

For cryptocurrencies, consumers can use real currency to purchase Bitcoins, trade Bitcoins for products and services, and sell Bitcoins to obtain real currency. The buying and selling of Bitcoins is primarily concentrated within cryptocurrency exchanges. These exchanges are companies that offer platforms for trading for a variety of cryptocurrencies, much like the New York Stock Exchange in the US. For Bitcoin, there are several big exchanges, such as Bitstamp (Luxembourg) and Kraken (United States). It should be noted that the pricing for Bitcoin is not the same among these exchanges. This is due to many factors, including how easy it can be converted to Bitcoin from the exchange to real money (liquidity), the demand and supply of Bitcoins, efficiency of the exchange, and technological competencies of the exchanges.

These exchanges differ from the conventional stock trading platform in that they do not have a shutdown period. Therefore, it would be impossible for manual trading to accommodate a full-time commitment. In addition, these exchanges do not have – nor do they need – a physical trading floor.

With the advent of machine learning (ML) algorithms, algorithmic trading has garnered tremendous popularity among financial traders. Combined with the availability of data, high-frequency trading (HFT) has permeated through the financial market. In fact, in 2009–2010, it was estimated that 60–70% of trading occurred is through HFT.[3] In a recent report, JP Morgan confirmed that about 60% of trading on exchanges is algorithmic.[4]

Algorithmic trading can broadly be defined as the use of computer algorithms to automatically execute trading decisions on financial exchanges. It is most commonly used in well-developed financial markets such as U.S. equities or other developed market currencies. However, the usage of algorithmic trading in secondary asset markets, such as emerging market equities, continues to grow. While algorithmic trading models can be deployed over many trading horizons, trading volume on the basis of such models predominantly occurs during shorter frequencies, such as minutes, hours, or days. When trading horizons shorten even further – to the single minute, second, or even millisecond level – this becomes what is known as HFT. Such trading, by necessity, is conducted exclusively via algorithms.

The application of ML to the market for cryptocurrencies presents an interesting research phenomenon. On the one hand, a cryptocurrency – particularly Bitcoin – is traded on exchanges in consideration for money, just like any other asset. To that extent, algorithmic trading in cryptocurrencies ought to be similar to algorithmic trading in modern equity or currency markets. On the other hand, Bitcoin still carries strong limitations that make it relatively difficult to conduct goods or services transactions with, as compared to more fungible and central-bank-managed currencies. In addition, while the value of one Bitcoin may (not) increase relative to such currencies, Bitcoin has no inherent value – it cannot, for example, produce dividend or coupon income, as stocks and bonds can. As a result, most market participants trading

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/ucis.

Bitcoin are purely speculative; few find it the best currency for buying goods and services with, and its sole source of profit for the buyer is the expectation that a subsequent buyer will be willing to pay even more for it. This uniquely speculative nature of the cryptocurrency market thus provides an opportunity to study algorithm dynamics in the context of a predominantly human and psychologically driven market.

Due to the near-feverish popularity of Bitcoin and the need for further understanding of the phenomenon, Bitcoin is poorly researched but content-rich. In this study, we utilize Design Science Research (DSR), a research paradigm in Information Systems, to present a trading algorithm for the research community. DSR is a research method that guides how to build and evaluate an Information Technology artifact and how the artifact solves a stated problem.[5]

To create our artifact, the HFT trading strategy for Bitcoin, we preprocessed data from the six exchanges and transformed the Open, High, Low, Close data for each minute to create financial indicators. We then used Random Forest (RF) to train a trading model using the aforementioned technical indicators to build the artifact. To evaluate the artifact, we first compared the RF model with a Deep Learning (DL) model. The result showed that the RF performed better than the DL model on average. To test the economic feasibility of the strategy, we obtained actual currency exchange data, namely the Japanese Yen (JPY) to U.S. Dollar (USD), also at the minute level and used them as the economic benchmark for the strategy. We found a significant opportunity for profit exists when applied to both.

Our results have important contributions in both descriptive and prescriptive knowledge.[6] Descriptively, we found that our trading strategy works well even when created with near-default settings for financial indicators. Our strategy is resilient enough to withstand data variation in start dates, end dates, prices, volumes, and base currencies, and even multicollinearity. Furthermore, our artifact indicates that 15 min is optimal for Bitcoin trading, and that it will beat a long-only strategy. Prescriptively, we encourage researchers without super computers to engage in Fintech research. Finally, kernel theories in behavioral finance serve as the catalysts for ideation, creation, and execution of research artifacts.

The rest of the paper is as follows. In Research Background, we included relevant studies in HFT, cryptocurrency research, and behavioral finance to set up the research theoretical foundation. In Methods, we highlighted Design Science Research as the research method. In Artifact Design and Search Process, we described how to create the Bitcoin trading algorithm artifact. In Evaluation, we evaluated the artifact with DL model, and further compared its performance versus foreign currency exchanges. In Discussion, we provide the descriptive and prescriptive knowledge contributions, and state research limitations. In Conclusion, we provide final thoughts on our research.

Research background

HFT

HFT has its start as early as 1998, when the Security Exchange Commission allowed electronic exchanges to be able to trade securities legally.[7] HFT is the use of computerized trading algorithms to buy and sell assets quickly and frequently, with a short holding period to earn minuscule margins on each trade. HFT have been used on various asset markets such as foreign exchanges, fixed income, equity, and derivatives. Interested readers should peruse ref.[7–10] for an in-depth background on HFT.

To effectively utilize HFT, different strategies have been concocted and tested, for instance, using the imbalance between order supply and demand,[11] trading around news,[12] and inter-exchange arbitrage of price discrepancies.[13,14] ML is a suitable application since it helps to facilitate research and practice in HFT.

Cryptocurrency research

Academic research in cryptocurrencies is nascent, with the majority of research focusing on either technical aspect of blockchain, the speculative or 'bubble-like' nature of the asset, or of price manipulation and informed trading. Baur et al.[15] argued that participants have speculative motivations because of Bitcoin's lack of correlation with traditional financial assets. Urquhart[16] extended the speculative hypothesis by identifying a statistical link between media attention and recent realized volatility and volume in the cryptocurrency. More insidiously, informed trading has been documented by Feng et al.,[17] who found that order imbalances between buyers and sellers in the market precede large price events. Feder et al.[18] also identified Bitcoin price manipulation in the market for Bitcoin, linking identifiably manipulative trades to subsequent trading price responses in the now-defunct Mt. Gox exchange.

Behavioral finance

Cryptocurrency markets are highly speculative. The exchanges are primarily used for trading profits. Because of significant volatility and liquidity concerns, these exchanges are not used primarily to facilitate transactions of actual goods and services. Therefore, in a market predominantly composed of participants devoted toward to the pursuit of trading profits, understanding through a strong behavioral lens is warranted.

Behavioral finance had its seminal beginnings in ref,[19] the first paper to articulate how an asset might carry unreasonably high value because of the expectation that someone else will subsequently pay a higher price for it. Shiller[20] documented irrational asset deviations from fundamental values: stock prices fluctuated by more than their economic fundamentals suggest. Over the last decade, the behavioral finance literature has bloomed, partly owing to the financial crisis of 2008–2009 and the Dot Com burst of 2000–2002. In particular, experimental studies involving investors' psychology and heuristics are related directly to this study. For example, Benoît et al.[21] and Ben-Davide et al.[22] highlighted the overconfidence of traders; Hirshleifer et al.[23] and Peng and Xiong[24] described the limitations in attention or cognitive processing ability of investors. Several studies discussed the frame-of-reference biases[25,26] while Ben-David and Hirshleifer[27] and Frydman[28] highlighted the disposition effect, which is often observed in investors' psychology.

While we cannot use the cryptocurrency market directly to conduct an experimental design on cross-sectional differences in investors' psychology, we can treat our study as a test on the market that is inherently driven by such behavioral factors: over-optimism, over-reaction, and bounded rationality. These factors contribute to the stratospheric rise of Bitcoin, where in 2017 alone, its annual price growth rate of 1,331% would, if continued, eclipse the entire world's GDP in 25 months (Note: The 1,331% statistic is calculated from our data on prices in 2017 in the Coincheck exchange and applied to Coindesk's market cap during the last week of 2017 – we compare this to world GPD using data from the CIA.[29]) Moreover, most professional investors shunned the Bitcoin market during our sample period.[30] The absence of such investors in a market tends to exacerbate irrational investment behavior.

From a behavioral perspective, overreaction, and over-optimism relate to chasing recent past performance and expecting that past performance to continue. Over-reaction in stock returns has been noted, as in De Bondt and Thaler,[31] who document a "chasing winners" situation. Chen et al.[32] developed a theoretical model for overreaction and suggested (theoretically) profit potential from such momentum reversals. While our results are at a higher frequency than the articles' empirical findings, our findings that technical features can be designed to take advantage of psychological overreaction in comparable asset markets are consistent.

The high-frequency nature of our trading also implies more complexity, at a level that an individual would be unable to grasp. This leads to our second connection with the theories behind behavioral finance – bounded rationality. Individuals can make sub-optimal trading mistakes because they are unable to fully process all the available information in time.[33] Bounded rationality occurs when individuals often make decisions on the basis of rules of thumb, and not through a detailed simulation of the data. This is computationally efficient, but not globally optimal.

To put this in perspective, if an individual were attempting to use technical features under a manual approach, they would have to cognitively map five calculations into an expected price change every minute, perpetually throughout the trading period. For just one exchange (Coincheck), with 1.44 million minute observations, this would amount to the reconciliation of 7.2 million cognitive tasks. It is clear that a non-algorithmic approach would naturally involve a great degree of cognitive rules-of-thumb, which may not represent the optimal trading decision. As such, we contribute to studies involving behavioral finance by highlighting the effectiveness of a system-based approach to trading in a highly speculative environment.

Overall, the above literature shows a wealth of knowledge established in HFT and behavioral finance and a nascent but pressing call for studies in cryptocurrency. As a result, our article is backed by a rich knowledge base and addresses an understudied phenomenon. We therefore add to the richness of knowledge in the fields of HFT and also open up future research venues in cryptocurrency research.

Methods

Our research follows the Design Science Research (DSR) paradigm mentioned in ref.[5,34] Specifically, we adhere to the seven guidelines in ref.[5] to conduct our research and rely upon the three DSR cycles for the artifact creation.[34] In addition, we leverage ref.[6] to delineate our research contribution in descriptive and prescriptive knowledge. Here, we describe the DSR guidelines and DSR cycles.

Design science research

In DSR, researchers seek to create Information Technology artifacts, which serve to extend the knowledge base.[35] The artifacts can be in a form of constructs, models, methods, instantiations, and design theories.[35,36] There are two research activities: build and evaluate. In build, research artifacts are created with roots in theoretical foundation; in evaluation, the artifacts are being benchmarked to expound its utility. Seminal research has discussed DSR at length, all highlighted the problem-solving aspects of the artifacts combined with the contribution to the knowledge base.[5,35,37,38]

The establishment of DSR creates an opportunity for a richer research but poses a risk of fuzzy and ill-defined research processes. As a result, Hevner et al.[5] has provided seven DSR guidelines to help researchers conduct DSR-related project systematically. The guidelines, their descriptions, and how they each applied in this research are delineated in Table 1, modeled after ref.[39]

As a research paradigm, DSR looks at the problems at hand in the environment, relates to the knowledge base on what solutions could be applicable, and creates an artifact to solve the aforementioned problems. Three DSR cycles, Relevance, Rigor, and Design, are designed to highlight the importance of these aspects in DSR. Figure 1 provides the DSR cycles adaptation for this research.

In the Relevance Cycle, this research focused on defining the problem, i.e. how to conduct trading in multiple highly volatile, speculative cryptocurrency markets. In the Rigor Cycle, we perused research from several subdomains in finance: HFT, cryptocurrency research, and behavioral finance to ideate, build, and evaluate our artifact. In addition, we used ML and DL techniques in the knowledge base to build and evaluate our artifact. Last, in the Design Cycle, we iterated between the two DSR activities to design and construct the artifact.

Artifact design and search process

In this section, we delineated the artifact search process, i.e. how the artifact was created.[5] We first presented the data source, followed by the data preparation and the algorithm design. Finally, we describe the artifact.

Data collection

We obtained Bitcoin trading data at the minute-level in six exchanges: Bitstamp, Btce, Btcn, Coinbase, Coincheck, and Kraken via web crawling the exchanges. These exchanges originate from countries where there are well-developed financial markets in trading Bitcoin. The Kraken exchange has two datasets,

Table 1. Hevner et al.[5] guidelines and their applications to this research.

Hevner et al.[5] Guidelines	Guideline Descriptions	Application to this research
1. Design as an Artifact	DSR produces a construct, model, method, instantiation, and/or theory as an artifact	The artifact is an HFT strategy through the use of the RF machine learning technique. It is both a method and an instantiation artifact.
2. Problem Relevance	The artifact has to provide solutions for the problems at hand.	There are multiple Bitcoin exchanges with divergent parameters. With a creation of HFT algorithms, business and individuals could capitalize on this highly volatile market.
3. Design Evaluation	The artifact has to undergo rigorous evaluation to show its utility.	We administer two evaluation procedures to our artifact. First, we compare the metrics of the RF model with a comparable model using DL and its economic values with long-only strategies. Second, we provide economic values to compare the efficacy and utility of our algorithms.
4. Research Contribution	DSR has to provide solid contribution to the knowledge base	We offer both descriptive and prescriptive knowledge to DSR. There are five descriptive and three knowledge contributions.
5. Research Rigor	Theoretical grounding is essential for both the build and evaluate phase of DSR.	We utilized established research in the HFT, cryptocurrency research, and behavioral finance domains to create and evaluate our artifacts
6. Design as a Search Process	The artifact has to be replicable (Gregor & Hevner, 2013).	The search process of the artifact is presented in this research to promote replicability.
7. Communication of research	This guideline discusses the need to convey DSR results effectively.	Using the guidelines from both (Gregor & Hevner, 2013; Hevner et al., 2004) to provide the structure and the direction of this research, we hope to disseminate DSR to both academia and practice.

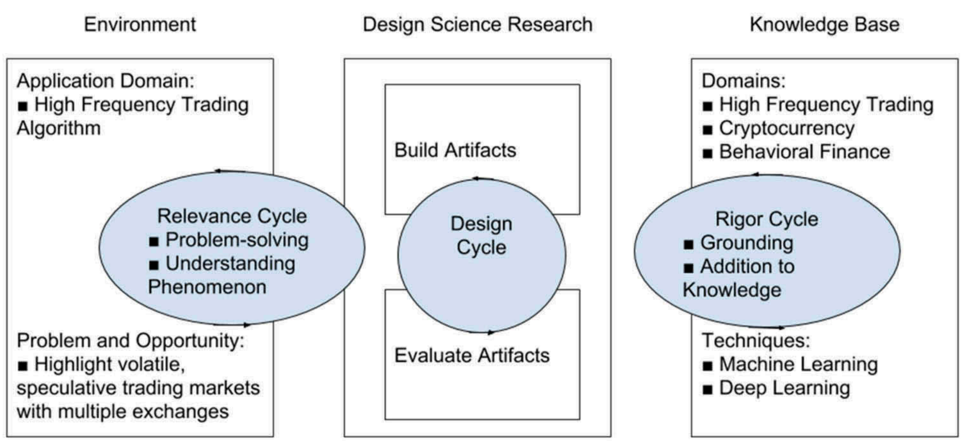

Figure 1. An adapted DSR cycles from (Hevner et al., 2004).

which makes up our seven datasets. The data contain timestamps, the Open-High-Low-Close prices, the volume of Bitcoins traded, and the volume of currency traded at each minute. There are several observable differences between each dataset, reflecting the complexity of the data. First, the datasets do not have the same time frame, and therefore have different numbers of records. This is because exchanges start in different time periods. Second, the datasets originate from different countries and utilize a different currency as the basis to determine Bitcoin value. Third, the price of Bitcoin varies between exchanges due to supply, demand, liquidity, and other technical factors such as the speed of trade execution and API calls allowance. Table 2 summarizes the datasets' metadata.

Data manipulation

In the beginning of each exchange, minute-level trading is few and far between. The minute-level trading data were not available abundantly until the exchanges attained some critical mass. As a result, the data frequently has Null value, indicating that there is no observable trading happening at that time. To impute data, we utilized a forward fill imputation, where the data is carried from the previous trading period to replace the Null value.

After the preliminary data cleaning, we created the following financial indicators: 1) Relative Strength Index, 2) Stochastic Oscillator, 3) Williams %R, 4) Moving average convergence divergence, and 5) On Balance Volume.

Table 2. Datasets' metadata.

Dataset	Host Country	Currency	Date Range (Year/Month/Day)	Min Open Price	Max Open Price	Number of Records
Bitstamp	Luxembourg	USD	2012/01/01–2017/10/20	$ 3.8	$ 5,846.43	3,045,857
Btce	Russia	USD	2012/01/01–2017/05/31	$ 3.88	$ 2,735.236	2,751,594
Btcn	China	CNY	2012/01/01–2017/05/31	¥ 25.81	¥ 18,947.99	2,746,814
Coinbase	USA	USD	2014/12/01–2017/10/20	$ 0.06	$ 5,864.05	1,459,076
Coincheck	Japan	JPY	2014/10/31–2017/10/20	¥ 20,000	¥ 657,313	1,562,030
Kraken_A	USA	EUR	2014/01/08–2017/05/31	€ 148.359	€ 2,402	1,716,589
Kraken_B	USA	USD	2014/01/07–2017/05/31	$ 175	$ 27,13.37	1,706,404

These indicators are prevalent in the trading literature and are conventionally used by finance professionals.

Relative strength index

The Relative Strength Index, RSI, measures the movement speed of changing price. RSI is calculated by:

$$RSI = 100 - \frac{100}{1 + RS_p}$$

where RS is the ratio between the average gain and the average loss over a certain period p. RSI is used to identify a general trend, capable of extrapolating the trading momentum.[40] A default time frame for RSI is 14 (p = 14), and a smaller time frame marks an increase in movement sensitivity. The range of RSI is between 0 and 100, and a score below 30 indicates an oversold scenario while a score above 70 indicates an overbought scenario.[40] With RSI, we can see how the price momentum changes overtime.

Stochastic oscillator

Stochastic oscillator is a popular momentum indicators. Invented by Lane,[41] this indicator puts a premium on the momentum movement of the price changes above price or volume. The formula of stochastic oscillator is:

$$\mathrm{SO} = 100 * \frac{\mathrm{C} - \mathrm{L_p}}{\mathrm{H_p} - \mathrm{L_p}}$$

Where C is the current closing price; H and L are respectively the highest and lowest price over a certain period p. Similar to RSI, the default timeframe is 14 (p = 14). The stochastic oscillator has a range of 0 to 100. A value of 20 or lower signifies overselling while a value of 80 or higher signifies overbuying.

Williams %R

Williams %R is another momentum indicator that watches the movement of stock price. It measures the closing price in relative to the spread between high and low price. Williams % R is calculated for each period by the following:

$$\%\ R = \frac{H_p - C}{H_p - L_p} * -100$$

Where C is the current closing price; H and L are respectively the highest and lowest price over a certain period p. Typically, the period would be 14. The range of RSI is from 0 to −100. If Williams %R is less than −80, it is oversold; when Williams %R is more than −20, it is overbought. Even though Williams %R could deem as an inverse of the stochastic oscillator, it provides an accurate signal of market reversal in future trading periods.[42]

Moving average convergence divergence (MACD)

The MACD is another worthwhile momentum indicator for the artifact. It is popular among traders thanks to its simplicity and effectiveness, for it provides both trend and momentum signals.[43] MACD produces a difference between two exponential smoothing moving averages, one in a longer period and the other one in a shorter period. It signifies how the two exponential smoothing moving averages converge and diverge. The general intuition is that when the short-term moving average outpaces the long-term moving average (above or below), this is a noise-reduced signal about the short-term future path of the asset.

With this intuition, MACD formula can be read as a signal line. When MACD is under the signal line, it indicates a sell signal and vice versa. The formulae for MACD and the signal line are:

$$MACD = EMA_p(C) - EMA_q(C)$$

and

$$Signal\ Line = EMA_r(MACD)$$

Where $EMA_p(C)\ and\ EMA_q(C)$ are the exponential smoothing averages of the closing price C over a period p and q. The period p is always shorter than the period q. Similarly, $EMA_r(MACD)$ is the exponential smoothing averages of the calculated MACD over a period r. Conventional settings for p, q, and r are 12, 26, and 9, respectively, although this can depend on measurement frequency.

On balance volume (OBV)

As opposed to the previous indicators that utilize only price, OBV is a cumulative indicator that focuses on the volume traded. Since volume movement precedes price movement, a changed OBV signals subsequent price change.[44] A rise in OBV indicates a price will move higher while a drop in OBV suggests a decrease. The formulae to calculate OBV is:

$$\text{If } C_p = C_{(p-1)} \rightarrow \mathrm{OBV(p) = OBV\,(p-1)}$$

$$\text{If } C_p < C_{(p-1)} \rightarrow \mathrm{OBV\,(p) = OBV\,(p-1) - V_p}$$

$$\text{If } C_p > C_{(p-1)} \rightarrow \mathrm{OBV\,(p) = OBV\,(p-1) + V_p}$$

Where C_p is the closing price at time p, V_p is the volume at time p. When the closing price of a stock is equal to its closing price of the previous period, the OBV remains the same. When the closing price increases ($C_p > C_{(p-1)}$), the trading volume is added into the previous OBV. In the same manner, when the closing price decreases, the trading volume is subtracted from the OBV of the previous period.

Artifact design

To create our HFT artifact, we selected a ML approach. ML has been utilized extensively by practitioners to create investment management services that automate financial trades and academic research has followed. For instance, Trippi and DeSieno[45] offered trading strategies for equity indices using neural networks; Dempster and Jones[46] utilized a genetic algorithm to create a trading system; and Gestel et al.[47] leveraged Support Vector Machine to trade T-Bills. These examples highlighted the presence of ML in various aspects of financial trading.

We elect RF, a type of classification tree ensemble model. An ensemble model creates a plethora of classification trees. The ensemble model will facilitate a "voting" mechanism among trees. RF contains multiple trees (thus creating a forest) with additional randomness built in.[48] The trees are independent from one another, and voting is a simple majority vote.[49]

To create the strategy, we removed duplicate time stamps and imputed prices using forward fill. Then, we create the five aforementioned financial indicators. While financial indicators typically work with "day" as the unit analysis, in our dataset, "minute" is the unit analysis. Finally, we select the CoincheckJPY, at random, to train the algorithm. RF has been run with the following tree structures: 30, 45, 50, 65, 75, and 100. Coupled with varying tree structures, we also used 30 trading periods ranging from 1 min to 90 days. Each combination was trained and tuned with 10-fold cross validation. Afterwards, each combination is used to predict prices in the remaining datasets. All in all, we formulated 648 combinations.

To compare each tree, we focus on F-1 due to two factors: first, F-1 metric is a harmonic scoring between Precision and Recall, and second, the scores between Precision, Recall, and F-1 are consistent across all combinations. Figures 2 and 3 depicts the F-1 metric for the buy and sell decisions across different periods and RF trees, respectively. To review the Precision metric for Buy and Sell decisions, please review Appendix 1 and 2. In addition, Appendix 3 and 4 display the Recall Metric for both Buy and Sell decision, respectively.

Both figures show that an increase in RF trees in Bitcoin trading do not necessarily provide an increase in the models' harmonic F-1 score. Even when there were improvements, the improvements were meager, and there were instances that having too many trees could reduce the model performance. Sensibly, there are two viable choices: an RF with 30 or 45 trees. As Occam's Razor dictates, RF 30 trees would be a better choice.

Furthermore, there are two trends observed in both figures. First, there seems to be a divergence of accuracy in the "Buy" portion. The model performs well when the timeframe is 30 min or less. However, the models performed worse, around 50%, at 60 min. The models increased in F-1 score onward, and at 90 days, the models performed admirably, but not as well as their 30-min-or-less counterparts. The same thing could not be said when looking at the "Sell" portion. As the timeframe increases, the models performed worse. At 60 min, the models hovered around 50% in F-1 score, but quickly diminished. At 90 days, the models reported a score of 30%, signaling inadequate predictions for any long position. All in all, at 15-min, the RF performs remarkably well. Based on above analysis, we selected the RF with 30 trees and 15-min as the timeframe of our strategy. Figure 4 describes the relative importance of each indicator in our model. RSI is the most important, outpacing other indicators.

Evaluation

In this section, we test the utility of our model. First, we compare the RF with another popular algorithm: Deep Learning (DL). Our comparison shows that the RF performs, on average, better than DL. Second, we put the RF to practical application to see whether the model could bring *economic* as well as statistical significance.

To create the DL models, we ran a binary cross entropy using three tensor layers with Adam optimizer[50] on the same dataset: CoincheckJPY. The DL model then was used on other datasets to predict either a buy or sell decision. Table 3 compares the predictive power between DL and RF models with three metrics: F-1, Precision, and Recall. The metrics generated from the RF are used as a benchmark for the differences. On average, the RF consistently performs better than its DL counterpart.

Economic value evaluation

In the second evaluation method, we ascribe a potential dollar value by running a rolling, out-of-sample simulation that would closely represent a live algorithmic trading system. First, we commit $1,000 in capital. With the earliest sample, we took 1 week of currency and signal data to train the RF. We then applied the

	RF trees					
Periods ..	30	45	50	65	75	100
1 min	93.23%	93.26%	93.22%	93.27%	93.28%	93.22%
5 mins	91.58%	91.66%	91.67%	91.73%	91.73%	91.71%
15 mins	97.48%	97.51%	97.52%	97.53%	97.54%	97.55%
30 mins	83.51%	84.47%	84.43%	84.83%	84.89%	84.96%
60 mins	50.06%	51.12%	50.56%	51.23%	51.32%	50.98%
1.5 hours	51.67%	53.13%	52.27%	52.98%	52.95%	52.62%
2 hours	52.65%	54.12%	53.20%	54.11%	54.19%	53.69%
2.5 hours	53.95%	55.68%	54.75%	55.75%	55.72%	55.19%
3 hours	54.77%	56.35%	55.45%	56.49%	56.53%	56.07%
6 hours	55.44%	57.31%	56.24%	57.38%	57.38%	56.86%
12 hours	57.20%	59.22%	58.36%	59.36%	59.52%	59.21%
1 day	59.17%	60.97%	60.03%	60.97%	61.02%	60.62%
2 days	60.90%	62.82%	61.93%	63.04%	63.09%	62.81%
7 days	64.97%	66.86%	66.17%	67.14%	67.22%	66.98%
14 days	66.80%	68.47%	67.83%	68.71%	68.80%	68.55%
30 days	71.87%	73.32%	72.88%	73.53%	73.60%	73.48%
60 days	72.25%	73.57%	72.98%	73.72%	73.67%	73.44%
90 days	72.30%	73.59%	72.90%	73.67%	73.65%	73.41%

F-1 metrics for buy decisions
50.06% 97.55%

Figure 2. F-1 metric for the buy decisions across different periods and RF trees.

Periods ..	RF trees 30	45	50	65	75	100
1 min	93.32%	93.34%	93.31%	93.33%	93.34%	93.29%
5 mins	90.07%	90.14%	90.18%	90.23%	90.21%	90.20%
15 mins	97.24%	97.26%	97.28%	97.29%	97.30%	97.31%
30 mins	82.55%	83.08%	83.47%	83.51%	83.56%	83.80%
60 mins	50.97%	49.84%	50.46%	49.73%	49.69%	49.95%
1.5 hours	51.87%	50.60%	51.34%	50.55%	50.57%	50.86%
2 hours	51.46%	49.97%	50.72%	49.83%	49.89%	50.31%
2.5 hours	50.52%	49.12%	50.03%	49.01%	48.97%	49.52%
3 hours	49.69%	48.29%	49.49%	48.40%	48.38%	49.05%
6 hours	47.07%	45.22%	46.34%	45.02%	44.98%	45.53%
12 hours	44.14%	41.72%	42.92%	41.58%	41.33%	41.88%
1 day	42.79%	40.47%	41.69%	40.40%	40.34%	40.86%
2 days	39.53%	36.97%	38.24%	36.59%	36.48%	36.93%
7 days	34.78%	31.70%	32.93%	31.18%	31.03%	31.59%
14 days	34.16%	31.70%	32.70%	31.36%	31.22%	31.67%
30 days	27.00%	24.16%	25.59%	24.22%	24.11%	24.29%
60 days	28.29%	26.66%	27.38%	26.55%	26.64%	26.94%
90 days	29.38%	27.52%	28.21%	27.39%	27.39%	27.65%

F-1 Metric for Sell decisions
24.11% 97.31%

Figure 3. F-1 metric for the sell decisions across different periods and RF trees.

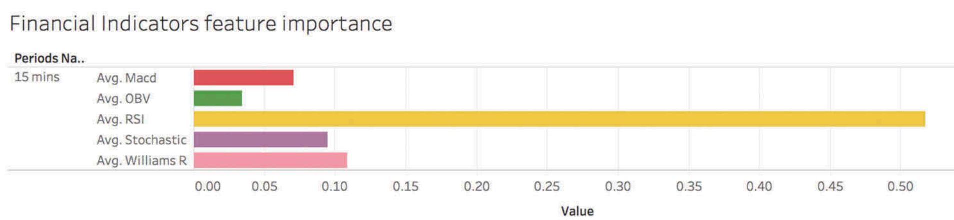

Figure 4. Financial Indicators feature importance in the trading strategy.

parameters from this model toward the following week and evaluate the trading profits/losses. Subsequently, we updated the data of the second week to train a new model, then used the parameters from that new model as trading signals for the third week, repeating throughout the entire sample. We utilized the following timeframes: 5, 15, and 360 min. The profits/losses from each trade are then accumulated (non-compounded). Figure 5 displays the pseudocode of our economic evaluation process. Corresponding return statistics are shown in Table 4. The cumulative profits to simply buying – regardless of signal content – are also shown in Figure 6. This last approach can be thought of as a naïve 'long-only' strategy. Out-of-sample weekly economic profits when using the RF, with parameters updated each week, amount to over \$9,000 and \$11,000 for 5- and 15-min trading frequencies, respectively, representing a return of 9 to 11 times capital. Economic profits when deploying the RF model with a trading frequency of 360 min are lower, but still result in a 1.8x return on capital, a significant improvement over the 'long-only' strategy (see Appendix 5). In addition, a sensitivity analysis using 2 and 4 week windows (figures in Appendix 6) showed slightly and monotonically declining results. Relative performance declines in the strategy over time, as Bitcoin markets draw more participants. This is consistent with our expectation that technical strategies that exploit behavioral biases of less sophisticated investors decline in performance as the market becomes more efficient, as posited by Poteshman and Serbin.[30]

Cryptocurrencies present a less developed and more speculative trading market. In contrast, developed market currencies have

Table 3. Comparing F-1, precision, and recall metrics between RF and DL models.

Dataset		Bitstamp USD	Btce USD	Btcn CNY	Coinbase	Kraken EUR	Kraken USD	Average Difference
DL	F1 Buy	97.12%	96.90%	95.43%	98.88%	97.95%	95.75%	
RF	F1 Buy	97.08%	96.70%	97.28%	98.80%	97.73%	95.78%	
Difference		−0.04%	−0.19%	1.86%	−0.07%	−0.22%	0.03%	0.23%
DL	F1 Sell	96.73%	96.68%	94.91%	98.65%	97.73%	95.57%	
RF	F1 Sell	96.69%	96.46%	97.10%	98.56%	97.47%	95.58%	
Difference		−0.05%	−0.23%	2.19%	−0.09%	−0.26%	0.02%	0.26%
DL	Precision Buy	97.41%	97.30%	93.70%	99.05%	98.35%	96.13%	
RF	Precision Buy	97.27%	96.81%	97.45%	98.82%	97.77%	95.99%	
Difference		−0.13%	−0.49%	3.75%	−0.22%	−0.59%	−0.14%	0.36%
DL	Precision Sell	96.41%	96.26%	96.89%	98.45%	97.29%	95.17%	
DL	Precision Sell	96.47%	96.34%	96.92%	98.54%	97.42%	95.36%	
Difference		0.06%	0.08%	0.03%	0.09%	0.14%	0.19%	0.10%
DL	Recall Buy	96.83%	96.50%	97.21%	98.71%	97.54%	95.37%	
RF	Recall Buy	96.89%	96.60%	97.12%	98.78%	97.69%	95.57%	
Difference		0.06%	0.10%	−0.10%	0.08%	0.14%	0.20%	0.08%
DL	Recall Sell	97.06%	97.11%	93.00%	98.85%	98.18%	95.97%	
RF	Recall Sell	96.90%	96.57%	97.28%	98.58%	97.52%	95.80%	
Difference		−0.16%	−0.54%	4.28%	−0.27%	−0.66%	−0.16%	0.41%

```
For frequency in 5, 15, and 360 minutes:
    Construct technical signals, and 'Buy'/'Sell' categorical dependent variable
    for week t, t = 1, ..., N
            Estimate RF model on week t (beginning with the first week of the sample), save parameters
            Apply RF parameters from week t to week t + 1 technical signals, get 'buy'/'sell' predictions
                    For each sequential trade:
                            If predict 'buy', multiply actual return series in week t + 1 by 1
                            If predict 'sell', multiply actual return series in week t + 1 by −1
                    Take trading return series from above, multiply each return by $1,000
                            #e.g., 1.2% return on one 15 minute trade = .012*$1,000=$12 profit
                    Cumulative sum the trading profit and losses for each trade in week t+1
    Sum cumulative (non-compounded) profits for week t = 2, ..., N, plot
```

Figure 5. Pseudo code of economic evaluation.

Table 4. Bitcoin log returns with a $1,000 investment with 5, 15, 360 min, and long only trading periods.

Period	Cumulative Profits	Annualized Average Returns	Sharpe Ratio	Annual Return (by Year) 2015	2016	2017
5 min	$9,362.45	804.21%	8.11	718.83%	−6.01%	54.87%
15 min	$11,107.66	657.45%	8.22	931.68%	46.56%	204.73%
360 min	$1,782.18	114.90%	1.77	97.33%	25.94%	210.54%
Long only	$910.99	58.75%	1.16	31.47%	66.51%	80.13%

many large, diverse trading participants. Therefore, it is interesting to see how the RF performed in a more established market. Thus, we applied the RF to trading in the spot exchange market for the JPY versus the USD to compare economic performance. Our aim is to shed light on the differences in profitability and out-of-sample performance when financial markets are relatively more liquid, efficient, and sophisticated, and therefore less subject to behavioral trading biases. The results are shown in Table 5 and Figure 7.

With the exception of the 5-min interval, the RF produces sizable economic benefits. The greatest results occur at the 15-min interval, producing a non-compounded profit of just under $1,500 on the $1,000 capital invested, a 51.32% annual return. While this is indeed economically significant, Bitcoin/JPY trade resulted in an $11,252 return on $1,000 capital, a 394.81% annual return. In other words, while algorithmic trading profits and out-of-sample performance of the RF model are still positive in the more efficient USD/JPY exchange rate, performance is much more exceptional in the erratic and heavily speculative Bitcoin/JPY exchange rate.

In summary, both evaluations help to solidify the artifact. First, the artifact has a high accuracy and precision, and it also exceeds performance against another high-performance algorithm. Second, by providing economic valuation of the artifact against a long only strategy plus comparing it against other trading commodity, the artifact sufficiently demonstrates its utility and efficacy. Therefore, we conclude that the artifact passes both evaluations.

Discussion

The above results showed that the algorithm performed well across multiple exchanges. In this section, we compare our research with previous Bitcoin algorithm research and delineate our descriptive and prescriptive contributions to the knowledge base. Afterwards, we present the limitations of the research.

Research in trading Bitcoin using algorithms is still fledgling, despite continued interest. Table 6 places our research among comparable research in predicting Bitcoin prices.[51–54] Our research confirmed the use of RF as a suitable algorithm, as suggested by ref.[51] Overall, the strategy presented in our research achieved higher results than other research presented in Table 6.

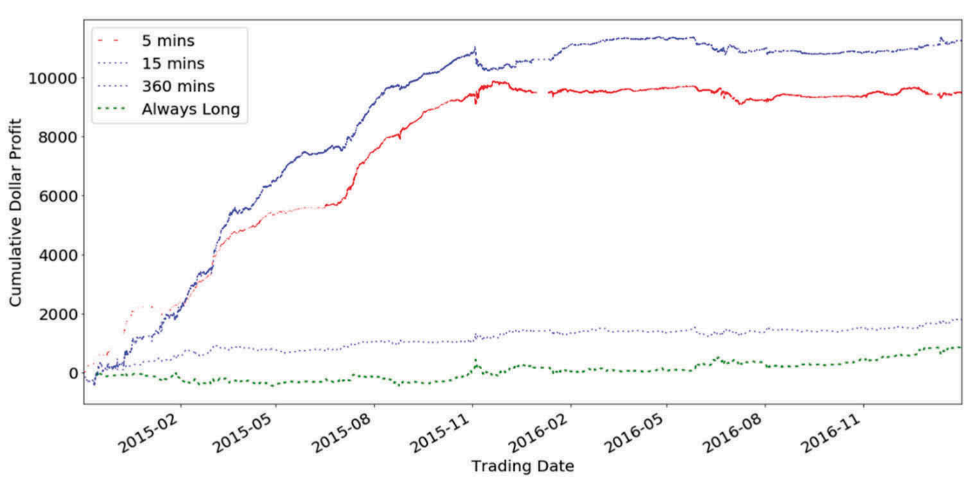

Figure 6. Bitcoin trading returns in cumulative dollar profit with several trading periods.

Table 5. Currency cumulative profit (in USD) and log returns, with a $1,000 investment under 5, 15, and 360 min trading intervals.

Period	Cumulative Profits	Annualized Average Return
5 min	($375.29)	−18.85%
15 min	$1,482.91	74.12%
360 min	$310.12	15.43%
Long only	($52.11)	−2.67%

Descriptive contributions

There are five descriptive, scientific contributions that the artifact offers. First, even though financial indicators might warrant setting calibrations, we show that default settings for these indicators work well. However, it is should be noted that careful calibrations will inevitably create better algorithms. It is no doubt that the algorithm could use more nuanced settings. Nevertheless, the default settings serve well as a benchmark for future research.

Second, by using one exchange to build our strategy and use it against other exchanges, we found that ML are tolerant to a wide variety of differences among exchanges: start dates, end dates, volumes, cryptocurrency prices, and base currency prices. Though these exchanges only pertain to one cryptocurrency, Bitcoin, the result transference shows that it is possible to train using one exchange and run in another, furthering the utility and capability of the artifact.

Third, our artifact indicates 15 min is an optimal interval given our minute-interval data. Using any interval that is less than 15 min could result in good return. Trading using 30-min as the interval results in the worst performance. Over a longer interval, namely in days, the strategy holds up well with "buy" decisions but fails miserably with "sell" decisions.

Fourth, the strategy is superior to the 'long-only' strategy, both in cryptocurrency and in a more developed currency. However, while a HFT trading strategy is profitable, investors need to be prepared for the emotional rollercoaster with this highly speculative market.

Fifth, RF is shown to be effective despite multicollinearity occurring in ML features, potentially leading to overfitting. The phenomenon is described by Bollinger, the creator of Bollinger band, "A cardinal rule for the successful use of technical analysis requires avoiding multicollinearity amid indicators". Many investment indicators like the ones utilized in this research used similar data to create them, thus multicollinearity is unavoidable. Despite this issue, ML did well in transferring predictive power across different exchanges.

Prescriptive contributions

We offer three prescriptive contributions, consistent with ref.[6] First, without access to super computers, creating, tuning, and comparing algorithms in real time is improbable. To run the

Table 6. Compare and contrast between this research and other research.

	Features used	Research direction	Trading horizon	Algorithm used	Result
This research	Technical indicators	Predicting the buy and sell decisions cross-exchanges	15-min	Random Forest	F-1: 97%
Madan et al.[50]	Bitcoin features	Predicting daily future price change	10-min	Random Forest	Accuracy: 57%
Jang and Lee[51]	Bitcoin features	Predicting price	Daily	Bayesian Neural Network	RMSE: 0.0256
Pichl and Kaizoji[52]	Log returns	Capturing the volatility of prices	1-day, 5-day, 10-day	Heterogeneous Autoregressive model for Realized Volatility including jumps	Statistically significant with p-value < 0.01
McNally, et al.[53]	Closing price	Predicting price	Daily	Long Short Term Memory	Accuracy: 52% RMSE: 8%

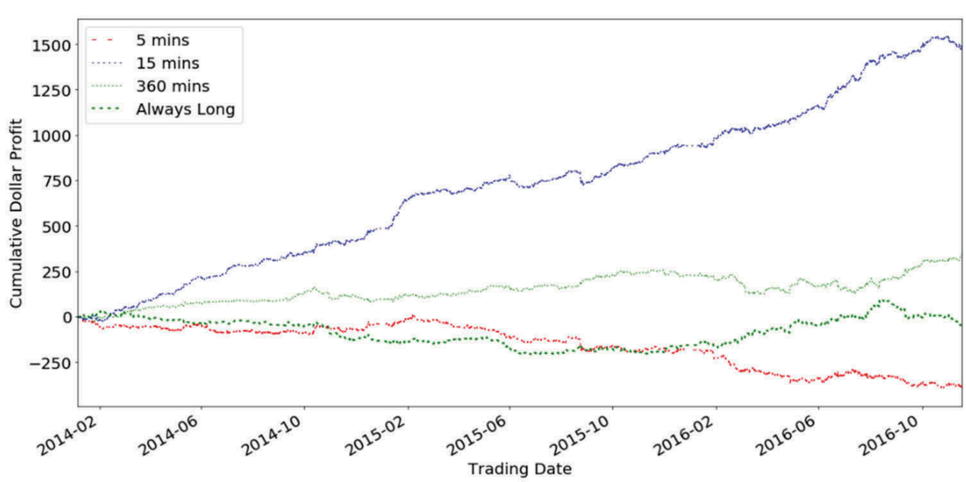

Figure 7. Cumulative dollar profit from currency trading in the JPY-USD exchange rate (in USD) under 5, 15, and 360 min trading intervals.

trees, it took our computer approximately 70 h of uninterrupted processing to run 648 algorithms for RF only. With DL and evaluation methods, the run time was as high as 150 h. This is partly due to the large amount of data and the high complexity of the algorithms. Despite this issue, researchers without access to high performance computers should not be discouraged to pursue research in Fintech. If anything, we proved that we could without a presence of one.

In addition, we ran into a computational issue when it comes to evaluation. With each out-of-sample prediction, we need to predict each data point and continue to use the rolling window to the next set of data points. Going through an enormous amount of data and computation made it almost impossible to derive the results. It is somewhat expected since Python is not as robust as C or Java. Nevertheless, Python has been a de facto tool for data scientists and algorithm designers. Future researchers and practitioners should take into consideration the "slowness" of Python if they choose to implement the algorithm. A robust application using a lower language like C or Java is warranted.

Finally, the behavioral finance constructs of overoptimism, overreaction, and bounded rationality informed our ideation, direction of the research, and the creation of our artifacts. Given these cognitive limitations, our study highlighted the effectiveness of a system-based approach to trading in this highly speculative environment with an overwhelming presence of information, adding an additional dimension to cryptocurrency research. We posit that kernel theories that are used in DSR are not limited to the design of the artifact but can also be extended into informing the overall research direction.

Limitations and future directions

The HFT trading strategy we offer here is only one of many strategies that could be concocted. Researchers and practitioners could use other algorithms to create better performing strategies. The intent is to present the process and results expected from a benchmark case. We hope that researchers and practitioners in the future could showcase another algorithm that is far superior to ours.

Second, the mix of indicators presented in this article is only a fraction of available indicators. We posit that choosing a good blend of indicators will reduce multicollinearity problem and also improve predictive capabilities. There are various types of indicators: trend (e.g. MACD and Forecast Oscillator), volatility (e.g. Bollinger Band and Relative Volatility Index), momentum (e.g. Price Rate-of-Change and RSI), cycle (e.g. Cycle Lines and Fourier Transform), market strength (e.g. Klinger Oscillator and OBV), and support and resistance indicators (e.g. Projection Bands and Andrews' Pitchfork). Future research should explore optimal sets of indicators for HFT trading.

Third, we were able to obtain only seven Bitcoin trading datasets from six exchanges. There are other popular exchanges throughout the world that utilize different currencies that were not part of the research such as Coinmama, Bitpanda, and Bitfinex. Future research could extend a discussion between more exchanges and how these exchanges could relate to the financial markets of specific countries which they are based.

Fourth, the results of this research were only for HFT trading in Bitcoin. Researchers and practitioners should extend this research to other cryptocurrencies such as Litecoin, Ripple, or Ethereum to see whether the HFT strategy is generalizable. We also note that practitioners should beware in directly applying the findings in this research to create their own strategy. Although the results shown are positive, it should not be used as a basis for predicting price fluctuations in the future.

Conclusion

In this research paper, we created an HFT strategy for Bitcoin using RF. HFT strategies have been used by practitioners to various degrees, and there are currently no studies on the creation and the efficacy of such trading algorithms. We offer the research community a look at how such an HFT strategy can be created, evaluated, and utilized through DSR. We hope that the strategy here can be used as a benchmark to be measured against.

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Appendix 1. Precision Metrics for Buy Decisions

Precision Buy

Periods ..	RF trees 30	45	50	65	75	100
1 min	0.9619	0.9617	0.9618	0.9609	0.9608	0.9604
5 mins	0.8942	0.8936	0.8948	0.8949	0.8942	0.8946
15 mins	0.9759	0.9748	0.9756	0.9752	0.9756	0.9760
30 mins	0.8515	0.8505	0.8597	0.8549	0.8552	0.8595
60 mins	0.5249	0.5261	0.5255	0.5262	0.5267	0.5257
1.5 hours	0.5426	0.5438	0.5430	0.5427	0.5427	0.5424
2 hours	0.5484	0.5480	0.5471	0.5473	0.5480	0.5475
2.5 hours	0.5525	0.5536	0.5537	0.5534	0.5531	0.5533
3 hours	0.5545	0.5549	0.5566	0.5561	0.5563	0.5576
6 hours	0.5526	0.5530	0.5530	0.5525	0.5523	0.5524
12 hours	0.5546	0.5548	0.5552	0.5551	0.5549	0.5555
1 day	0.5689	0.5688	0.5690	0.5689	0.5689	0.5689
2 days	0.5815	0.5821	0.5822	0.5821	0.5821	0.5822
7 days	0.6027	0.6030	0.6030	0.6030	0.6031	0.6032
14 days	0.6384	0.6380	0.6381	0.6381	0.6381	0.6383
30 days	0.6638	0.6638	0.6656	0.6657	0.6658	0.6656
60 days	0.7154	0.7149	0.7149	0.7152	0.7154	0.7155
90 days	0.7389	0.7349	0.7352	0.7347	0.7348	0.7349

Precision Metrics For Buy Decisions

0.5249 0.9760

Appendix 2. Precision Metrics for Sell Decisions

Periods ..	RF trees 30	45	50	65	75	100
1 min	0.9119	0.9126	0.9119	0.9130	0.9133	0.9126
5 mins	0.9275	0.9300	0.9290	0.9301	0.9310	0.9300
15 mins	0.9712	0.9729	0.9724	0.9731	0.9729	0.9726
30 mins	0.8095	0.8249	0.8193	0.8284	0.8291	0.8280
60 mins	0.4885	0.4852	0.4871	0.4849	0.4850	0.4853
1.5 hours	0.4959	0.4945	0.4952	0.4936	0.4936	0.4939
2 hours	0.4949	0.4934	0.4933	0.4925	0.4932	0.4932
2.5 hours	0.4932	0.4947	0.4945	0.4944	0.4941	0.4941
3 hours	0.4907	0.4923	0.4933	0.4936	0.4937	0.4944
6 hours	0.4732	0.4752	0.4742	0.4747	0.4745	0.4740
12 hours	0.4613	0.4631	0.4628	0.4634	0.4633	0.4637
1 day	0.4558	0.4579	0.4568	0.4579	0.4579	0.4574
2 days	0.4307	0.4326	0.4321	0.4328	0.4329	0.4326
7 days	0.4086	0.4111	0.4102	0.4115	0.4116	0.4119
14 days	0.3800	0.3817	0.3813	0.3825	0.3828	0.3829
30 days	0.3575	0.3592	0.3620	0.3623	0.3632	0.3626
60 days	0.2978	0.2982	0.2979	0.2990	0.2992	0.2991
90 days	0.2870	0.2844	0.2840	0.2843	0.2843	0.2842

Precision Metrics For Sell Decisions

0.2840 0.9731

Appendix 3. Recall metrics for Buy Decisions

Periods ..	RF trees 30	45	50	65	75	100
1 min	90.82%	90.89%	90.81%	90.95%	90.99%	90.91%
5 mins	93.88%	94.12%	94.02%	94.11%	94.21%	94.11%
15 mins	97.37%	97.53%	97.48%	97.55%	97.53%	97.50%
30 mins	81.98%	83.92%	82.96%	84.20%	84.28%	84.02%
60 mins	47.94%	49.78%	48.80%	49.97%	50.10%	49.54%
1.5 hours	49.39%	51.97%	50.44%	51.77%	51.73%	51.14%
2 hours	50.69%	53.49%	51.81%	53.52%	53.62%	52.69%
2.5 hours	52.74%	56.01%	54.17%	56.17%	56.16%	55.07%
3 hours	54.15%	57.28%	55.28%	57.43%	57.51%	56.44%
6 hours	55.69%	59.56%	57.31%	59.78%	59.79%	58.69%
12 hours	59.16%	63.63%	61.63%	63.93%	64.32%	63.54%
1 day	61.86%	65.97%	63.82%	66.02%	66.12%	65.21%
2 days	64.24%	68.59%	66.54%	69.15%	69.28%	68.61%
7 days	70.63%	75.24%	73.50%	75.95%	76.15%	75.50%
14 days	70.23%	74.08%	72.57%	74.63%	74.84%	74.22%
30 days	78.61%	82.16%	80.86%	82.49%	82.65%	82.35%
60 days	73.45%	76.29%	75.04%	76.60%	76.49%	75.98%
90 days	71.42%	74.21%	72.84%	74.40%	74.37%	73.90%

Recall Metrics For Buy Decisions

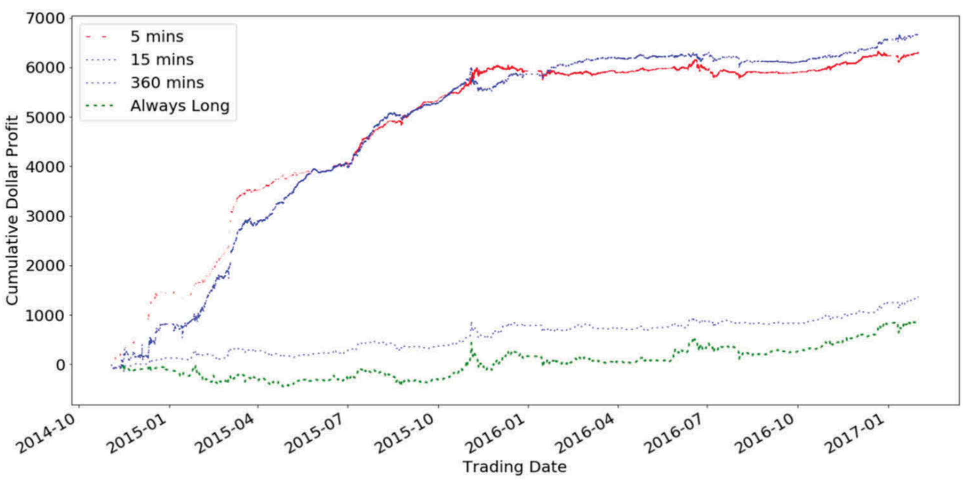
47.94% 97.55%

Appendix 4. Recall metrics for Sell Decisions

Periods ..	RF trees 30	45	50	65	75	100
1 min	90.82%	90.89%	90.81%	90.95%	90.99%	90.91%
5 mins	93.88%	94.12%	94.02%	94.11%	94.21%	94.11%
15 mins	97.37%	97.53%	97.48%	97.55%	97.53%	97.50%
30 mins	81.98%	83.92%	82.96%	84.20%	84.28%	84.02%
60 mins	47.94%	49.78%	48.80%	49.97%	50.10%	49.54%
1.5 hours	49.39%	51.97%	50.44%	51.77%	51.73%	51.14%
2 hours	50.69%	53.49%	51.81%	53.52%	53.62%	52.69%
2.5 hours	52.74%	56.01%	54.17%	56.17%	56.16%	55.07%
3 hours	54.15%	57.28%	55.28%	57.43%	57.51%	56.44%
6 hours	55.69%	59.56%	57.31%	59.78%	59.79%	58.69%
12 hours	59.16%	63.63%	61.63%	63.93%	64.32%	63.54%
1 day	61.86%	65.97%	63.82%	66.02%	66.12%	65.21%
2 days	64.24%	68.59%	66.54%	69.15%	69.28%	68.61%
7 days	70.63%	75.24%	73.50%	75.95%	76.15%	75.50%
14 days	70.23%	74.08%	72.57%	74.63%	74.84%	74.22%
30 days	78.61%	82.16%	80.86%	82.49%	82.65%	82.35%
60 days	73.45%	76.29%	75.04%	76.60%	76.49%	75.98%
90 days	71.42%	74.21%	72.84%	74.40%	74.37%	73.90%

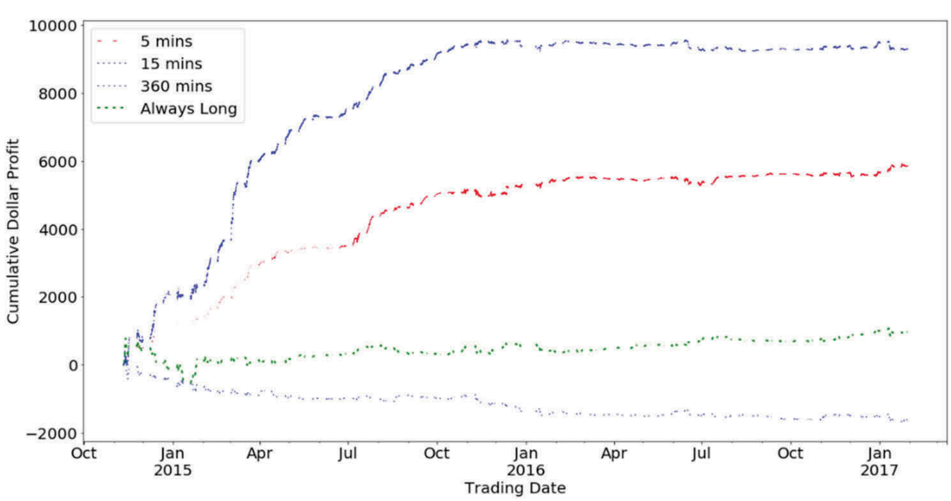
Recall Metrics For Sell Decisions
47.94% 97.55%

Appendix 5. Trading on 'Buy' Signals Only



Appendix 6. Alternative Parameter Estimation Windows of 2 weeks and 4 weeks

For 2 weeks estimation



For 4 weeks estimation