American Journal of Business and Cooperative Research
Volume.7, Number 3; July-September, 2023;
ISSN: 2836-9203 | Impact Factor: 6.90
http://zapjournals.com/Journals/index.php/AJBCR
Published By: Zendo Academic Publishing

ASSESSING FINANCIAL RISKS AND CRIMES IN VIRTUAL CURRENCY TRADING

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Article Info
Keywords: Virtual currencies, financial crimes, transaction data, regulation, price volatility.

Abstract
The increasing adoption of virtual currencies in financial markets has raised concerns about financial risks and crimes associated with their trading. This paper explores the challenges in regulating virtual currency platforms and the need for a comprehensive approach to address these issues. It highlights the difficulties in obtaining transaction data, identifying transaction risks, and the overall lack of supervision in the virtual currency market, which has led to various financial crimes.

To tackle these challenges, the paper proposes a method to classify trading entities based on transaction data, aiming to distinguish between legitimate and illegal activities involving virtual currencies. Additionally, the study investigates the impact of significant events, such as trading platform collapses, on virtual currency price volatility. This analysis sheds light on which virtual currencies are more susceptible to such events and which ones are less affected.

In summary, this research aims to provide insights into the relationship between trading entities and virtual currencies, with a focus on identifying and mitigating financial risks and crimes in the virtual currency market.

1. Background and significance of the study

With the continuous innovation of financial technology, more and more trading entities have joined the trading of virtual currencies. Relying on blockchain technology, the most representative of which, Bitcoin, had a high price, decentralization, and bubbles attracted many speculators. The virtual currency market was filled with many bubbles, leading to numerous financial risks and crimes. Today, due to its trading characteristics, there are still a series of problems in trading virtual currency platforms, such as difficulty obtaining transaction data, difficulty in identifying transaction risks, inadequate supervision, and various financial crimes have emerged.

There are few identifiable financial crime problems and a need to regulate virtual currencies. Only after each "minefield" are there regulatory and institutional updates. Many studies have shown a strong correlation between

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the behavior of trading entities and economic events and the price of virtual currencies and related financial crimes, so the relationship between trading entities and virtual currencies must be clarified.

This paper firstly examines how to determine whether a trading subject is using virtual currencies for illegal and criminal acts from the perspective of transaction data, making a nodal classification.

Finally, from the perspective of event research, this paper examines the impact of more significant trading subjects, i.e., trading platform collapse events, on virtual currency price volatility to examine which coins are affected more and which are affected less.

2. Literature review

Since the emergence of blockchain technology, virtual currency transactions have greatly impacted the physical and centralized trading system, Zhen Yuanyun (2022) [1] proposed that virtual currencies have legal supervision difficulties and economic crime facilitation and other problems, virtual currency financial crime problems are emerging one after another, regulatory issues need urgent attention. According to existing research, virtual currencies are difficult to quantify due to the characteristics of blockchain. Dimitrios Koutmos (2018)[2] studied the empirical link between Bitcoin returns and trading activity, and Halvor Aarhus Aalborg (2019)[3] and others have detailed the quantitative indicators that explain and predict Bitcoin.

Chawla (2002) [4] et al. proposed the SMOTE method, the existing related algorithms have problems such as difficult identification, low recognition efficiency, and low recognition accuracy, in order to improve the recall rate, accuracy and other indicators of virtual currency abnormal transaction recognition, and better identify abnormal transaction behavior in the virtual currency platform, this paper uses synthetic minority oversampling technology to construct an individual learner, and uses the integrated algorithm of the Bagging class to calculate abnormal transactions. Significantly improve recognition efficiency and accuracy.

Seth Armitage (1995) [5] summarized and sorted out the outliers and application scope of the event research method, and there are currently few studies on the correlation between external events and virtual currencies, Ying Sing LIU, Liza LEE (2020) [6] used the ARMAGARCH model to study the impact of external events (COVID-19, Sunday effect, and information flow) on the volatility of Bitcoin yields. In order to further explore the relationship between external economic events and virtual currency, this paper innovatively uses the event research method, takes the collapse of the cryptocurrency platform FTX as the gathering point, selects the head virtual currency, explores the impact of the bankruptcy event of the trading platform on the price trend of virtual currency, and obtains the impact of external shocks on the yield of virtual currency.

3. Empirical analysis

3.1 Bitcoin trading data node classification analysis

3.1.1 Data set source

This paper uses the Bitcoin transaction dataset published by Elliptic, which includes node, edge, and token information for transactions. Here, nodes represent transactions; edges represent bitcoin transfer information between transactions, i.e., the output of one trade is spent as input by the next, and tokens represent the properties of transactions, including "normal," "abnormal," and "unknown" values. The dataset contains 203,769 nodes and 234,355 edges, with each transaction node having 166 features.

The distribution of the three categories is plotted at different time steps, with no significant correlation between time steps and types, as shown in Figure 1.

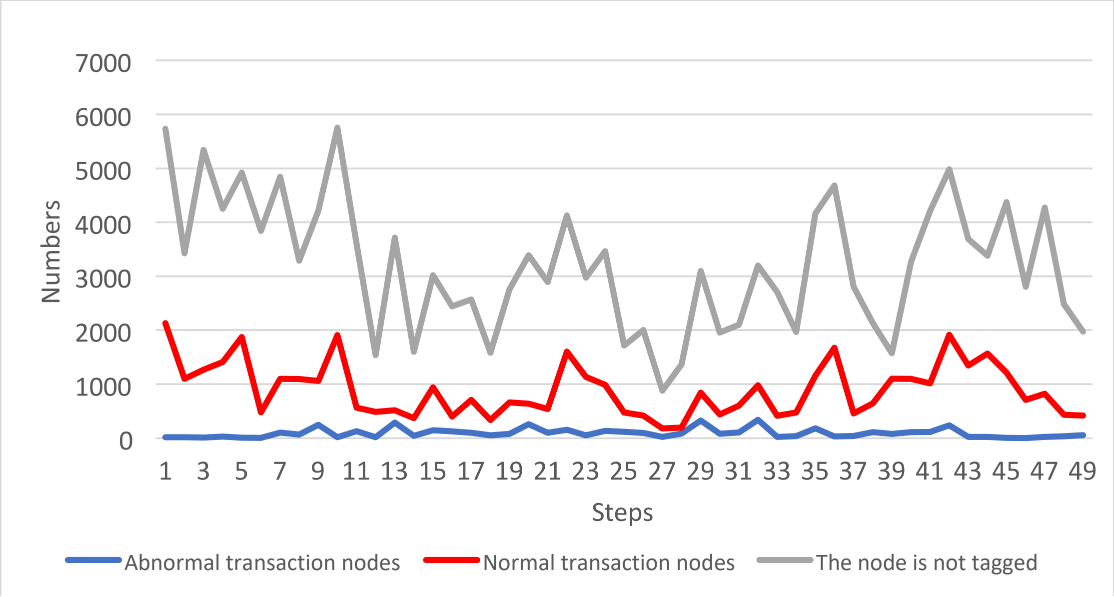


Figure 1: Categories of trading entities at different time steps

3.1.2 Data processing

The data set was pre-processed to obtain more accurate detection results. Nodes and tags were merged according to the corresponding relationships, and nodes marked as "unknown" were removed, resulting in 42,019 normal and 4,545 abnormal transaction nodes.

The proportion of abnormal and normal samples in the filtered dataset is approximately 11%. Since the output categories of many anomaly detection models are based on thresholds, the presence of thresholds may cause the model output to be biased towards the more dominant type when there is an imbalance between the proportion of normal and abnormal samples in the training data. The problem of data imbalance in dichotomous classification problems is usually addressed by sampling the data set, as shown in Figure 2 and Figure 3.

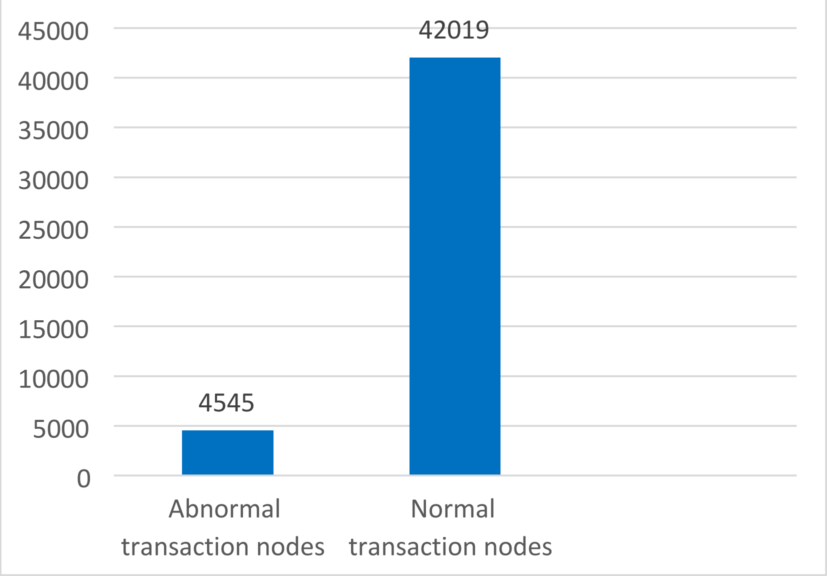


Figure 2: Category distributed strip shape

This study uses the Synthetic Minority Class Oversampling Technique (SMOTE). The basic idea of the SMOTE

them to the dataset.

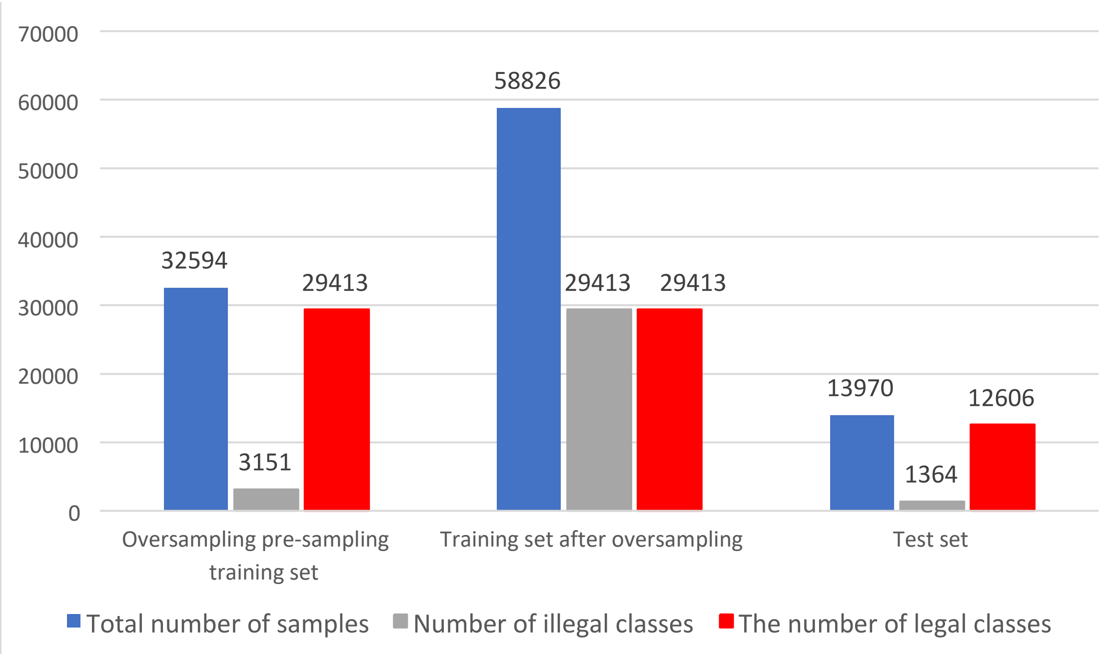


Figure 3: Une balanced dataset processing results

algorithm is to interpolate the minority class samples to synthesize new models and add

In this paper, 70% of the Ellptic dataset is randomly selected as the training set, and the remaining 30% as the test set for anomaly detection, and an oversampling operation is performed on the training set.

Four supervised algorithms are used to detect the feature set in the anomaly detection stage. The four supervised algorithms are Logistic Regression, Random Forest, Adaptive Boosting, and Decision Tree.

3.1.3 Evaluation indicators

Abnormal transaction detection can be considered a dichotomous problem, divided into only two categories, normal and abnormal. Therefore we first draw a confusion matrix and then use the confusion matrix to calculate the four commonly used evaluation metrics, Accuracy, Precision, Recall, and F1 values, as shown in the following equations, as shown in Table 1:

Table 1: Evaluation indicator confusion matrix

	Unusual transactions (actual)	Regular trading (actual)
Unusual transactions (forecast)	TP	FP
Regular trading (forecast)	FN	TN

$TTTT+TTTT$

$AAAAAAAAAAAAAAA =$ (1)

$TTTT+FFTT+FFTT+TTTT$

$TTTT$

$PPAAPPAAPPPPPPPPP =$ (2)

$TTTT+FFTT$ $TTTT$

$RRPPAAAARRRR =$ (3)

$TTTT+FFTT$

$2*TTPPPPPPPPPPPPPPPP*RRPPPPRRRRRR$

F1 = (4)

$TTPPPPPPPPPPPPPPPP+RRPPPPRRRRRR$

3.1.4 Analysis of results

The experimental environment uses Windows 11 operating system, DGL machine learning development framework, and Python as the development language. Anomaly monitoring was performed on the feature set in the original data, and the results are shown in the table 2 below.

Table 2: Machine model Learning Classification Result

	Precision	Recall	F1	accuracy
AdaBoost	0.6984	0.8043	0.7697	0.9210
DecisionTree	0.7346	0.8158	0.7676	0.9356
RandomForest	0.8620	0.8217	0.8404	0.9645
LR	0.5445	0.6293	0.3249	0.3545

Depending on how the individual learners are generated, the integration algorithms can be broadly classified into two categories, serially developed Boosting, such as Adaboost, and parallel caused Bagging, such as a random forest. The RF algorithm achieved the best detection results, with a recall rate of 82.17%, an accuracy rate of 86.2%, and an F1 reaching 84%. The integrated algorithm of the Bagging class has higher metrics, such as recall and accuracy in calculating anomalous transactions, than the integrated algorithm of the Boosting class. The tree-integrated model achieves better prediction results in predicting abnormal Bitcoin transactions, making it more suitable for building a strange transaction detection system with this model.

3.2 Correlation analysis based on event study

3.2.1 Event selection

This section studies the impact of cryptocurrency platform FTX bankruptcy on virtual currency prices. As the second largest cryptocurrency trading platform in the industry, the bankruptcy of FTX triggered a major earthquake in the currency industry, with most currency prices falling. On November 2nd, the cryptocurrency market news website Coindesk reported that Alameda Research Company borrowed tens of billions of dollars from the FTX Exchange and used the majority of the money to buy FTT to support its market value, as Alameda had as much as $6.112 billion in FTX issued FTT tokens on its books. In response, investors in the industry have expressed fear and concern about the flow of FTT, and have sold FTT. The market price of FTT has declined, and the cofounder of the world's largest cryptocurrency exchange, Coinan, has sold 20% of FTX's equity; Over a period of three days, investors withdrew over $6 billion from the FTX exchange. On November 6th, Zhao Changpeng, CEO of Coin An, publicly stated that Coin An Exchange would choose to liquidate the remaining FTTs in its investment portfolio, leading to a further decline in FTT prices. On November 9th, FTX sought help from Coin An, but after Coin An conducted due diligence on FTX, it quickly abandoned its acquisition plan. On the 9th, the market price of FTT plummeted by 90%. Finally, on November 11th, FTX Group collapsed and the second largest exchange in the virtual currency market collapsed.

Based on this, November 11, 2022 is taken as the event date, and the event window period is set as 9 trading days before and after the event date, thus including some important time points before the FTX bankruptcy event. It is estimated that the window period is 110 trading days to 10 trading days before the event; For expected returns, this article will use market models to calculate, where the S&P Cryptocurrency Financial Index will be used as the cryptocurrency market index, which reflects the largest and most liquid cryptocurrency and aims to provide both centralized and decentralized financial services or products, weighted by the market value of the cryptocurrency.

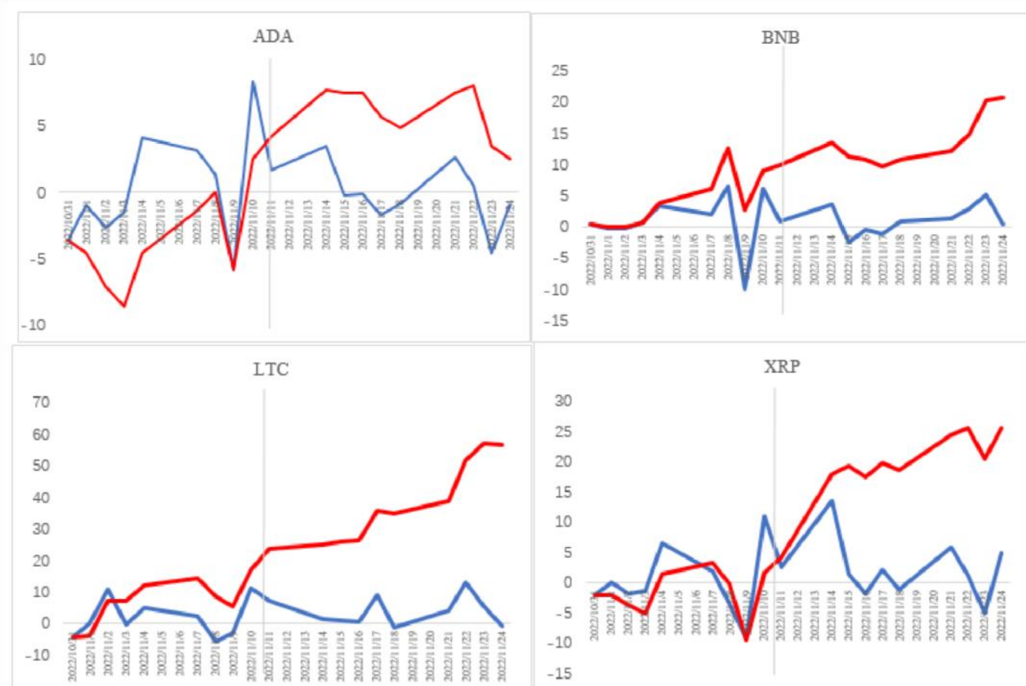
The abnormal return rate is the difference between the actual return rate and the expected return rate, and the cumulative abnormal return rate is a simple sum of the abnormal returns of each virtual currency during the event window period.

3.2.2 Research Currency Selection

This paper will select the cryptocurrencies with the top 20 market values and long data cycles as the research subject, and a total of 8 cryptocurrencies (ADA, BNB, BTC, ETH, DOGE, LTC, TRX and XRP). The historical data of all virtual currencies are from CoinMarketCap (coinmarketcap. com) website.

3.2.3 Result analysis

The abnormal return rate and cumulative abnormal return rate are shown in the following figure 4. Among them, the abnormal returns of ADA, BNB, and LTC coins did not change much before the FTX bankruptcy event, indicating that their actual returns were similar to the expected returns of investors. However, in the days after the event date, the cumulative returns continued to increase, and the abnormal returns continued to be positive. This indicates that after the FTX bankruptcy, the expected returns of investors' currencies were lower than their actual returns, which lasted for a long time, indicating that the impact of the event still exists.



The blue line represents AR, and the red line represents CAR.

Figure 4: Currency AR and CAR Analysis I

Compared to the above four currencies, the yield changes before and after the events in the following four currencies are relatively small. Compared to the changes in AR and CAR after the event, the abnormal returns of BTC, DOGE, TRX, and ETH coins fluctuated more significantly before the event, and near the event date, AR was negative, indicating that investors overestimated their returns at that time; For a period of time after the 10th, the AR of these four currencies was positive, and investors felt that in the event of FTX bankruptcy, the currency yield would decrease. However, over time, the AR and CAR of the currencies gradually tended to zero, and the influencing factors of the event weakened , as shown in Figure 5.

The blue line represents AR, and the red line represents CAR.

Figure 5: Currency AR and CAR AnalysisII

In summary, four coins (ADA, BNB, LTC, XRP) had lower expected returns than actual returns after the FTX collapse event and were affected for a long time; the last four coins (BTC, DOGE, TRX, ETH) had significant changes in abnormal returns before the event, but after the event, AR and CAR gradually converged to zero and were affected by the possibility for a short time.

4. Summary

To study the relationship between virtual currency and trading entities, this article starts from two perspectives: micro and macro. At the micro individual level, this article constructed a machine learning model to classify nodes at the real transaction data level. It was found that Bagging type integrated decision trees outperform other machine learning algorithms in classification results and can be used for abnormal transaction monitoring. At the macro currency level, this paper conducts research through the event study method. This article finds that some currencies, such as ADA, BNB, LTC, and XRP, are significantly affected by the collapse of cryptocurrency trading platforms and have been affected for a longer period of time; Some currencies, such as BTC, DOGE, TRX, and ETH, are less affected by this event and have been affected for a shorter period of time. Among them, BTC and ETH, the two currencies with the largest market value, are less affected by this event, indicating that the collapse of trading platforms is more likely to affect currencies with smaller market values.

References

Zhen Yuanyun. Legal Risks and Regulation of Virtual Currency [J]. Academic Journal of Humanities & Social Sciences, 2022, 5(17).

Dimitrios Koutmos. Bitcoin returns and transaction activity [J]. Economics Letters, 2018, 167.

Chipere, Mike. Virtual currency as an inclusive monetary innovation for the unbanked poor[J]. Electronic Commerce Research & Applications, 2018, 28:37-43.DOI:10.1016/j.elerap.2018.01.004.

Chawla N V, Bowyer K W, Hall L O, et al. SMOTE: synthetic minority over-sampling technique [J]. Journal of artificial intelligence research, 2002, 16(1): 321–357.

Seth Armitage. Event Study Methods and Evidence On Their Performance [J]. Journal of Economic Surveys, 1995, 9(1).

Hogarth K, Dawson D. Implementing e-Learning in Organisations: What E-Learning Research Can Learn From Instructional Technology (IT) and Organisational Studies (OS) Innovation Studies[J]. International journal on E-learning, 2008, 7(1):p.87-105.