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RESEARCH ARTICLE

Bitcoin Ordinals: Bitcoin Price and Transaction Fee Rate Predictions

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ABSTRACT Ordinals, a method for creating unique digital assets on the Bitcoin blockchain, has significantly impacted the blockchain over the past year, yet there is a notable lack of research on it. This study is the first to demonstrate that Bitcoin Ordinals-related data are crucial features for predicting Bitcoin transaction fee rates and prices. Our main contributions are threefold. 1) Dataset Construction: We construct a dataset that includes Bitcoin chain data, Ordinals index data, and Ordinals market data, as well as a dataset excluding Ordinals-related data. Our findings reveal that the fluctuation in the number of Ordinals inscriptions tends to correlate with market activity. When the Ordinals market is active, the share of Ordinals inscribed fees and the average Bitcoin transaction fee rate remain high. We argue that the upgrades of SegWit and Taproot drove the creation and development of Bitcoin Ordinals. Combined with users' interest in Ordinals, this in turn affected the Bitcoin blockchain and its price; 2) Prediction: Using three metrics (MAE, RMSE, and MAPE) and the TemporalFusionTransformer model as a baseline, our comparative experiments show that Bitcoin Ordinals-related data is essential for predicting Bitcoin transaction fee rates and prices. This finding aids investors and participants in the Bitcoin Ordinals market in avoiding losses and leveraging congestion-related arbitrage opportunities, thus enabling more accurate decision-making in the cryptocurrency market; 3) Chronos Model: Additionally, the fine-tuned Chronos model achieves metrics comparable to or better than those of the TemporalFusionTransformer for shorter time intervals, especially in low-noise environments. With its outstanding zero-shot prediction performance, fast execution, and easy cloud deployment, the Chronos model allows investors and market participants to quickly obtain high-quality predictions without requiring complex data features.

INDEX TERMS Bitcoin ordinals, Bitcoin price prediction, bitcoin transaction fee rate prediction, Chronos, TemporalFusionTransformer.

I. INTRODUCTION

Bitcoin is a decentralized cryptocurrency mentioned in a paper written in 2008 by a person who goes by the pseudonym Satoshi Nakamoto [14]. Bitcoin transactions are recorded on a public ledger called the blockchain, and anyone can view the history of Bitcoin through the Bitcoin Index. The decentralized nature of Bitcoin allows it to operate independently, the impact and consequences of which are having an increasing impact on a wider range of industries and business models [15]. Bitcoin surpassed $106,000 per coin on December 18, 2024, after more than a decade of volatile ups and downs.

Just as Satoshi Nakamoto inscribed the phrase "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks" in the genesis block on January 3, 2009, Bitcoin has been able to record text on the blockchain since its creation. Bitcoin Ordinals are a type of sat ordering, where the sat is the smallest and indivisible unit of Bitcoin. 1 BTC is divided into 10^8 sats, and then each sat is assigned an ID based on the mining time as well as the order in which the transfers are made, thus creating irreplaceable attributes on the Bitcoin chain similar to those necessary for the NFT (Non-Fungible Token). NFTs are blockchain-based digital assets that are

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unique and irreplaceable, representing items such as images, music, text, and so on.

Segregated Witness (SegWit) is an upgrade to the Bitcoin protocol that increases the block size limit and enhances the efficiency and security of the Bitcoin network by separating transaction signatures from transaction data. Taproot is another major upgrade to Bitcoin that enhances privacy, scalability, and the ability to execute complex transactions by combining Schnorr signatures with a new scripting language called Tapscript.

Due to technology upgrades at SegWit in 2017 and Taproot in 2021, Casey Rodarmor launched Ordinals on the main Bitcoin network on January 20, 2023 [1]. When a user uses an Ordinals inscription, the user actually receives a number of sats storing arbitrary information that is entirely on the Bitcoin chain and can be launched in tracked using Ordinals Index-based software. BRC-20, on March 2023 by an anonymous person named domo on Twitter, is an experimental token standard based on Taproot and Ordinals that enables the deployment, minting, and transfer of fungible tokens are based on text JSON format using Ordinals Inscription on the Bitcoin chain [2].

From February 2023 to April 2024, the price of Bitcoin continued to rise, as did the total market capitalization of Ordinals-related assets and the Ordinals fees paid. Ordinals-related fees accounted for 15.45% of Bitcoin's total transaction fees and maintained a higher percentage as protocols based on the issuance of assets on the Bitcoin blockchain, such as Ordinals, developed. For example, Runes, a new token protocol created by Casey Rodarmor on April 20, accounts for roughly 45% of total Bitcoin transaction fees since its launch [5]. So intuitively, protocols such as Ordinals that are issued based on Bitcoin blockchain assets should be very much linked to Bitcoin prices and Bitcoin transaction fees. So it is very valuable to make an attempt to predict the Bitcoin price and Bitcoin transaction fees (rates) using data related to Ordinals.

The Bitcoin transaction fee rate is measured in sat/B and is calculated as (the number of bitcoins for transaction fee $\times$ 10^8)/byte. The memory pool is a queue of pending and unconfirmed transactions for Bitcoin network nodes, and the priority of pending Bitcoin transactions is determined by their rate, meaning that a higher transaction fee rate will move transactions further up the memory pool. As the demand for Bitcoin transactions grows, transaction fees increase over time [4]. Bitcoin attracts miners through two financial incentives, block rewards and transaction fees, which are halved every 4 years and eventually approach 0, so ultimately the only compensation for miners is the Bitcoin transaction fee. The fees for using Ordinals and BRC-20 are based solely on Bitcoin transaction fee rates, and the interest generated by Ordinals and BRC-20 leads to a surge in the number of transactions in the memory pool and, in turn, affects the cost of executing a transaction in the Bitcoin blockchain [3].

Bitcoin ordinals-related assets have been growing over the year, and at its peak, the market capitalization has reached billions of dollars, and all the actions using ordinals are based solely on the most crucial factor of Bitcoin transaction rates. It is becoming more and more important to ensure the success of Bitcoin ordinals-related transactions with more appropriate transaction rates, and how to utilize inscription operations to acquire Bitcoin ordinal assets with more appropriate transaction rates.

The way Ordinals and BRC-20 assets are issued results in a perpetually limited number of assets being issued, and the rules under which Bitcoin operates result in the pursuit of valuable assets that can easily lead to congestion in the Bitcoin chain and a rapid rise in Bitcoin transaction rates if the ordinal market becomes emotional. On the one hand, this may lead to losses for early ordinal operators who are unable to successfully acquire assets due to low transaction rates, and on the other hand, it may generate huge arbitrage gains if they are able to successfully acquire assets early. So the need for more accurate predictions of Bitcoin transaction rates arises.

As Bitcoin ordinal numbers continue to evolve and have a significant impact on the Bitcoin chain, it is also a valuable topic to study the role of Bitcoin ordinal data as a new feature for Bitcoin price prediction. This study aims to address three primary research questions: First, what are the impacts and characteristics of activities related to Ordinals on the Bitcoin blockchain and market activities in the Ordinals market? Second, what impact do Bitcoin Ordinals-related data have on predicting Bitcoin transaction fees and prices? Third, what are the advantages of using the Chronos model for predicting Bitcoin transaction fees and prices compared to other models?

II. RELATED WORK

A. ORDINALS

There is less research related to Ordinals. Bertucci studied the initial wave of ordinal coins from December 14, 2022, to April 16, 2023, and argued that rates for Ordinals inscriptions tend to be lower than regular transactions, and that ordinal inscriptions decrease when transaction fees are high [16].

Binance Research's report "A New Era for Bitcoin?" argues that ordinals and inscriptions have brought new life to Bitcoin development, attracting a new group of players with different voices and perspectives, and adding life and enthusiasm to an NFT and DeFi market that has been slow to develop in the ecosystem [6]. Increased transaction fees incentivize blockchain security, meaning that inscription-based innovations have a positive impact on Bitcoin's long-term sustainability. Binance Research's reports "BRC-20 tokens: a primer" and "The Future of Bitcoin #2: Tokens" argue that Ordinals, Inscription, BRC-20, and Runes are all influencing and working to solve Bitcoin's fee problem and motivating Bitcoin's development activities [3], [5].

B. BITCOIN PRICE PREDICTION

The field of Bitcoin price prediction can generally be divided into two subfields: classification studies, which predict the rise and fall of Bitcoin prices, and regression studies, which predict the actual prices of Bitcoin. Our research primarily focuses on the latter.

In terms of feature selection, various studies have explored different approaches. For example, Aggarwal et al. investigated whether Bitcoin prices could be predicted using only the price of gold through CNN, LSTM, and GRU models, concluding that LSTM yielded the best results, though the predicted values still deviated significantly from the actual Bitcoin prices [7]. Jagannath et al. utilized on-chain data related to miners, users, and exchanges to predict Bitcoin prices, demonstrating the utility of such data [8]. García-Medina and Huynh showed that Bitcoin prices could be influenced by social media momentum [9]. Chen employed data from other cryptocurrencies, forex markets, and social media in a more detailed and comprehensive Bitcoin price prediction study, finding that different variables affect Bitcoin price predictions differently over time [10].

This study primarily uses the TemporalFusionTransformer (TFT) model and the Chronos model. TFT, a time series model proposed by Lim et al., combines LSTM with Transformer layers to achieve high-performance multi-horizon time series forecasting and provides interpretable insights into temporal dynamics [11]. Murray et al. also successfully applied TFT for cryptocurrency price prediction [12].

The Chronos model, proposed by AF Ansari et al., is a pre-trained time series prediction model based on a language model architecture that performs exceptionally well with zero-shot predictions [13]. Utilizing the AutoGluon library, Chronos models are straightforward to integrate and deploy in the cloud [19]. This type of model has not previously been applied to Bitcoin price prediction.

C. BITCOIN TRANSACTION FEE RATE PREDICTION

The focus on Bitcoin transaction fees in recent years has been mainly on confirmation time and miners' revenues. For example, Azzolini et al. used a probabilistic logistic model to analyze how fees affect confirmation time and miners' revenues [18]. Gundlach et al. argued that the timing of Bitcoin transaction confirmations is analogous to the bankruptcy time in the corresponding Cramer-Lundberg process [17].

Not much research has focused on Bitcoin transaction fee rate prediction in recent years, but the popularity of Ordinals and BRC-20 in 2023-2024, and the popularity of Runes in 2024, protocols grounded on the Bitcoin blockchain, are having an increasing impact and incentive on Bitcoin itself. There is a growing interest in the Bitcoin transaction fee rate, a protocol that affects the Bitcoin blockchain, as well as a growing interest in the Bitcoin transaction fee rate, which affects the Bitcoin blockchain. The prediction of Bitcoin transaction fee rates, the most critical factor affecting the cost of all the behaviors of the protocols (Ordinals, BRC-20, Runes, etc.), is also becoming more and more relevant in the future, so this paper makes an attempt to predict the Bitcoin transaction fee rates.

III. METHODOLOGY

A. TEMPORAL FUSION TRANSFORMER (TFT)

The Temporal Fusion Transformer (TFT) is a neural network architecture designed for multi-horizon time series forecasting, combining high-performance forecasting with interpretability. The TFT model consists of several key components:

Input Processing: Handles static, known, and observed time-varying covariates using embeddings for categorical variables and normalization for continuous variables.

Gated Residual Network (GRN): Applies non-linear processing selectively using Gated Linear Units (GLUs).

Temporal Layer: Applies the same operation to each time step.

Attention Mechanism: Captures long-term dependencies and interactions between time steps.

Key equations of the TFT model are:

Gated Linear Unit (GLU):

$$\mathrm{GLU}(x) = x \odot \sigma(Wx + b), \tag{1}$$

where x is the input vector, σ is the sigmoid function, W and b are the parameter matrix and vector, respectively, and $\odot$ denotes element-wise multiplication.

Multi-Head Attention:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \tag{2}$$

where Q (queries), K (keys), and V (values) are projections of the input, and d_k is the dimension of the keys.

Quantile Loss Function:

$$L_{\mathrm{quantile}}(y, \hat{y}) = \max(\tau(y - \hat{y}), (1 - \tau)(\hat{y} - y)), \tag{3}$$

where y is the true value, $\hat{y}$ is the predicted value, and τ is the quantile level.

The model is trained using the quantile loss function, suitable for probabilistic forecasting, with the Adam optimizer and learning rate scheduling. Interpretability is achieved through variable selection mechanisms and attention weights, providing insights into the most relevant time steps and features for predictions.

B. CHRONOS

Time Series Tokenization

To utilize language models for time series data, the observations $x_i \in \mathbb{R}$ are first mapped to a finite set of tokens. This involves two main steps: scaling and quantization.

Scaling: Time series data can vary significantly in scale, posing optimization challenges for deep learning models. To facilitate better optimization, individual time series are normalized. Specifically, mean scaling is used, which normalizes each entry by the mean of the absolute values in the historical context:

$$\tilde{x}_i = \frac{x_i}{\frac{1}{C}\sum_{i=1}^{C}|x_i|}. \tag{4}$$

Quantization: The scaled time series $\tilde{x}_{1:C+H}$ is still real-valued and needs to be converted into discrete tokens. This is achieved by selecting B bin centers and defining a quantization function q that maps real values to discrete tokens. The quantization function q and dequantization function d are defined as follows:

$$q(x) = \begin{cases} 1 & \text{if } -\infty \leq x < b_1, \\ 2 & \text{if } b_1 \leq x < b_2, \\ \vdots & \\ B & \text{if } b_{B-1} \leq x < \infty \end{cases} \tag{5}$$

$$d(j) = c_j \tag{6}$$

This part uses uniform binning to ensure robustness across different datasets.

Objective Function

Chronos is trained to minimize the cross-entropy between the quantized ground truth labels and the predicted distribution. The loss function for a single tokenized time series, including EOS tokens, is defined as:

$$\ell(\theta) = -\sum_{h=1}^{H+1}\sum_{i=1}^{|V_{ts}|} 1(z_{C+h+1} = i)\log p_\theta(z_{C+h+1} = i|z_{1:C+h}). \tag{7}$$

This categorical cross-entropy loss allows the model to learn arbitrary distributions, including multimodal ones, without modifying the language model architecture.

Forecasting

Chronos models generate probabilistic forecasts by autoregressively sampling from the predicted distribution $p_\theta(z_{C+h+1}|z_{1:C+h})$. The sampled token IDs are mapped back to real values using the dequantization function d, and then unscaled by applying the inverse scaling transformation. This process yields the actual forecast values.

This methodology ensures that Chronos can effectively handle diverse time series datasets, leveraging the strengths of language models for accurate and flexible time series forecasting.

C. EVALUATION CRITERIA

To evaluate the prediction accuracy of the machine learning model, this study employs three error metrics: MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error). These metrics are defined as follows:

$$\text{MAE} = \frac{1}{m}\sum_{t=1}^{m}|y(t) - \hat{y}(t)|, \tag{8}$$

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(y(t) - \hat{y}(t))^2}, \tag{9}$$

$$\text{MAPE} = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{y(t) - \hat{y}(t)}{y(t)}\right|. \tag{10}$$

These error metrics are used to quantify the prediction performance of the model. MAE and RMSE measure the average absolute error and the root mean squared error between the predicted and actual values, respectively, while MAPE provides a percentage representation of the relative error.It is important to note that MAE and RMSE can only be compared for model results based on the same sample. There is no meaningful comparison between the experimental results of different data samples.

IV. DATASET

We use Dune.com to gather Bitcoin and Ordinals data, which simplifies querying the Bitcoin blockchain and Ordinals index with an SQL-like language. This allows us to obtain data on Ordinals-related indicators, Ordinals Marketplace, and Bitcoin Basic Indicators to build a dataset with one-hour intervals:

TABLE 1. Dataset description (1-hour interval).

Column Name	Description
Time	From February 14, 2023 17:00:00 to April 11, 2024 06:00:00, one hour is the time interval.
Ordinals_Inscription	Number of Ordinals inscriptions in 1 hour
Total_Inscriptions	Total number of inscriptions
Ord_total_fees	Total cost of Ordinals inscription
Ord_Size_Usage	Size used by Ordinals in 1 hour
Ord_vSize_Usage	vSize used by Ordinals in 1 hour
Ord_hour_fees	1 hour's worth of Ordinals inscription costs (BTC)
Ave_tra_fee_rate	Bitcoin average transaction fee rate in 1 hour (sats/b)
Size	Total Bitcoin block size in 1 hour
Weight	Total Bitcoin block weight in 1 hour
Hash_rate	Hash rate
Num_addresses	Number of Active Addresses for Bitcoin
Tx_count	Number of transactions
Price	Bitcoin price
Ma_50	50-day moving average of Bitcoin
Ma_100	100-day moving average of Bitcoin
Ma_200	200-day moving average of Bitcoin
Hour_market_TotalV	The total trading volume of 9 Ordinals markets within 1 hour (USD)
Hour_market_TotalT	The total number of transactions in 9 Ordinals markets within 1 hour
Cnt	The total number of unique users in 9 Ordinals markets in 1 hour

TABLE 2. Dataset description (1-day interval).

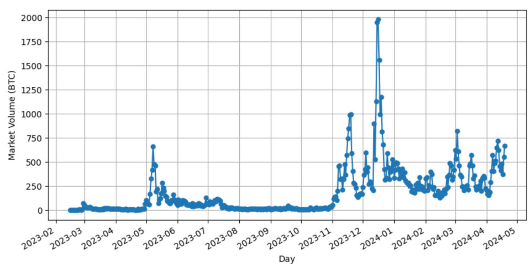
Column Name	Description
Time	From February 15, 2023 to April 11, 2024
Daily_avg_size	Average size of all blocks for the day
Total_Inscriptions	Value of the last hour of the day
Ord_total_fees	Value of the last hour of the day
Other features	Mean value

We should emphasize that virtually all of the data in this dataset is available directly on the Bitcoin blockchain.

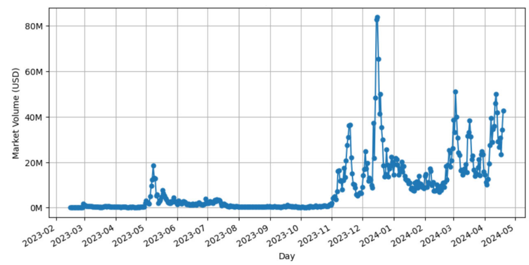
V. DATA ANALYSIS

Figure 1 shows the total volume, the number of daily users, and the number of transactions based on the nine Ordinals markets on the Bitcoin chain each day, visualizing the overall

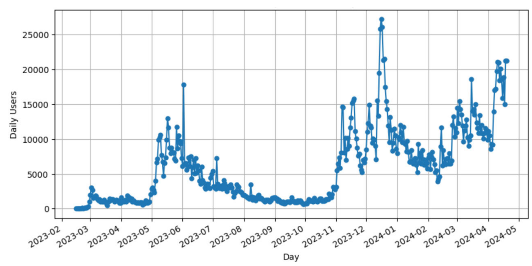
Ordinals market activity pattern. Figure 2 presents the metrics related to Ordinals inscriptions on the Bitcoin chain. The first part displays the number of Ordinals inscriptions per day, while the second part shows the number of Ordinals inscriptions per block. This allows for a more intuitive representation when Ordinals markets are highly active, and sudden anomalies in block Ordinals inscriptions overlap significantly. The third section illustrates Ordinals fees and non-Ordinals fees, with a green line indicating Ordinals' percentage of total Bitcoin transaction fees, providing a clearer representation of the significant impact of Ordinals activities on the Bitcoin chain. Figure 3 is a representation of the change in bitcoin's transaction fee rates (sats/B).



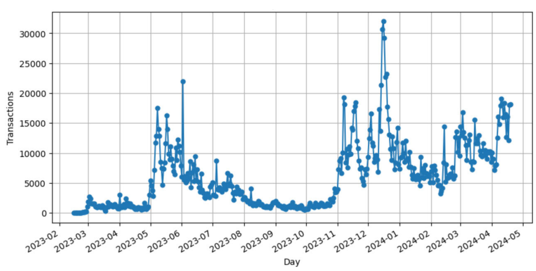
(a) Ordinals Marketplace Total Volume(BTC)



(b) Ordinals Marketplace Total Volume(USD)



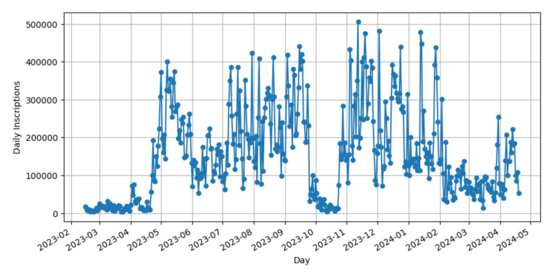
(c) Ordinals Marketplace Total Daily Users



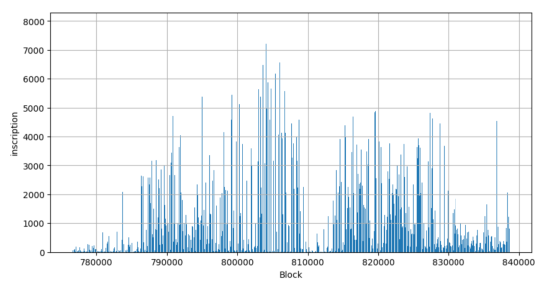
(d) Ordinals Marketplace Total Transactions

FIGURE 1. Ordinals marketplace.

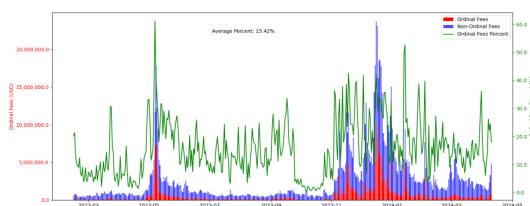
Based on Figures 1, 2 and 3 we know that the Ordinals market volume, transactions and the number of unique users peaked on December 16, 2023. The volume of $837,266,663, transactions of 31,991, and the number of unique users of 27,197 also represent the peak of market activity, with Ordinals inscription fees at 42% of total fees and an average Bitcoin transaction fee rate of 385sats/B(byte). However, on December 15, 2023, Ordinals inscription fees were 28% of total fees and the average Bitcoin transaction fee rate was 245sats/B. This suggests that at the peak of Ordinals market activity, Bitcoin transaction fees and Ordinals inscription fees can still reach a high share, which is in line with Louis' study of the December 14, 2022 to April 16, 2023. So Ordinals inscriptions tend to have lower rates than regular transactions, but when Bitcoin transaction fees are high, the increase and decrease in the number of ordinal inscriptions tends to be based on the market activity, as the share of Ordinals inscription fees and the average Bitcoin transaction fee rate will remain high when the Ordinals market is active.



(a) Daily Number of Ordinals Inscription



(b) Ordinals Inscription Per Block



(c) Ordinals Inscription Fees and Shares

FIGURE 2. Ordinals inscription.

Figures 4-5 show the total daily volume, the number of daily users, and the number of transactions for the nine Ordinals markets on the Bitcoin chain, visualizing the change in share of four metrics for the nine different Ordinals markets. Refer to Figure 4 for Ordinals market share, "ordinals wallet", "ordinals market", and "ordswap"

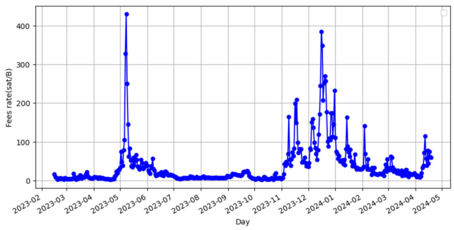
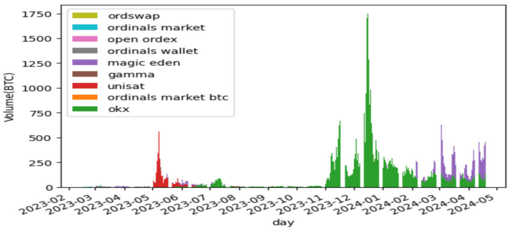
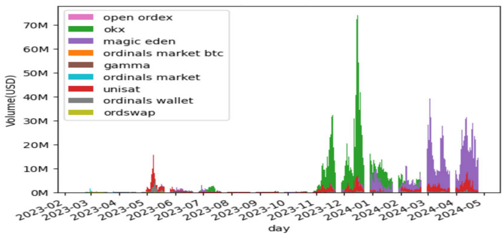


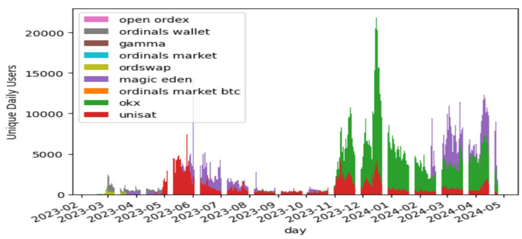
FIGURE 3. **Fees rate.**



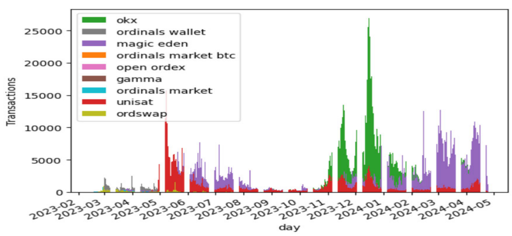
(a) Volume by Marketplace (BTC)



(b) Volume by Marketplace (USD)



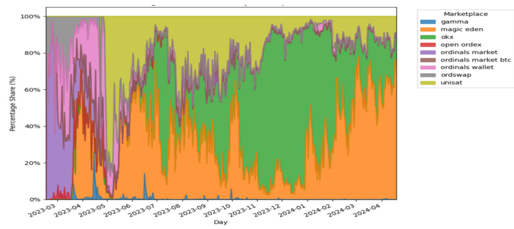
(c) Unique Daily Users by Marketplace



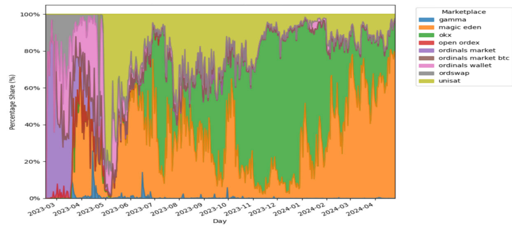
(d) Transactions by Marketplace

FIGURE 4. **Marketplace.**

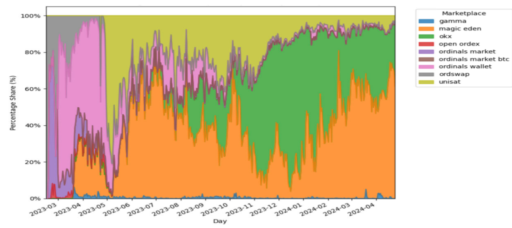
markets were overwhelmingly dominant,in the initial wave before April 16, 2023. But after May 2023, "Unisat", "Magic eden" and "OKX" dominated almost all of the ordinals market share. "OKX" had the lion's share of the market around December 16, 2023, probably due to the fact that trading of the BRC-20 tokens peaked around that time. And after January 2024 magic eden keeps increasing its market share probably because of the hype associated with NFT in anticipation of runes.



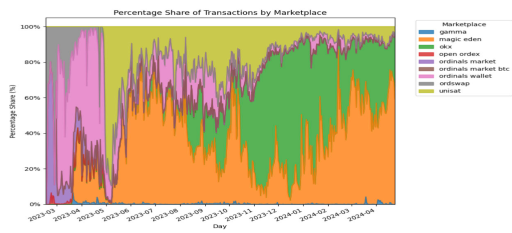
(a) Percentage share of Volume by Marketplace(BTC)



(b) Percentage share of Volume by Marketplace(USD)

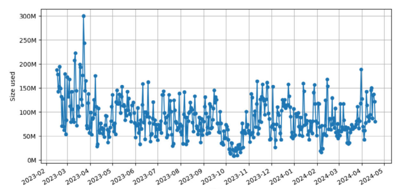


(c) Percentage share of Unique Daily Users by Marketplace

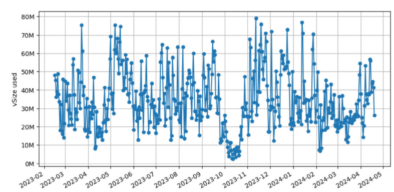


(d) Percentage share of Transactions by Marketplace

FIGURE 5. **Percentage marketplace share.**



(a) Used by Ordinals Daily Size



(b) Used by Ordinals Daily vSize

FIGURE 6. **(v)Size of ordinals inscription.**

As a result of the SegWit and Taproot upgrades, Figure 6 compares the Size and vSize used by Ordinals inscriptions. According to Figure 6, we can observe that the small peak in the Ordinals market in May 2023 and the highest peak in December 2023 coincide with the small and highest peaks in Bitcoin transaction rates. With the exception of October 2023, the daily usage of Ordinals has remained high. During the initial wave prior to April 16, 2023, Ordinals inscriptions maintained a higher usage, despite the lower number of inscriptions, likely due to the hype surrounding Ordinals NFTs, which typically required more bytes for inscriptions.

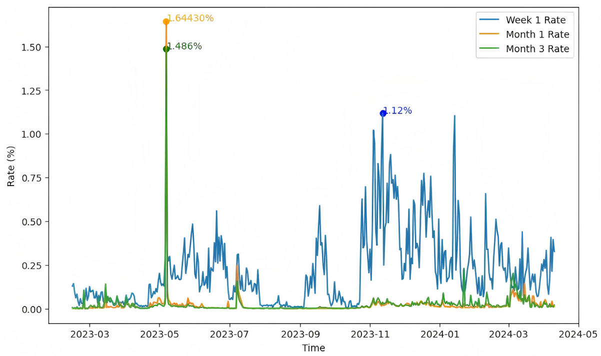


FIGURE 7. Retention rate analysis of ordinals inscriptions.

Figure 7 shows the analysis of Ordinals inscriptions retention rates. We chose 1 week, 1 month, and 3 months to calculate the retention rates. We found that during the first peak in April-May 2023, the 1-month and 3-month retention rates reached their highest levels at 1.6443% and 1.486%, respectively. In contrast, the 1-week retention rate reached its highest level at 1.12% during the second peak in November-December 2023 and remained higher in the surrounding period. This suggests that the first peak is characterized by long-term investments, while the subsequent peaks are characterized by short-term investments.

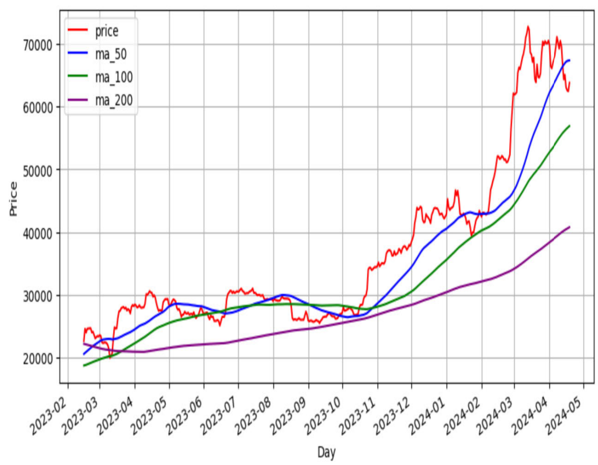


FIGURE 8. Bitcoin price.

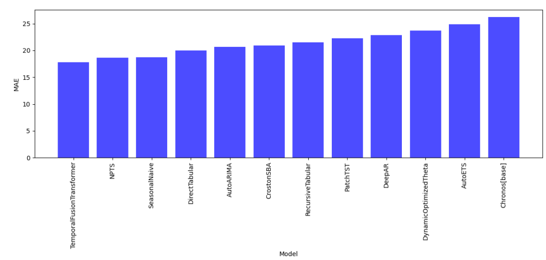
According to Figures 1-6, we can find a strong connection between Ordinals-related data and Bitcoin transaction fee rates. According to Figure 8, the Bitcoin price generally increased from February 15, 2023, to April 11, 2024. However, it is difficult to determine if Ordinals-related data can be used as a feature for Bitcoin price prediction based solely on Figures 1-7. Therefore, we need to further investigate the effect of Ordinals-related data on Bitcoin transaction fee rates and Bitcoin price predictions.

VI. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

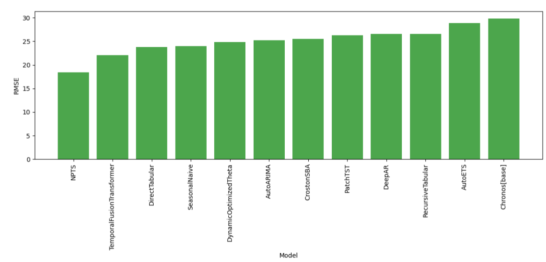
A. BASELINE MODEL SELECTION

In order to examine the effect of the presence or absence of Ordinals-related features on the predicted scores, we need to conduct comparative experiments between the full dataset and the dataset with Ordinals-related features removed, so we need to select the benchmark model. We use the 12 models in AutoGluon and the full dataset to predict Bitcoin transaction fee rates and Bitcoin prices, then set the prediction length to 24 and 30, respectively.

So, based on the combined MAE and RMSE results for the 12 models in Figures 9-10, TemporalFusionTransformer is the best choice as a benchmark model among the 12 models. According to Table 3, we know that Chronos is much faster than TemporalFusionTransformer in prediction. In Bitcoin price prediction, the Chronos and TemporalFusionTransformer models have close results, but TemporalFusionTransformer runs almost 40 times slower in terms of speed.



(a) MAE

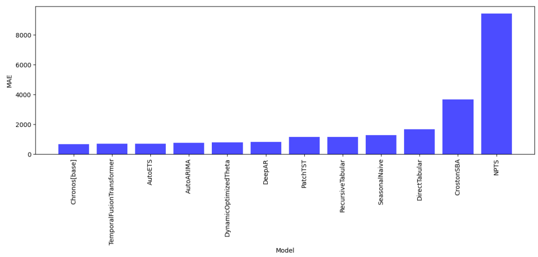


(b) RMSE

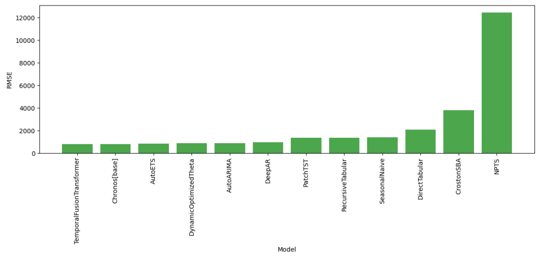
FIGURE 9. Fee rate prediction model ranking.

B. EFFECT OF ORDINALS-RELATED FEATURES ON BITCOIN TRANSACTION RATE PREDICTION

Multi-window backtesting of time series models measures prediction accuracy using the last prediction_length time step



(a) MAE



(b) RMSE

FIGURE 10. Price prediction model ranking.

TABLE 3. Runtime.

Model	pred_time_val	fit_time_marginal
Temporal Fusion Transformer	0.064	90.975
Chronos-t5-base	2.258	0.018

of each validation split as a retention set, which assesses the robustness and generalizability of the model across time.

We use the Temporal Fusion Transformer (TFT) as a benchmark model for comparative experiments and calculate its MAE, RMSE, and MAPE metrics. However, we observe that the dataset with Ordinals-related features removed yields slightly better metrics than the full dataset, with MAPE consistently exceeding 0.4. This discrepancy may stem from increased noise in the predicted time intervals. To address this, we employ AutoGluon's preset `best_quality` mode (validated through multi-window backtesting) and evaluate the last 8 windows using MAPE as the primary metric. Notably, MAE and RMSE are not directly comparable across different time intervals. With a prediction length of 24, we further validate our hypotheses by selecting data prior to February 24, 2024 as the new dataset (`Use_full`), which is tested via backtesting with full features. The six experimental cases are summarized in Table 4, and the corresponding MAPE results are illustrated in Figure 11.

We found that the dataset with Ordinals removed is better than the full feature dataset before validation with backtesting. However, after validation with backtesting, the MAPE for the dataset with full features decreased to around 0.3, while the MAPE for the dataset with Ordinals removed increased to 0.6, which we proved is because the Ordinals-related features allow the baseline model to better understand and predict sudden changes in bitcoin's transaction fee rates and a large number of outliers. And

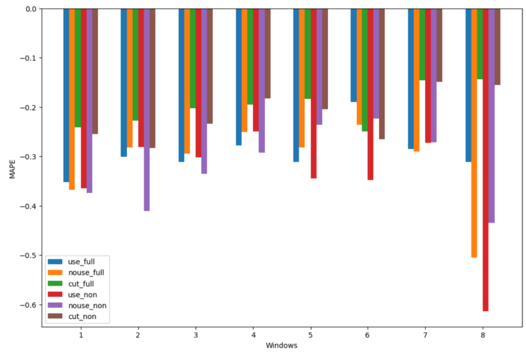


FIGURE 11. MAPE results.

TABLE 4. Description of different validation methods.

Cases	Description
Use_full	Validated using the full feature dataset and using backtesting.
Nouse_full	Using the full feature dataset and no validation with backtesting (Evaluate results using only multi-window backtesting).
Cut_full	Using the full feature dataset and a dataset from a time before February 24, 2024 and validate it with backtesting.
Use_non	Validated using the dataset with Ordinals removed and backtested.
Nouse_non	Using the dataset with Ordinals removed and not validated with backtesting (Evaluate results using only multi-window backtesting).
Cut_non	Using the dataset with Ordinals-related features removed and time before February 24, 2024 and validated using backtesting.

we can also find (when comparing the two datasets at the time before February 24, 2024) that the overall metrics of the dataset with Ordinals-related features are better than the metrics of the dataset with Ordinals-related features removed when there is less noise.

Based on the data analysis, we can infer that the rise in Runes Pre-mint activity after March 2024 reflects many users' expectations that Runes will be deployed on block 840000 on April 20, 2024. This anticipation has resulted in some anomalous noise on Ordinals. While TFT can interpret this noise well, as verified by multiple backtests, Chronos does not. Therefore, we used data up to February 24, 2024, in our subsequent study of Bitcoin transaction fee rate projections.

C. CHRONOS AND TEMPORALFUSIONTRANSFORMER IN BITCOIN TRANSACTION RATE PREDICTION

To compare the differences between the Chronos and TemporalFusionTransformer models in terms of MAE and RMSE, we note that Chronos cannot validate using backtesting when faced with a large number of outliers and noise, as shown in Table 5. Consequently, the metrics for Chronos are far worse than those for TemporalFusionTransformer. Therefore, we select the dataset with complete features and data prior to February 24, 2024.

TABLE 5. Comparison of MAE and RMSE between Chronos and TFT (length:Prediction length).

Model	MAE		RMSE	
	12	24	12	24
Temporal Fusion Transformer	9.764	13.493	11.092	18.802
Chronos-t5-base	21.580	26.236	22.691	29.848

Since we found the Chronos model is more suitable for prediction of longer time intervals like days, months, and years, and our dataset is based on 1 hour time intervals, we need to try to fine-tune the Chronos pre-trained model. We use KernelSynth, given in the Chronos model paper, which uses a Gaussian process to generate new time series, controlling the characteristics of the generated time series through parameters in KERNEL_BANK.

TABLE 6. Results for Chronos and TFT(Before February 24th) - MAE (C: Chronos-t5).

Length	TFT	C-base	C-tuned	C-small	C-fine-tuned
12	3.056	3.141	2.799	3.479	2.829
24	1.954	2.170	1.935	2.237	1.939
48	2.171	2.188	2.017	2.270	2.089

TABLE 7. Results for Chronos and TFT(Before February 24th) - RMSE (C: Chronos-t5).

Length	TFT	C-base	C-tuned	C-small	C-fine-tuned
12	3.798	4.756	4.410	4.914	4.464
24	3.290	3.290	2.997	3.831	2.919
48	2.867	2.859	2.784	2.956	2.889

We generated 30,000 kernel series that are more focused on 1 hour periodicity to fine-tune Chronos-t5-base and Chronos-t5-small. Compare the results of the Chronos pre-trained model, the fine-tuned Chronos model and the TemporalFusionTransformer (TFT) model with prediction_lengths of 12, 24, and 48.In order to avoid errors, the metrics for the chronos-related models are calculated individually with averages obtained after 100 runs, while the metrics for TemporalFusionTransformer's models are validated through multiple windows of backtesting. The results and graphs are shown in Tables 6-7 and Figures 12–14.

So, We think TemporalFusionTransformer performs much better than the Chronos correlation model in time periods with a lot of noise. During more normal time periods, there is not much difference between the metrics of the TemporalFusionTransformer model and the Chronos pre-trained model, and the metrics of the fine-tuned Chronos model are overall better than the metrics of the TemporalFusionTransformer model and the Chronos pre-trained model.

Considering that the performance of Chronos in Figure 9-10 is not good when the baseline model is selected for the complete data set, and is even worse than SeasonalNaive, it is very valuable to select some

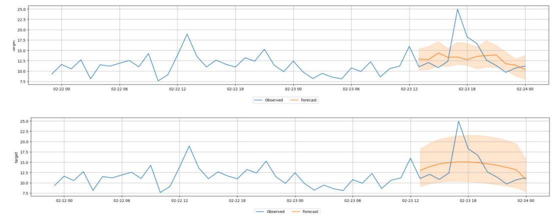


FIGURE 12. Prediction_lengths=12,TFT and Chronos.

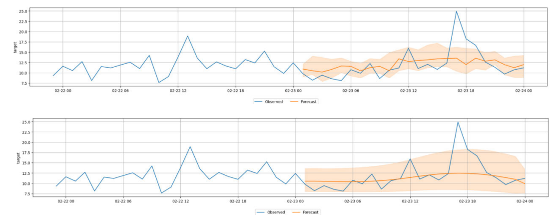


FIGURE 13. Prediction_lengths=24,TFT and Chronos.

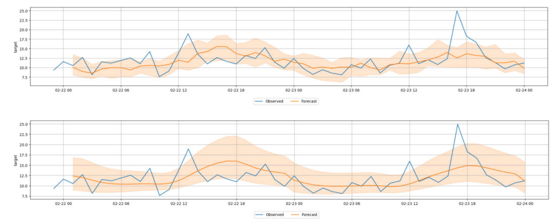


FIGURE 14. Prediction_lengths=48,TFT and Chronos.

baseline models for further research. We select AutoARIMA, SeasonalNaive, and Naive as baselines to further verify our conjecture, as these models provide a simple and interpretable reference point. We obtain the results of MAE and RMSE in Table 8-9.

When the prediction length is 48, the Naive model performs the best, and as the prediction length decreases, the performance of the Naive model worsens. This suggests that the Naive model is better at capturing long-term stability. Based on the results of the SeasonalNaive model, we believe this is because the prediction length is too long, causing the periodicity to weaken, which aligns with the characteristics of Bitcoin transaction fees, making it unsuitable for long-term predictions.

According to the results of AutoARIMA and Table 6-7, AutoARIMA performs the best at a prediction length of 12, but the fine-tuned Chronos-t5-base model's results are the closest to it. We believe that Chronos and TFT capture short-term complex patterns, so they perform well at prediction lengths of 24 and 12, but are not suitable for longer prediction lengths (e.g., 48), further demonstrating the potential of fine-tuning the Chronos model.

To further confirm the difference between the fine-tuned model and the pre-trained model, we converted the hourly dataset to a daily dataset. The results, shown in Table 10, indicate that the fine-tuned model's metrics were overall worse than those of the pre-trained model in the daily

TABLE 8. Results for AutoARIMA, NaiveSeasonal and Naive - MAE.

length	AutoARIMA	Naive	Seasonal Naive
12	2.662	4.475	3.488
24	2.682	2.731	3.013
48	2.439	2.033	3.140

TABLE 9. Results for AutoARIMA, NaiveSeasonal and Naive - RMSE.

length	AutoARIMA	Naive	Seasonal Naive
12	4.524	4.885	5.211
24	3.699	3.728	4.214
48	3.205	3.089	4.124

dataset. This further validates our idea that fine-tuning the Chronos model with a kernel series more suitable for the corresponding time interval can improve its performance. Chronos, which is suited for interval-corresponding tasks, outperforms TFT overall.

TABLE 10. Results for datasets with one day as the time interval (Fee rate) (C: Chronos-t5).

Model	MAE	RMSE	MAPE
TFT	3.999	5.670	0.297
C-base	3.999	5.286	0.286
C-tuned	4.124	5.548	0.300
C-small	4.256	5.716	0.304
C-fine-tuned	4.511	6.188	0.343

D. IMPACT OF ORDINALS DATA ON BITCOIN PRICE PREDICTION

We attempted Bitcoin price prediction using a dataset with a one-day interval. Since the dataset did not contain exchange data, the results were not optimal for Bitcoin price prediction metrics. Instead, the focus was on determining the impact of Ordinals data on Bitcoin price prediction. We compared the TemporalFusionTransformer (TFT) model on the full dataset and on the dataset with Ordinals-related features removed. The results and graphs are shown in Table 11 and Figure 15. We found that the metrics drastically worsened after the removal of the Ordinals-related features, indicating that these features play a significant role in Bitcoin price prediction. While the Chronos-t5-base and TFT models showed similar metrics, both performed much better than the Chronos-t5-small model.

TABLE 11. Model performance comparison (C: Chronos-t5).

Model/Result	MAE	RMSE	MAPE
TFT	4324.007	4894.200	0.062
TFT (No_Ord)	5986.423	6480.179	0.087
C-base	4298.152	5251.932	0.064
C-small	6269.377	6633.374	0.093

E. FEATURE IMPORTANCE ANALYSIS

In order to analyze in further detail the importance of each feature for prediction, we performed an importance analysis

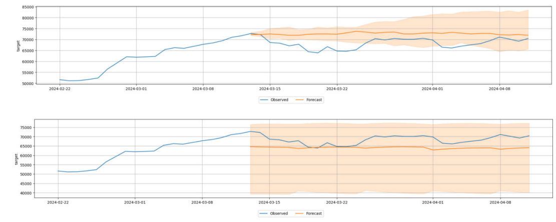


FIGURE 15. TFT and Chronos.

shown in Tables 12-13.We find that Ordinals-related data all play a role in bitcoin transaction fee rate prediction, with the 3 most important features being the number of Ordinals inscriptions, the fees spent on Ordinals and the number of unique users using the Ordinals market. This adds conviction to the conclusion of our previous data analysis that the increase or decrease in the number of Ordinals inscriptions tends to depend on market activity, in other words users' greed.

TABLE 12. Hourly Bitcoin transaction fee rate prediction—feature importance.

Feature	Importance	Stdev	n	p99_low	p99_high
Ordinals_Inscription	-0.005647	0.029598	5.0	-0.066591	0.055296
Size	0.025538	0.067250	5.0	-0.112932	0.164007
Weight	0.068059	0.085987	5.0	-0.108990	0.245108
Price	0.017220	0.047760	5.0	-0.081119	0.115558
Ma_50	0.048157	0.062981	5.0	-0.081521	0.177836
Ma_100	0.004190	0.063190	5.0	-0.125920	0.134300
Ma_200	0.056453	0.057874	5.0	-0.062709	0.175616
Hour_Market_TotalV	0.029343	0.091684	5.0	-0.159435	0.218120
Hour_Market_TotalT	0.022312	0.059383	5.0	-0.099960	0.144583
Cnt	0.047416	0.093082	5.0	-0.144241	0.239074
Total_Inscriptions	0.035871	0.081134	5.0	-0.131185	0.202926
Ord_Size_Usage	0.031023	0.040598	5.0	-0.052569	0.114614
Ord_vSize_Usage	0.021341	0.030458	5.0	-0.041371	0.084054
Ord_Hour_Fees	0.066454	0.060695	5.0	-0.058517	0.191426
Ord_Total_Fees	0.058139	0.064691	5.0	-0.075060	0.191338
Hash_Rate	0.002157	0.066312	5.0	-0.134381	0.138695
Num_Addresses	0.030398	0.068710	5.0	-0.111077	0.171873
Tx_Count	0.012632	0.123565	5.0	-0.241790	0.267054

The four features of Ordinals-related data that we find to be of the highest importance for Bitcoin price prediction are the number of Ordinals inscriptions, the fees spent by Ordinals, the vSize used by Ordinals, and the trading volume of the Ordinals market. These data reflect the activity of the Ordinals market and the usage of Ordinals inscriptions. In other words, the greed of users using Ordinals can explain the variation in Bitcoin price to a certain extent. The vSize used by Ordinals is much more important than the size used by Ordinals. Combined with previous inferences, we argue that the upgrades of SegWit and Taproot drove the creation and development of Bitcoin Ordinals. Combined with users' greed for Ordinals and their use, this in turn had many effects on the Bitcoin blockchain and its price.

TABLE 13. Daily Bitcoin price prediction-feature importance.

Feature	Importance	Stdev	n	p99_low	p99_high
Ord_Total_Fees	3.762370	0.0	5.0	3.762370	3.762370
Total_Inscriptions	2.792057	0.0	5.0	2.792057	2.792057
Ordinals_Inscription	0.384115	0.0	5.0	0.384115	0.384115
Weight	0.412760	0.0	5.0	0.412760	0.412760
Daily_Avg_Size	-1.749479	0.0	5.0	-1.749479	-1.749479
Ave_Tra_Fee_Rate	-0.041927	0.0	5.0	-0.041927	-0.041927
Ma_50	5.536719	0.0	5.0	5.536719	5.536719
Ma_100	0.104687	0.0	5.0	0.104687	0.104687
Ma_200	2.540234	0.0	5.0	2.540234	2.540234
Market_TotalV	1.794271	0.0	5.0	1.794271	1.794271
Market_TotalT	0.922656	0.0	5.0	0.922656	0.922656
Cnt	-0.111068	0.0	5.0	-0.111068	-0.111068
Ord_Size_Usage	0.112760	0.0	5.0	0.112760	0.112760
Ord_vSize_Usage	2.087370	0.0	5.0	2.087370	2.087370
Ord_Hour_Fees	-0.294010	0.0	5.0	-0.294010	-0.294010
Hash_Rate	1.073568	0.0	5.0	1.073568	1.073568
Num_Addresses	-0.233854	0.0	5.0	-0.233854	-0.233854
Tx_Count	-0.120833	0.0	5.0	-0.120833	-0.120833

F. ANALYSIS OF RESULTS

Ordinals correlation features have a significant impact on predicting Bitcoin transaction rates, which can effectively capture sudden rate changes and outliers, and are also useful for predicting Bitcoin prices. When there is more noise, the TemporalFusionTransformer model is validated using backtesting better than the Chronos model, which can fine-tune the pre-trained model based on the periodic generation of kernel series at specific time intervals in order to improve its performance in specific tasks. When the noise is smaller, the fine-tuned Chronos model outperforms the TemporalFusionTransformer model. Figure 16 shows the overall structure of our paper.

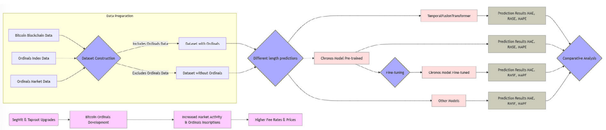


FIGURE 16. Constructed comparative experiments demonstrating that Bitcoin Ordinals-related data is critical for predicting Bitcoin transaction rates and prices.

VII. CONCLUSION

This paper constructs a dataset containing Bitcoin blockchain data, Ordinals index data, and Ordinals market data. We find that the number of Ordinals inscriptions does not decrease uniformly when Bitcoin transaction fees are high. The increase or decrease in the number of Ordinals inscriptions tends to depend on market activity. When the Ordinals market is active, the share of Ordinals inscriptions and the average Bitcoin transaction fee rate remain high. We argue that the upgrades of SegWit and Taproot drove the creation and development of Bitcoin Ordinals. Combined with users' interest in Ordinals, this, in turn, had significant effects on the Bitcoin blockchain and its price.

To further investigate whether Bitcoin Index-related data is useful for Bitcoin price and transaction rate prediction, we added a dataset with Ordinals-related data removed. Using three metrics (MAE, RMSE, and MAPE) and the TemporalFusionTransformer model as a baseline for comparative experiments, we demonstrate that Bitcoin Ordinals-related data can serve as an important feature. This helps investors and participants in the Bitcoin Ordinals market avoid losses and leverage congestion-related arbitrage opportunities, thus making more accurate decisions in the cryptocurrency market.

It is further demonstrated that the fine-tuned Chronos model achieves metrics close to or even better than those of the TemporalFusionTransformer in time series prediction for shorter time intervals, especially in low-noise environments. This illustrates the promise of the fine-tuned Chronos model for cryptocurrency predictions. Combined with Chronos' excellent zero-shot prediction performance, fast execution, and easy cloud deployment, this helps investors and participants in the cryptocurrency market quickly obtain high-quality predictions without needing to collect more complex data features.

The limitations of this study are:

1) The dataset was collected exclusively from the Bitcoin chain, and some of the Ordinals market data may have minor biases.
2) Data from centralized exchanges was not used.
3) The model still has considerable room for fine-tuning, and the metrics are not optimal.

In the future, we plan to use a wider range of datasets, extend the timeframe of the dataset, use more models, and incorporate data from centralized exchanges to conduct a more comprehensive study of Ordinals-related data. We believe that not only Ordinals but also Runes and Bitcoin Layer 2, as well as activities that are either on the Bitcoin blockchain or strongly related to it, may be useful for predicting Bitcoin prices and transaction fees and hold significant research value.

APPENDIX A
CODE, MODEL, AND DATASET

The codebase used in this paper can be found: https://github.com/MxwangSD/Bitcoin_Ecosystem_Data_prediction.

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