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Bachelor Thesis International Bachelor Economics and Business Economics

Idiosyncratic volatility puzzle in cross-section of cryptocurrencies.

The investigation of idiosyncratic volatility prices in crypto markets

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Abstract

The goal of the thesis is to investigate whether idiosyncratic volatility is priced in the cross-section of expected cryptocurrency returns. Given the past literature on volatility price in cross-section of stocks, in particular: Ang et al. (2006) paper "The Cross- Section of Volatility and Expected Returns" the idiosyncratic volatility puzzle tends to be a controversial topic ever since. In this research Fama-MacBeth regression analysis as well as univariate portfolio-level analysis will be performed to ultimately suggest a positive relationship between IVOL and expected returns of cryptocurrencies.

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1. Introduction and literature review.

1.1 History of the Idiosyncratic Volatility Puzzle

In the past, most of the attention, when it comes to the predictability of stock returns and volatility was given to time-series relationships of the market (Campbell and Hentschel (1992)). However, more recently in 2006 Ang et al. researched the idiosyncratic volatility in a *cross-section* of expected stock returns. The paper is most famous for the discovery of the *negative* relationship between idiosyncratic volatility and stock returns cross-sectionally. The authors estimate around -1% annual change in returns for the portfolio consisting of the highest idiosyncratic volatility stocks when compared to the portfolio consisting of the lowest idiosyncratic volatility stocks (5 Portfolios in total). Book-to-market ratio, size, momentum, liquidity, and exposure to aggregate volatility risk have also failed to explain the phenomenon later known as the idiosyncratic volatility puzzle (later IVP). The findings are contradicting the classical theory of finance, in which IVOL is not priced in the cross-section, thus the controversy of the topic.

R. F Stambaugh at el. (2012) provide an explanation for the negative empirical relationship between IVOL and expected return in a cross-section of *equities.* Analysis suggests that higher IVOL is related to higher arbitrage risk and that allows for greater mispricing (expected return is negatively (positively) related to IVOL among overpriced (underpriced) securities; second - arbitrage is asymmetric (short-sellers face higher risk in comparison to buyers). Barberis and Huang (2008) argued that investors overweight small chances of large gains (prospect theory) and prefer stocks with higher IVOL, thus, causing them to be overpriced. Byoer et al. (2010) represent the proxy for expected idiosyncratic skewness in a form of forecasts and conclude that it helps explain the IVP. The K.Hou et al. (2016) study concluded that all explanations for IVP existing at that time account for 29-54% of the actual explanation. The phenomenon to this day has different views and understandings as it remains considered not fully solved.

1.2 Difference between stocks and cryptocurrencies.

The root idea of cryptocurrency was designed to be an alternative to currencies. Zhang and Li, (2020) describe cryptocurrencies as computer-managed public ledger entries that can function as money. Holders of crypto can use them to settle transactions online, however, due to its highly volatile nature, the cryptocurrency market is mostly used as an investment vehicle as investors time and time again try to find and exploit arbitrage opportunities. (Balcilar et al,2017). (Binda, 2020) also finds crypto to be more often used as an investment instrument than as an alternative for currencies. For more than 10 years, we have been witnessing a sharp development in cryptocurrency markets. Global cryptocurrency market capitalization is more than one trillion USD (CoinGecko 2022) which is equivalent to the whole silver market capitalization and if the market showcases similar growth patterns it will possibly take over gold in terms of market capitalization in the future. This leads to the conclusion that cryptocurrency is relevant today and possibly will get more relevant in the future.

Since both traditional assets and cryptocurrencies are often used as investment instruments one may ask what the differences are. A few investigations have been made to study movements between cryptocurrency returns and more traditional asset returns. Biere et al. (2015) found approximately no correlation between traditional assets and cryptocurrencies and that significant risk can be reduced via diversifying investment portfolios with the inclusion of Bitcoin. Bouri et al. (2019) argue that cryptocurrency returns can be predicted whereas classical theory does not suggest the same for traditional assets. Wei (2018) showcases similar findings to that of Bouri et al. (2019). Where after examining 456 cryptocurrencies they find that a portion of cryptocurrencies still represents signs of non-independence and autocorrelation. The evidence encourages significant differences between cryptocurrency and stock markets.

1.3 Hypothesis.

In this thesis, the examination of the cross-section of cryptocurrencies with different innovations to idiosyncratic volatility is going to be the main goal. Does the idiosyncratic volatility puzzle remain in the cryptocurrency markets and if so, does it have a positive or negative influence on the predicted cryptocurrency returns? To understand, whether there are arbitrage opportunities, whether the cryptocurrency market is consistent with the traditional asset theory, or does it showcase similarities in terms of abnormalities found in equity markets, the univariate portfolio analysis as well as Fama and MacBeth regression will be performed.

H$_0$: *Idiosyncratic volatility has no influence on the price of cryptocurrencies in a cross-section.*

H$_a$: *Idiosyncratic volatility is priced in the cross-section of cryptocurrencies, and it helps predict the expected return in a cross-section.*

2. Data and Summary Statistics

This section represents the relevant information of the sample used. The discussion of data collection processes and sources takes place. The way some of the variables are constructed is covered in the *methodology* section.

2.1 The reasons and sources of data.

To form adequate regressions and portfolios with which the comparisons between cryptocurrencies with different IVOL can be made, the question of how many cryptos to use, which source of historical data to rely on, and how many cryptocurrencies to take for how long of a period must be answered. Firstly, the popularity of cryptocurrency has been growing at an exponential rate for the last 10 years. The number of cryptocurrencies that exist has also increased by more than 100 times over the lifetime of the market. Thus, to have diverse enough portfolios at each point in time (to have at least 10 cryptos each day), the last 5-year period of cryptocurrency market historical data has been chosen. The 5 years have also been the most relevant as cryptocurrency has gained most of its popularity throughout the period. Top 500 cryptocurrencies based on size account for more than 90% of the whole market capitalization during the sample period. (The exact number of cryptos used is 503) Zhang and Li (2020) have also used 500 cryptocurrencies.

Papers like (Liu et al. 2020) have helped conclude that coinmarketcap.com is the source to use for cryptocurrencies. *Daily* data from 2017 May to 2022 May from coinmarketcap.com has been collected. Then 503 cryptocurrencies with any trading record have been used to guarantee that the investor has the same information available at all points in time. Using github.com the data has been scraped; then dataminer.io was used for cryptocurrency APIs and then all the files have been merged with the creation of the script using Python. Fama-French 3 factors are used in the form of SMB, HML, and MRKTF and taken from mba.tuck.dartmouth.edu. Summary statistics of relevant variables are introduced in **table 1**. The proxy for market return is created using the market index from spglobal.com[1]

[1] For cryptocurrency market return S&P Cryptocurrency Broad Digital Market Index from spglobal.com was used, the way this index is constructed, and its methodology and more documentation can be found at spglobal website.

Table 1. Summary statistics of data

	Mean	Std.dev
IVOL	.120	1.658
Market Index return	.006	.008
Cryptocurrency return	.008	.154
SMB	.018	.690
HML	.168	1.356
MKTRF	.132	1.446

Table 1 represents a summary the variables used in the thesis. The difference between the stock market and the cryptocurrency market is observed as the average idiosyncratic volatility in the U.S. stock market is approximately 2.3% (Guo and Savickas, 2008) which can be interpreted as evidence of speculation and high risk in a cryptocurrency market. IVOL displays a mean of 12% which is different from the empirical literature which seems to suggest an approximately 21% average. However, the sample period is also shorter which may explain this difference. For instance, in 2017 the average IVOL was around 0.6 (Zhang and Li, 2020). Note that this is a sign of convergence between traditional assets and cryptocurrency markets. Additionally, different cryptocurrencies have made it to the top 500 by market capitalization and they contain different idiosyncratic volatilities. Apart from IVOL, the table does not display deviations from the literature.

Table 2. Correlation between the price of crypto, IVOL, and market index return.

	IVOL	MIR	Price
IVOL	1		
MIR	.002	1	
Price	-.005	.009	1

3. Methodology

In this section variable creation techniques, relevant regressions, and the results are covered. Subsequently, the hypothesis is tested, and the methods used in the analysis are described.

3.1 Variable creation.

Firstly, daily returns of the Market index as well as each cryptocurrency which was calculated by dividing one day's closing price by the closing price of the day before and subtracting 1 from the answer, more specific:

$$\frac{ClosingPriceDay2}{ClosingPriceDay1} - 1 = ReturnOnDay2$$

The IVOL was constructed in the following manner. To begin with, in the general theory of finance, prices of the cryptocurrencies are driven by a common market factor and crypto-specific shocks. The residual volatility or in other words, "what is left" from the model is the idiosyncratic volatility. It is cryptocurrency-specific volatility. The estimated market model of cryptocurrency return is:

$$(\mathbf{1})\ R_{i,t} = Alpha_{i,t} + Beta_{i,t} R_{m,t} + \epsilon_{i,t}$$

$R_{i,t}$ is the expected return of cryptocurrency i on day t, $R_{m,t}$ is the market return, and $\epsilon_{i,t}$ is the idiosyncratic return (cryptocurrency-specific return). Cryptocurrency's idiosyncratic volatility is the standard deviation of a residual. More specific:

$$(\mathbf{2})\ IVol_{i,t} = \sqrt{var(\epsilon_{i,t})}$$

The 90-day worth of lagged returns is taken from the past to estimate future values. The regression **(1)** is run on a 90-day basis to retrieve the residuals and ultimately calculate IVOL for each crypto each day. The within-month daily return data was used to estimate equation **(1)** for each cryptocurrency. The reason the daily returns have been chosen is described below, in the portfolio-level analysis paragraph. The residuals are reported values for the last observation in the rolling window.

3.2 Portfolio-level analysis.

Based on IVOL for each cryptocurrency at every point in time cryptos are separated into 5 different quintiles. E.g., the 1st quintile is 20% of the cryptocurrencies that have the lowest idiosyncratic volatility, and the 5th quintile contains 20% of cryptos that have the highest IVOL. For example, Bitcoin falls to the 4th quintile based on its idiosyncratic volatility. Depending on the quintile the cryptocurrency has fallen into, its return is separated into the assigned portfolio for later univariate portfolio analysis e.g., Bitcoins return is assigned to a portfolio 4. There are 5 different portfolios in total and each of them contains an equal number of cryptocurrencies at each point in time except for the times where the number of cryptos is not divisible by 5. For instance, at the point in time where there are 249 cryptos, one of the portfolios will have to have 49 cryptocurrencies in it. **Table 3** represents the average returns of each portfolio. The portfolios are calculated with equal weights. The reason for this is that the money invested in a portfolio is pre-determined at all points in time for the analysis to be realistic. The method of daily sorts is different from Ang et al. (2006), Bali and Cakici (2008,) and Zhang and Li (2020) because of the extreme volatility that has been documented in the cryptocurrency market, additionally, the history of crypto is relatively short and thus, the daily sorts should offer greater accuracy.

Table 3. Portfolios return summary statistics

	Mean	Std. dev.
Portfolio 1 returns	-.0015	.020
Portfolio 2 returns	.0004	.033
Portfolio 3 returns	.0034	.038
Portfolio 4 returns	.0085	.042
Portfolio 5 returns	.0323	.068

The pattern of positive IVOL influence on expected crypto returns can be observed in **table 3**. But no conclusion can be drawn yet. To test the null hypothesis of IVOL having no effect on the return of the cryptocurrency, the regression for each portfolio FF3 factor will be used. In particular:

$$(\mathbf{3})\ Return_i = \alpha_i + \beta_i MKTRF + \beta_{1,i} SMB + \beta_{2,i} HML + \varepsilon_i$$

The results of the 5 regressions are represented in table 4. Stars represent the significance level. *- significant at 10%, **-significant at 5%, ***- significant at 1%. It reports 90-day ahead alphas. The numbers in the parenthesis represent the t-statistics of the regressions. The FF3 alpha is the constant of the regression, and it shows how did the portfolio perform compared to the market (negative alpha means that the portfolio underperformed compared to the market). The 5th portfolio with the largest idiosyncratic volatility has the highest coefficient of the FF3 alpha 0.0308 (3.08%) significant at 1%, while the 1st portfolio has the lowest FF3 alpha coefficient of -0.0029 (0.3%) significant at 5%. |5-1| Is the true difference between portfolios 5 and 1. The pattern of positive idiosyncratic volatility influence on expected cryptocurrency returns can be recognized throughout all the portfolios e.g., the 2nd portfolio's FF3-Alpha is larger than the 1st portfolio's

Alpha, 4th portfolio's Alpha is larger than the 3rd portfolio's Alpha. As can be seen in table 4, most of the coefficients of FF3 alphas are significant even at the 1% level.

Table 4. Regressed portfolio summary statistics.

Portfolio	MKTRF	SMB	HML	FF3-Alpha	R^2
1	-.26**	-.06	.05	-.0029**	.02
	(2.54)	(-0.27)	(0.41)	(-1.99)	
2	.54***	-.18	-.09	-.0018	.04
	(3.70)	(-0.54)	(0.53)	(-0.88)	
3	.59***	-.11	.10	.0009	.03
	(3.52)	(-0.28)	(0.48)	(0.36)	
4	.66***	-.15	-.07	.0070***	.03
	(3.53)	(-0.34)	(-0.32)	(2.62)	
5	.89***	-.90	-.14	.0308***	.03
	(2.8)	(--1.25)	(-0.38)	(6.85)	
|5-1|	1.15	0.30	0.19	0.034	

3.3 The highest IVOL portfolio vs the lowest IVOL portfolio.

After comparing each of the portfolios, the difference in returns between portfolios 5 and 1 is generated as a new variable. The reason for this is to test whether the high IVOL portfolio has different returns than a low IVOL portfolio. The results can be observed in **table 5** column number (1). Then the same regression is run with the controls of FF3 factors. The coefficient of 0.034 (3.4%) is significant at a 1% level with a t-stat of 8.94 and should be interpreted as the following: cryptocurrencies in the highest IVOL portfolio on average outperform the cryptocurrencies in the lowest IVOL portfolio by 3.4% on average. The findings do not change course when adjusting for risk (FF3 factors). This results in more evidence to conclude there is a difference between cryptocurrencies with different IVOL parameters in terms of expected returns. This would be consistent with Wei Zhang and Yi Li (2020) who also report a positive coefficient and conclude that high IVOL cryptocurrencies are expected to outperform low IVOL cryptos.

Table 5. Regressed difference between portfolio 5 and 1 returns without (1) and with (2) adjusted risk with FF-3 factors.

	(1)	(2)
MKTRF		.60***
		(2.34)
SMB		-.80
		(-1.37)
HML		-.20
		(-0.60)
Intercept	.034***	.033***
	(8.94)	(8.82)
Adj R-squared	.000	.001

3.4 Fama and MacBeth regression.

A significant relationship between IVOL and cryptocurrency returns cross-sectionally has been found so far, however, the portfolio-level analysis may omit a sizable amount of information in the cross-section (Bali et al., 2011). Therefore, another method of calculating idiosyncratic volatility premium in the cross-section of cryptocurrency will be performed. It is the Fama and MacBeth regression. The regression reports the average of the individual factor risk premium found at each point in time. The coefficient of IVOL is positive and significant at the 1% level as can be seen in table 6 and thus it is additional evidence for the positive relation of IVOL and the expectation of returns of cryptocurrencies cross-sectionally. Note that Newey-West standard errors have been used to perform the Fama and MacBeth regression to account for autocorrelation as well as correct for heteroskedasticity.

Table 6. Fama-MacBeth's (1973) regression with Newey-West adjusted standard errors. Numbers in parenthesis represent t-statistics.

IVOL	Intercept	Adj. R-squared
.1727***	-.0087**	.0493
(7.86)	(-2.92)	

Ang et al. (2006) argue that size, momentum, liquidity, volume, and price may influence idiosyncratic volatility price. Bali and Cakici (2008) argue similarly. Both papers, however, were examining the cross-section of stocks rather than cryptocurrencies. On the other hand, Zhang and Li (2020) after performing Fama and MacBeth's (1973) regression only found size and price to have a significant relation with crypto returns. Which may be a limiting factor for the interpretation of the results found in **table 6**. It is still to be determined whether other variables explain the variation in the cryptocurrency return.

4. Results and Limitations

This section covers the results of the analyses used in the methodology section; this includes the interpretation. Major thesis-specific and empirical literature suggested limitations are discussed.

4.1 Results.

Firstly, portfolio-level analysis shows the trend of idiosyncratic volatility having a positive influence on expected cryptocurrency returns. The FF3-Alpha for the portfolio with the lowest IVOL rounds to -0.29% and is significant at a 5% level while the alpha for the highest IVOL portfolio is approximately 3.08% and is significant at a 1% level. The interpretation of the above-mentioned results is that on average, the highest IVOL portfolio outperforms the market by 3.08%, while the lowest IVOL portfolio is outperformed by the market by 0.29%. The trend of the positive influence of IVOL on expected crypto returns can be observed throughout all the portfolios. Secondly, after running the regression on the raw difference in returns between the highest IVOL portfolio vs the lowest IVOL portfolio a noteworthy result was found. Overall, the difference between portfolios is roughly 3.3% and is significant at the 1% level. The findings are consistent with Zhang and Li (2020). In other words, cryptos with higher past exposure to changes in aggregate market volatility are expected to perform better than those with lower idiosyncratic volatility. Third, Fama and MacBeth's regression further evidence of IVOL having a positive risk premium in a cross-section of cryptocurrencies which is also consistent with the empirical literature. It would be considered an abnormality as it is considered now in the traditional assets market as it contradicts the traditional theory of finance in which IVOL is not priced. Additionally, the investigation suggests that the cryptocurrency market demonstrates opposite results to those of Ang et al. (2006) where the authors argue for the negative relationship between IVOL and stocks.

4.2 Limitations.

Size, momentum, liquidity, and volume may have influenced the results (Bali and Cakici, 2008). Which has some evidence to not be relevant e.g., Ang et al. (2006) and Zhang and Li's (2020) papers in which the findings are robust to the above-mentioned factors report similar results after controlling for the above-mentioned factors. But it also has some evidence to be relevant, for example, Liu et al. (2020) find that size and momentum can capture the cross-sectional expected cryptocurrency returns. Bali and Cakici (2008) also suggest that interaction of the IVOL effect with firm size may induce contamination in the portfolios, therefore, they use different volatility-weighting schemes. Overall, it is not yet clear whether size, momentum, liquidity or volume may drive results. In addition, one can also argue that different weighting schemes do not represent reality accurately if portfolios are weighted equally. More specifically, the position that Bitcoin was in during the sample period might have driven the results. Similarly, to Zhang and Li (2020), Bitcoin today is still the biggest cryptocurrency in the market (Yi et al., 2018). BTC accounts for more than 50% of the total market capitalization and the largest portion of total trading volume as well. The same goes for other big coins such as Ethereum.

Another limitation of the investigation performed is the sample period chosen which is 5 years' worth of data. The most relative years of cryptocurrency were the trading volume, as well as market capitalization, which was the largest ever in history were the reasons to choose this long of a period. However, it is not all the historical data cryptocurrency has to offer which is more than 10 years. On the other hand, including all the historical data would have possibly created more biases because of the low volume and less diversification available in portfolio analysis e.g., in 2012 there were significantly fewer cryptocurrencies than there are now. Also, the IVOL of cryptocurrencies, as stated in the data and summary statistics section used to be significantly higher in the past which may be an argument for a larger discrepancy between crypto and traditional asset markets, which ultimately leads to more evidence of possible speculation.

4.3 Peso story described in Ang et al. (2006) paper.

Since cryptocurrencies were found to be a "fashionable" investment choice (Foursekis and Grigoriadis, 2021, Balcilar et al, 2017) while Cunha et al. 2019 describe cryptocurrencies as extremely volatile assets. This may lead to a potential peso story for which Ang et al. (2006) also have raised concerns. A peso story in finance describes the small possibility of unlikely events happening in the future and that it might drive the prices of assets in the present. It is also supported by large negative moves in the crypto market. Although the sample of the investigation includes a few negative shocks to the prices it still can be relevant as investing in crypto is that much riskier compared to traditional assets.

5. Discussion and Conclusion

In this section, the results of the study will be discussed together with the hypothesis and closed by a conclusion of the investigation.

5.1 Discussion.

There has not been as much research, especially on how idiosyncratic volatility is priced cross-sectionally in cryptocurrency markets, compared to traditional asset markets yet, as crypto also does not share the same length of history. As cryptocurrency gains popularity and relevancy, the gap between equity/commodities markets may narrow. This thesis helps to fill this space by a small portion. The findings of the investigation contradict classic finance theory and report the opposite results of the abnormality found by Ang et al. in the year 2006. The authors of the paper "The Cross-Section of Volatility and Expected Returns" find a negative relationship between idiosyncratic volatility and the expectancy of stock returns. This thesis reports the positive relationship between idiosyncratic volatility and the expected cryptocurrency return, by conducting the portfolio-level investigation as well as the Fama-MacBeth regression. The null hypothesis of IVOL having no effect on the expected crypto returns may be rejected due to evidence found. However, the findings are not robust to different weighting schemes, sample sizes, and holding periods. It is also not clear whether the effect would be more significant in underpriced assets.

5.2 Conclusion.

The economic implication of the findings, if the results were true, would be the possible arbitrage opportunities as the investor could realize larger profits investing in higher idiosyncratic volatility cryptocurrencies. The person would be able to take up more idiosyncratic risk and thus receive a larger compensation for it. The difference between a portfolio consisting of the highest IVOL cryptos to that of the lowest IVOL cryptos is significant. Nevertheless, the results should be interpreted carefully since to this day little research has been done on this topic in comparison to traditional assets such as stocks or commodities, and even in the traditional finance theory, the idiosyncratic volatility puzzle is considered to *yet be solved*. Which asks for further research to be done.

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