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On pricing DeFi tokens

[0000-0002-2794-7726] Florentina Şoiman^{1,2} and Mathis Mourey²

¹Univ. Grenoble Alpes, CNRS, LJK, F-38040 Grenoble, France

²Univ. Grenoble Alpes, Grenoble INP, CERAG, 38000 Grenoble France

[Firstname.Lastname]@univ-grenoble-alpes.fr

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Abstract

This study examines the effectiveness of a Fama-French 3 Factors model in explaining DeFi tokens returns. Initial results show that all the risk factors (the market, size, and value factors) considered are priced by the market. Surprisingly, expected returns are negatively related to the size factors, indicating that larger DeFi tokens yield more returns than smaller tokens. DeFi tokens seem to be the first crypto-assets to suffer from this phenomenon. Furthermore, we show that once accounting for cross-sectional correlations, no risk factors are significantly related to expected returns anymore. This result suggests that DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market. Our findings emphasize the importance of using technological variables in pricing Blockchain-based assets, such as for example, network variables.

Keywords: DeFi Tokens, Fama-French 3 Factors, Fama-McBeth, Asset pricing, Blockchain.

JEL Codes: E39, G12, F39.

1 Introduction

Decentralized Finance (DeFi) platforms provide financial services that rely on cryptocurrencies and crypto-tokens. The intention is to bring a digital and decentralized alternative to traditional banking and investment services (Anker-Sorensen & Zetzsche, 2021). The launch of Blockchain-based decentralized finance platforms has been a turning point for financial applications since it allows users to do more with their crypto-assets than just send them from point A to point B. DeFi platforms can perform most of the things banks do — lend, trade assets, earn interest, buy insurance, borrow, trade, and much more (Coinbase.com, n.d.). In order to be able to do all these activities, DeFi platforms are supported by complex tokens with different functions depending on the service needed. Because of their functionalities, DeFi tokens could be considered a sub-class of the crypto-tokens, similar in a way to the Initial Coin Offering (ICO) tokens. They fulfill multiple roles, such as facilitating access to different products or platform services, can be traded or sold in exchange for cryptocurrencies, and last but not least, DeFi tokens can be held to earn a profit (Le Moign, 2019).

The existing literature (Corbet et al., 2023; Maouchi et al., 2021; Schar, 2021; Yousaf et al., 2022) often describes the DeFi market as a sub-sector of the crypto-market and the DeFi tokens as a distinct asset class from cryptocurrencies. The following rationale could justify this class separation between the two crypto-assets: from a practical viewpoint, DeFi tokens and cryptocurrencies are similar only because they both use Blockchain. At the same time, DeFi are a distinct technology as they require smart contracts to function. From here stems our motivation to study the behavior of DeFi tokens, and we expect them to be uniquely different in terms of risk and return.

The DeFi market is relatively young, as the first official DeFi platform, MakerDAO, was launched in late 2017 (Coinmarketcap.com, 2022). As a consequence of its youth, DeFi-related literature is scarce and comprises only subjects such as the platform's liquidity and efficiency (Gudgeon et al., 2020), DeFi's potential in the context of traditional financial economy (Zetzsche et al., 2020), financial bubbles (Corbet et al., 2023; Maouchi et al., 2021), the risk transmission among crypto-assets (Karim et al., 2022), and the lack of regulation within DeFi market (Anker-Sorensen & Zetzsche, 2021; Aramonte et al., 2021; C. Chen et al., 2020; Y. Chen & Bellavitis, 2019; Johnson,

2021; Popescu, 2020; Stepanova & Erins, 2021; Wronka, 2021). The existing crypto-related literature has shown the importance of crypto-assets in the diversification of equity portfolios (Ankenbrand & Bieri, 2018; Briere et al., 2015), this being valid as well during stressed periods such as COVID-19 (Goodell & Goutte, 2021). From here, we assume that DeFi tokens could be as well used by investors to maximize their profits and diversify risks. From our knowledge, DeFi tokens (DeFis) returns' properties have not yet been explored in the current literature.

To enclose this gap, our goal is to study the financial behavior of DeFi tokens and answer the following research question: 'Is the Fama-French 3 Factor model relevant to explain DeFi tokens returns?'. We propose a Fama-French 3 Factor model (FF3F) adapted to the DeFi market and examine if it can explain the tokens' returns. The reason why we employ the Fama-French model is because we believe that the DeFi market suffers from a size effect. A major risk present in the crypto-market is the cyber-crimes. Crothers (2021) shows that the highest-priced crypto-assets are the main targets of cyber-attacks. Therefore, as DeFi tokens increase in popularity and value, they could become the next targets. Based on the above rationale, we expect that big tokens are the ones most exposed to (cyber) risks (which is the opposite of the stock market)¹, risks that will reflect in higher compensation for investors and higher returns.

We construct the size and value factors using DeFi data. For the traditional High Minus Low (HML) factor, we propose to replace the book value with an equivalent variable characteristic to this market, the Total-Value-Locked (TVL²). As a market benchmark, we chose the Nasdaq index for Decentralized Finance (ticker: *DEFX*). As initial results, we obtained that all the risk factors considered are priced by the market. Afterward, we perform additional tests, such as the Fama-MacBeth procedure. Once the cross-sectional correlations are considered, our results change, and none of the risk factors are priced. However, we have observed that the market factor is the closest to being significant. This result suggests that the market risk could be an important driver for DeFis returns, and it should be considered in future studies. We conclude that the results obtained in this study prove the fact that DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market, or at least not by using

¹According to the financial theory (Fama & French, 1996), we know that in the stock market, smaller firms tend to be riskier, hence tend to provide a higher return for investors.

²TVL refers to the amount of funds attached to a DeFi project. We consider it the equivalent of the book value in this market.

just financial data. Our findings emphasize the importance of using technological variables in pricing Blockchain-based assets, such as network variables.

The contributions made by this work are multiple: (1) from our knowledge, we are the first ones to test if the market, size, and value factors explain DeFi returns and to examine the cross-section of DeFi tokens returns; (2) we constructed the TVL-to-Market ratio as an equivalent for this market of the 'Book-to-market ratio'; and last but not least (3) we have constructed the size and value factors using DeFi data.

The paper proceeds as follows. Section 2 provides the theoretical background based on which this paper has been developed. Section 3 describes the data used, the chosen model methodology, and the factors' construction. Section 4 reports the empirical results. The final section summarizes the results and offers conclusions.

2 Theoretical background

A proper valuation method can help assess the real worth of an asset hence helping buyers and traders decide whether an investment is profitable. The valuation of assets has long been one of the main persistent problems in finance. As an answer to this problem, the financial theory presumes that asset prices are generally set based on their present discounted value of dividends, in other words, their fundamental or intrinsic value (Tirole, 1985). The literature on this topic assumes that the fundamental value represents the 'real' value of an asset.

Up to now, there is no universal technique used to measure or calculate the fundamental value of an asset. However, several methods can be considered depending on someone's needs and the asset type in question. For example, in the case of stocks, the mainly used valuation techniques are based on dividend payments, earnings, and book value. Certain assets, such as land, commodities, or even currencies, are more difficult to value. Determining their fundamental value based on discounted dividend method is not possible, and in such cases, a utility-based framework is often applied. For example, if the gold's price is based on its utility, the valuation is influenced by factors such as industrial demand and flow supply. According to Blanchard & Watson (1982), mispricing is more likely to happen in markets where fundamentals are difficult to assess.

As a special asset class by nature, crypto-assets have been extensively studied (Bouri et al., 2017; Jiang et al., 2022). In particular, most studies focus on the relationship between cryptocurrency prices and their ‘fundamental’ value. While some studies showed that bitcoin is a purely speculative asset, hence has a no fundamental value (Cheah & Fry, 2015; Kallinterakis & Wang, 2019); others argue that cryptocurrencies, in general, do have a fundamental value, despite the difficulty of deriving it (Beigman et al., 2021; Dowd, 2014). Following the logic of (Tirole, 1985), Biais et al. (2020) have tested and confirmed that cryptocurrencies have similar fundamental value to fiat money: *‘transactional benefits are to cryptocurrencies what dividends are to stocks’* (Biais et al., 2020, p. 2), meaning that the more cryptocurrencies are used to transact (purchasing power), the bigger their value will be. Furthermore, significant attention has been brought to the network effects role in the valuation process of crypto-assets (Athey et al., 2016; Cong et al., 2021; Y. Liu & Tsyvinski, 2021; Zimmerman, 2020). In the crypto-market, the network effect is proxied by variables such as transaction and address count, users’ numbers, and any other variable that could be used to estimate the Blockchain adoption rate. The network effect is especially important in the valuation process of the crypto-tokens and other Blockchain-based crypto-assets that do not attain transactional benefits, such as cryptocurrencies. For example, one of the Cong et al. (2021)’s main assumptions in his token valuation model is that the expected platform’s increase in productivity (and value) is the result of the network growth. In other words, the network effects make crypto-assets and Blockchain technology more valuable as more people join the network, and as a result, the entire crypto-ecosystem becomes more valuable.

As stated before, the valuation of assets has been long one of the main persistent problems in finance. Thus, for the purpose of determining the (theoretical) fair value of an asset, academics proposed several models to price securities, among which the most well-known are the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). These pricing frameworks aim to consider the risks incurred by holding a security and price it accordingly. The CAPM model has been developed based on Markowitz (1952, 1959)’s work on portfolio selection. It is a single-factor model that assumes that the return of a security is linearly related to its market risk. Since idiosyncratic risk can be diversified, the pricing model considers only the systematic risk, which cannot be diversified, as an important factor in asset valuation. The APT model has been developed by Ross (1976) as an alternative to the

CAPM. Compared to CAPM, APT considers multiple systematic risk factors. The nature of the factors is undefined and can vary from company-specific to macroeconomic risk.

Several studies (Chan et al., 1991; Fama & French, 1992; Gibbons et al., 1989) have shown that for different periods, the relationship between stocks' return and market risk has disappeared. Hence the CAPM failed to fully explain the expected returns on investment. In 1992, Fama & French (1992) proposed a new empirical pricing model that incorporates two new risk factors in addition to the CAPM's market risk factor: the size factor (small minus big) and the value factor (high book-to-market minus the low book-to-market). Afterward, different models have followed, extending the CAPM to six possible factors: Carhart (1997) proposed a risk factor called momentum, and Fama & French (2015) introduced two additional factors: the profitability and the investment risk factor.

Pricing crypto-assets has proven to be challenging, especially since they are a separate asset class from traditional assets (Corbet et al., 2019; Dyhrberg, 2016; Y. Liu et al., 2022). An important strand of literature tackles the modeling of cryptocurrency returns and examines various risk factors specific to this market. Similar to traditional markets, the crypto-market is driven by a size effect, meaning that small-capitalization cryptocurrencies yield more than high-capitalization ones (Jia et al., 2022; W. Liu et al., 2020; Shen et al., 2020). Other risk factors studied in the crypto-related literature are momentum, volatility, liquidity, and (investor's) attention.

3 Data, factors construction & model

This section presents our data set, our approach to computing the factors for the FF3F model, and the model itself.

3.1 Data

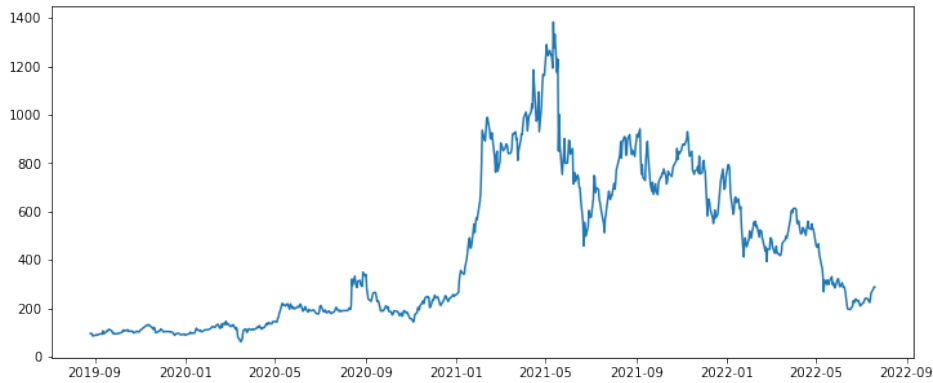
This article uses various types of data. First, we retrieved financial information for DeFi tokens from CoinmarketCap.com. The data spans from 01-01-2019 to 20-07-2022. The frequency is weekly and contains information for more than 400 tokens. As a market benchmark, we chose the Nasdaq index for Decentralized Finance (ticker: *DEFX*). We downloaded the weekly prices for the *DEFX* index³ from the Eikon Database. The database we have

³The index was created in 2019.

obtained for DEFX spans from 2019 to 2022, as it is shown in Figure 1. The summary statistics for the average returns of the DeFi tokens and for their index are provided in section 3.2, Table 1.

Figure 1: **NASDAQ index for DeFi: ticker DEFX**

Price of the DEFX index provided by NASDAQ between 2019 and 2022. The frequency displayed on the graph is daily.



To compute our factors, we retrieve DeFi-specific data, namely, the TVL. The TVL shows how much funds are committed to a specific DeFi platform. We know that the more successful a DeFi platform is, the bigger the TVL should be. This variable thus resembles the ‘*book-value*’ of a firm. The TVL information has been retrieved from DeFiLama.com. The data is at the weekly frequency, spans from 01-01-2019 to 20-07-2022, and contains information for more than 600 DeFi platforms. After merging the financial information for DeFi tokens and the TVL data, we have 88 tokens in total, for which we have complete information. That being said, for this study, we have used 88 DeFi tokens, for which we have both financial data and TVL information. We display our sample information with DeFi tickers, names, and chain type in Appendix 6.2, Table 5, Table 6, Table 7 and Table 8.

3.2 Constructing Fama-French factors

This work examines the relevance of the FF3F model in the DeFi market. We now construct the risk factors following the original paper’s methodology (Fama & French, 1992). The three factors are the market, the size (SMB), and the value (HML) factors. We re-balance the factors on a monthly basis. As a market factor, we use the market index DEFX. In this paper, we assume that the risk-free rate is null⁴. This assumption is based on the existing literature

⁴We are not sure that the usual risk-free rate used in the stock market (10Y T-Bills) is relevant for the DeFi market. However, we made some tests, including the risk-free rate (10Y T-Bills) downloaded from the Fama website, and found no difference in our results.

Figure 2: The construction of Fama-French factors

Here we show how we split our data sample into 6 portfolios in order to compute the loading factors with DeFi data for the Fama-French 3 Factor model.

	Median ME	
70th Percentile TVL/M	Small Value	Big Value
	Small Neutral	Big Neutral
30th Percentile TVL/M	Small Growth	Big Growth

on cryptocurrencies (Grobys & Sapkota, 2019; Shen et al., 2020) and on the fact that choosing a relevant risk-free rate for the DeFi market seems difficult. Following the methodology of Fama & French (1996), we construct six portfolios: Small Value (SV), Small Neutral (SN), Small Growth (SG), Big Value (BV), Big Neutral (BN), and Big Growth (BG). We now detail the construction of the size and value factors. We now detail the construction of the size and value factors, which is also graphically presented in Figure 2.

- **SMB:** The size factor, Small Minus Big (SMB), is computed by splitting the DeFi tokens into two categories: small and big tokens. We construct equally weighted portfolios for large and small DeFis based on their market capitalization. Given our dataset (only 88 DeFi tokens in total), we follow the approach of Dimson et al. (2003), deviate from the original methodology of Fama & French (1996), and choose a 50% breakpoints⁵. Choosing higher breakpoints for our portfolios allows for a larger number of DeFi tokens per portfolio and limits the impact of one DeFis on the portfolio's return. Our factor is then,

$$\begin{aligned}
 SMB(t) = & 1/3 * (SV(t) + SN(t) + SG(t)) \\
 & -1/3 * (BV(t) + BN(t) + BG(t)).
 \end{aligned} \tag{1}$$

With $SMB(t)$ being the value of the SMB factor at time t , $SV(t)$, $SN(t)$, $SG(t)$ represent the return of the portfolios of small DeFi tokens at time t , and $BV(t)$, $BN(t)$, $BG(t)$ represent the return of the portfolios of large DeFi tokens at time t .

- **HML:** The value factor, High Minus Low (HML), is computed by splitting the DeFis into three groups:

⁵The original breakpoints for the size factor are 10%/90% (Fama & French, 1996), splitting the stocks into three groups: small, middle and big.

growth, neutral, and value tokens. Originally, the split is based on the Book-to-Market ratio (Fama & French, 1996). As DeFis do not have an equivalent for the book value, we chose to substitute it with the TVL measure. We then split our DeFis based on the TVL-to-Market ratio. The breakpoints are 30%/70%. The DeFis being in the lower 30% constitute the component for the portfolio of growth DeFis. The upper 30% are the value DeFis. We then compute the HML factor as follows,

$$HML(t) = 1/2 * (SV(t) + BV(t)) - 1/2 * (SG(t) + BG(t)). \quad (2)$$

With $HML(t)$ being the value of the HML factor at time t , $SV(t)$, $BV(t)$ the return of the portfolios of DeFis having a high TVL-to-Market ratio at time t , and $SG(t)$, $BG(t)$ the return of the portfolios of DeFis having a low TVL-to-Market at time t .

We provide in Table 1, the summary statistics for the average of our returns as well as for each of our factors.

The correlation among factors is displayed in Table 2.

Table 1: Descriptive Statistics: Returns of DeFi tokens & Fama-French factors

Summary statistics for the average returns of 88 DeFi tokens, and for the Market, Size (SMB), and Value (HML) factors. The data consists of weekly returns. The Mean, Standard Deviation (SD), Min, Median, and Max are expressed in percentages and are annualized.

	Mean	SD	Min	Median	Max	Kurtosis	Skewness
Market	0.591	13.398	-52.062	0.000	50.343	2.73817	-0.20970
SMB	-1.160	09.031	-37.623	-1.251	52.093	7.74530	0.60716
HML	-1.107	10.003	-63.225	0.000	47.440	18.95651	-2.25403
Defis	-0.298	17.395	-81.279	-0.059	91.972	13.54434	0.58247

3.3 Fama-French 3 Factor model

As in the original research of Fama & French (1996), we construct the FF3F model as a regression of the returns of DeFi tokens against the corresponding risk factors.

$$R_i(t) = \alpha_i + \beta_{i,Market} Market(t) + \beta_{i,SMB} SMB(t) + \beta_{i,HML} HML(t) + \varepsilon_i(t). \quad (3)$$

Table 2: Correlation between Fama-French factors

Pearson correlation coefficients between weekly returns of the Market, Size, and Value factors. The level of significance is expressed as: *:**10%**, **:5%, * * *:1%.

	Market	HML	SMB
Market	1.0***		
HML	-0.076	1.0***	
SMB	0.066	0.151**	1.0***

Where $R_i(t)$ is the vector of return of the i^{th} DeFi token; α_i is the intercept of the OLS regression for i^{th} DeFi token; $\beta_{i,factor}$ is the sensitivity of the i^{th} DeFi token with the $factor$, and $\varepsilon_i(t)$ is the error vector. The Regression 3 is repeated for the 88 DeFis in our sample. The regression presented in Equation 3 allows estimating the factor loadings. In order to obtain the risk premium required by investors, we perform the following cross-sectional regression,

$$R_i(t) = \alpha + \lambda_{Market} * \hat{\beta}_{i,Market}(t-1) + \lambda_{SMB} * \hat{\beta}_{i,SMB}(t-1) + \lambda_{HML} * \hat{\beta}_{i,HML}(t-1) + \epsilon \quad (4)$$

Where $R_i(t)$ is the vector of expected returns for all DeFi tokens; λ_{Market} is the regression coefficient for the loading of the *Market* factor; $\beta_{i,\hat{Market}}$ is the vector of estimated sensitivities to the *Market* factor; λ_{SMB} is the regression coefficient for the loading of the *SMB* factor; $\beta_{i,\hat{SMB}}$ is the vector of estimated sensitivities to the *SMB* factor; λ_{HML} is the regression coefficient for the loading of the *HML* factor; $\beta_{i,\hat{HML}}$ is the vector of estimated sensitivities to the *HML* factor estimated in Regression 3; and ϵ is the error vector.

However, a regular OLS regression fails to capture cross-sectional correlations. Such a problem will result in biased t-values for the coefficients estimated in Regression 4, leading to unreliable significance levels. To address that issue, we perform the Fama-MacBeth procedure to obtain robust significance levels for our risk premiums. Following the original methodology of Fama & MacBeth (1973), we perform cross-sectional regression for each time step in our sample. Formally,

$$\begin{aligned}
R_i(1) &= \alpha_1 + \lambda_{1,Market} * \hat{\beta}_{i,Market}(0) + \lambda_{1, SMB} * \hat{\beta}_{i,SMB}(0) + \lambda_{1,HML} * \hat{\beta}_{i,HML}(0) + \epsilon_1; \\
R_i(2) &= \alpha_2 + \lambda_{2,Market} * \hat{\beta}_{i,Market}(1) + \lambda_{2,SMB} * \hat{\beta}_{i,SMB}(1) + \lambda_{2,HML} * \hat{\beta}_{i,HML}(1) + \epsilon_2; \\
&\dots \\
R_i(T) &= \alpha_T + \lambda_{T,Market} * \hat{\beta}_{i,Market}(T-1) + \lambda_{T,SMB} * \hat{\beta}_{i,SMB}(T-1) + \lambda_{T,HML} * \hat{\beta}_{i,HML}(T-1) + \epsilon_T.
\end{aligned} \tag{5}$$

The Equations 5 are essentially a repetition of the Regression 4 for each time step available. The risk premiums λ are obtained by taking the average of all λ_t for $t = 1 \rightarrow T$. This method allows computing the standard error of λ as follows,

$$SE_\lambda = \frac{SD(\lambda_t)}{\sqrt{T-1}} \tag{6}$$

Where SE_λ is the standard error of the estimate and $SD(\lambda_t)$ is the standard deviation of all λ_t for $t = 1 \rightarrow T$, with T being the amount of time step for our sample.

4 Results

We start our analysis by running the FF3F model⁶ on our 88 DeFis. We find that, on average, the model explains 13.1% of the variations in weekly DeFis returns. Turning to the risk premium in the DeFi market, we perform the cross-sectional regression in Equation 4. Our results are depicted in Figure 3 and in Table 3.

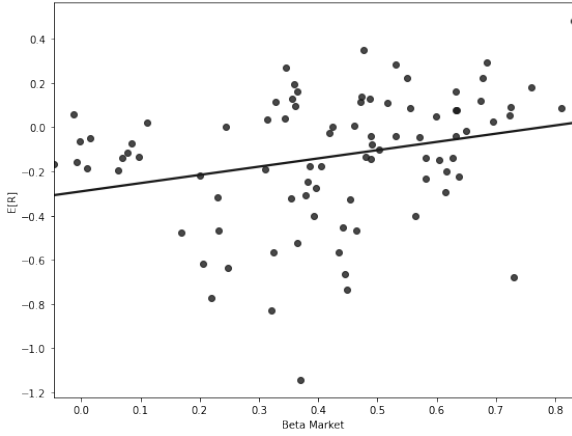
Our results highlight various facts about the pricing of risk in the DeFi market. Figure 3a shows a clear positive relationship between the β_{Market} and DeFis returns. This result is consistent with the existing financial theory, where any additional unit of systematic risk must be rewarded with supplementary returns. Figures 3b and 3c display more interesting results: the relationship between returns and the exposure to the size and value factors is negative!

All these results are shown in the OLS regression output presented in Table 3. As it can be observed, we find a negative intercept with high significance, which is similar to the research done on pricing cryptocurrencies (Jia et al., 2022; Shahzad et al., 2021). At the same time, all the relationships between the returns and the risk factors β are significant. The market is the only variable that stands out to be positively related to the returns. The explanations for such a fact in finance are straightforward. The market is usually the primary source of financial risk, and any

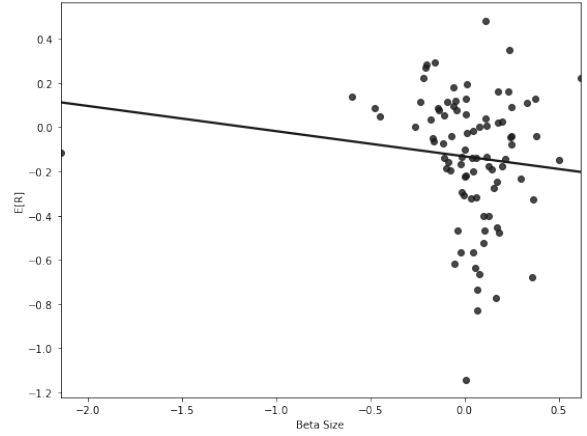
⁶The regressions follow the Equation 3.

Figure 3: Regressions plots: Returns vs. Factor Loadings

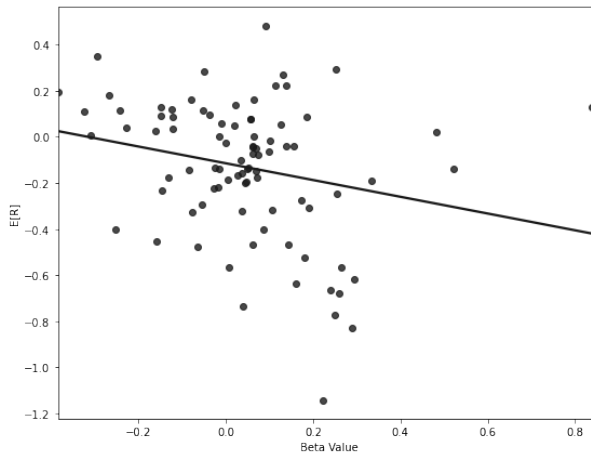
Scatter plots with a linear regression line between returns of DeFi tokens and their respective β for each risk factor. Figure (a) shows a positive linear relationship between the return in t and market beta in $t-1$. Figure (b) shows a negative relationship between returns and the size loading. Figure (c) shows a negative relationship between the returns and the TVL-to-market loading.



(a) Market Factor



(b) Size Factor



(c) Value Factor

additional unit of risk needs to be rewarded with an additional return.

As certain anomalies have been found in the stock market (the relationship between stock returns and market risk has disappeared), this event has propelled the research on additional risk factors (Fama & French, 1993, 1996). For example, the size factor provided us with one of the first explanations of why assets with the same systematic risk do not have the same rate of return. Because smaller firms tend to be riskier, hence tend to provide a higher expected return for investors. Surprisingly, the DeFi market seems to contradict this logic. We find a strongly signif-

Table 3: **OLS Regression: Risk Premia**

Results for the OLS regression performed between expected returns of 88 DeFi tokens and their respective sensitivity to the Market, Size, and Value factors. SE stands for Standard error, and the p-value is provided in the $P > |t|$ column.

(a) OLS Regression: Performance

Model:	OLS	R-squared:	0.191
F-statistic:	6.628	Adj. R-squared:	0.163

(b) OLS Regression: Coefficients & Significance

	Estimate	SE	t	P > t 	[0.025	0.975]
Intercept	-0.2726	0.066	-4.117	0.000	-0.404	-0.141
Market	0.3997	0.140	2.847	0.006	0.121	0.679
SMB	-0.2781	0.103	-2.713	0.008	-0.482	-0.074
HML	-0.4533	0.150	-3.031	0.003	-0.751	-0.156

icant negative relationship between size and expected returns. This result suggests that larger DeFi provides higher expected returns than smaller tokens. This phenomenon is apparently not surprising for the academic literature, as it has previously appeared in the other financial markets outside US (Heston et al., 1999). We think that an explanation for the ‘negative’ size effect is that the DeFi market is highly heterogeneous⁷. We think that an explanation for this could be that DeFi tokens’ increase in value represents one of the driving forces behind the rise in cyber-crime, a fact confirmed for the cryptocurrency market (Crothers, 2021). Therefore, as DeFi tokens increase in popularity and value, they could become the next target in cyber-attacks. For this reason, investors may ask for higher compensation for the incurred risks, which eventually will reflect in a return increase.

Adapting the HML factor of Fama & French (1996) to the DeFi market provides some unexpected results. Fama & French (1996) initially argued that the HML factor proxies relative distress, as weak firms tend to have high Book-

⁷There is a big difference between the large capitalization and the small capitalization DeFi tokens. This is a noteworthy mention, as our results are robust regardless of the change in the breakpoints. By this, we mean that the big-cap tokens drive the DeFi market and our results.

to-Market ratios. The HML factor, in our case, is negatively related to the return, which contradicts the rationale provided by Fama for the stock market. Better said, our results show that the tokens with the lowest TVL-to-Market ratio are the ones that are the riskiest. This risk could be as well the consequence of the high price (the market value is high), which tends to transform crypto-assets into the next cyber-attack targets (Crothers, 2021).

The results obtained from our OLS regression do not account for various effects, such as cross-sectional correlations within the sample. We perform the Fama-MacBeth procedure to address this limitation and obtain robust significance levels for our coefficients. The results are provided in Table 4⁸. We find that once the cross-sectional correlations are accounted for, none of the factors are actually priced by the market. The market factor is the closest to being significant, suggesting that it might still be an important driver for DeFis returns. However, the size and value effects appear completely irrelevant. An explanation for this could be that DeFi platforms are relatively new and very technical. As previously stated, this market is immature and compared to other financial markets, it is largely unknown to the public, acting more as a niche. The largest DeFi platforms are the most known and attract the most attention. Due to this, they experience substantial growth and provide high returns to their investors. What actual risks are priced in these returns cannot, for now, be explained by the traditional asset pricing models based on the stock market, or at least not by using just financial data. Furthermore, these results emphasize the importance of using technological variables in pricing Blockchain-based assets, such as network variables.

5 Conclusion

In this chapter, we examine the effectiveness of the FF3F model, consisting of market, size, and value factors, to assess DeFi token returns. To compute our factors, we retrieve DeFi-specific data. Afterward, we constructed the risk factors following the original paper's methodology (Fama & French, 1992). A particular effort has been put into the construction of the value factor. As there is no 'book value' for DeFi tokens, we have found a substitute: the TVL. TVL refers to the amount of funds attached to a DeFi project; therefore, we consider it to be the equivalent of the book value in this market. Furthermore, we have split our DeFi tokens based on the TVL-to-market ratio, which is the DeFi market equivalent of the Book-to-Market ratio. As a market risk factor, we have used the index DEFX,

⁸To have a graphical representation of Fama-McBeth's results, see Appendix 6.1 Figure 4.

Table 4: **Fama-MacBeth: Risk Premia**

Results for the Fama-MacBeth regressions performed between the returns of 88 Defi tokens at time t , and their respective sensitivity to the Market, Size and Value factors at $t-1$. Each estimate is computed by averaging all (186) cross-sectional estimates provided in Figure 4. The standard errors (SE) are computed following Equation 6. The p -values are computed for a two-tailed t -test.

	Estimate	SE	t	P> t
Intercept	-0.0108	0.004	-3.028	0.003
Market	0.0205	0.014	1.461	0.146
SMB	-0.0085	0.013	-0.633	0.528
HML	-0.0123	0.011	-1.117	0.265

proposed by Nasdaq.

A proper valuation method can help assess the real worth of an asset hence helping buyers and traders decide whether an investment is profitable. The valuation of assets has long been one of the main persistent problems in finance. The DeFi market is relatively young, as the first official DeFi platform, MakerDAO, was launched in late 2017 ([Coinmarketcap.com](https://coinmarketcap.com), 2022). As a consequence of its youth, DeFi-related literature is relatively scarce. From our knowledge, we are the first ones to explore the DeFis returns' properties.

Our results with the FF3F show that all the risk factors considered in this model are priced by the market. We found that the relationships between expected returns and the exposure to the size and value factors are negative. If such findings are not surprising for the academic literature, as it has previously appeared in the other financial markets outside US ([Heston et al., 1999](#)), DeFi tokens seem to be the first crypto-assets to suffer from this phenomenon. We think that an explanation for this could be the fact that DeFi's increase in value attracts cyber-attacks, a fact confirmed for the cryptocurrency market([Crothers, 2021](#)). Therefore, as DeFi tokens increase in popularity and value, they could easily become the next casualties. For this reason, investors may ask for higher compensation for the incurred risks, which eventually will reflect in a return increase.

Furthermore, we decided to perform additional tests, such as the Fama-MacBeth procedure. Once the cross-sectional correlations are taken into consideration, our results change, and none of the risk factors are priced. However, we have observed that the market factor is the closest to being significant. This result suggests that the market risk could be an important driver for DeFis returns, and it should be considered in future studies. We conclude that the results obtained in this study prove the fact that DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market, or at least not by using just financial data. In line with (Biais et al., 2020) and based on the results obtained from this study, we think that measuring the value of Blockchain-based assets correctly depends on using non-financial variables such as the network size.

A limitation of this study is our sample size. Because of the differences in the data available for financial and TVL information, we have not been able to cluster more DeFi tokens together. We, therefore, wonder if a bigger sample would have provided the same results. As a future path for research, it could be interesting to construct other risk factors, such as liquidity, volatility, or network factors, and test their capacity to capture the cross-sectional variation in DeFi tokens returns.

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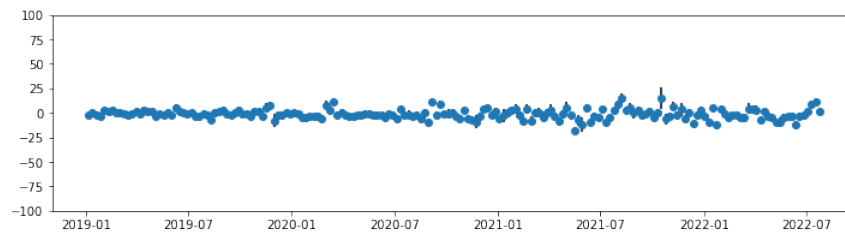
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6 Appendix

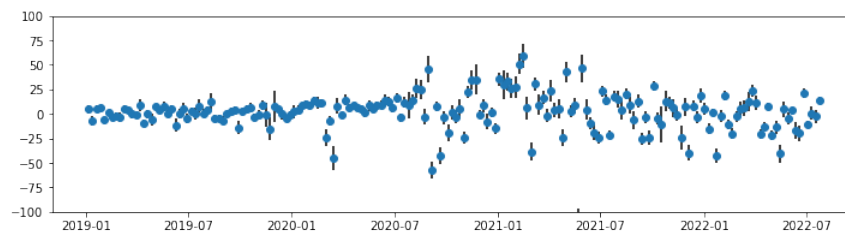
6.1 Figures

Figure 4: Fama-MacBeth: Cross-sectional coefficients over time

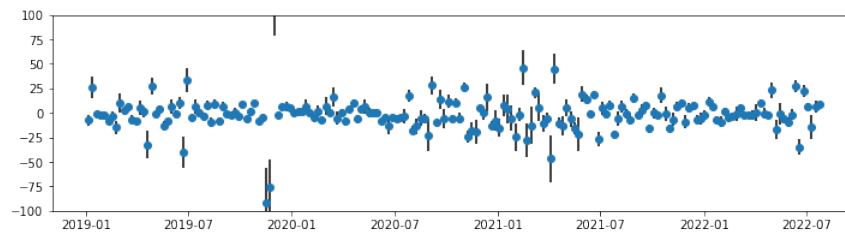
Scatter plots of cross-sectional coefficients of the returns against their respective factor loadings. The cross-sectional coefficients are computed from 186 cross-sectional regressions as depicted in Equation 5. The vertical black bar represents the OLS standard error of the estimate. Figure (a) shows the results for the intercept over time. Figure (b) shows the results for the Market factor over time. Figure (c) shows the results for the Size factor over time. Figure (d) shows the results for the Value factor over time.



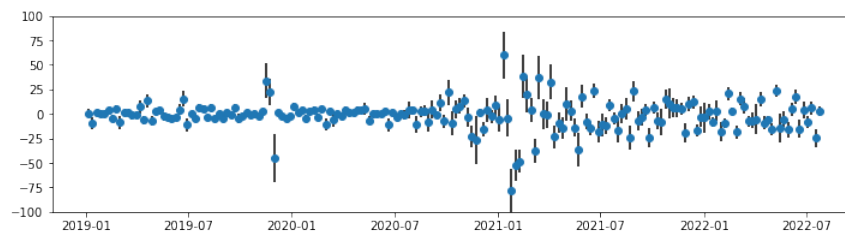
(a) Intercept



(b) Market Factor



(c) Size Factor



(d) Value Factor

6.2 Tables

Table 5: List of DeFi Tokens (1/4)

Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name and the Blockchain technology related to that particular DeFi platform.

Ticker	Name	Chains
CAKE	CakeDAO	Avalanche
TAROT	Tarot	Fantom, Optimism
HARD	Kava Lend	Kava
SUSHI	SushiSwap	Ethereum, Polygon, Arbitrum, Avalanche
RGT	Rari Capital	Ethereum, Arbitrum
CREAM	CREAM Finance	Ethereum, BSC, Polygon, Arbitrum
TRU	TrueFi	Ethereum
AUTO	Autofarm	BSC, Polygon, Cronos, Heco, Fantom, Avalanche
QI	Benqi Lending	Avalanche
VVS	VVS Finance	Cronos
ANKR	Ankr	Ethereum, BSC, Avalanche, Fantom, Polkadot
CHESS	Tranchess	BSC
ROOK	Rook	Ethereum
TIME	Wonderland	Avalanche, Ethereum
KP3R	Keep3r Network	Ethereum
FLM	Flamingo Finance	NEO
BNT	Bancor	Ethereum
OUSD	Origin Dollar	Ethereum
MMO	MM Optimizer	Cronos
DF	dForce	BSC, Arbitrum, Ethereum, Polygon, Optimism
COMP	Compound	Ethereum
DODO	DODO	BSC, Ethereum, Polygon, Aurora, Arbitrum

Table 6: List of DeFi Tokens (2/4)

Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name and the Blockchain technology related to that particular DeFi platform.

Ticker	Name	Chains
BADGER	Badger DAO	Ethereum, Arbitrum, BSC
DYDX	dYdX	Ethereum
LDO	Lido	Ethereum, Solana, Moonbeam, Moonriver, Terra
MDX	MDEX	Heco, BSC
MTA	mStable	Ethereum, Polygon
LRC	Loopring	Ethereum
PNT	pNetwork	Ethereum, BSC, Telos, Bitcoin, ORE, EOS
AAVE	AAVE V2	Ethereum, Polygon, Avalanche
WBTC	WBTC	Ethereum
FLX	Reflexer	Ethereum
CRV	Curve	Ethereum, Polygon, Avalanche, Fantom
QUICK	Quickswap	Polygon
SNX	Synthetix	Ethereum, Optimism
INV	Inverse Finance	Ethereum
RPL	Rocket Pool	Ethereum
NFTX	NFTX	Ethereum, Arbitrum
MKR	MakerDAO	Ethereum
BABY	BabySwap	BSC
UNI	Uniswap	Ethereum, Polygon, Arbitrum, Optimism, Celo
BELT	Belt Finance	BSC, Heco, Klaytn
XVS	Venus	BSC

Table 7: List of DeFi Tokens (3/4)

Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name and the Blockchain technology related to that particular DeFi platform.

Ticker	Name	Chains
WING	Wing Finance	Ontology, BSC, OntologyEVM, Ethereum, OKExChain
KAVA	Kava	Kava
CVX	Convex Finance	Ethereum
PERP	Perpetual Protocol	Optimism, Ethereum
ACA	Acala LCDOT	Acala
MET	Metronome	Ethereum
RAY	Raydium	Solana
KEEP	KEEP Network	Ethereum
IDLE	Idle Finance	Ethereum, Polygon
VSP	Vesper	Ethereum, Avalanche, Polygon
FXS	Frax	Ethereum, Fantom
ALCX	Alchemix	Ethereum, Fantom
INJ	Injective	Ethereum
BSW	BiSwap	BSC
SDT	StakeDAO	Ethereum, Polygon, Avalanche, Harmony, BSC
BUNNY	Bunny	BSC, Polygon
RUNE	Thorchain	Ethereum, Binance, Bitcoin, Doge, Litecoin
ALPACA	Alpaca Finance	BSC, Fantom
REN	RenVM	Ethereum, Arbitrum, Solana, Polygon, Fantom
ALPHA	Homora	Avalanche, Ethereum, BSC, Fantom
DFI	DefiChain DEX	DefiChain
BEL	Bella Protocol	Ethereum
VTX	Vector Finance	Avalanche
NXM	Nexus Mutual	Ethereum
RSR	Reserve	Ethereum

Table 8: List of DeFi Tokens (4/4)

Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name and the Blockchain technology related to that particular DeFi platform.

Ticker	Name	Chains
BAL	Balancer	Ethereum, Polygon, Arbitrum
FIS	Stafi	Ethereum, CosmosHub, Polygon, Stafi, BSC
PICKLE	Pickle	Ethereum, Polygon, Arbitrum, Aurora, Optimism
BANANA	ApeSwap	BSC, Polygon
UMA	Outcome Finance	Ethereum, Polygon, Boba
BIFI	Beefy Finance	Fantom, Polygon, BSC, Avalanche, Arbitrum
DHT	dHEDGE	Ethereum, Polygon, Optimism
BNC	Bifrost	Bifrost
YFI	Yearn Finance	Ethereum, Fantom, Arbitrum
ARMOR	Aarmor	Ethereum
SLND	Solend	Solana
DVF	Rhino.fi	Ethereum
FARM	Harvest Finance	Ethereum, Polygon, BSC
KSP	KlaySwap	Klaytn
LQTY	Liquity	Ethereum
EPS	Ellipsis Finance	BSC
FEI	Fei Protocol	Ethereum
SRM	Serum	Solana
STRK	Strike	Ethereum
MLN	Enzyme Finance	Ethereum