Economics Letters 239 (2024) 111746

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Intricacy of cryptocurrency returns

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ARTICLE INFO

Keywords:
Cryptocurrency returns
Machine learning
Explainable artificial intelligence
Intricacy

ABSTRACT

This paper quantifies the intricacy, i.e., non-linearity and interactions of predictor variables, in explaining cryptocurrency returns. Using data from several thousand cryptocurrencies spanning 2014 to 2022, we observe a notably high level of intricacy. This provides a quantitative measure why linear models are often outperformed by machine learning algorithms in predicting cryptocurrency returns. Furthermore, we document that the intricacy in these predictions is considerably larger compared to stocks. Our analysis reveals that interactions are gaining importance over time, while individual non-linearity of the drivers is diminishing. This adds to the emerging literature on spillover effects between cryptocurrencies, traditional finance and the economy. This finding is important for investors as well as regulators as the high intricacy proposes challenges to both actors in the market.

1. Introduction

The application of machine learning has grown rapidly in recent years. Gu et al. (2020) demonstrate that machine learning-based stock portfolios outperform traditional strategies. Additionally, Bryzgalova et al. (2020) highlight the importance of interactions in grouping similar stocks for trading strategies. Furthermore, Chen et al. (2024) apply machine learning models to estimate asset pricing models for single stock returns. Machine learning also shows promise for other asset classes, such as bonds or hedge funds, as evidenced by studies like Bianchi et al. (2021) and Wu et al. (2021). Cryptocurrencies have emerged as an established alternative asset class, with private yet professional investors increasingly considering them in their asset allocation. Predicting cryptocurrency returns has become a prominent focus in the literature, with machine learning models consistently outperforming classical statistical models (Akyildirim et al., 2021; Liu et al., 2021, 2023; Cakici et al., 2024). Thus, the relationship between predictor variables and returns appears to be intricate, characterized by marginal non-linearity and interactions among these predictors. This paper aims to quantify the importance of marginal non-linearity and predictor interactions for cryptocurrency returns. This quantification enhances understanding of why machine learning methods outperform simpler ones and can further explain documented spillover effects between traditional financial assets and cryptocurrencies in the literature (Blau et al., 2021; Jia et al., 2021; Borri et al., 2022; Yousaf et al., 2023; Gubareva et al., 2023). The question remains open regarding how spillover effects in the literature affect return prediction and predictor's functional form. Economically, understanding market stability intricacies means evaluating simultaneous impacts of various markets, emphasizing predictor interactions. This quantification helps assess the magnitude of impact when multiple markets change together. Investors need this insight as they integrate data from multiple markets into return predictions, uncertain about singular or joint impacts.

Utilizing a large sample of approximately 2800 cryptocurrencies spanning from 2014 to 2022, our contributions are manifold. First, the dominance of intricacy is evident, with at least 86% attributed to it. This percentage significantly surpasses that of large stocks, which peaks at 36% (Nagl, 2023). Consequently, the structure of cryptocurrency return predictions presents greater challenges than that of large stocks. However, intricacy is decreasing over time, indicating a convergence to stock market levels. Second, we observe a trend where the importance of interactions among drivers is increasing over time, while individual non-linearity is diminishing. Hence, in recent times, returns are influenced more jointly by drivers rather than individually, contrasting with the early days of the cryptocurrency universe. This highlights that various markets impact the cryptocurrency market jointly, suggesting higher-order spillover effects.

2. Data

Our dataset spans cryptocurrencies from January 2014 to December 2022 using data retrieved from coinmarketcap.com (Liu et al., 2022). To avoid survivorship bias, we include both active and inactive cryptocurrencies. Following Liu et al. (2022), we only select cryptocurrencies with a marketcapitalization of at least 1 million USD and a listing duration of at least eight weeks. We exclude the cryptocurrencies INNBCI, BTWTY, and KRT due to implausible values for market

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https://doi.org/10.1016/j.econlet.2024.111746
Received 12 February 2024; Received in revised form 22 April 2024; Accepted 5 May 2024
Available online 7 May 2024

Table 1
Descriptive statistics of weekly cryptocurrency returns.

Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
N.Coins	57	56	102	442	880	803	1074	1899	1887	2791
Mean	−0.042	−0.013	0.000	0.128	−0.048	−0.010	0.015	0.013	−0.030	−0.005
Std	0.165	0.145	0.155	0.387	0.197	0.140	0.171	0.217	0.131	0.190
Min	−0.516	−0.515	−0.502	−0.507	−0.554	−0.394	−0.562	−0.445	−0.567	−0.567
25% Q	−0.147	−0.092	−0.084	−0.098	−0.182	−0.100	−0.085	−0.122	−0.102	−0.112
50% Q	−0.065	−0.015	−0.012	0.041	−0.054	−0.018	0.000	−0.014	−0.023	−0.017
75% Q	0.030	0.054	0.060	0.253	0.062	0.064	0.098	0.101	0.040	0.073
Max	0.728	0.660	1.157	2.911	0.734	0.573	0.844	1.245	0.427	2.911

Note: N.Coins depicts the number of unique cryptocurrencies in that year.

capitalization and other information, following Ammann et al. (2022). After applying these filters 2791 cryptocurrencies are in the dataset. We divide each year into 52 weeks, with the first 51 weeks consisting of seven days each and the last week consisting of the last eight days. Subsequently, the returns are shifted by one week to relate all current information to the return of the following week. Table 1 provides the cryptocurrency return's descriptive statistics.

Predicting cryptocurrency returns hinges on identifying suitable drivers and their functional form in the prediction model. Some studies underscore the significance of cryptocurrency-specific information (Ozdamar et al., 2021; Jia et al., 2021; Liu et al., 2022). Additionally, macroeconomic variables, stock market data, and commodities are crucial determinants (Liu et al., 2023). Others stress the importance of uncertainty-related variables (Colon et al., 2021; Lucey et al., 2022). We consider the most common drivers across various categories. Cryptocurrency-specific variables include market capitalization, return volatility, maximum return, past one and eight-week returns, as well as the illiquidity measure by Amihud (2002). Commodities are represented by a comprehensive commodity index and weekly gold price returns. For macroeconomic data, we utilize the yield spread between Baa and Aaa rated bonds, the yield spread between the 10-year treasury and 3-month treasury constant maturity bill, the VIX, and the weekly return of S&P500 as well as NASDAQ. Regarding uncertainty-related variables, we incorporate the US and Global Economic Political Uncertainty index by Baker et al. (2016), along with the Policy Crypto Uncertainty index proposed by Lucey et al. (2022). A detailed description of the drivers and data sources is available in Online Appendix B, Table B.1.

3. Methods

As Liu et al. (2023) demonstrates that XGBoost outperforms other models, such as Lasso, in predicting cryptocurrency returns, we utilize Lasso (linear) and XGBoost (non-linear) to investigate the intricacy of cryptocurrency returns .

Measuring intricacy

We employ a well-known method, Accumulated Local Effect (ALE) Plots, introduced by Apley and Zhu (2020). The main aim of ALE plots is to calculate a function $\Theta_{ALE}(X_j)$ that quantifies how much the prediction of the model $f(X)$ changes on average for every value of feature $X_j \in \mathbb{R}^{N\times 1}$, where $j = 1,\dots,p$. Here, N is the number of observations, and p is the number of predictors. This function entails the individual (non-linear) impact of X_j on $f(X)$. Additionally, the function $\Theta_{ALE}(X_j)$ can be calculated for interaction effects up to order p. In simple terms, the ALE function $\Theta_{ALE}(X_j)$ allows us to decompose the prediction function $f(X)$ into the individual impact of the predictors and the impact of all possible interactions among these predictors. For a detailed description of ALE Plots, please refer to Online Appendix A.

Following Apley and Zhu (2020), we can calculate an R^2-like measure, describing the extent to which the prediction can be explained by individual non-linearity. The proposed R^2_{ALE} by Apley and Zhu (2020) is defined as:

$$R^2_{ALE} = \frac{var\{\sum_{J\subsetneq\{1,\dots,p\}} \Theta_{ALE}(X_J)\}}{var\{f(X)\}} \quad (1)$$

Table 2
Variants of intricacy.

Definition	Measured intricacy	Interpretation
1 - $R^2_{ALE,linear}$	Overall intricacy	Importance of individual non-linearity and all possible orders of interactions
1 - R^2_{ALE}	Interactions	Importance of all possible interactions
R^2_{ALE} - $R^2_{ALE,linear}$	Individual non-linearity	Importance of individual non-linearity

Apley and Zhu (2020) show that $R^2_{ALE} = 1$ if we add all ALE functions up to order p. Nagl (2023) expands this approach by introducing another variant called $R^2_{ALE,linear}$. This quantifies how well a linear model could approximate the prediction of the machine learning model, providing insight into the linearity in predictions. The $R^2_{ALE,linear}$ is defined as:

$$R^2_{ALE,linear} = \frac{var\{\sum_{j=1}^{p} \Theta^{linear}_{ALE}(X_j)\}}{var\{f(X)\}} \quad (2)$$

where $\Theta^{linear}_{ALE}(X_j)$ is calculated by fitting a linear regression of X_j onto $\Theta_{ALE}(X_j)$. We can use Eqs. (1) and (2) to quantify various intricacy levels, depicted in Table 2:

4. Results

To train the models, we employ an expanding window approach, where data is sequentially expanded by one quarter (i.e., 13 weeks). The initial time slice covers data until the end of 2017 (2017 Q4). The data are randomly split into an 80% training sample and a 20% testing sample, implementing a cross-sectional split to control for overfitting. Additionally, we perform a time series split, where the testing data is the subsequent quarter, but find no difference regarding the intricacy. After training the algorithms, finding hyperparameters, and measuring intricacy, we add the next time slice, i.e., 2018 Q1. We observe that XGBoost clearly outperforms Lasso in every quarter considered, which is in line with the findings of Liu et al. (2023). Further details on hyperparameter selection and the performance of both models can be found in Online Appendix C.

Intricacy over time

Fig. 1 illustrates the amount of intricacy, as defined in the first line of Table 2.

The intricacy measure is calculated each time new hyperparameters are fitted, ranging from 78.7% to 94.1%. We observe a downward trend of intricacy in the crypto market from mid-2019 onwards. Nagl (2023) applied a similar approach to all constituents of the S&P 500 index, finding intricacy ranging from 6% to 36% from 1995 until 2016. Hence, intricacy in the stock market is considerably lower. However, as the crypto market evolves, its intricacy becomes more similar to stocks. Therefore, the convergence of the intricacy values can be interpreted as a sign of the increasing maturity of the crypto market.

As intricacy arises from individual non-linearity of the drivers or various interactions between them, Fig. 2 dissects this effect.

Over time, the importance of interactions increases, whereas the importance of non-linearity decreases. This shift implies that intricacy is

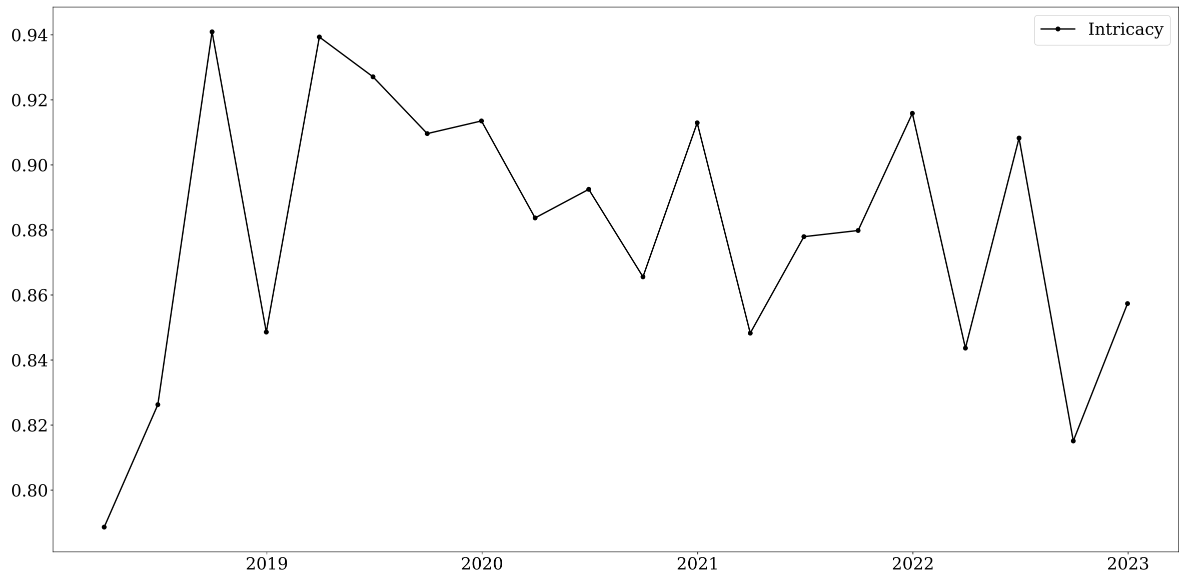

Fig. 1. Intricacy over time.

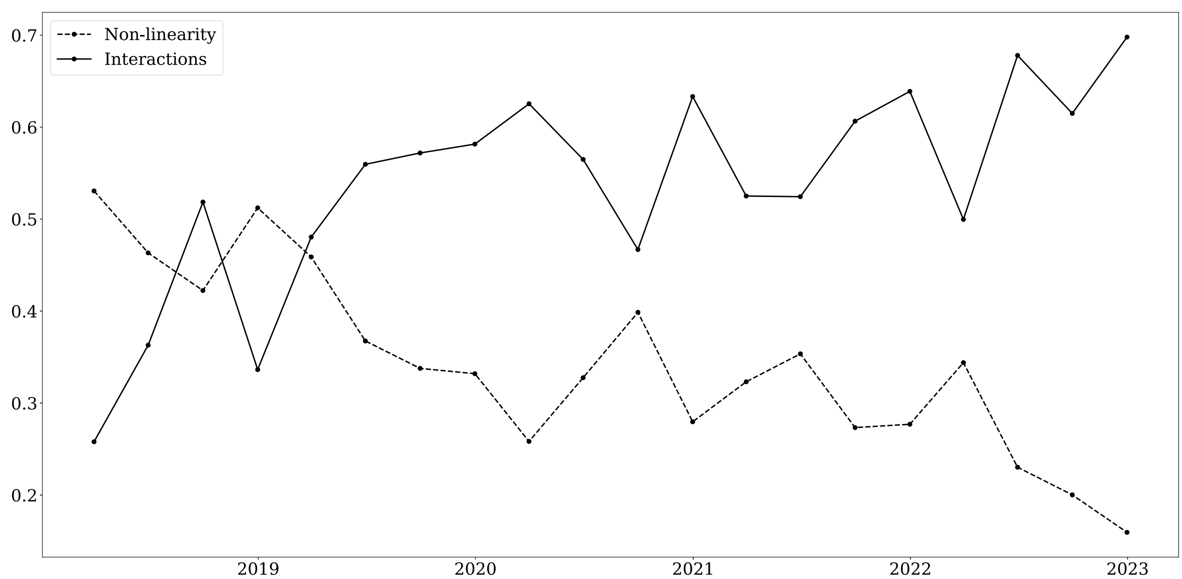

Fig. 2. Non-linearity and interactions over time.

leaning more towards joint effects rather than individual non-linearity of the drivers. This increased importance may indicate a greater integration of cryptocurrencies with other asset classes or spillover effects. This adds to the literature on spillover effects, by showing that spillover effects are (jointly) important for cryptocurrencies. By incorporating various drivers from different asset classes, the increased interactions may suggest that they collectively influence cryptocurrencies more nowadays than in the early days of the crypto market. This interpretation is in line with Corbet et al. (2018) who shows that until 2017 the correlation between crypto and other financial assets was very low. Similar evidence until 2019 is provided by Gil-Alana et al. (2020) and Jia et al. (2021). To test the robustness of our findings, we calculate the intricacy for more or less liquid cryptocurrencies. We find that the conclusions drawn remain the same. Furthermore, we redo our analysis using only the top 100 coins by market cap at the end of the estimation period to further reduce the impact of illiquidity of smaller coins on our results. Moreover, we redo our analysis by using two-year simple splits to ensure that the expanding window hides some time-variation in the more recent samples. For both robustness checks, our conclusions remain the same.[1] Detailed results to all robustness checks can be found in Online Appendix D.

To further investigate the importance of interactions, we calculate SHAP interaction values in Online Appendix E. SHAP values are standard for explaining machine learning models and are frequently used. Summing up the detailed analysis in Online Appendix E, the most important interaction at the onset of the COVID-19 pandemic was between the *UCRY Policy Index* and *Gold Bullion LBM*, highlighting the significance of uncertainty around crypto policy and the safe-haven property of gold. With the start of the Federal Reserve's first rate hike in March 2022, the most important interaction was between *DBAA-DAAA* and *T10Y3M*, both indicating changes in the interest rate environment. This suggests that crypto returns react sensitively to changes in interest rates as well as to fears of a recession in the United States. Considering the time variation of the importance of interactions for individual

[1] We thank an anonymous reviewer for suggesting these robustness checks.

features, we observe that the interest rate environment shows large interactions during the rate hike period. Furthermore, gold exhibits large interaction values only during COVID-19, but not before or afterward. This indicates that the importance of interactions of individual features is not stable over time and varies with different degrees of economic uncertainty and important macroeconomic events. This adds further to the literature on spillover effects. For example, Aharon et al. (2021) showed that cryptocurrencies and US yield curves are connected in stressful times, but not in normal times. We extend this evidence by showing that the yield curves also interact more with other drivers during those times. Furthermore, Jiang et al. (2022) demonstrated tail risk spillover, i.e., connectedness during extreme events. Similar evidence is found by Lahiani et al. (2021) and Ahn (2022).

5. Conclusion

We observe an decrease in the intricacy of cryptocurrency predictions; however, the intricacy is notably high compared to large stocks. Additionally, we find evidence of an increasing importance of interactions, while the importance of individual non-linearity of the drivers is decreasing. Overall, high intricacy of cryptocurrencies is important for investors seeking to develop profitable strategies for cryptocurrencies. As many different joint impacts become more important, building and implementing trading strategies become more challenging. From a regulatory perspective, the relatively high intricacy may require regulatory frameworks tailored to address the challenges posed by this intricacy.

Data availability

Data will be made available on request.

Acknowledgment

We would like to thank the Project DEAL for funding the Open Access publication.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2024.111746.

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