MELİSA ÖZDAMAR
ESSAYS IN ASSET PRICING
Bilkent University 2022

# ESSAYS IN ASSET PRICING

A Ph.D. Dissertation

by
MELİSA ÖZDAMAR

The Department of Business Administration
İhsan Doğramaci Bilkent University
Ankara
January 2022

*To my family*

# ESSAYS IN ASSET PRICING

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

MELİSA ÖZDAMAR

In Partial Fulfillment of the Requirements for the Degree of
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## ABSTRACT

ESSAYS IN ASSET PRICING

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This thesis is composed of four essays exploring the pricing behavior of different financial markets. In the first essay, we investigate the explanatory power of CAPM beta on cross-section of expected stock returns by allowing beta to vary according to the fluctuations in the business cycle. This study contributes to the empirical literature on time-varying beta by documenting that there exists a significant relationship between risk and return whenever we control for the output level. In the second essay, we analyze whether and how investors price the introduction of a regulation that provides a deduction for equity financing of Turkish firms listed on Borsa Istanbul. We find that investors react positively to the introduction of Allowance for Corporate Equity (ACE) regulation and the companies which the market ex-ante prices to benefit the most from the tax shield do ex-post raise more equity relative to companies which the market expects to benefit the least. Alongside of the stock markets, the cryptocurrency markets appeal high attention by the recent empirical studies since it presents a unique feature for financial investment. In the third essay, we explore the significance of maximum daily return (MAX) in the cross-sectional pricing of expected future returns in the cryptocurrency market. Our findings provide evidence for a positive and statistically significant relationship between extreme positive returns and subsequent cryptocurrency returns. Results are robust to controls for size, price, momentum, short-term reversal, liquidity, volatility, skewness, and investor attention. The final chapter focuses on how retail investor attention and institutional investor attention affect returns, idiosyncratic risk and volatility in the cryptocurrency market. We report that there exists a contrary impact of retail and institutional investor attention on cryptocurrency returns and idiosyncratic volatility, however, we show that both have an boosting effect on liquidity of the cryptocurrency market.

Keywords: Cross-section of stock returns, allowance for corporate equity, cryptocurrency market, MAX effect, idiosyncratic volatility, liquidity.

# ÖZET

VARLIK FİYATLANDIRMASI ALANINDA MAKALELER



Özdamar, Melisa

Doktora, İşletme

Tez Danışmanı: Doç. Dr. Levent Akdeniz

2. Tez Danışmanı: Doç. Dr. Ahmet Şensoy



Ocak 2022



Bu tez, farklı finansal piyasaların fiyatlama davranışlarını araştıran dört makaleden oluşmaktadır. Tezin ilk bölümünde, finansal varlıkları fiyatlama modeli risk faktörünün, konjonktür hareketlerindeki dalgalanmalara göre değişmesine izin vererek, beklenen hisse senedi getirilerinin kesiti üzerindeki açıklayıcı gücünü araştırıyoruz. Bu çalışma, ekonomik çıktı seviyelerini kontrol ettiğimizde, risk ve getiri arasında önemli bir ilişki olduğunu belgeleyerek zaman değişimli beta hakkındaki ampirik literatüre katkıda bulunmaktadır. İkinci bölümde, Borsa İstanbul'da işlem gören Türk firmalarına öz sermaye vergi finansmanı için indirim sağlayan düzenlemenin getirilmesini yatırımcıların fiyatlandırıp fiyatlamadıklarını ve nasıl fiyatlandırdıklarını analiz ediyoruz. Yatırımcıların, Kurumsal Sermaye Ödeneği (ACE) düzenlemesinin getirilmesine olumlu tepki verdiklerini ve gerçekten, piyasa fiyatlandırmasına göre vergi kalkanından en fazla fayda sağlaması beklenen şirketlerin, piyasanın en az yararlanmasını beklediği şirketlere göre daha fazla öz sermaye artırdığını görüyoruz. Hisse senedi piyasalarının yanı sıra, kripto para piyasaları, finansal yatırım için benzersiz bir altyapı sunduğundan, son ampirik çalışmalar tarafından oldukça yüksek rağbet görmektedir. Üçüncü bölümde, kripto para piyasasında gelecekteki beklenen getirilerin kesitsel fiyatlandırmasında maksimum günlük getirinin (MAX) önemini araştırıyoruz. Bulgularımız, aşırı pozitif getiriler ile müteakip kripto para birimi getirileri arasında pozitif ve istatistiksel olarak anlamlı bir ilişki olduğuna dair kanıt sağlamaktadır. Sonuçlar; büyüklük, fiyat, momentum, kısa vadeli getiri, likidite, volatilite, çarpıklık ve yatırımcı duyarlılığı kontrollerine karşı devamlı ve sağlamdır. Son bölüm, bireysel yatırımcı ilgisinin ve kurumsal yatırımcı ilgisinin kripto para piyasasındaki getirileri, özel durum riskini ve piyasa volatilitesini nasıl etkilediğine odaklanmaktadır. Bireysel ve kurumsal yatırımcıların dikkatinin kripto para getirileri ve özel durum riski üzerinde ters etkileri olduğunu, ancak her ikisinin de kripto para piyasasının likiditesi üzerinde artırıcı bir etkisi olduğu ampirik olarak gözlemlenmektedir.

Anahtar sözcükler: Hisse senedi getirilerinin kesiti, kurumsal sermaye ödeneği, kripto para piyasası, maksimum günlük getiri (MAX) etkisi, özel durum riski, likidite.

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# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# CHAPTER 1

# INTRODUCTION

## 1.1. Overview

This thesis investigates the pricing of different financial assets in various financial markets. On the one hand, the equity market has long been subjected to substantial empirical research to explore the stock return predictability. On the other hand, the rapid developments in digital technology establishes financial investors distinctive instruments within the cryptocurrency market. The uncertainty that investors face everyday affects their investment behavior and in return, prices in the financial markets. Moreover, investors do not hold homogeneous beliefs as the theory suggests. Technological innovations enable traders to not only access information easily and rapidly but also reach a limited number of resource if only grabs their attention (Kahneman and Tversky, 1973; Grossman and Stiglitz, 1980; Huberman and Regev, 2001). Therefore, information is perceived asymmetrical by the investors and therefore, the prices of financial assets are influenced by their limited assessment capabilities. Each chapter of this thesis discusses the pricing models from another viewpoint using different statistical approaches.

In Chapter 2, we focus on the variability in the cross-section of expected stock returns. The CAPM model, which theoretically documents the relationship between market risk and return, has long been subjected to criticisms depending upon its nature that is prone to erroneous empirical applications. Since beta is not a constant factor in reality, conditional CAPM gains considerable support empirically based on time-varying beta (Ferson and Harvey, 1991, 1993; Jagannathan and Wang, 1993; Bali et al., 2017). Utilizing the methodology of Fama and French (1992) and considering all non-financial firms in the NYSE, AMEX, and NASDAQ, we investigate whether CAPM beta has an explanatory power stock returns, controlling for the output level. By allowing beta variable to vary over the business cycle, we show that beta is statistically and economically significant whereas other variables such as size, book-to-market, leverage and earnings-price ratio remain insignificant to capture the stock return predictability. Results are robust to controls for recession and expansion periods separately, consideration of a narrower band over the business cycle, and alternative measure of economic conditions.

Chapter 3 discusses pricing of a new tax regulation (Allowance for Corporate Equity -ACE-) in the Turkish equity market, which enables firms to consider a deduction for equity issues, whenever they calculate taxable profits. Using the non-financial firms in BIST-100 index of Borsa Istanbul, we report that investors ex-ante price the tax shield that Turkish firms would enjoy and react positively to the introduction of a legislation that provides a deduction for new equity issues. Besides, we report that not all firms are equally affected by the equity tax shield. Cumulative abnormal returns prove significantly higher for levered firms who may find it easier to switch from debt to equity financing and for firms that have income to shield from tax. Furthermore, the most levered firms and the firms with the highest income, whom investors ex-ante expect to benefit most from the regulation, do indeed issue more equity to take advantage of the tax benefits of the new regulation. This study contributes to the literature on how tax regulation in general and ACE in particular affect stock market pricing of firms. To our knowledge, this is the first empirical study that documents whether and how investors price the introduction of ACE.

The sceptical yet unstoppable evolution of the cryptocurrency market has drawn significant investor attention recently since it offers a unique investment experience in terms of electronic payment systems and lacking a regulatory mechanism. This unusual financial market offers many different and unexplored areas of research such as the impact of maximum daily return (MAX) on cryptocurrency prices (Bali et al., 2011). In Chapter 4, we investigate the significance of extreme positive returns in the cross-sectional pricing of cryptocurrencies. Through portfolio-level analyses and weekly cross-sectional regressions on all cryptocurrencies in our sample period, we provide evidence for a positive and statistically significant relationship between the maximum daily return within the previous month (MAX) and the expected returns on cryptocurrencies. In particular, univariate portfolio analysis shows that weekly average raw and risk-adjusted return differences between portfolios of cryptocurrencies with the highest and lowest MAX deciles are 3.03% and 1.99%, respectively. Results are robust with respect to the differences in size, price, momentum, short-term reversal, liquidity, volatility, skewness, and investor sentiment.

Lastly, Chapter 5 analyzes the impact of retail investor attention and institutional investor attention on returns, idiosyncratic risk and liquidity of the cryptocurrency market. We find that retail investor attention has a negative effect on cryptocurrency returns whereas institutional investor attention has a positive effect. Besides, retail investor attention aggravates but institutional investor attention constrains the idiosyncratic risk. We find significant evidence that both retail and institutional investor attention boosts liquidity of the cryptocurrency market. We further study the potential cross-sectional variations of the investor attention impact of idiosyncratic risk and liquidity. The results indicate that retail investor attention exacerbates idiosyncratic volatility for high-cap and illiquid cryptocurrencies in the period of unstable market conditions whereas it has a constructive effect on liquidity in low global economic policy uncertainty. Even though institutional investor attention is significantly effective throughout all conditions, the absolute value of coefficients underline its constructive impact on both idiosyncratic risk and liquidity for small-cap cryptocurrencies within relatively stable and rising external market environment. The main contribution of this chapter is that, to our knowledge, it is the first study to investigate the impact of institutional investor attention on the cryptocurrency market.

# CHAPTER 2

# THE CROSS-SECTION OF EXPECTED STOCK RETURNS CONTROLLING FOR THE OUTPUT LEVEL

## 2.1. Introduction

The asset pricing literature investigates the stock return predictability over the past few decades. Extensive research has been conducted to explain the variability in the cross-section of stock returns. Although the theory emphasizes a linear and consistent relation between risk and return, currently there exists substantial empirical evidence indicating that betas vary over time and stock returns are linked to fluctuations in economic conditions. Specifically, Akdeniz (2000) documents that the dynamic relationship between risk and return is contingent upon the level of economic output. In this study, our aim is to investigate whether and how beta explains the cross-section of expected stock returns, controlling for the output level. By the replication of Fama and French (1992) methodology, we examine the validity of the Capital Asset Pricing Model (CAPM) beta, which we allow to vary over the business cycle, combined with other actors such as size, book-to-market equity, leverage and earnings-price ratios to explain stock returns, using a wider range of data for an extended period of time.

Going back to the theoretical fundamentals, the asset pricing model developed by Sharpe (1964); Lintner (1965) and Black (1972) indicate that the expected stock returns can be explained by the sensitivity of the stock to the overall movements in the market, which is represented by the beta coefficient. The model follows Tobin (1958) and Markowitz (1959) in the sense that the market portfolio is assumed to be mean-variance efficient. Empirical tests of CAPM conducted earlier in the literature by Black et al. (1972) and Fama and MacBeth (1973), mainly support the primary estimate of theoretically introduced beta being the only explanatory variable to describe cross-sectional variation across portfolios. They report an almost positive linear relationship in which high-beta stocks tend to have higher average returns in comparison with low-beta stocks.

The validity of this asset-pricing model has long been the subject of considerable academic discussions. More recently, number of factors different from the market risk coefficient have identified as a matter of empirical tests in order to better explain the cross-section of expected returns. Such anomalies of CAPM have been investigated vastly in the literature: firm capitalization by Banz (1981) and Keim (1983), earnings-price ratio by Ball (1978) and Basu (1983), ratio of book value of common equity per share to market price per share by Rosenberg et al. (1985), leverage by Bhandari (1988), book-to-market equity by Fama and French (1992) are some of the significant variables that are observed to have explanatory power over the cross-section of expected returns. In addition, Cochrane (1996) and Lettau and Ludvigson (2001b) introduce additional risk factors by regressing the market return on the dividend-to-price ratio and long-short yield spread, and a consumption-wealth-income ratio.

Initially, Banz (1981) suggests the size effect as an anomaly of capital asset pricing model and shows that small (low market value) stocks tend to have higher betas and higher average excess returns when compared to large stocks. The relationship between average return and beta for size-sorted portfolios is found to be steeper that the security market line of CAPM. Fama and French (1992) sort stocks by both size and $\beta$, and document a flat relationship, that is, the returns on high-beta stocks are not higher than the returns of low-beta stocks with the same size. Regarding the size-related empirical studies, Keim (1983, 1986), Reinganum (1983) and Roll (1983) report a size-related January effect.

Fama and French (1992) examine the joint roles of market $\beta$, size, earnings-price ratios, leverage, and book-to-market equity in cross-section of average returns on NYSE, AMEX and NASDAQ stocks. And they practically reject the inferences of CAPM based on two outcomes: the $\beta$ coefficient does not seem to explain the cross-sectional variations of expected returns, and the combination of size and book-to-market equity is found to explain significantly the cross-section of expected stock returns along with absorbing the roles of leverage and E/P variables. They conclude that neither average returns are positively related to market $\beta$ as the SLB model suggests nor it helps explaining the cross-section of expected stock returns. To the extend that empirical evidence has discredited the validity of CAPM, Fama and French (1993) assert a three-factor model, which introduces several empirical anomalies to explain cross-section of expected stock and bond returns.

As another factor of CAPM anomalies, the value effect is discussed to have the explanatory power over expected returns. In order to determine the value effect, certain ratios of market value to accounting measures such as earnings, book value of equity (Basu, 1983; Rosenberg et al., 1985; Fama and French, 1992), yield spreads between long-term and short-term interest rates and between low-and-high-quality bond yields (Campell, 1987; Fama and French, 1989; Keim and Stambaugh, 1986), the dividend yield or payout ratio (Lamont, 1998), the book-to-market ratio (Lewellen, 1999), the share of equity in new finance (Nelson, 1999; Baker and Wurgler, 2000), and the level of consumption relative to income and wealth (Lettau and Ludvigson, 2001a) are taken into consideration.

De Bondt and Thaler (1985) document that stocks with lower returns over the past three to five years tend to perform significant positive returns in the future. The momentum effect is indicated by Jegadeesh and Titman (1993) in such a way that buy stocks, which had high return performance and sell stocks, which had low return performance for the past three to twelve months, are inclined to outperform in the future. In addition to the earlier findings, Fama and French (2008) report that accruals, net stock issues, and momentum are other main reasons of asset price anomalies, regardless of the size group. Value and momentum effects in 18 emerging stock markets are examined by Cakici et al. (2013). They use notably recent data from January 1990 to December 2011, and document a strong evidence of value and momentum effects in stock markets.

Momentum effect is found to be significantly higher for small stocks. Moreover, a negative correlation between the value and momentum returns is observed. And they indicate that local factors help explain the cross-section of market returns, implying an emerging market segmentation. Carhart (1997) augments the three-factor model of Fama and French (1993) to include an additional momentum factor in the model. The indication that past winners outperform past losers is explained by his four-factor model and although the one-year momentum effect of Jegadeesh and Titman (1993) is considered, individual funds are observed in fact as not earning high returns by following the momentum strategy in stocks.

There exists a remarkable literature on liquidity as a predictor of stock returns. Primarily, Kyle (1985) states three liquidity characteristics, depth, tightness and resilience. Several different dimensions of market liquidity such as number of shares tradable at bid-offer prices, immediacy, bid-ask spread, are identified by Harris (1990) and O'Hara (1995). Therefore, multidimensional features of liquidity entail the usage of different measures. Bernstein (1987) investigates the liquidity concept in the common stock market and he concludes that even though both liquidity and efficiency are important characteristics of a financial market, they are not necessarily compatible; higher liquidity leads to lower efficiency in the market. Amihud and Mendelson (1986)) analyze a positive relationship between expected asset returns and relative bid-ask spread – that implies illiquidity. Brennan et al. (1998) examine the risk-adjusted returns on the individual securities, a strong negative relationship is determined between average returns and the trading volume – that is compatible with the liquidity premium of asset prices. Contrarily, Pastor and Stambaugh (2003) find evidence that the cross-section of expected stock returns are related to the stocks' sensitivities to innovations in aggregate liquidity. Substantial results have shown that the higher the sensitivity, the higher the expected returns, even after exposures to the market return as well as size, value and momentum factors are accounted for. Thus, stocks with higher return exposure to the market-wide liquidity fluctuations perform higher expected returns.

Going back to the beginning, for investors to construct an efficient portfolio with the highest expected return – given their level of risk appetite, they need to the establish the tangency portfolio, where the capital market line and mean-variance efficient frontier coincides in theory. The aforementioned tangency portfolio is supposed to be the optimal weighting adjusted between all the risky and risk-free assets existing within the market. However, it is not always possible to calculate the tangency portfolio since the mean and covariance values are empirically unobservable in general. Even though all of the mean, variance and covariance values are to be known, the market includes countless number of assets and therefore, there exists infinite permutations of portfolio combinations essentially and calculation is not likely. CAPM is the theory, which is developed for facilitating the allowance for the investors to reasonably deduce the efficient portfolio.

The CAPM is based upon certain assumptions such as the investors consider only the mean and variances of their portfolio's return and hold homogeneous beliefs about the means and variances of all feasible portfolios and the frictionless markets. According to the CAPM theory, the tangency portfolio is the market portfolio itself. And every investor should optimally hold a combination of the risk-free asset and the market portfolio. The key implication here is that although it is not possible to estimate the tangency portfolio, there is no need to select the tangency portfolio for the optimal investment decision; what CAPM suggests is that the investor can simply choose a market portfolio – mimicking the returns of a tangency portfolio, and still achieve an optimal, i.e. mean-variance efficient, level of investment.

However, CAPM has been subjected to multiple criticisms and most of the empirical tests of CAPM has yielded some anomalies. Roll (1977) criticizes the CAPM theory viciously and he points that not being possibly observable and identifiable renders the market portfolio inherently untestable. There exist numerous options for market proxies, yet none of them is certain to mimic the market portfolio returns accurately. But the market portfolio is the focus of attention driving the results of CAPM, thus Roll indicates that the empirical tests utilizing market proxies do not provide clear evidence whether to accept or reject the CAPM theory. On the one hand, the expected returns of all assets are linearly correlated with their beta values when calculated with regard to the tangency portfolio. However, the market proxy might still be mean-variance efficient, even though CAPM is wrong and the actual market portfolio is not mean-variance efficient, as a consequence the test fails to reject the CAPM theory (Type II error). On the other hand, in case CAPM is actually true, the market proxy might fail to imitate the market portfolio returns and thus may not be mean-variance efficient. As a result, the test using inefficient market portfolio rejects the CAPM theory incorrectly (Type I error).

Empirical tests intend to test the validity of unconditional CAPM are virtually testing whether the market proxy is mean-variance efficient. Besides, various kinds of tests considering stock returns vs. business cycle, output growth and/or economic expansions have been performed to test CAPM theory. The studies conducted so far revealed the fact that CAPM beta is not sufficient empirically to explain stock returns and thus, alternative models have been constructed with better predictors. Multi-factor models indicate to show the explanatory power of size effect, value effects such as book-to-market equity, dividend yield and level of consumption, momentum effects and liquidity effects on the cross-section of expected returns. On the other hand, studies reveal the time-varying nature of estimated betas and report that conditional betas help explain the predictability of stock returns, which is sensitive to economic conditions (Harvey, 1991; Ferson and Harvey, 1991, 1993). Ghysels (1998) points out the importance to capture the dynamics of beta risk while applying the conditional models. Akdeniz et al. (2003) and Yayvak et al. (2015) utilize the threshold CAPM model to explain the changes in beta and market risk, which substantiate with respect to the economic environment.

Jagannathan and Wang (1996) state that erroneous mistake of static CAPM is because it assumes that stock return is a good proxy for aggregate wealth portfolio and beta is a constant factor in time. By relaxing these assumptions and allowing beta to vary over the business cycle, many studies find supporting evidence for the time-varying conditional CAPM to explain cross-section of expected returns (Jagannathan and Wang, 1993, 1996; Bali et al., 2017). Akdeniz (2000) documents that the dynamic relationship between return and risk is dependent on the output level. By conducting simulation analysis using stylized facts to produce data, the paper investigates the empirical predictions of CAPM. In order to avoid from a potential fallacy originated from the averaging process, the data is split according to the output level and only those periods with similar levels of output are considered for the replication of Fama and French (1992). Results show supporting evidence for a significant CAPM beta, where the size effect vanishes once the output level is controlled.

In this paper, we investigate the binary and multiple relations between beta, size, book-to-market, leverage, and earnings-price ratio in the cross-section of average stock returns. Following Fama and French (1992), our data incorporates NYSE, AMEX, and NASDAQ stocks and our analysis spans the period from the beginning of July 1963 to the end of December 2017. First, we replicate the Fama and French (1992) methodology and obtain very similar findings in cross-sectional regression model. Then, we detrend the US real GDP data with respect to NBER business cycle dates and designate a symmetrical gap around the mean value. This procedure enables us to examine the periods having similar economic conditions and consider betas varying over the business cycle. By utilizing only those periods, we conduct the same regression analysis. Contrary to the findings of Fama and French (1992) and in line with the findings of Akdeniz (2000), the average slopes of beta obtained from univariate regression prove significant for both 1963-1990 period (0.12% with a t-statistic of 2.48) and 1963-2017 period (0.53% with a t-statistic of 1.93). Moreover, the explanatory power of size and book-to-market on expected stock returns disappear once we control for the output level. The results are robust to controls for peak and trough periods alone, designating a narrower gap, and alternative measure of the economic conditions.

This study contributes to the literature by investigating the relationship between risk and return from another angle. We test the Fama and French (1992) model using a broader data for an extended period of time for examining the validity of the CAPM beta combined with other actors such as size, book-to-market equity, leverage and earnings-price ratios to explain the cross-section of expected returns. Taking into consideration the economic output levels, we control for the business cycles, and we partially document that CAPM beta is still alive. Besides, we contribute to the existing literature on time-varying beta by allowing portfolio betas to vary according to the fluctuations in the business cycle. By this way, the analyses enable us to capture the potential explanatory power of non-static beta, which is evidenced in the empirical literature (Wang, 2003; Petkova and Zhang, 2005; Santos and Veronesi, 2006; Basu and Stremme, 2007; Adrian and Franzoni, 2009). To our knowledge, this is the first study to test a linear factor model by controlling for detrending real GDP data as the economic output. Moreover, our methodology emphasizes a changing risk variable based on similar economic conditions to explain return, which disentangles the erroneous assumption of constant asset betas.

The remainder of the paper is organized as follows. Section 2.2 provides the data source, sample selection and variable description. Section 2.3 discusses the methodology of beta calculation, detrending real GDP data based on the business cycle fluctuations, and reports the empirical results of the cross-sectional regression model. In Section 2.4, we conduct additional analysis to test the robustness of our findings. Finally, Section 2.5 concludes.

## 2.2. Data and variable description

### 2.2.1. Data source and sample selection

Following Fama and French (1992), we use all non-financial firms in the NYSE, AMEX, and NASDAQ.[1] We collect return information from CRSP and merged annual COMPUSTAT data of income statement and balance sheet. Our sample period spans from the beginning of July 1963 through the end of December 2017. We match the stock returns from July of year $t$ to June of year $t+1$ with the accounting data of year-end $t-1$. To be included in the sample, a firm should have active trading activity for December of year $t-1$ and June of year $t$, and it must have accounting information for year-end of $t-1$.

### 2.2.2. Variable construction

We construct most of our variables following Fama and French (1992). We use market equity of a firm at the end of December of year $t-1$ to calculate its book-to-market, leverage and earnings-price ratios for $t-1$, and its market equity for June of year $t$ to measure its size. The calculations for market equity (ME),

[1] We consider only non-financial firms in the sample because the understanding and levels of leverage for financial and non-financial firms are substantially different. Although high leverage is common for financial firms, it might mean financial distress for non-financials.

book equity (BE)[2], and stockholder's equity are as described in equation (2.1), equation (2.2) and equation (2.3), respectively.

$$\begin{aligned}\text{Market Equity (ME)} &= \text{CRSP Price } x \\ &\text{Shares outstanding (CRSP of COMPUSTAT)}\end{aligned} \tag{2.1}$$

$$\begin{aligned}\text{Book Equity (BE)} &= \text{COMPUSTAT Book value of stockholder's equity} + \\ &\text{Balance sheet deferred taxes } + \text{Investment tax credit (if available)} - \\ &\text{Book value of preferred stock}\end{aligned} \tag{2.2}$$

$$\begin{aligned}\text{Stockholder's equity} &= \text{Book value of common equity} + \\ &\quad \text{Par value of preferred stock} \\ &= \text{Book value of assets } - \text{Total liabilities}\end{aligned} \tag{2.3}$$

Then, Book-to-Market (BE/ME) ratio used to form portfolios in June of year *t* equals the ratio of BE for the fiscal year ending in calendar year *t-1* to ME at the end of December of *t-1*. Besides, we compute earnings (E) as described in equation (2.4).

$$\begin{aligned}\text{Earnings (E)} &= \text{COMPUSTAT Total earnings before extraordinary items} \\ &+ \text{Income statement deferred taxes } - \text{Preferred dividends}\end{aligned} \tag{2.4}$$

Then, Earnings/Price (E/P) ratio used to form portfolios in June of year *t* equals the ratio of E for the fiscal year ending in calendar year *t-1* to ME at the end of December of *t-1*. Finally, we use COMPUSTAT total book assets (A) to calculate two different leverage measures, market leverage as described in equation (2.5), and book leverage as described in equation (2.6).

$$\text{Market Leverage} = \text{Book Assets (A) / Market Equity (ME)} \tag{2.5}$$

$$\text{Book Leverage} = \text{Book Assets (A) / Book Equity (BE)} \tag{2.6}$$

Table 2.1 shows the descriptive statistics of variables for the period of Fama and French (1992) paper, between July 1963 and December 1990. The average number of firms for this period is 8,863. Table 2.2 reports the descriptive

[2] Depending on the availability, we use in the order of redemption, liquidation, or par value to estimate the book value of preferred stock.

statistics of variables for the period between July 1963 to December 2017. The average number of firms for the period has increased to 16,473. The documented standard deviation of each variable is high enough to indicate that volatility of stocks greatly differ.

——————————**INSERT TABLES 2.1 and 2.2 HERE**——————————

## 2.3. Empirical results

### 2.3.1. Beta estimation and regression model

Our initial step is to replicate the methodology of Fama and French (1992) to make sure our findings are in line and we are on the right track to investigate the role of real GDP when estimating predicted returns in the stock market. To estimate beta, we first sort NYSE stocks by ME to find NYSE decile breakpoints. Based on these breakpoints, we allocate our sample consisting of NYSE, AMEX and NASDAQ stocks, to ten size portfolios. Then, we subdivide each size decile into ten portfolios with regards to pre-ranking betas, which are computed on monthly returns between two-five years prior to July of year $t$. Therefore, in June of each year, we assign firms to 100 size-beta portfolios and we estimate equal-weighted monthly portfolio returns for the next twelve months in that year. These returns constitute the post-ranking monthly returns for beta estimation. Utilizing CRSP value-weighted portfolio of NYSE, AMEX, and NASDAQ stocks as a proxy for the market portfolio, we estimate betas by calculating the sum of slopes from the regression of the portfolio return on the prior and current month's market portfolio returns. We assign the estimated post-ranking beta of a size-beta portfolio to each stock in the portfolio. Table 2.3 shows average returns (Panel A), post-ranking betas (Panel B), and average size (Panel C) of the portfolios formed on size (Down) and pre-ranking beta (Across) for the period between July 1963 and December 1990, following Fama and French (1992). The post-ranking betas across all 100 size-$\beta$ range from 0.52 to 1.71, which is nearly 2.5 times the spread of 0.48, the range obtained using size portfolios alone. This indicates that the range of post-ranking betas enhances by forming portfolios on both size and pre-ranking betas.

INSERT TABLE 2.3 HERE

Using the post-ranking beta variables allocated individually to each stock, we conduct the cross-sectional regression approach of Fama and MacBeth (1973). In particular, for each month, we regress the stock returns on size, book-to-market equity, market leverage, book leverage, and earnings/price ratio. Each variable is winsorized at 0.5% level from upper and lower tails without removing any observation. The time-series averages of the monthly regression slopes and the Newey and West (1987) adjusted t-statistics are reported in Table 2.4 for July 1963 to December 1990. The results in Table 2.3 and Table 2.4 are very similar to those documented in the Fama and French (1992), which shows that the replication of the methodology works fine. Although beta is insignificant, size and book-to-market variables are significant to explain the cross-section of average stock returns. The univariate regression of ln(ME) reports a coefficient of -0.15% with a t-statistic of -2.94 whereas the univariate regression of ln(BE/ME) reports a coefficient of 0.40% with a t-statistic of 5.32. Average slopes of the two leverage variables, market leverage and book leverage, are statistically significant with opposite signs and same magnitudes in absolute value. We use earnings-price dummy variable whenever earnings are negative since firms with only positive earnings could have an explanation over the relationship between earnings-price and expected returns. Results indicate that firms with positive earnings have significantly higher average stock returns.

INSERT TABLE 2.4 HERE

### 2.3.2. Business Cycle Stage Formation

We collect the expansion and contraction dates announced by the National Bureau of Economic Research (NBER) for the sample period. Then, we separate the corresponding business cycles into four different stages. The purpose of this division is to separate peak and trough periods into early and late segments so that we can analyze whether and how different stages affect average stock returns and other stock characteristics. Table 2.5 lists the actual NBER peak and trough dates in Panel A and how the business cycles are divided into four distinct stages in Panel B.[3] We conduct cross-sectional regressions of stock returns on the variables as discussed in Section 2.3.1 and four additional dummy variables. These different dummy variables are assigned regarding the four different stages formed according to NBER business cycle dates. Table 2.6 presents the regression results for the period from July 1963 to December 1990 in the first two rows and results for the period from July 1963 to December 2017 in the last two rows. The results are very similar for both sample periods, which point that investor expectations about the stock returns are positive and statistically significant for Stage I and Stage II, where the beginning and continuation periods of expansions are considered, respectively. However, for Stage III, the period of early recessions, we obtain highly insignificant coefficients. Finally, at Stage IV, the dummy coefficients are nearly two-fold of those of the first two stages and statistically significant, which indicate that the investor expectations increase greatly in the second stages of recessions, just before the expansions begin. The regression results signal that the significance of the size and book-to-market variables documented by Fama and French (1992) might differ whenever betas are allowed to vary over the business cycle.

——————**INSERT TABLES 2.5 and 2.6 HERE**——————

### 2.3.3. Detrending real GDP data

The replication process and analysis regarding different business cycle stages pave the way for our next step before employing our baseline regression model. Considering NBER business cycle dates, we detrend the quarterly real gross domestic product (GDP) data of United States (US) using Hodrick-Prescott (HP) filter. HP filter is one of the most common econometric methods utilized in macroeconomics for partitioning the long-run trend of data series from short-run fluctuations (Hodrick and Prescott, 1997; De Jong and Sakarya, 2016).[4] Figure 2.1 shows the US real GDP increase (top graph) and the percentage change of US real GDP (bottom graph) throughout the years of our sample period. After

[3] When there are an odd number of months between trough and peak dates, the extra month was included in the earlier stage. The actual month a trough date occurs is included in Stage IV, and the actual month a peak date occurs is included in Stage II.

[4] Allowing for the trend dates to coincide with the NBER chronology, different methods of decomposition yield similar results (Perron and Wada, 2009; Yamada, 2018).

the process of HP filtering, the detrending US real GDP data is shown in Figure 2.2. Simply, the trending data has been smoothed out the short-term fluctuations towards following an increasing and decreasing pattern representing the long-term trends around the x-axis.

——————————**INSERT FIGURES 2.1 and 2.2 HERE**——————————

### 2.3.4. Cross-sectional regression model controlling for the output level

The main aim of this study is to investigate whether and how beta, size, book-to-market, leverage, and earnings-price variables affect cross-section of average stock returns, controlling for the output level. Detrending real GDP data helps us to consider those periods, which have output levels that are close to the mean output level. We designate a gap surrounding the x-axis in the positive and negative sides as shown by the symmetrical red lines in Figure 2.2. Then, we rerun the same Fama and French (1992) methodology described in Section 2.3.1 and conduct the regression model with regards to only those periods remaining in between the two bands. Table 2.7 and Table 2.8 present the baseline cross-sectional regression results of the expected stock returns for the period spanning from July 1963 through the end of December 1990 and for the period spanning from July 1963 through the end of December 2017, respectively.

——————————**INSERT TABLES 2.7 and 2.8 HERE**——————————

Empirical studies on conditional betas document an intertemporal relationship between equity portfolio risk and expected returns whenever betas are allowed to vary over time (Bollerslev et al., 1988; Bali, 2008; Bali and Engle, 2010; Bali et al., 2017). Similar to those studies, our goal is to employ time-varying portfolio risk, but different from that approach, we calculate varying betas throughout the business cycle. The average slope from monthly univariate regression of average stock returns on beta is 0.12% (0.53%), with a Newey-West adjusted t-statistic of 2.48 (1.93) for the period between 1963-1990 (1963-2017). The statistical significance of beta remains solid in all of the multivariate regression models for both periods. However, the significance of size and book-to-market variables documented by Fama and French (1992) disappears whenever the output level is controlled and beta is allowed to vary over the business cycle. Similarly, market leverage, book leverage and earnings/price ratio remain insignificant to explain expected stock returns. In the full specifications, the beta coefficient is reported as 0.12% with a Newey-West adjusted t-statistic of 2.59 in Table 2.7 and as 0.47% with a Newey-West adjusted t-statistic of 1.94 in Table 2.8. The results indicate that neither the impact level nor the significance level change with additional explanatory variables, which persist insignificant at all times. These findings add another dimension to the empirical studies such as Akdeniz (2000), Basu and Stremme (2007), and Adrian and Franzoni (2009), which signal a potential explanatory power of a non-static beta on cross-sectional returns.

### 2.4. Robustness checks

#### 2.4.1. Peak and trough periods

In the previous section, we document that controlling for the output level, beta is significant to explain the cross-section of expected stock returns. Besides, when we allow for variation in beta depending on the business cycle periods, there remains no signs of a reliable relation between size or book-to-market variables and average return as well as the earnings-price ratio and the opposite roles of market leverage and book leverage to capture the expected stock returns as evidenced by Fama and French (1992). In this section, our main purpose is to investigate the robustness of beta significance by further separating the output information into peak and trough periods. Similar to the methodology used in Section 2.3.4, we individually control for the output level by considering only those periods where US real GDP experience expansions or recessions. Then we apply the same procedure as discussed in Section 2.3.1. Table 2.9 reports the cross-sectional regression results of the expected stock returns of peak periods in Panel A and trough periods in Panel B for the period spanning from July 1963 through the end of December 1990. Similarly, Table 2.10 shows the regression results of peak periods in Panel A and trough periods in Panel B for the period spanning from July 1963 through the end of December 2017.

**INSERT TABLES 2.9 and 2.10 HERE**

Recent literature argues that betas vary over the business cycle and these time-varying betas partially explain the documented size and book-to-market impact (Lettau and Ludvigson, 2001b; Wang, 2003; Petkova and Zhang, 2005; Santos and Veronesi, 2006; Ang and Chen, 2007; Adrian and Franzoni, 2009). Our study additionally investigate the role of beta in explaining stock returns conditioning on the recession and expansion periods. Table 2.9 and Table 2.10 indicate that the significance of beta persists in case we consider peak periods and trough periods separately. Moreover, the significance of beta is higher in peak periods than in trough periods. The average slopes from the monthly regressions of returns on beta alone are 0.25% (with a t-statistic of 3.48) and 0.83% (with a t-statistic of 4.23) for the peak periods in between 1963-1990 and 1963-2017, respectively. For the trough periods, coefficients are 0.23% (with a t-statistic of 1.98) and 0.24% (with a t-statistic of 1.96) as reported in Table 2.9 and 2.10, respectively.

### 2.4.2. Narrower gap

In Section 2.3.4, we fit symmetrical bands and use the periods remaining in between these two lines to allow beta vary over the business cycle. In this section, we narrow down the gap in between these two bands further to explore the robustness of beta significance on expected stock returns. Figure 2.3 shows the narrower symmetrical lines designated on the detrending real GDP graph. We follow the same methodology and conduct cross-sectional regression using the periods remaining between the marked gap. This allows us to consider similar output levels by which the fluctuations in beta do not influence the validity of the model. Table 2.11 and Table 2.12 indicate the cross-sectional regression results of the stock returns for the 1963-1990 period and 1963-2017 period, respectively. Results emphasize the significance of beta and insignificance of other variables. The average beta coefficients prove positive and statistically significant at 1% significance level whereas all other variables remain highly insignificant at univariate and multivariate regressions. Utilizing a narrower gap confirms the importance of calculating pre-ranking betas accurately by controlling for the business cycle fluctuations, and then establishing the regression model on solid basis.

————INSERT FIGURE 2.3, TABLES 2.11 and 2.12 HERE————

### 2.4.3. Alternative measure of the output

In the study, we employ US real GDP data as the measure of output. In order to further investigate the persistence of beta significance and better capture the effect of beta on cross-section of average stock returns, we use an alternative measure of output. Following Afshar et al. (2007); McMillan (2021), we collect the Purchasing Manager's Index (PMI) monthly data from Bloomberg Terminal.[5] By constructing two symmetrical lines around the mean value of PMI (as shown in Figure 2.4) and applying the same methodology, we conduct Fama and French (1992) cross-sectional regression analysis. Table 2.13 and Table 2.14 present the regression results of the expected stock returns using an alternative measure of US economic condition for the 1963-1990 period and 1963-2017 period, respectively. The coefficients are very similar to those reported in Table 2.7 and Table 2.8. The findings evidence that the results of this paper are not dependent upon different measures of business cycles and beta significantly explains future stock returns once the output level is controlled.

————INSERT FIGURE 2.4, TABLES 2.13 and 2.14 HERE————

## 2.5. Conclusion

Following Akdeniz (2000), this study aims to replicate the asset-pricing model of Fama and French (1992) to investigate the binary and multiple relations between market $\beta$, size, book-to-market equity, leverage, earnings-price ratios in the cross-section of average returns on NYSE, AMEX and NASDAQ stocks, and try to evaluate the joint roles in between by allowing beta to vary according to the fluctuations in the business cycle. In particular, controlling for the output level,

[5] PMI is a composite index referring to seasonally adjusted diffusion indices. It is an important indicator used by industrialized economies to evaluate the confidence on future economic performance and growth. For more information on PMI, please refer to https://data.nasdaq.com/data/ISM/MAN_PMI-pmi-composite-index.

i.e. the real GDP figures, the objective of this study briefly is to analyze empirically the validity of CAPM beta to explain the expected stock returns. Fama and MacBeth (1973) regression results give statistically significant beta coefficients to explain the cross-section of expected stock returns. Univariate regressions give average coefficients of 0.12% (with a t-statistic of 2.48) and 0.53% (with a t-statistic of 1.93) for the period between 1963-1990 and 1963-2017, respectively. Similarly, multivariate regression results report beta coefficients of 0.12% (with a t-statistic of 2.59) and 0.47% (with a t-statistic of 1.94), respectively. Once the output level is controlled and beta is allowed to vary over the business cycle, the significance of size and book-to-market documented by Fama and French (1992) vanishes and all explanatory variables except beta remain insignificant. The persistence of the significant relationship between risk and return is robust to controls for recession and expansion periods separately, test of a narrower gap within the business cycle, and alternative measure of economic conditions.

This study invalidates the general consensus that CAPM is unable to explain the cross-sectional stock returns. The model is fragile in nature since it is prone to variable misspecification and therefore, mispricing of financial assets. The role of this paper is to highlight the empirical fallacy of considering a static beta as well as the importance of time-varying market beta calculation with respect to business cycle fluctuations. We believe this research study is important with respect to enlightening the empirical utilization of the Capital Asset Pricing Model, which is used by the practitioners within the world of finance to explain the expected stock returns over the course of many years. This paper substantiates the need of an accurate model specification and highly promising for further development, nevertheless, the pursue of a satisfactory specification still continues.

*Table 2.1:* Descriptive statistics of the main variables for 1963-1990 period
Table reports summary statistics of the main variables used in the study. The sample is merged across two databases, CRSP and COMPUSTAT spanning the period from July 1, 1963 to December 31, 1990. Minimum, maximum, mean, median, and standard deviations of each variable from monthly calculations are shown. The definitions of the variables are as described in Section 2.2.2.

| | Minimum | Maximum | Mean | Median | St Dev |
|---|---|---|---|---|---|
| Return | -0.9167 | 8.0714 | 0.0112 | 0.0000 | 0.1534 |
| ME | 0.0008 | 184,120 | 383 | 38 | 2,016 |
| BE | -5,553 | 87,224 | 235 | 24 | 1,363 |
| BE/ME | -129,300 | 261,840 | 6 | 0.6961 | 696 |
| A/ME | 0.0002 | 399,440 | 16 | 1 | 1,275 |
| A/BE | -11,894 | 4,053 | 2 | 2 | 49 |
| E/P | -16,256 | 39,153 | 0.5430 | 0.0667 | 103 |
| Number of Firms | 8,863 | 8,863 | 8,863 | 8,863 | 8,863 |

*Table 2.2:* Descriptive statistics of the main variables for 1963-2017 period

Table reports summary statistics of the main variables used in the study. The sample is merged across two databases, CRSP and COMPUSTAT spanning the period from July 1, 1963 to December 31, 2017. Minimum, maximum, mean, median, and standard deviations of each variable from monthly calculations are shown. The definitions of the variables are as described in Section 2.2.2.

| | Minimum | Maximum | Mean | Median | St Dev |
|---|---|---|---|---|---|
| Return | -0.9722 | 19 | 0.0119 | 0.0000 | 0.1819 |
| ME | 0.0008 | 734,260,000 | 20,958 | 90 | 3,021,500 |
| BE | -36,060 | 359,960 | 658 | 42 | 4,806 |
| BE/ME | -129,300 | 370,860 | 6 | 0.5384 | 891 |
| A/ME | 0.0000 | 1,377,700 | 19 | 1 | 2,793 |
| A/BE | -11,894 | 87,702 | 3 | 2 | 217 |
| E/P | -62,446 | 70,845 | 0.2642 | 0.0423 | 163 |
| Number of Firms | 16,473 | 16,473 | 16,473 | 16,473 | 16,473 |

*Table 2.3:* Average monthly returns, post ranking betas and average size of portfolios sorted on size and then pre-ranking betas

Table reports average monthly returns (Panel A), post-ranking betas (Panel B) and average size (Panel C) over the period from the beginning of July 1963 to the end of December 1990. Average monthly returns are the time-series averages of the monthly equal-weighted portfolio returns, in percent. Post-ranking betas of each portfolio are calculated as the sum of the regression slopes from a regression of monthly returns on the prior and current month's returns on the value-weighted portfolio of NYSE, AMEX, and NASDAQ stocks. The average size of a portfolio equals the time-series average of monthly ln(ME) averages for stocks in the portfolio.

*Panel A. Average Monthly Returns (in Percent)*

| | All | Low-$\beta$ | $\beta$-2 | $\beta$-3 | $\beta$-4 | $\beta$-5 | $\beta$-6 | $\beta$-7 | $\beta$-8 | $\beta$-9 | High-$\beta$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Small-ME | 1.50 | 1.69 | 1.55 | 1.77 | 1.63 | 1.54 | 1.52 | 1.36 | 1.60 | 1.49 | 1.39 |
| ME-2 | 1.27 | 1.22 | 1.38 | 1.36 | 1.29 | 1.63 | 1.65 | 1.35 | 1.34 | 1.38 | 1.12 |
| ME-3 | 1.22 | 1.09 | 1.21 | 1.08 | 1.66 | 1.31 | 1.17 | 1.29 | 1.30 | 1.29 | 0.78 |
| ME-4 | 1.24 | 1.18 | 1.15 | 1.49 | 0.99 | 1.37 | 1.08 | 1.45 | 1.11 | 1.35 | 0.99 |
| ME-5 | 1.30 | 1.28 | 1.44 | 1.38 | 1.42 | 1.40 | 1.17 | 1.14 | 1.31 | 1.19 | 1.07 |
| ME-6 | 1.18 | 1.05 | 1.50 | 1.25 | 1.17 | 1.13 | 1.21 | 1.15 | 0.99 | 1.05 | 1.01 |
| ME-7 | 1.09 | 0.91 | 1.23 | 1.22 | 1.01 | 1.17 | 1.16 | 1.24 | 0.66 | 1.32 | 0.75 |
| ME-8 | 1.12 | 0.89 | 0.99 | 1.31 | 1.17 | 1.25 | 0.98 | 1.17 | 1.07 | 0.99 | 0.96 |
| ME-9 | 1.03 | 0.93 | 0.88 | 0.97 | 1.16 | 1.10 | 1.23 | 1.03 | 0.87 | 0.91 | 0.62 |
| Large-ME | 0.99 | 1.03 | 0.95 | 1.08 | 0.95 | 0.99 | 0.89 | 1.05 | 0.73 | 0.74 | 0.59 |

*Panel B. Post-Ranking $\beta$s*

| | All | Low-$\beta$ | $\beta$-2 | $\beta$-3 | $\beta$-4 | $\beta$-5 | $\beta$-6 | $\beta$-7 | $\beta$-8 | $\beta$-9 | High-$\beta$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Small-ME | 1.42 | 1.04 | 1.21 | 1.27 | 1.35 | 1.36 | 1.39 | 1.42 | 1.57 | 1.62 | 1.68 |
| ME-2 | 1.38 | 0.89 | 1.17 | 1.12 | 1.20 | 1.34 | 1.39 | 1.39 | 1.47 | 1.63 | 1.71 |
| ME-3 | 1.35 | 0.90 | 1.11 | 1.06 | 1.13 | 1.20 | 1.33 | 1.36 | 1.46 | 1.52 | 1.69 |
| ME-4 | 1.33 | 0.83 | 1.02 | 1.07 | 1.10 | 1.26 | 1.37 | 1.35 | 1.48 | 1.55 | 1.66 |
| ME-5 | 1.26 | 0.66 | 0.82 | 1.01 | 1.07 | 1.22 | 1.25 | 1.35 | 1.41 | 1.49 | 1.67 |
| ME-6 | 1.22 | 0.59 | 0.78 | 0.99 | 1.12 | 1.18 | 1.25 | 1.29 | 1.43 | 1.46 | 1.64 |
| ME-7 | 1.19 | 0.56 | 0.88 | 0.96 | 1.12 | 1.13 | 1.23 | 1.27 | 1.37 | 1.44 | 1.65 |
| ME-8 | 1.10 | 0.52 | 0.75 | 0.94 | 1.02 | 1.13 | 1.19 | 1.25 | 1.30 | 1.32 | 1.55 |
| ME-9 | 1.04 | 0.61 | 0.71 | 0.89 | 1.00 | 1.04 | 1.20 | 1.15 | 1.29 | 1.26 | 1.48 |
| Large-ME | 0.94 | 0.59 | 0.71 | 0.79 | 0.88 | 0.96 | 1.06 | 1.11 | 1.16 | 1.19 | 1.42 |

| *Panel C. Average Size (ln(ME))* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Low-$\beta$ | $\beta$-2 | $\beta$-3 | $\beta$-4 | $\beta$-5 | $\beta$-6 | $\beta$-7 | $\beta$-8 | $\beta$-9 | High-$\beta$ |
| Small-ME | 2.50 | 2.31 | 2.49 | 2.53 | 2.54 | 2.54 | 2.51 | 2.54 | 2.50 | 2.49 | 2.36 |
| ME-2 | 3.57 | 3.63 | 3.34 | 3.19 | 3.47 | 3.38 | 3.38 | 3.93 | 3.96 | 3.89 | 3.71 |
| ME-3 | 3.93 | 3.90 | 3.58 | 3.93 | 3.98 | 3.84 | 4.01 | 4.18 | 4.09 | 4.01 | 4.14 |
| ME-4 | 4.12 | 4.07 | 4.27 | 4.14 | 4.46 | 4.07 | 4.66 | 4.44 | 4.55 | 4.55 | 4.25 |
| ME-5 | 4.49 | 4.28 | 4.41 | 4.27 | 4.97 | 4.36 | 4.92 | 4.90 | 4.89 | 4.69 | 4.76 |
| ME-6 | 4.89 | 4.59 | 5.01 | 5.14 | 4.99 | 4.97 | 5.03 | 5.01 | 5.12 | 5.02 | 4.89 |
| ME-7 | 5.25 | 5.10 | 5.34 | 5.65 | 5.17 | 5.13 | 5.67 | 5.69 | 5.67 | 5.55 | 5.13 |
| ME-8 | 5.69 | 5.89 | 6.01 | 6.13 | 5.98 | 5.97 | 5.99 | 5.93 | 5.89 | 5.72 | 5.55 |
| ME-9 | 6.14 | 6.13 | 6.53 | 6.89 | 6.39 | 6.74 | 6.77 | 6.45 | 6.46 | 6.38 | 6.24 |
| Large-ME | 6.66 | 6.60 | 6.99 | 7.32 | 7.71 | 7.85 | 7.84 | 7.21 | 7.02 | 6.88 | 6.76 |

*Table 2.4:* Cross-sectional predictability of stock returns

Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 1990. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of firms is 2457.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.14 | | | | | | |
| (0.50) | | | | | | |
| | -0.15*** | | | | | |
| | (-2.94) | | | | | |
| -0.56 | -0.14*** | | | | | |
| (-1.22) | (-2.97) | | | | | |
| | | 0.40*** | | | | |
| | | (5.32) | | | | |
| | | | 0.38*** | -0.38*** | | |
| | | | (4.98) | (-3.89) | | |
| | | | | | 0.28 | 3.42*** |
| | | | | | (1.34) | (3.39) |
| | -0.12** | 0.27*** | | | | |
| | (-2.50) | (3.86) | | | | |
| | -0.13*** | | 0.26*** | -0.36*** | | |
| | (-2.64) | | (3.57) | (-3.69) | | |
| | -0.17*** | | | | 0.08 | 2.03** |
| | (-3.64) | | | | (0.45) | (2.07) |
| | -0.14*** | 0.25*** | | | -0.15 | 0.87 |
| | (-3.13) | (3.56) | | | (-0.85) | (0.99) |
| | -0.15*** | | 0.24*** | -0.33*** | -0.13 | 0.82 |
| | (-3.21) | | (3.24) | (-3.36) | (-0.76) | (0.89) |

*Table 2.5:* NBER peak and trough dates and business-cycle stage formation
Table reports the National Bureau of Economic Research (NBER) business cycle reference dates and dates of business-cycle stage formation. Panel A lists the actual peak and trough dates as set by NBER for the sample period. Panel B reports how the corresponding business cycles were separated into four different stages. Number of months in duration are given in parentheses. $n$ equals the number of months within the stage and the total number of months equals 682.

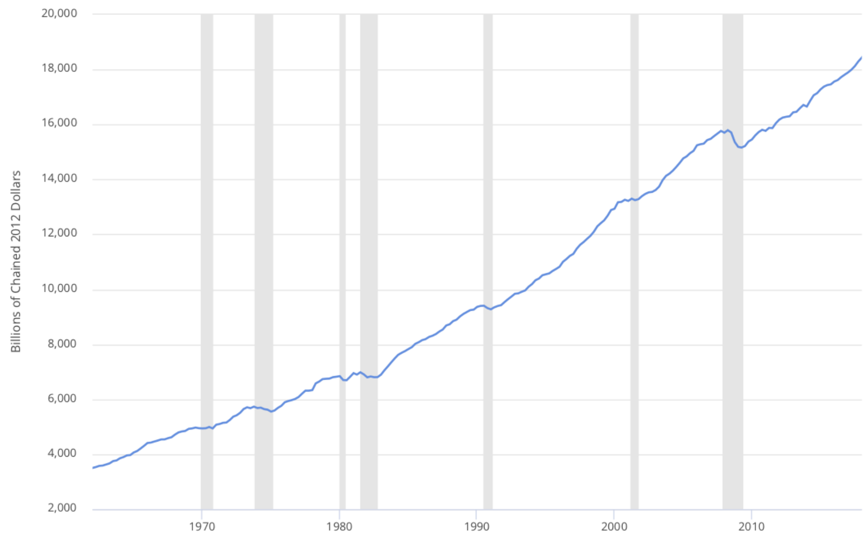
| *Panel A. NBER business cycle reference dates* | |
|---|---|
| Trough | Peak |
| February 1961 | April 1960 |
| November 1970 | December 1969 |
| March 1975 | November 1973 |
| July 1980 | January 1980 |
| November 1982 | July 1981 |
| March 1991 | July 1990 |
| November 2001 | March 2001 |
| June 2009 | December 2007 |
| | February 2020 |

| *Panel B. Dates of stages and months in duration* | | | |
|---|---|---|---|
| Stage I (n=313) | Stage II (n=286) | Stage III (n=42) | Stage IV (n=41) |
| 3/61–7/65 (53) | 8/65–12/69 (53) | 1/70–6/70 (6) | 7/70–11/70 (5) |
| 12/70–5/72 (18) | 6/72–11/73 (18) | 12/73–7/74 (8) | 8/74–3/75 (8) |
| 4/75–8/77 (29) | 9/77–1/80 (29) | 2/80–4/80 (3) | 5/80–7/80 (3) |
| 8/80–1/81 (6) | 2/81–7/81 (6) | 8/81–3/82 (8) | 4/82–11/82 (8) |
| 12/82–9/86 (46) | 10/86–7/90 (46) | 8/90–11/90 (4) | 12/90–3/91 (4) |
| 4/91–3/96 (60) | 4/96–3/01 (60) | 4/01–7/01 (4) | 8/01–11/01 (4) |
| 12/01–12/04 (37) | 1/05–12/07 (36) | 1/08–9/08 (9) | 10/08–6/09 (9) |
| 7/09–10/14 (64) | 11/14–12/17 (38) | | |

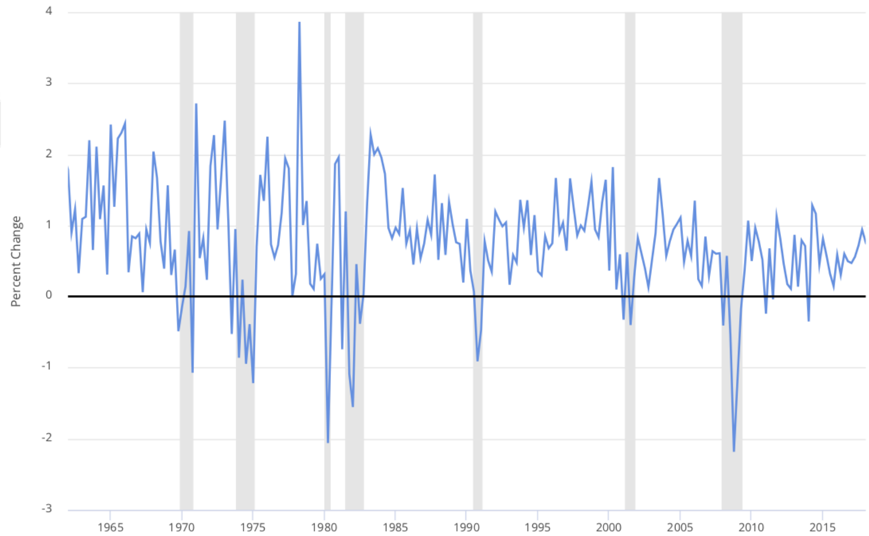
*Table 2.6:* Cross-sectional predictability of stock returns in case of business-cycle stage formation

Table reports the average slopes from multivariate regression of stock returns on $\beta$, size, book-to-market, leverage, earning-price ratio, and four different dummy variables based on business cycle stages, for the periods of 1963-1990 and 1963-2017. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 2017. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. Stage I dummy equals 1 if the data belongs to Stage I, 0 otherwise. Stage II dummy equals 1 if the data belongs to Stage II, 0 otherwise. Stage III dummy equals 1 if the data belongs to Stage III, 0 otherwise. Stage IV dummy equals 1 if the data belongs to Stage IV, 0 otherwise. All main variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| | $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** | **Stage I Dummy** | **Stage II Dummy** | **Stage III Dummy** | **Stage IV Dummy** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1965-1990** | 0.35 | -0.20*** | 0.42 | 0.12 | -0.02 | -0.22 | 0.13 | 0.74*** | 0.74*** | 0.07 | 1.51*** |
| | (1.09) | (-3.53) | (0.88) | (0.25) | (-0.05) | (-0.95) | (0.11) | (3.67) | (3.29) | (0.52) | (3.86) |
| **1965-2017** | 0.03 | -0.24*** | 0.79 | 1.11 | -1.01 | 0.03 | -0.01 | 0.66*** | 0.43*** | 0.05 | 1.11*** |
| | (1.14) | (-5.42) | (1.14) | (1.59) | (-1.46) | (0.26) | (-0.01) | (7.56) | (4.81) | (1.20) | (6.70) |




*(a)* US Real GDP




*(b)* US Real GDP % change

*Figure 2.1:* U.S. Real GDP
This figure presents the US real GDP data (on the top) and the percentage change of US real GDP (at the bottom) for the sample period from July 1963 to December 2017. Gray shaded lines represent recession periods in the United States.

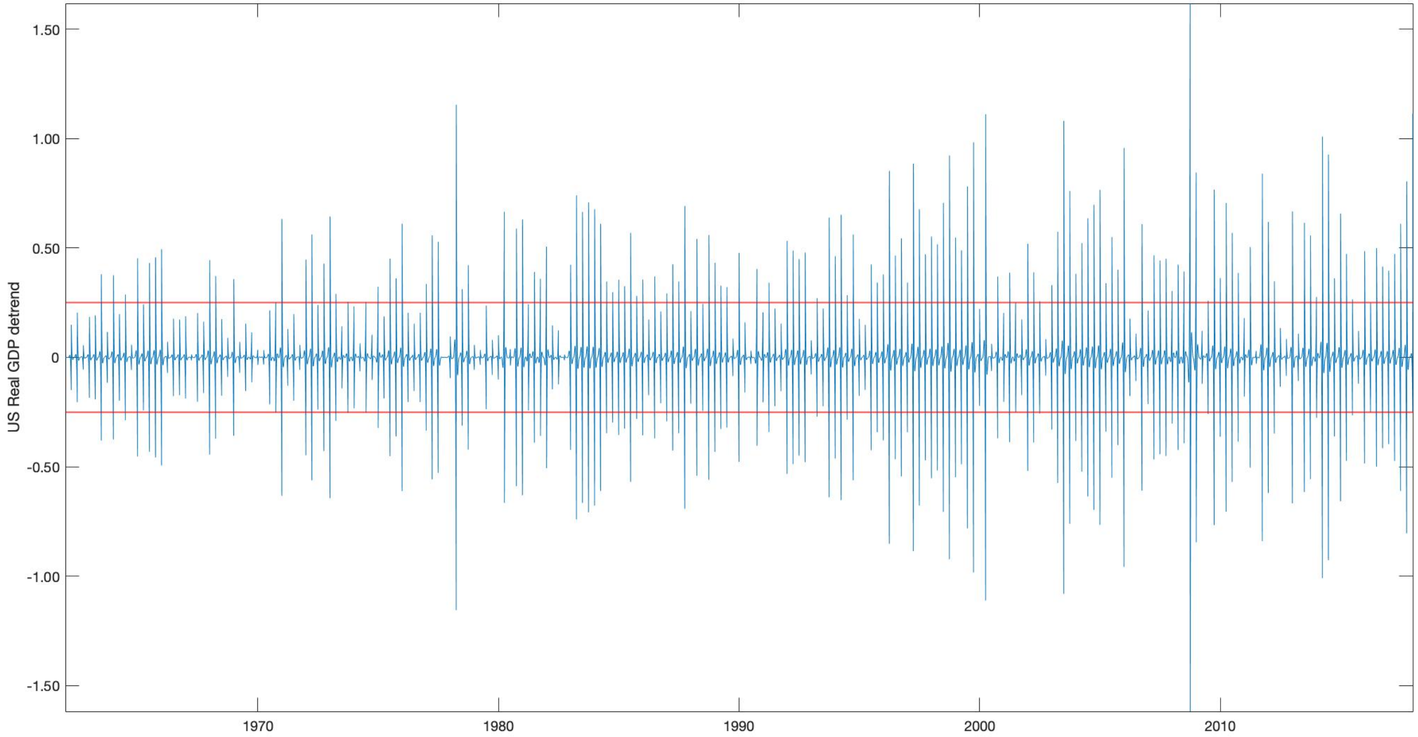



*Figure 2.2:* US Real GDP detrended according to NBER business cycle dates marked with designated gap lines

*Table 2.7:* Cross-sectional predictability of stock returns controlling for the output level
Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for detrending real GDP. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 1990. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of stocks is 2753.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.12** | | | | | | |
| (2.48) | | | | | | |
| | -0.09 | | | | | |
| | (-1.59) | | | | | |
| 0.11** | -0.09 | | | | | |
| (2.48) | (-1.02) | | | | | |
| | | 0.14 | | | | |
| | | (1.51) | | | | |
| 0.11** | | 0.13 | | | | |
| (2.45) | | (1.52) | | | | |
| | | | 0.13 | -0.09 | | |
| | | | (1.64) | (-1.24) | | |
| | | | | | 0.17 | 0.17 |
| | | | | | (0.91) | (0.37) |
| | -0.08 | 0.07 | | | | |
| | (-1.44) | (1.22) | | | | |
| | -0.08 | | 0.07 | -0.08 | | |
| | (-1.49) | | (1.20) | (-1.05) | | |
| 0.09** | | | 0.12 | -0.08 | | |
| (2.39) | | | (1.64) | (-1.16) | | |
| | -0.09 | | | | 0.03 | -0.04 |
| | (-1.38) | | | | (0.21) | (-0.07) |
| | -0.08 | 0.10* | | | -0.03 | -0.45 |
| | (-1.40) | (1.65) | | | (-0.22) | (-0.95) |
| | -0.08 | | 0.10 | -0.09 | -0.04 | -0.50 |
| | (-1.31) | | (1.53) | (-1.31) | (-0.29) | (-0.93) |
| 0.13*** | -0.08 | 0.26 | -0.17 | 0.18 | -0.06 | -0.58 |
| (2.59) | (-1.34) | (0.77) | (-0.50) | (0.53) | (-0.49) | (-1.11) |

*Table 2.8:* Cross-sectional predictability of stock returns controlling for the output level
Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for detrending real GDP. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 2017. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of stocks is 11531.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.53* | | | | | | |
| (1.93) | | | | | | |
| | -0.37 | | | | | |
| | (-0.97) | | | | | |
| 0.64** | -0.37 | | | | | |
| (2.20) | (-1.45) | | | | | |
| | | 0.33 | | | | |
| | | (1.64) | | | | |
| 0.60** | | 0.34 | | | | |
| (2.24) | | (1.29) | | | | |
| | | | 0.36 | -0.15 | | |
| | | | (1.46) | (-1.49) | | |
| | | | | | 0.89 | 0.84 |
| | | | | | (1.64) | (1.27) |
| | -0.33 | 0.16 | | | | |
| | (-1.35) | (1.36) | | | | |
| | -0.33 | | 0.18 | -0.07 | | |
| | (-1.28) | | (1.32) | (-0.72) | | |
| 0.53* | | | 0.38 | -0.14 | | |
| (1.92) | | | (1.10) | (-1.45) | | |
| | -0.33** | | | | 0.52* | 0.11 |
| | (-1.96) | | | | (1.80) | (0.17) |
| | -0.29 | 0.20* | | | 0.48* | -0.45 |
| | (-1.38) | (1.71) | | | (1.82) | (-0.73) |
| | -0.29 | | 0.23* | -0.12 | 0.41 | -0.70 |
| | (-1.35) | | (1.83) | (-1.19) | (1.57) | (-1.09) |
| 0.47* | -0.29 | -2.19 | 2.44 | -2.30 | 0.31 | -0.86 |
| (1.94) | (-1.41) | (-1.30) | (1.43) | (-1.36) | (1.32) | (-1.34) |

*Table 2.9:* Cross-sectional predictability of stock returns controlling for the output level separately for peak and trough periods
Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for detrending real GDP at times of expansion and contraction. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 1990. Panel A reports the regression results peak periods and Panel B reports the regression results for trough periods. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average numbers of stocks are 2572 for Panel A and 2487 for Panel B.

*Panel A. Peak periods*

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.25*** | | | | | | |
| (3.48) | | | | | | |
| | 0.18 | | | | | |
| | (1.58) | | | | | |
| 0.23*** | 0.18 | | | | | |
| (2.88) | (1.29) | | | | | |
| | | 0.28 | | | | |
| | | (1.21) | | | | |
| 0.23*** | | 0.26 | | | | |
| (3.45) | | (1.63) | | | | |
| | | | 0.27* | -0.18 | | |
| | | | (1.74) | (-1.43) | | |
| | | | | | 0.34 | 0.35 |
| | | | | | (0.71) | (0.65) |
| | 0.16* | 0.14 | | | | |
| | (1.65) | (1.22) | | | | |
| | 0.15* | | 0.14 | -0.16 | | |
| | (1.70) | | (1.21) | (-1.00) | | |
| 0.19*** | | | 0.25* | -0.16 | | |
| (3.39) | | | (1.70) | (-1.37) | | |
| | 0.18* | | | | 0.06 | -0.07 |
| | (1.89) | | | | (0.61) | (-0.04) |
| | 0.15* | 0.20* | | | -0.06 | -0.90 |
| | (1.70) | (1.66) | | | (-0.24) | (-0.55) |
| | -0.15 | | 0.20 | -0.19 | -0.07 | -1.00 |
| | (-1.21) | | (1.53) | (-1.14) | (-0.59) | (-0.99) |
| 0.27*** | -0.16 | 0.52 | -0.34 | 0.35 | -0.12 | -1.16 |
| (2.59) | (-1.50) | (0.67) | (-0.96) | (0.28) | (-0.89) | (-1.04) |

*Panel B. Trough periods*

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.23** | | | | | | |
| (1.98) | | | | | | |
| | -0.12* | | | | | |
| | (-1.83) | | | | | |
| 0.22** | -0.11 | | | | | |
| (1.97) | (-1.61) | | | | | |
| | | 0.11 | | | | |
| | | (1.52) | | | | |
| 0.21* | | 0.11* | | | | |
| (1.8)8 | | (1.69) | | | | |
| | | | 0.09 | -0.09 | | |
| | | | (1.27) | (-1.34) | | |
| | | | | | 0.21* | 0.24 |
| | | | | | (1.65) | (1.20) |
| | -0.11* | 0.03 | | | | |
| | (-1.91) | (0.46) | | | | |
| | -0.11* | | 0.01 | -0.07 | | |
| | (-1.66) | | (0.23) | (-1.07) | | |
| 0.21* | | | 0.09 | -0.10 | | |
| (1.84) | | | (1.35) | (-1.60) | | |
| | -0.11* | | | | 0.05 | 0.05 |
| | (-1.91) | | | | (0.55) | (0.28) |
| | -0.11* | 0.02 | | | 0.03 | 0.07 |
| | (-1.88) | (0.40) | | | (0.33) | (0.35) |
| | -0.11* | | 0.00 | -0.07 | 0.08 | 0.17 |
| | (-1.81) | | (0.07) | (-1.09) | (1.08) | (0.76) |
| 0.21* | -0.11 | 0.02 | -0.02 | -0.06 | 0.07 | 0.15 |
| (1.95) | (-1.11) | (0.06) | (-0.07) | (-0.19) | (0.91) | (0.70) |

*Table 2.10:* Cross-sectional predictability of stock returns controlling for the output level separately for peak and trough periods

Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for detrending real GDP at times of expansion and contraction. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 2017. Panel A reports the regression results peak periods and Panel B reports the regression results for trough periods. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average numbers of stocks are 11457 for Panel A and 11235 for Panel B.

*Panel A. Peak periods*

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.83*** | | | | | | |
| (4.23) | | | | | | |
| | 0.38* | | | | | |
| | (1.78) | | | | | |
| 1.07*** | 0.42 | | | | | |
| (3.63) | (1.55) | | | | | |
| | | 0.23 | | | | |
| | | (1.44) | | | | |
| 0.77*** | | 0.26* | | | | |
| (4.20) | | (1.72) | | | | |
| | | | 0.19 | -0.19 | | |
| | | | (1.01) | (-1.32) | | |
| | | | | | 1.30* | 0.84 |
| | | | | | (1.79) | (0.78) |
| | 0.38* | 0.02 | | | | |
| | (1.69) | (0.13) | | | | |
| | 0.39* | | -0.03 | -0.11 | | |
| | (1.75) | | (-0.19) | (-0.77) | | |
| 0.68*** | | | 0.21 | -0.19 | | |
| (4.09) | | | (1.24) | (-1.37) | | |
| | -0.32 | | | | 0.96* | 0.07 |
| | (-1.60) | | | | (1.86) | (0.06) |
| | -0.31 | 0.10 | | | 0.83* | -0.48 |
| | (-1.51) | (0.80) | | | (1.90) | (-0.47) |
| | -0.32 | | 0.05 | -0.22 | 0.79* | -0.32 |
| | (-1.60) | | (0.34) | (-1.50) | (1.95) | (-0.29) |
| 0.77*** | -0.34 | 0.71 | -1.08 | 0.96 | 0.70* | -0.59 |
| (3.34) | (-1.22) | (0.71) | (-0.65) | (0.59) | (1.87) | (-0.54) |

*Panel B. Trough periods*

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.24** | | | | | | |
| (1.96) | | | | | | |
| | -0.35* | | | | | |
| | (-1.83) | | | | | |
| 0.20** | -0.33* | | | | | |
| (1.99) | (-1.65) | | | | | |
| | | 0.42* | | | | |
| | | (1.67) | | | | |
| 0.43* | | 0.43* | | | | |
| (1.93) | | (1.65) | | | | |
| | | | 0.53* | -0.10 | | |
| | | | (1.73) | (-0.76) | | |
| | | | | | 0.48 | 0.84 |
| | | | | | (0.98) | (1.09) |
| | -0.28** | 0.30 | | | | |
| | (-2.03) | (1.64) | | | | |
| | -0.26* | | 0.40* | -0.03 | | |
| | (-1.87) | | (1.87) | (-0.24) | | |
| 0.38* | | | 0.54* | -0.08 | | |
| (1.92) | | | (1.83) | (-0.65) | | |
| | -0.34** | | | | 0.09 | 0.15 |
| | (-2.02) | | | | (0.20) | (0.22) |
| | -0.27 | 0.29* | | | 0.13 | -0.41 |
| | (-1.60) | (1.82) | | | (0.32) | (-0.59) |
| | -0.26* | | 0.41** | -0.02 | 0.03 | -1.09 |
| | (-1.68) | | (2.12) | (-0.12) | (0.06) | (-1.63) |
| 0.18** | -0.25 | -1.08* | 1.00* | -0.58* | -0.08 | -1.13* |
| (1.97) | (-1.50) | (-1.90) | (1.70) | (-1.70) | (-0.24) | (-1.70) |

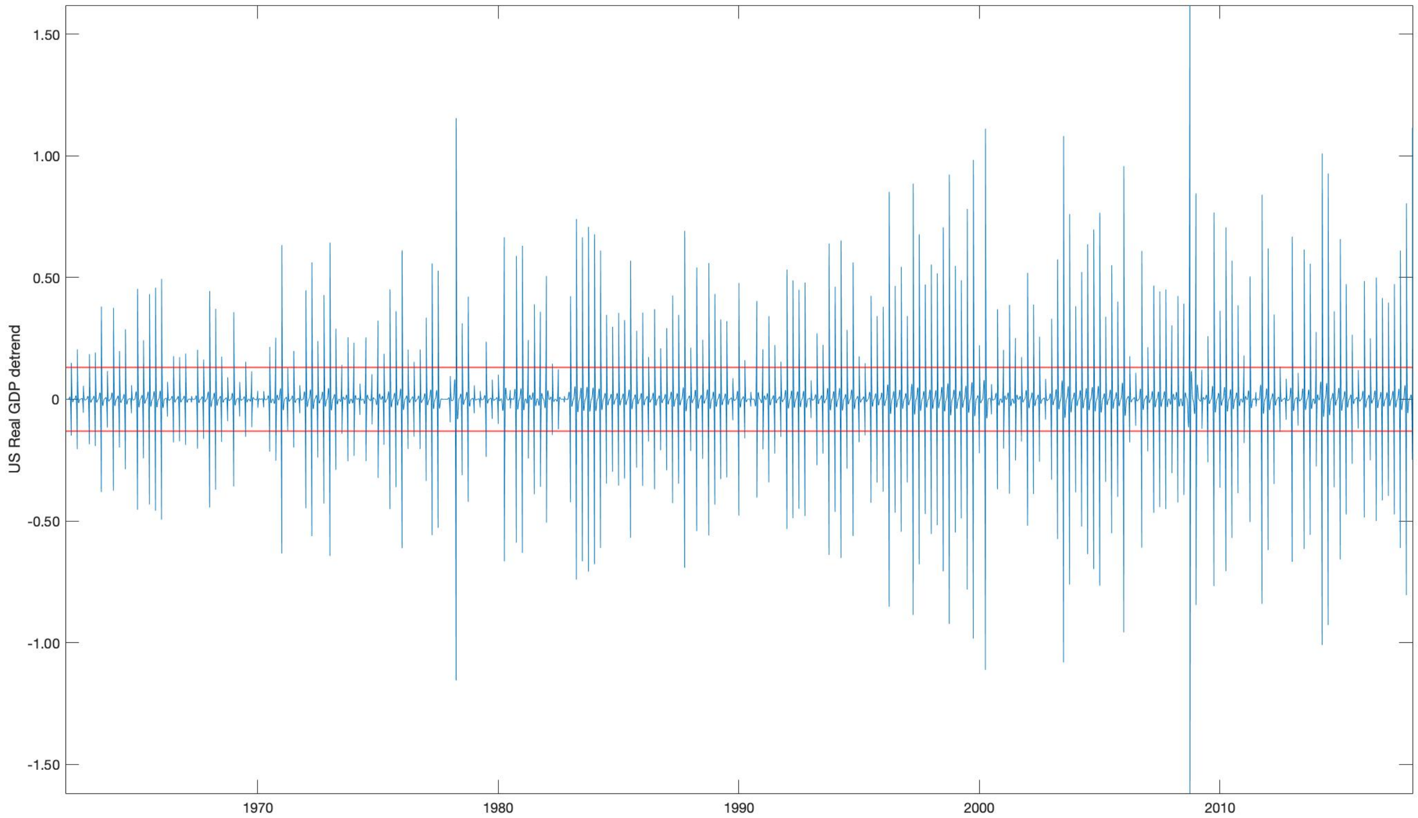



*Figure 2.3:* US Real GDP detrended according to NBER business cycle dates marked with narrower designated gap lines

*Table 2.11:* Cross-sectional predictability of stock returns controlling for the output level within a narrower gap

Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for detrending real GDP with a narrower gap. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 1990. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of stocks is 2428.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.29*** | | | | | | |
| (3.28) | | | | | | |
| | -0.02 | | | | | |
| | (-1.31) | | | | | |
| 0.22*** | -0.02 | | | | | |
| (2.64) | (-1.03) | | | | | |
| | | 0.08 | | | | |
| | | (1.04) | | | | |
| 0.31*** | | 0.05 | | | | |
| (2.91) | | (1.03) | | | | |
| | | | 0.02 | -0.01 | | |
| | | | (1.01) | (-0.90) | | |
| | | | | | 0.01 | 0.04 |
| | | | | | (0.42) | (0.28) |
| | -0.04 | 0.08 | | | | |
| | (-0.96) | (0.95) | | | | |
| | -0.03 | | 0.06 | -0.03 | | |
| | (-0.97) | | (1.09) | (-1.01) | | |
| 0.33*** | | | 0.02 | -0.02 | | |
| (2.93) | | | (1.01) | (-1.03) | | |
| | -0.01 | | | | 0.02 | 0.00 |
| | (-0.81) | | | | (0.14) | (0.00) |
| | -0.01 | 0.03 | | | -0.03 | -0.19 |
| | (-0.82) | (0.96) | | | (-0.12) | (-0.73) |
| | 0.00 | | 0.03 | -0.02 | -0.02 | -0.18 |
| | (-0.76) | | (1.02) | (-0.93) | (-0.15) | (-0.54) |
| 0.32*** | -0.03 | 0.01 | -0.02 | 0.07 | -0.03 | -0.29 |
| (3.00) | (-0.74) | (0.16) | (-0.26) | (0.31) | (-0.34) | (-0.76) |

*Table 2.12:* Cross-sectional predictability of stock returns controlling for the output level within a narrower gap

Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for detrending real GDP with a narrower gap. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 2017. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of stocks is 9952.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.72*** | | | | | | |
| (3.80) | | | | | | |
| | -0.18 | | | | | |
| | (-0.28) | | | | | |
| 0.62*** | -0.20 | | | | | |
| (2.96) | (-0.31) | | | | | |
| | | 0.21 | | | | |
| | | (1.35) | | | | |
| 0.63*** | | 0.22 | | | | |
| (3.12) | | (1.07) | | | | |
| | | | 0.20 | -0.05 | | |
| | | | (0.91) | (-1.02) | | |
| | | | | | 0.54 | 0.58 |
| | | | | | (0.92) | (0.84) |
| | -0.36 | 0.18 | | | | |
| | (-0.56) | (1.00) | | | | |
| | -0.30 | | 0.18 | -0.09 | | |
| | (-0.47) | | (0.86) | (-0.21) | | |
| 0.55*** | | | 0.12 | -0.03 | | |
| (2.99) | | | (0.81) | (-0.92) | | |
| | -0.17 | | | | 0.31 | 0.03 |
| | (-0.13) | | | | (1.22) | (0.02) |
| | -0.17 | 0.13 | | | 0.43 | -0.13 |
| | (-0.14) | (1.30) | | | (0.92) | (-0.26) |
| | -0.24 | | 0.10 | -0.02 | 0.24 | -0.64 |
| | (-0.10) | | (0.93) | (-0.83) | (0.85) | (-0.96) |
| 0.53*** | -0.28 | -1.09 | 1.17 | -1.07 | 0.26 | -0.74 |
| (3.29) | (-0.14) | (-1.10) | (0.60) | (-0.56) | (0.63) | (-0.86) |

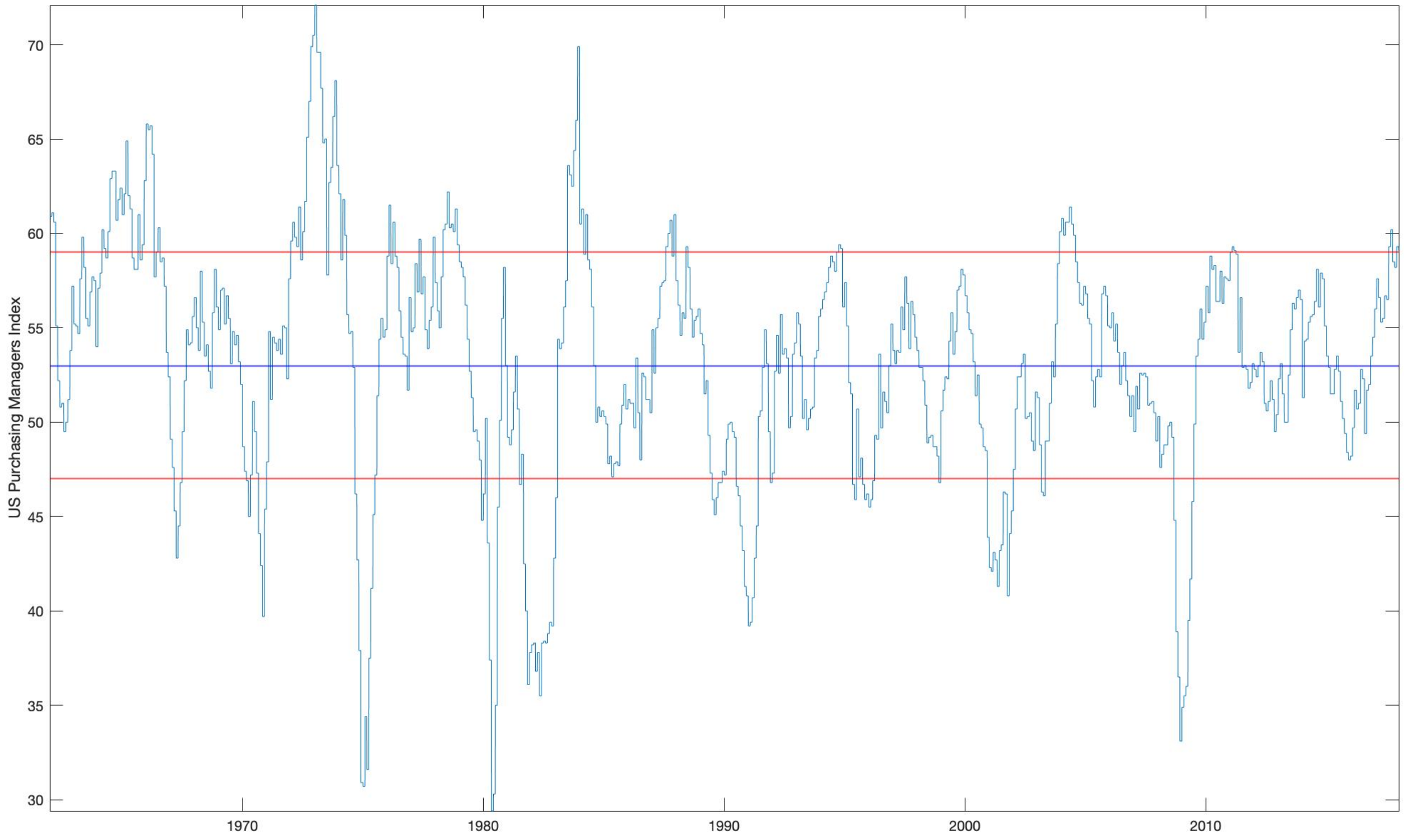



*Figure 2.4:* US Purchasing Manager's Index (PMI) marked with designated gap lines

*Table 2.13:* Cross-sectional predictability of stock returns controlling for an alternative measure of output
Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for Purchasing Manager's Index (PMI). PMI is a composite index referring to seasonally adjusted diffusion indices. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 1990. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of stocks is 2698.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.30*** | | | | | | |
| (2.68) | | | | | | |
| | -0.11 | | | | | |
| | (-1.53) | | | | | |
| 0.25** | -0.10 | | | | | |
| (2.55) | (-1.00) | | | | | |
| | | 0.29 | | | | |
| | | (1.43) | | | | |
| 0.21** | | 0.11 | | | | |
| (2.54) | | (1.22) | | | | |
| | | | 0.16 | -0.07 | | |
| | | | (1.35) | (-1.13) | | |
| | | | | | 0.07 | 0.06 |
| | | | | | (1.13) | (0.66) |
| | -0.10 | 0.13 | | | | |
| | (-1.34) | (0.92) | | | | |
| | -0.09 | | 0.02 | -0.08 | | |
| | (-1.44) | | (0.81) | (-1.08) | | |
| 0.14** | | | 0.14 | -0.10 | | |
| (2.46) | | | (1.38) | (-1.13) | | |
| | -0.08 | | | | 0.02 | -0.14 |
| | (-1.48) | | | | (0.65) | (-0.05) |
| | -0.09 | 0.18 | | | -0.05 | -0.23 |
| | (-1.60) | (1.52) | | | (-0.45) | (-0.88) |
| | -0.10 | | 0.12 | -0.06 | -0.05 | -0.46 |
| | (-1.43) | | (1.15) | (-1.02) | (-0.74) | (-0.97) |
| 0.15*** | -0.09 | 0.24 | -0.20 | 0.09 | -0.06 | -0.82 |
| (2.62) | (-1.10) | (0.46) | (-0.65) | (0.85) | (-0.90) | (-0.98) |

*Table 2.14:* Cross-sectional predictability of stock returns controlling for an alternative measure of output

Each month, we conduct a cross-sectional regression of stock returns on $\beta$, size, book-to-market, leverage and earning-price ratio, controlling for Purchasing Manager's Index (PMI). PMI is a composite index referring to seasonally adjusted diffusion indices. The sample is merged across two databases, CRSP and COMPUSTAT for the period from the beginning of July 1963 trough the end of December 2017. The definitions of the variables are as described in Section 2.2.2. We calculate the natural logarithm of size, book-to-market, market leverage and book leverage variables. If earnings are positive, E/P dummy is 0 and earnings-price ratio equals the ratio of total earnings to market equity. If earnings are negative, E/P dummy is 1 and earnings-price ratio equals 0. All variables are winsorized at 0.5% level from upper and lower tails. Newey-West (1987) adjusted t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The average number of stocks is 11152.

| $\beta$ | **ln(ME)** | **ln(BE/ME)** | **ln(A/ME)** | **ln(A/BE)** | **E/P Dummy** | **E(+)/P** |
|---|---|---|---|---|---|---|
| 0.54** | | | | | | |
| (2.17) | | | | | | |
| | -0.47 | | | | | |
| | (-0.67) | | | | | |
| 0.44** | -0.44 | | | | | |
| (2.01) | (-1.57) | | | | | |
| | | 0.29 | | | | |
| | | (1.37) | | | | |
| 0.54** | | 0.43 | | | | |
| (2.07) | | (1.53) | | | | |
| | | | 0.42 | -0.15 | | |
| | | | (1.19) | (-1.34) | | |
| | | | | | 0.23 | 0.40 |
| | | | | | (1.11) | (0.74) |
| | -0.41 | 0.27 | | | | |
| | (-1.48) | (1.51) | | | | |
| | -0.35 | | 0.16 | -0.04 | | |
| | (-0.76) | | (1.20) | (-0.82) | | |
| 0.33** | | | 0.26 | -0.15 | | |
| (2.21) | | | (1.08) | (-1.08) | | |
| | -0.43* | | | | 0.48 | 0.04 |
| | (-1.78) | | | | (1.27) | (0.33) |
| | -0.39 | 0.38 | | | 0.40 | -0.58 |
| | (-1.38) | (1.06) | | | (1.36) | (-0.56) |
| | -0.37 | | 0.30 | -0.06 | 0.61 | -0.30 |
| | (-1.47) | | (1.49) | (-1.09) | (1.12) | (-1.07) |
| 0.61** | -0.48 | -1.22 | 1.88 | -1.76 | 0.36 | -0.67 |
| (2.04) | (-1.31) | (-1.17) | (1.08) | (-1.03) | (1.06) | (-0.98) |

# CHAPTER 3

# THE EFFECT OF TAX REGULATION ON FIRM VALUE: THE TURKISH CASE OF ALLOWANCE FOR CORPORATE EQUITY (ACE) REGULATION

## 3.1. Introduction

Modigliani and Miller (1963) started a large literature on how tax benefits of debt affect capital structure decisions.[1] Debt financing provides a tax shield since interest expense is tax deductible. In most countries around the world, equity financing does not provide the tax shield that debt financing does. IFS Capital Taxes Group (1991) and Devereux and Freeman (1991) proposed a new tax regulation (Allowance for Corporate Equity –ACE–) that provides a deduction for equity issues when a company calculates its taxable profits.[2] Croatia in 1994 is the first country to enact ACE (Keen and King, 2002). So far, Brazil in 1996, Italy in 1997, Austria in 2000, Belgium in 2006, and Turkey in 2015 implemented the regulation that provides a tax shield for equity financing.

We investigate whether and how the introduction of a regulation that provides a tax deduction for equity financing affects shareholder value in Turkish firms listed on Borsa Istanbul. We find that investors price the introduction of ACE as positive news. Furthermore, abnormal returns prove significantly higher for

[1] Refer to Graham (2013), Feld et al. (2013) and Graham and Leary (2011) for excellent reviews on the literature that studies how taxes affect capital structure.

[2] Refer to IFS Capital Taxes Group (1991) and Isaac (1997) for discussion and viability of ACE regulation.

levered firms who may find it easier to switch from debt to equity financing and for firms that have income to shield from tax. We also find that firms in the highest leverage and income bins increase cash equity more than firms in the lowest leverage and income bins. Difference-in-difference analysis shows that the firms which the market ex-ante prices to benefit most from the tax regulation do ex-post raise more equity relative to firms which the market expects to benefit least.

This study contributes to the literature on how tax regulation in general and ACE in particular affect stock market pricing of firms and corporate decision-making. To our knowledge, this is the first empirical study that investigates whether and how investors price the introduction of ACE. The literature on ACE focuses on how the regulation affects tax revenue (Keen and King, 2002; Oropallo and Parisi, 2007), and changes the financing decision of the firm (Staderini, 2001; Klemm, 2007; Princen, 2012). We focus on investor reaction to the ex-ante anticipated effect of the tax regulation and the ex-post change in the capital structure of sample firms. The very short-term abnormal returns observed around introduction of the equity tax shield provide a clean measure of how investors price the tax shield that the new regulation brings. Furthermore, the results indicate that market expectations on who will benefit most from the regulation is validated by the ex-post financing decision to issue equity.

The remainder of the paper is organized as follows. We describe our sampling framework and method in Section 3.2. Section 3.3 discusses the empirical results and, finally, Section 3.4 concludes.

### 3.2. Sampling Framework and Research Method

We first identify the announcement date of ACE. We conduct keyword searches in Bloomberg and archives of three major Turkish newspapers. The announcement date, 17 March 2015 (Day [0]), is the date when specifics of ACE are revealed and discussed in The Grand National Assembly of Turkey.[3] The

[3] The newspaper account of discussions in The Grand National Assembly of Turkey is available at https://www.haberler.com/torba-kanun-teklifi-tbmm-plan-ve-butce-komisyonu-7082528-haberi/.

equity tax shield, which allows firms to deduct 50 percent of new stock issues multiplied by the average loan interest rate (as determined by The Central Bank of the Republic of Turkey) from their taxable income, entered into force on 1 July 2015.[4],[5] The regulation aims to encourage firms to issue equity instead of debt.[6] A firm that needs to raise outside capital can issue debt or equity. In Turkey, 100% of interest payments on debt are tax deductible whereas ACE offers a deduction rate of 50% on equity. For the average Turkish firm, 1 TL of additional debt offers a tax shield of t * i TL (where t is the corporate tax rate and i is the borrowing cost) whereas 1 TL of additional equity offers a tax shield of t * i * 0.50 (where we assume that the average loan rate used in ACE which is set by the Central Bank equals 'i', the borrowing cost of the average Turkish firm). Debt still offers a 50 percent more tax shield than equity for the average Turkish corporation. However, compared to before, ACE halves the tax benefits of debt relative to equity. Allowance for Corporate Equity regulation applies to all firms incorporated in Turkey except for financial institutions (such as banks and insurance companies) and government-owned enterprises. Our sample covers the 89 non-financial firms in the BIST-100 Index (the main index for Borsa Istanbul).

We adopt the event study method of Brown and Warner (1985) to measure the market reaction to the ACE regulation.[7] We calculate daily returns for each

[4]Interested readers may refer to http://www.resmigazete.gov.tr/eskiler/2015/04/20150407-19.htm for the full tax bill.

[5]The tax bill demonstrates how the tax deduction for new equity issues will work with the following example. Assume Company XYZ issues additional equity of 1 TL as of January 1, 2016. Average loan interest rate (as determined by The Central Bank of the Republic of Turkey) is 13.57% as of December 31, 2016. Then, the equity tax deduction is as follows:
Increase in equity x Loan interest rate x Time x Deduction rate = 1 TL x 13.57% x (12/12) x 50% = 0.06785 TL
The tax shield using the 20 percent corporate tax rate for a 1 TL increase in equity corresponds to 0.01357 TL in the year of the issue. Firms increasing cash capital benefit from the tax shield of 0.01357 TL not only in the year of issue but also in every year following the issue. Hence, the net present value of future tax shields arising from the 1 TL increase in equity (using the Central Bank's loan interest rate of 13.57% and the perpetuity formula 0.01357/0.1357) will be 0.10 TL. In case of subsequent capital reductions, the reduced amount of capital is not taken into account in the tax shield calculation. Interested readers may refer to http://www.resmigazete.gov.tr/eskiler/2016/03/20160304-9.htm.

[6]ACE regulation in Turkey offers a notional interest deduction (NID) from incremental cash capital against the effective interest cost deduction of debt. The aim is to address the debt bias in corporate sector. Refer to Zangari (2014) for the comparison of how Italy and Belgium practice ACE to eliminate the debt bias.

[7]Refer to MacKinlay (1997) and Krivin et al. (2003) for excellent reviews on the literature for event study method and Basdas and Oran (2014) on event studies that focus on Turkey.

stock starting 304 trading days before the announcement (event date) and ending 20 trading days after the announcement using adjusted share prices from DataStream. The estimation window covers 229 trading days before the event window (Day [-304, -75]). The event window starts 75 trading days before and ends 20 trading days after the announcement date (Day [-74, +20]). We start the event window 75 trading days before 17 March 2015 since on 29 December 2014 the chairman of Capital Markets Board of Turkey talked about the prospect of introducing a tax shield for equity financing.[8] We do not consider 29 December 2014 as the event date since the specifics and coverage of the regulation was not revealed. We measure investor reaction to the tax regulation using abnormal returns that difference realized returns in the event window from the mean of returns in the estimation window.[9]

### 3.3. Empirical Results and Discussion

Abnormal returns on the announcement date for the 89 non-financial firms covered in the tax bill average 2% and prove statistically significant. Cumulative abnormal returns (CAR) in the three-day window around the announcement date average 3% and are also statistically significant.[10] Investors evaluate the tax shield proposed in ACE as positive news and price the tax shield at the announcement. Investors that have not yet observed any changes in capital structure anticipate the future increase in equity issuance and price the expected value of the tax shield that would result from the increase in equity issues. The literature starting with Staderini (2001) in Italy, Keuschnigg and Dietz (2007) in Switzerland, Princen (2012) in Belgium, Finke et al. (2014) in Germany, and Petutschnig and Rünger (2017) in Austria document that firms do indeed issue more equity after the introduction of tax incentives for equity issuance.

ACE regulation states that firms who increase cash capital after 1 July 2015 can

[8]The specifics of the Chairperson's televised statement are available at https://www.bloomberght.com/haberler/haber/1692619-spkertas-forexte-kayipkazanc-orani-yuzde-87.

[9]We use the mean-adjusted model to calculate abnormal returns. Unreported results available upon request are robust to using other models such as the market model. We do not use the market model as our benchmark model since sample firms constitute 89 percent of the market index and we would be taking the average of abnormal returns coming from a weighted average of the sample returns.

[10]Five-day CARs (2.88%) and seven-day CARs (2.62%) indicate qualitatively similar results.

benefit from the tax incentive. We hypothesize that levered firms have more room to increase equity capital. Market reaction to the ACE announcement should then be higher in firms with lower equity-to-debt ratios. We sort the 89 non-financial firms in the sample into three bins of 30, 30 and 29 firms, respectively, according to their equity-to-debt ratio. Panel A of Table 3.1 reports abnormal returns on and three-day CARs around the announcement date in the three bins sorted according to leverage. Investor reaction to ACE announcement is most pronounced in the most levered firms (CARs of 3.88% and statistically significant) and least pronounced in the least-levered firms (CARs of 2.65% and statistically insignificant).[11] In line with our hypothesis that levered firms with room to increase their equity capital may benefit more from the tax shield, abnormal returns increase across the equity-to-debt bins.

Firms can benefit from the tax bill only if they have income to shield. Thus, we hypothesize that market reaction to ACE for firms with large income streams will be more pronounced. We use EBIT (earnings before interest and taxes) normalized by total assets to measure the relative magnitude of income. We sort the 89 non-financial firms into three bins of 30, 30 and 29 firms, respectively, according to their EBIT-to-asset ratio. Panel B of Table 3.1 reports abnormal returns on and three-day CARs around the announcement date in the three bins of 30, 30 and 29 firms. Investor reaction to the announcement of ACE increases in the level of income that the firm can protect from tax. Three-day CARs for the 30 (29) firms with the largest (smallest) income stream is 4.96 (1.79) percent and statistically significant (insignificant).[12,13]

**INSERT TABLE 3.1 HERE**

We analyze whether the ex-ante expectations of the market on which firms will benefit most from the regulation is validated by the ex-post equity issuance of

[11] Statistical tests using Brown and Warner (1985) and Corrado (1989) prove similar.

[12] Market reaction differs according to industry. Abnormal returns in communications, consumer goods and utilities prove significant and returns in technology, real estate, basic materials, and conglomerate industries prove insignificant.

[13] We also test market reaction for firms sorted according to their age and size (Beck et al., 2006; Farre-Mensa and Ljungqvist, 2016). Abnormal returns in the three bins sorted according to age and size do not exhibit a clear difference in one direction. Results are available upon request.

sample firms. We conduct a difference-in-difference (DID) analysis[14] and compare the increase in cash equity in the one-, two-, three- and four-years following ACE in the full sample and in the subsamples of firms classified according to equity-to-debt and EBIT-to-asset ratios. The percentage increase in cash equity averages 40%, 77%, 87%, and 123% at the end of 2015, 2016, 2017 and 2018 (all statistically significant increases except for 2015), respectively. Panel A of Table 3.2 shows that firms in the most-levered bin increase their equity capital by 91 percent in 2016, two years after the passing of ACE, relative to 2014, the last year before ACE was introduced whereas the increase in cash capital for the least levered bin is 11%. Panel B of Table 3.2 reports that firms in the highest income bin increase cash equity by 188% between 2014 and 2016 whereas firms in the lowest income bin raise cash equity by 15%.[15] Firms that the market expects to benefit most from the tax regulation (as measured by the abnormal returns around announcement) do indeed issue more equity relative to other firms.

**INSERT TABLE 3.2 HERE**

### 3.4. Conclusion

The three-day cumulative abnormal returns around the announcement of ACE average 3% for non-financial firms that are covered in the tax bill. Furthermore, not all firms are equally affected by the tax bill. Investors differentiate between firms who will potentially benefit more from the tax shield based on the level of leverage and income stream. Furthermore, the ex-ante expectations of the market are corroborated by the ex-post equity issuance of sample firms. Our findings are novel in that we show how tax regulations that allow for equity tax shields change corporate decision-making and how investors ex-ante price the effect of these changes.

Our results are specific to listed (public) firms due to lack of data on private

[14] We thank the anonymous referee for this suggestion. Refer to An (2012), Panier et al. (2015) and Clemente-Almendros and Sogorb-Mira (2016) for similar examples of difference-in-difference (DID) analysis.

[15] For example, Afyon Cimento Sanayi issued 97 million TL cash equity as of July 24, 2015. The recognized equity tax deduction in 2015 and 2016 financial reports was 7.11 million and 16.45 million TL, respectively.

firms. Results may not generalize to private (non-listed) firms since their ability to access debt and equity markets might differ (Goyal et al., 2011; López-Gracia and Sogorb-Mira, 2014). Therefore, the results reported here might not be extrapolated to a general firm context. Furthermore, the results are also specific to Turkish firms. In future work, we aim to investigate cross-country differences in investor reaction to tax regulation that provides tax shield to equity.

*Table 3.1:* Differences in market reaction to the ACE tax regulation

Table reports abnormal returns on and three-day CARs around the announcement date in subsamples of firms classified according to equity-to-debt ratio in Panel A and EBIT-to-asset ratio in Panel B. Equity-to-debt ratio is book value of owners' equity (in cash) divided by total debt as of the end of 2014. EBIT-to-asset ratio is EBIT divided by total assets as of the end of 2014. The stocks are sorted from the highest to lowest ratios and divided into three bins. Abnormal returns (AR) and cumulative abnormal returns (CAR) reported in the first and fourth rows are in percentages. Brown and Warner t-statistics are reported in second and fifth rows. Corrado t-statistics are reported in third and sixth rows. The seventh rows show the number of observations. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

**Panel A - Market reaction to the tax bill according to firm leverage**

| | **Equity to Debt bins** | | |
|---|---|---|---|
| | **1 - Least Levered** | **2** | **3 - Most Levered** |
| **AR (event date)** | 1.21 | 2.38 | 2.43 |
| | *1.27* | *2.44*** | *2.35*** |
| | *0.95* | *2.05*** | *2.11*** |
| **CAR [-1, +1]** | 2.65 | 2.73 | 3.88 |
| | *1.60* | *1.62* | *2.16*** |
| | *0.97* | *1.72** | *2.43*** |
| ***# of observations*** | *30* | *30* | *29* |

**Panel B - Market reaction to the tax bill according to income stream**

| | **EBIT to Asset bins** | | |
|---|---|---|---|
| | **1 - Highest Income** | **2** | **3 - Lowest Income** |
| **AR (event date)** | 2.25 | 1.96 | 1.80 |
| | *2.23*** | *2.03** | *1.81** |
| | *1.85** | *1.81** | *1.58* |
| **CAR [-1, +1]** | 4.96 | 2.43 | 1.79 |
| | *2.84**** | *1.46* | *1.04* |
| | *2.71*** | *1.47* | *0.98* |
| ***# of observations*** | *30* | *30* | *29* |

*Table 3.2:* Differences in book value of owners' equity (in cash)

Table reports differences in book values of owners' equity (in cash) in subsamples of firms classified according to equity-to-debt ratio in Panel A and EBIT-to-asset ratio in Panel B. Differences (in percentages) are calculated as the book value of owners equity (in cash) as of the end of 2015, 2016, 2017 and 2018, minus that of 2014 divided by that of 2014. Results for all sample covers 89 non-financial firms and are reported in first rows. Results for the most and least levered (highest and lowest income) bins, composed of the same firms as in Table 3.1, are reported in second and third rows. The fourth rows report differences between differences of book values of owners' (in cash) of most and least levered (highest and lowest income) bin. All values reported in first, second, third and fourth columns are in percentages. The fifth columns show the number of observations. t-statistics are reported in fifth rows. * denotes significance at 10%.

**Panel A - Differences in the lowest and highest equity-to-debt ratio bin**

| | **2015** | **2016** | **2017** | **2018** | **# of observations** |
|---|---|---|---|---|---|
| **Full Sample** | 40.05 | 77.33 | 87.24 | 123.47 | 89 |
| **Most Levered** | 2.80 | 90.57 | 91.75 | 189.32 | 29 |
| **Least Levered** | 6.20 | 11.40 | 18.69 | 23.24 | 30 |
| **Difference-in-difference** | -3.41 | 79.17 | 73.06 | 166.08 | |
| | *-1.06* | *1.08* | *1.00* | *1.75** | |

**Panel B - Differences in the highest and lowest EBIT-to-asset ratio bin**

| | **2015** | **2016** | **2017** | **2018** | **# of observations** |
|---|---|---|---|---|---|
| **Full Sample** | 40.05 | 77.33 | 87.24 | 123.47 | 89 |
| **Highest Income** | 108.82 | 188.27 | 192.59 | 198.26 | 29 |
| **Lowest Income** | 6.93 | 15.05 | 28.77 | 129.44 | 30 |
| **Difference-in-difference** | 101.89 | 173.21 | 183.82 | 68.81 | |
| | *0.93* | *1.74** | *1.26* | *0.45* | |

# CHAPTER 4

# LOTTERY-LIKE PREFERENCES AND THE MAX EFFECT IN THE CRYPTOCURRENCY MARKET

## 4.1. Introduction

With the invention of Bitcoin (Nakamoto, 2008) followed by altcoins, the skeptical yet unstoppable rise of the cryptocurrency market has drawn significant attention in recent years. This unique financial market provides many key features to be explored. One of these features is the effect of maximum daily return (MAX) on cryptocurrency prices. In their seminal paper, Bali et al. (2011) introduce the MAX effect showing that stocks with extreme historical positive returns are inclined to exhibit lower returns in the future. This effect in asset pricing has received empirical support by many studies in the stock market literature, including Fong and Toh (2014), Barinov (2018), and Hung and Yang (2018). In this study, following Bali et al. (2011), we investigate the role of lagged extreme positive returns in the cross-sectional pricing of cryptocurrencies.[1]

Recently, the cryptocurrency market has attracted increased attention from investors as it offered a brand new and distinguished investment opportunity.[2] Unlike other financial assets, cryptocurrencies are based on electronic cash payment systems without any participation of higher authority or physical

[1]The literature on MAX effect and lottery-like preferences can be further tied to the collective opinion dynamics of investors in financial markets. For more information on this subject, see Zha et al. (2021).

[2]As a subgroup of new Fintech innovations, cryptocurrencies have been attracting attention to the greatest extent in recent years. For more information on other novel Fintech approaches, see Kou et al. (2021a) and the references therein.

representation. It provides online trading through an algorithm that helps trace transactions. This attractive financial asset has an infinite divisibility with low transaction costs. The literature has indicated certain features of the cryptocurrency market, such as price clustering (Urquhart, 2017a), diversification benefits (Corbet et al., 2018a; Kajtazi and Moro, 2019; Urquhart and Zhang, 2019; Akhtaruzzaman et al., 2020), pricing bubbles (Corbet et al., 2018b), volatility dynamics (Katsiampa et al., 2019; Shen et al., 2020; Akyildirim et al., 2020), and arbitrage opportunities (Makarov and Schoar, 2020).

A group of recent studies investigate the predictability of cryptocurrencies, that is, the inefficiency in this market. However, the results are somewhat contradictory.[3] For example, Caporale et al. (2018) examines the return persistence—and therefore predictability—of the cryptocurrency market and shows a positive correlation between past and future returns of four main cryptocurrencies. Similarly, Zhang et al. (2018) and Al-Yahyaee et al. (2018) report inefficiency in the cryptocurrency market, and Tzouvanas et al. (2019) shows that momentum effect exists in the short-term. Akyildirim et al. (2021) finds evidence that the cryptocurrency market is inefficient even in the weak form as it is possible to predict future returns by applying machine learning tools on historical prices.[4] Contrariwise, Vidal-Tomas and Ibanez (2018) and Sensoy (2019) argue that the efficiency of Bitcoin has evolved over time. Focusing on momentum effects in cryptocurrencies, Grobys and Sapkota (2019) indicates a slight efficiency in the cryptocurrency market. Wei (2018) shows that as market liquidity increases, return predictability diminishes. However, the study reports signs of efficiency improvement only for Bitcoin while other cryptocurrencies remain inefficient.

As stated above, the predictability of cryptocurrency returns has been studied in detail by many researchers in the recent years. However, there is room to explore this concept, especially with respect to different dimensions, such as investor preferences. For example, empirical literature provides evidence that investors exhibit preference for lottery-like assets. Kumar (2009) documents the likelihood

[3] Refer to Corbet et al. (2019) for an excellent review on the literature of cryptocurrency markets.

[4] While this study uses a direct approach in feature selection, further advancements could be applied by choosing the model features in two stages. For an example, see Kou et al. (2021b).

of individual investors to choose assets with a relatively low probability of a large payoff. The author defines these assets as low-priced with high idiosyncratic volatility and high idiosyncratic skewness. Following this argument, Bali et al. (2011) investigate the investor preference over lottery-like stocks using MAX as a proxy for extreme returns. In addition, they argue that regarding the tendency to extreme positive returns, these under-diversified investors show preference for skewness. Moreover, Fong and Toh (2014) uncover the dependency of MAX effect on investor sentiment and show that certain groups of institutional investors are also prone to gamble in high MAX stocks. Previous studies have shown that, in addition to the US equity market, European (Annaert et al., 2013; Walkshäusl, 2014), Australian (Zhong and Gray, 2016), Hong Kong (Chan and Chui, 2016), Chinese (Nartea et al., 2017), and Brazilian (Berggrun et al., 2019) stock markets demonstrate the presence of the MAX effect.

Motivated by these different lines of literature, we investigate whether and how the MAX effect exists in the cryptocurrency market. Following Bali et al. (2011), we start by sorting cryptocurrencies according to their maximum daily return in the past month. We examine weekly returns on the resulting portfolios for the period between January 2014 and September 2020.[5] The average difference between weekly returns on the highest and lowest value-weighted MAX portfolios is found to be 3.03%, whereas the difference in corresponding three-factor alphas is 1.99%, both being significant with the Newey and West (1987) adjusted t-stat of 4.10 and 3.72, respectively. The results are robust to sorting cryptocurrencies each week based on averages of two, three, four, and five highest daily returns within the past month. This suggests that portfolios with the highest past extreme returns outperform portfolios with the lowest past extreme returns in the future. In addition to the documented investor preference over lottery-like assets, a positive difference between high MAX and low MAX portfolios indicates a permanent impact of extreme positive returns. For further examination, we perform bivariate portfolio analysis on raw returns and compare three-factor alphas, controlling for various characteristics, such as size, price, momentum, short-term reversal, and illiquidity. The bivariate analysis differs from the univariate analysis by double sort where we first categorize coins

[5] We consider weekly returns as in the cryptocurrency market, trading and investor reactions to market sentiment is faster than the traditional financial markets (Dyhrberg, 2016; Hong, 2017).

according to a certain characteristic and then sort by MAX to detect the MAX effect cleared from any other potential impact. The bivariate portfolio analysis and Fama and MacBeth (1973) cross-sectional regressions provide supporting evidence for the MAX effect. The univariate regression of MAX on lagged MAX, as well as the multivariate regression with seven additional control variables, produces positive, considerably large, and extremely significant MAX coefficient.

We contribute to the cryptocurrency literature by investigating the relationship between maximum daily returns and expected future returns. Coin-level cross-sectional regressions show that the MAX effect has an explanatory power over future cryptocurrency returns. Our results contradict with the findings of Grobys and Sapkota (2019), Jia et al. (2020), and Grobys and Junttila (2021). Grobys and Sapkota (2019) report no supporting evidence of momentum effects by testing 143 cryptocurrencies and indicate that the cryptocurrency market is not as inefficient as earlier studies suggest. Moreover, Jia et al. (2020) examine the predictive power of higher moments on the cross-section of expected returns using 84 cryptocurrencies. They document a significant return predictability of higher moments and a negative significant relationship between positive extreme returns and future returns. Similarly, Grobys and Junttila (2021) investigate the speculative behavior in the cryptocurrency market by utilizing a data set of 20 coins excluding Bitcoin for the period between January 2016 and December 2019. They report that investors tend to prefer cryptocurrencies with high payoffs and low subsequent returns. However, we note that these studies have limited samples, and we believe that the sample size is crucial for obtaining accurate results. Therefore, in this analysis, we use all cryptocurrencies over $5 million market capitalization with publicly available data. This gives us 17 cryptocurrencies at the beginning of our sample period, which reaches up to 523 cryptocurrencies in the end. Our sample is very close to the entire universe of cryptocurrencies traded in the market, which enhances the robustness of our findings.[6] Furthermore, the conclusion of Li et al. (2020a) is consistent with our results that cryptocurrencies with the highest extreme returns pursue their superior performance in the future.

[6] 2000 cryptocurrencies narrow down to 973 in total, when we apply $5 million market cap filter to exclude illiquid cryptocurrencies and obtain more reliable and robust results. However, when we conduct the same analyses using all of 2000 coins, the outcomes are similar to those presented in the study. Results are available upon request.

In this study, we additionally analyze the volatility effect on subsequent cryptocurrency returns. Ang et al. (2006) report that there exists a negative relationship between idiosyncratic volatility and expected returns, whereas Zhang and Li (2020) argue a contrary positive relation for cryptocurrencies. We find a high correlation between idiosyncratic volatility and maximum daily returns and suspect whether MAX acts as a substitute for volatility, which would make this effect transient in the cryptocurrency market. We examine this problem by performing bivariate portfolio analysis on MAX, wherein the sorting on the volatility component is performed by using both Garman and Klass (1980) volatility (VOL) and idiosyncratic volatility (IVOL) for robustness. Precisely, we first sort portfolios based on maximum daily returns, controlling for VOL (IVOL), and report a value-weighted average raw difference between high MAX and low MAX portfolios of 1.58% (0.91%) with a t-stat of 5.17 (2.72). The high significance of returns indicate that MAX effect is valid and persistent. Furthermore, when we sort portfolios according to IVOL, controlling for MAX, we obtain insignificant differences for raw return and alpha differences between the highest and lowest idiosyncratic volatility deciles. We further conduct a cross-sectional regression analysis and find supporting evidence for a significant MAX effect and an insignificant volatility effect over expected returns. Consequently, the positive explanatory power of MAX on subsequent returns is robust to controls for various volatility measures.

Moreover, we examine the relationship between extreme positive returns and skewness. Empirical findings document that more positively skewed portfolios yield subsequent lower returns (Harvey and Siddique, 2000; Smith, 2007; Mitton and Vorkink, 2007; Conrad et al., 2013). However, Brunnermeier and Gollier (2007) and Barberis and Huang (2008) theoretically show that this result is more likely to be reasoning from the overoptimism for low-price and low-probability states in which extreme returns are overweighted. Studies on cryptocurrencies present conflicting results on the impact of skewness on the cross-section of returns (Balcilar et al., 2017; Wei, 2018). In addition, Jia et al. (2020) indicate that return predictability of skewness is affected by extreme positive returns. Therefore, we further analyze the relationship between MAX and skewness to test whether extreme positive returns proxy for skewness. We use two different measures, total skewness (TSKEW) and idiosyncratic skewness (ISKEW) (Boyer et al., 2010), and conduct bivariate portfolio analyses, along with cryptocurrency-level cross-sectional return regressions. Our findings demonstrate that the MAX effect is robust when we control for total and idiosyncratic skewness.

Finally, we investigate the impact of investor sentiment on maximum daily returns as many studies in the empirical literature show that investor sentiment has an effect on cross-sectional returns (Baker and Wurgler, 2006, 2007; Da et al., 2015; He et al., 2019). Specifically, Stambaugh et al. (2012) document that overpricing of stocks is more prevalent during high sentiment periods. Fong and Toh (2014) demonstrate the dependence of MAX effect over investor sentiment and report that—controlling for the past sentiment—the significance of MAX effect decreases. Regarding the crytocurrency market, Karalevicius et al. (2018) report that investors are inclined to overreact to news on media; thus, Bitcoin prices act according to the sentiment direction. In addition, Polasik et al. (2015) indicate that Bitcoin returns are contingent upon popularity, media sentiment, and the total number of transactions. To investigate the speculative bubbles with relatively high returns in the cryptocurrency market, Chen and Hafner (2019) utilize StockTwits sentiment analysis and report high volatility during low sentiment periods. Considering the sentiment impact reported in the literature, we conduct a bivariate portfolio analysis, controlling for the investor sentiment. We observe that the difference between high MAX and low MAX value-weighted portfolio raw returns equals 2.80% (3.25%) with a Newey-West adjusted t-stat of 3.16 (1.98) during the low (high) sentiment period. Furthermore, we plot the time-series of cumulative long-short portfolio returns and investor sentiment. In line with the findings of Fong and Toh (2014), in the cryptocurrency market, we report that the performance of long-short hedge portfolio based on MAX is higher following high sentiment periods. Our results support the momentum impact of extreme positive returns. Nevertheless, the MAX effect continues to be robust after controlling for the investor sentiment as it remains significant in both high and low sentiment states.

The remainder of the paper is organized as follows. Section 4.2 presents univariate and bivariate portfolio-level analyses and coin-level cross-sectional regressions. Section 4.3 discusses the relationship between extreme returns and volatility measures, while Sections 4.4 and 4.5 focus on the connection of extreme returns with skewness and investor sentiment, respectively. Finally, Section 4.6 concludes the paper.

### 4.2. Maximum daily return and the cross-section of expected returns

We use daily closing prices of all cryptocurrencies with publicly available data.[7] We exclude cryptocurrencies with market capitalization below $5 million, and we incorporate a new coin into the sample after waiting for six months.[8] The data source is CoinMarketCap (https://coinmarketcap.com/coins/), and our sample spans the period from the beginning of January 2014 to the end of September 2020. Sample size starts with only 17 cryptocurrencies at the beginning and reaches up to 523 cryptocurrencies by the end of the period under examination.

#### 4.2.1. Variable construction

We construct most of our variables following Bali et al. (2011). Our variable of interest is the maximum daily return within the past month ($MAX$), calculated weekly for each coin, as described in equation (4.1).

$$\mathrm{MAX}_{i,t} = max(R_{i,d}), \quad d = 1, ..., D_m \tag{4.1}$$

where $\mathrm{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$, and $D_m$ is the number of trading days in month m.[9] To estimate $BETA$, we follow Scholes and Williams (1977) and Dimson (1979) and consider lag, current, and lead returns on market index. We estimate equation (4.2) weekly for each coin using daily returns

[7] List of cryptocurrencies are available upon request.

[8] We thank the anonymous referee for this suggestion. Cryptocurrencies with low market capitalization show extreme low liquidity, which complicates the application of practical trading strategies in reasonable sizes. Moreover, when a coin is initially launched, price behavior might be very strange until it is adopted by users, miners, and traders. It takes some time for it to gain substantial acceptance and liquidity. Therefore, we consider cryptocurrencies with market caps over $5 million and exclude the first six months of price behavior out of our sample.

[9] The meaning of *trading days* in the cryptocurrency market is different from that in the traditional stock market, as the coin market is always active. In our analysis, we assume a week and a month to be 7 and 28 trading days, respectively.

within a month.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \epsilon_{i,d} \tag{4.2}$$

where $R_{m,d}$ is the cryptocurrency market portfolio return on day $d$, and $r_{f,d}$ is the risk-free rate on day $d$.[10] We measure *SIZE* by the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. As another size variable, we measure *PRICE* by the natural logarithm of one plus the cryptocurrency's price by the end of previous week. The momentum variable (*MOM*) is calculated weekly for each coin as the cumulative return over the previous three weeks starting two weeks ago, that is, the cumulative return from week t-4 to week t-2. Short-term reversal (*REV*) is defined as the cumulative return on cryptocurrency $i$ within the past week, that is, the cumulative return in week t-1. To measure illiquidity (*ILLIQ*), we follow Amihud (2002) and calculate the ratio of absolute daily cryptocurrency return to its mean dollar trading volume each week, as shown in equation (4.3).

$$\text{ILLIQ}_{i,t} = \frac{1}{D} \sum_{d=1}^{D} \frac{|R_{i,d}|}{VOLD_{i,d}} \tag{4.3}$$

where $\text{VOLD}_{i,d}$ is the respective trading volume in dollars and D is the total number of trading days in a week. Our final variable of interest is volatility (*VOL*). To estimate weekly volatility of each coin, we follow Garman and Klass (1980) and use equation (4.4).

$$\text{VOL}_{i,t} = \sqrt{\frac{N}{D} \sum_{d=1}^{N} \left[ \frac{1}{2} \left( log \frac{H_{i,d}}{L_{i,d}} \right)^2 - (2log(2) - 1) \left( log \frac{C_{i,d}}{O_{i,d}} \right)^2 \right]} \tag{4.4}$$

where $N$ is the total number of trading days in a month and $D$ is the total number of trading days in a week. $H_{i,d}$, $L_{i,d}$, $C_{i,d}$ and $O_{i,d}$ are the highest, lowest, closing, and opening price of cryptocurrency $i$, respectively, on day $d$.[11]

[10] We construct a daily value-weighted cryptocurrency market index using all sample cryptocurrencies. Risk-free rate is the one-month T-bill return.

[11] There exists a high cross-correlation between MAX and idiosyncratic volatility, which causes multicollinearity in the regression models. Therefore, we use Garman-Klass volatility (then the correlation coefficient between MAX and volatility becomes 0.0028) to capture the intraday information, which seems to have a considerable impact on price variability (Eross et al., 2019; Mensi et al., 2019; Jia et al., 2020).

Table 4.1 shows descriptive statistics of variables. Our main variable of interest, MAX, has a mean value of 22% with a lower median value of 16%. In addition, MOM, REV, and VOL averages are 7%, 2%, and 91%, respectively. Mean and median values of ILLIQ is slightly low, which indicates that we have been able to remove the most illiquid coins out of the sample.

—————————————**INSERT TABLE 4.1 HERE**—————————————

### 4.2.2. Univariate portfolio analysis

We form decile portfolios by sorting cryptocurrencies based on MAX values and present the value-weighted and equal-weighted average weekly returns in Table 4.2. Portfolio 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily returns during the previous month. The first column of Table 4.2 shows that the value-weighted average raw return difference between decile 10 (high MAX) and decile 1 (low MAX) is 3.03% per week with a corresponding Newey-West adjusted t-stat of 4.10. Similarly, as shown the third column of Table 4.2, the raw difference between the low MAX and high MAX equal-weighted portfolio returns average 2.45% per week with a t-statistic of 3.22. Table 4.2 also reports the intercept terms (alphas) from regressions of the value-weighted and equal-weighted portfolio returns on a constant, the excess market return, a size factor, and a momentum factor, following Fama and French (1993) and Carhart (1997). The excess cryptocurrency market return is the difference between cryptocurrency market index return and the risk-free rate. For the size factor, we follow Liu et al. (2020) and Zhang and Li (2020) and split cryptocurrencies per week into three groups by market capitalization. We form value-weighted portfolios for each size group and calculate the difference between average returns of small and big size portfolios. Similarly, for the momentum factor, we split cryptocurrencies per week into three groups by momentum.[12] We construct value-weighted portfolios for each momentum group, and we calculate the difference between average returns of the highest and lowest momentum portfolios. The difference between the high MAX and low MAX value-weighted portfolio's three-factor alphas equals 1.99% with a Newey-West adjusted t-stat of

[12] We compute momentum as the cumulative return over the past three weeks following Liu et al. (2020).

3.72, as shown in the last two rows of Table 4.2. The difference between the high MAX and low MAX equal-weighted portfolio alphas equals 2.44% with a Newey-West t-stat of 3.34. For both value-weighted and equal-weighted portfolios, the differences between average returns and three-factor alphas are both economically and statistically significant. In addition, we observe that as average MAX increases, both average returns and alphas increase monotonically. Contrary to the significant negative MAX effect in equity market (Bali et al., 2011; Hung and Yang, 2018), these findings show that portfolios of cryptocurrencies with the highest extreme returns continue to exhibit superior performance in the future.

**INSERT TABLE 4.2 HERE**

We repeat the univariate portfolio analysis by considering not only the unique extreme positive return (MAX) but also the averages of $N$ ($N = 2$, 3, 4, and 5) highest daily returns within the past month, denoted by MAX($N$). Table 4.3 presents the results of the analysis. Panel A reports the average return and alpha differences between the highest and lowest average MAX($N$) for the value-weighted portfolios, and Panel B shows those for the equal-weighted portfolios. We also show the results from Table 4.2 in the first column of Table 4.3 for ease of comparison. The value-weighted and equal-weighted average raw return differences between the high MAX($N$) and low MAX($N$) remain economically and statistically significant.

**INSERT TABLE 4.3 HERE**

Looking at Table 4.2 and Table 4.3, we may argue that investors expect the extreme positive daily return behavior to last in the future and thus they may be willing to purchase these coins for higher prices. To understand the persistence of the MAX effect and to discuss the relationship between extreme positive returns and certain characteristics of cryptocurrencies, we run the Fama and MacBeth (1973) regression models. In particular, for each week, we regress the maximum daily return within that particular month on the maximum daily return from the past month and seven lagged control variables. As explained in Section 4.2.1, our control variables are the market beta (BETA), the log of market capitalization (SIZE), the price of cryptocurrency (PRICE), the return over three weeks prior to the past week (MOM), the return in the previous week (REV), the Amihud illiquidity measure (ILLIQ), and the Garman-Klass volatility measure (VOL). For each of the 348 sample weeks, we winsorize all variables in the cross-section at 5% level from both upper and lower tails to get rid of the outlier effect without removing any observation. Table 4.4 presents the average coefficients form cross-sectional regressions and the Newey-West adjusted t-statistics. The first two rows of Table 4.4 show that the coefficient of MAX variable is positive with an extremely high statistical significance and the adjusted R-squared value over 68%. When we add the seven control variables to the regression, MAX coefficient remains positive and highly significant with the adjusted R-squared of over 75% while all other variables become insignificant. This significant explanatory power of MAX in the univariate regression on lagged MAX and multivariate regression with additional seven lagged variables indicate that a positive relation exists between the maximum daily return over the previous month and expected extreme positive cryptocurrency returns. In other words, coins with extreme positive returns are inclined to outperform in the following month.

**INSERT TABLE 4.4 HERE**

We further investigate the two extreme deciles (low MAX and high MAX) in the post-formation period and report the descriptive statistics in Table 4.5. We use approximately 55,000 weekly returns on cryptocurrencies. Unlike the equal-weighted portfolio calculation in Table 4.2 with different number of coins, we weigh all returns equally as presented in the first row of Table 4.5. For this reason, the mean return for low MAX is lower than the equal-weighted portfolio average return (in Table 4.2), and the mean return for high MAX is higher than that of Table 4.2. When compared to low MAX coins, high MAX coins have higher average returns with higher volatility and slightly more positive skewness. Moreover, upper tail behavior in percentiles presents that the high MAX returns at 90th, 95th, and 99th percentiles are nearly twofold of low MAX returns. The results demonstrate that there is a higher probability for high MAX coins to preserve extreme positive returns in the future.

**INSERT TABLE 4.5 HERE**

The analyses thus far uncover some evidence against the investor preference over lottery-like assets, which have a slight chance of a large future payoff in the future (Kumar, 2009; Bali et al., 2011). The MAX variable with a characteristic of high positive skewness construct a suitable basis for lottery-like behavior (Fong and Toh, 2014; Zhu et al., 2020). However, in the cryptocurrency market, we observe that if we buy a well performing coin portfolio and sell a poorly performing portfolio, there is a high probability of continuing to win significant positive returns in the future. Hence, the behavior of the cryptocurrency market signals inefficiency and resembles movement direction of the momentum factor (Jegadeesh and Titman, 1993). To understand more about the MAX portfolio composition, we report the summary statistics of cryptocurrencies in the decile portfolios in Table 4.6. The table presents the averages of the weekly median values of characteristics, which are the maximum daily return (MAX), the cryptocurrency market beta, the market capitalization (in millions of dollars), the price (in dollars), the cumulative return over the previous three weeks prior to the week before (MOM), the cumulative return over the past week (REV), the Amihud illiquidity measure (scaled by $10^{-5}$), and the Garman-Klass volatility measure.

**INSERT TABLE 4.6 HERE**

Table 4.6 shows that as we move from decile 1 (low MAX) to decile 10 (high MAX), the average of weekly median MAX values increase from 5.38% to 59.56% whereas the size values decrease from \$426.75 million to \$21.92 million. This indicates that high MAX portfolios are dominated by smaller-sized cryptocurrencies. This result is consistent with the findings of Chan et al. (1991) and Fama and French (1992) who document the high likelihood of relatively smaller firms to return higher profits. As the average of median daily maximum return increases through decile 1 to decile 10, the price also diminishes. The increase in the market beta indicates that cryptocurrencies in high MAX decile are slightly more exposed to market risk. The average values of the median momentum and short-term reversal variables both rise as we move from low

MAX decile to high MAX decile. These findings also support that past winners continue to perform better in the future (Jegadeesh and Titman, 1993). Furthermore, a mild increase exists in the illiquidity measure. Specifically, high MAX coins are found to be less liquid and more volatile. This contrary relationship is consistent with the findings of Wei (2018).

#### 4.2.3. Bivariate portfolio analysis

In this section, our goal is to understand whether the relationship between maximum daily returns and future returns on cryptocurrencies persists as discussed, when we control for size, price, momentum, short-term reversal, and liquidity. Following Bali et al. (2011), we perform the bivariate portfolio analysis where we first sort cryptocurrencies by a certain characteristic (such as size). We then categorize each of these deciles according to MAX. Thus, we obtain 100 cryptocurrency portfolios. Table 4.7 presents the results for MAX portfolio deciles by averaging across the ten deciles sorted by the characteristics.[13] Average returns and corresponding alphas for value-weighted portfolios and equal-weighted portfolios are reported in Panel A and Panel B of Table 4.7, respectively.

**INSERT TABLE 4.7 HERE**

Bivariate portfolio analysis presents the supporting evidence for our findings in Section 4.2.2. When we control for size, the value-weighted mean return difference between decile 10 (high MAX) and decile 1 (low MAX) is 2.73% with a Newey-West adjusted t-stat of 7.70. Furthermore, the corresponding value for the value-weighted average risk-adjusted return difference equals 2.47% with a t-stat of 2.71. Similarly, after controlling for price, momentum, short-term reversal, and liquidity, the value-weighted average return differences between the high MAX and low MAX portfolios are 1.75%, 1.69%, 1.48%, and 1.76% per week, respectively. For equal-weighted portfolios, average return differences between high MAX and low MAX portfolios are 2.08%, 1.82%, 1.77%, 1.70%, and 1.56% per week, respectively. All mean raw differences are economically and

[13]We do not report the findings of all 100 portfolios for brevity; however, comprehensive results are available upon request.

statistically significant. For value-weighted and equal-weighted portfolios, the differences between alpha values of high MAX and low MAX coins are statistically significant. As these results coincide with the findings of univariate portfolio studies, none of the cross-sectional effects, such as size, price, momentum, short-term reversal nor liquidity is powerful enough to explain further the highest extreme returns to high MAX cryptocurrencies.

#### 4.2.4. Cross-sectional return regressions

The portfolio analyses we have conducted thus far give supporting results of a positive MAX effect. In this section, we investigate the coin level cross-sectional relation between MAX and expected returns to observe whether a connection exists at the individual level.[14] We run Fama and Macbeth regressions of cryptocurrency returns on the lagged maximum daily return (MAX), market beta (BETA), log of market capitalization (SIZE), price of cryptocurrency (PRICE), return over three weeks prior to the past week (MOM), return in the previous week (REV), and the Amihud illiquidity measure (ILLIQ), as shown in equation (4.5).

$$
\begin{gathered}
\mathrm{R}_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}(MAX_{i,t}) + \gamma_{2,t}(BETA_{i,t}) + \gamma_{3,t}(SIZE_{i,t}) + \\
\gamma_{4,t}(PRICE_{i,t}) + \gamma_{5,t}(MOM_{i,t}) + \gamma_{6,t}(REV_{i,t}) + \gamma_{7,t}(ILLIQ_{i,t}) + \epsilon_{i,t+1}
\end{gathered} \tag{4.5}
$$

where $\mathrm{R}_{i,t+1}$ is the realized return on cryptocurrency $i$ in week $t+1$, and all independent variables are lagged one week. Rules on winsorization still apply. Table 4.8 presents the time-series averages of the slope coefficients over 348 weeks from January 2014 to September 2020.

**INSERT TABLE 4.8 HERE**

The univariate regression of maximum daily return on future cryptocurrency returns results in a positive and statistically significant relationship. The average slope, $\gamma_{1,t}$, equals 8.21% with a robust t-stat of 3.14. Considering the spread

[14] Refer to Liu and Tsyvinski (2018) and Liu et al. (2019) for excellent studies on cross-sectional cryptocurrency returns and predictability.

between median of MAX between decile 10 and decile 1 from Table 4.6, we can estimate approximately 445 basis points difference in the expected weekly returns among high MAX and low MAX deciles of median coins. The economic magnitude of this difference is extremely significant as well as encouraging for the investors to buy cryptocurrencies with the highest daily extreme returns. In addition to MAX, the univariate regressions show that SIZE and PRICE have an explanatory power over the expected returns, which is consistent with the findings of Li et al. (2020b). The average slopes of MOM (3.92%) and REV (9.62%) variables are positive and significant at 5% and 1%, respectively. Momentum having a positive explanatory power over future returns coincides with the findings of Liu et al. (2020) while contradicting with the results of Grobys and Sapkota (2019). When the regression is run with the six control variables except MAX, no significant explanatory variable is found. Nevertheless, as shown in the last row of Table 4.8, when we embrace all variables in the regression, MAX shows a higher significance with a coefficient of 28.43% and a t-stat of 6.14. The regression results show that, contrary to Jia et al. (2020), the cross-sectional regressions are a strong evidence for an economically and statistically significant positive relation between extreme returns and expected returns in the cryptocurrency market.

### 4.3. Extreme Positive Returns and Volatility

The literature on cross-sectional studies of volatility and expected return have revealed inconsistent results (Ang et al., 2006; Bali and Cakici, 2008; Fu, 2009). In the cryptocurrency market, Zhang and Li (2020) report a positive and nontemporal relationship between idiosyncratic volatility and future returns using more than 500 coins. In particular, cryptocurrencies with a high maximum daily return within a month also have high volatility, as shown in Table 4.6. Depending on the substantial connection between idiosyncratic volatility and maximum daily returns, we examine whether MAX effect acts as a proxy for volatility; this section investigates in detail the relation among them. First, Table 4.9 shows the average weekly cross-sectional correlation coefficients between six variables: the maximum daily return within the past month (MAX), average of the highest five daily returns within the past month (MAX(5)), the minimum daily return within the past month (MIN) as described in equation (4.6), monthly realized total volatility (TVOL) as described in equation (4.7), monthly realized idiosyncratic volatility (IVOL) as described in equation (4.8), the and Garman-Klass volatility (VOL).

$$\mathrm{MIN}_{i,t} = min(R_{i,d}), \quad d = 1, ..., D_m \tag{4.6}$$

where $\mathrm{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$ and $D_m$ is the number of trading days in month $m$,

$$\mathrm{TVOL}_{i,t} = \sqrt{var(R_{i,d})} \tag{4.7}$$

$$\mathrm{IVOL}_{i,t} = \sqrt{var(\epsilon_{i,d})} \tag{4.8}$$

with $\epsilon_{i,d}$ is the innovation on cryptocurrency obtained from equation (4.9).

$$\mathrm{R}_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d} - r_{f,d}) + \epsilon_{i,d} \tag{4.9}$$

**INSERT TABLE 4.9 HERE**

Table 4.9 shows that in our cryptocurrency sample, very high average cross-sectional correlations exist between TVOL and IVOL (coefficient of 0.99), TVOL and MAX (coefficient of 0.77), and IVOL and MAX (coefficient of 0.80). MAX and MAX(5) are highly correlated as expected, which indicates that they can act as perfect substitutes for each other. On the contrary, there is a very low correlation between Garman-Klass volatility (VOL) and maximum daily return (MAX), which is why we use this variable as the volatility factor in our analysis.

Second, we perform the bivariate portfolio analysis to further examine the relationship between volatility and expected returns on cryptocurrencies. Similarly, as discussed in Section 4.2.3 and presented in Table 4.7, we sort cryptocurrencies by MAX, controlling for VOL and IVOL. In order to do that, we form decile portfolios that are sorted based on VOL and IVOL. We then rank each volatility decile according to MAX and conduct value-weighted and equal-weighted portfolio analysis.[15] The results for average returns across MAX

[15] We repeat the same bivariate portfolio analysis by replacing MAX with MAX(5) and obtain very similar results to those reported in Table 4.10. For brevity, we do not report these findings

deciles, the corresponding three-factor alphas, and the Newey-West adjusted t-statistics are shown in Panel A of Table 4.10. The value-weighted average raw difference between decile 10 (high MAX) and decile 1 (low MAX) is 1.58% (0.91%) per week with a t-stat of 5.17 (2.72) when we control for VOL (IVOL). Alpha values are also economically and statistically significant. By allowing deciles to contain cryptocurrencies with all levels of volatility and dispersion based on MAX, we show that the power of MAX effect to explain future returns persists. In addition to value-weighted portfolios, the differences between high MAX and low MAX deciles and their significance levels are conformable to those in Table 4.3 and Table 4.7.

**INSERT TABLE 4.10 HERE**

Furthermore, in Panel B of Table 4.10, we conduct the reverse sort. We form deciles of cryptocurrencies ranked by IVOL and VOL, controlling for extreme positive returns. The average raw differences between the high VOL and low VOL deciles of both value-weighted and equal-weighted portfolios as well as three factor alpha differences remain insignificant. The results in Table 4.10 report no effect of volatility and idiosyncratic volatility on future returns, which is consistent with the findings of Bali and Cakici (2008) but contradicts with the significant positive relation indicated by Zhang and Li (2020). We observe that when we control for volatility and idiosyncratic volatility, coins with extreme positive returns continue to show superior performance in the future. However, when the data is controlled for MAX, the effect of volatility and idiosyncratic volatility on future returns disappear. This analysis further sheds light on the positive relation between the highest extreme returns and expected returns in the cryptocurrency market.

Third, we investigate the cross-sectional relationship between volatility and expected returns. Table 4.11 presents the results of Fama-Macbeth regressions. Rules on winsorization still apply. In univariate regressions, the average slope of MAX is 8.21% with a t-stat of 3.14. However, the volatility coefficient (1.68%) is not significant (t-stat=1.51), which supports the finding that volatility remains

in the paper, but the results are available upon request.

inefficient in explaining future returns in equal-weighted portfolios.[16] When future returns are regressed on MAX and volatility together, the significance of MAX increases whereas VOL remains insignificant with a negative coefficient. When six other control variables are added to the regression, the insignificance of VOL remains unchanged. We might suspect that the positive relation between idiosyncratic volatility and expected returns reported by Zhang and Li (2020) is reasoning from the fact that IVOL acts as a proxy for MAX. Furthermore, we consider MIN in our regression analysis to further understand the effect of volatility. As MIN is also highly correlated with volatility, it might exhibit a similar behavior with MAX if our results are a consequence of volatility effect. Table 4.11 also shows the Fama-Macbeth regression results with MAX, MIN, and VOL. The univariate regression coefficient of MIN is 9.36% with a t-stat of 2.31, which is significant at 5% level. The positive sign of MIN might indicate that a decrease in a cryptocurrency's value does not necessarily mean lower future returns. In all of 7 regressions presented in Table 4.11, MAX coefficient remains statistically significant after controlling for MIN, VOL, BETA, SIZE, PRICE, MOM, REV, and ILLIQ. These results confirm our findings in univariate and bivariate analyses with the interpretation that in the cryptocurrency market, the MAX effect is not temporal and a positive relation exists between the highest extreme returns and future expected returns.

**INSERT TABLE 4.11 HERE**

### 4.4. Extreme Positive Returns and Skewness

In this section, we investigate the connection between extreme positive returns and skewness. The literature highlights investor preference over positive skewness (Arditti, 1967; Kraus and Litzenberger, 1976; Scott and Horvath, 1980). Harvey and Siddique (2000) shows the relationship between momentum effect and systematic skewness. By measuring conditional skewness, Harvey and Siddique (2000) and Smith (2007) indicate that portfolios with a higher skewness tend to underperform in the future. In addition, Mitton and Vorkink (2007) and Boyer et al. (2010) find negative correlation among idiosyncratic skewness and

[16] In cross-sectional regressions, the averaging process weigh each coin equally.

expected returns. Nevertheless, Brunnermeier and Gollier (2007) and Barberis and Huang (2008) show that at least theoretically, skewness is not the reason for these underperforming stocks. On the contrary, Wei (2018) reports strong positive skewness in cryptocurrency returns whereas Balcilar et al. (2017) show that Bitcoin returns are left-skewed. Jia et al. (2020) document that extreme positive returns have a significant effect over return predictability of higher moments. Considering the literature on the impact of skewness on expected returns, we question whether the MAX effect is robust to controls for skewness measures. We use two different measures to evaluate skewness, total skewness (TSKEW), and idiosyncratic skewness (ISKEW). TSKEW is the measure for the third moment of returns and calculated as described in equation (4.10).

$$\mathrm{TSKEW}_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D} \left( \frac{R_{i,d} - \mu_i}{\sigma_i} \right)^3 \tag{4.10}$$

where $\mathrm{D}_t$ is the number of trading days in month $t$, $\mathrm{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$, $\mu_i$ is the average of returns on cryptocurrency $i$ in month $t$, and $\sigma_i$ is the standard deviation of returns on cryptocurrency $i$ in month $t$. We compute ISKEW after Boyer et al. (2010) as described in equation (4.11).

$$\mathrm{R}_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \theta_i(R_{m,d} - r_{f,d})^2 + \epsilon_{i,d} \tag{4.11}$$

where as usual $\mathrm{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$, $\mathrm{R}_{m,d}$ is the cryptocurrency market portfolio return on day $d$, $\mathrm{r}_{f,d}$ is the risk-free rate on day $d$, and $\epsilon_{i,d}$ is the idiosyncratic return on day $d$. The idiosyncratic skewness (ISKEW) of cryptocurrency $i$ in month $t$ equals the skewness of daily residuals $\epsilon_{i,d}$ in month $t$.

Initially, we conduct the bivariate portfolio analysis where we first sort cryptocurrencies based on the skewness measure and then rank each of these deciles by MAX. Table 4.12 presents the results of the analysis. The first (second) column of Table 4.12 reports that, after controlling for TSKEW (ISKEW), the value-weighted mean return difference between high MAX and low MAX deciles is 2.95% (2.65%) with a Newey-West adjusted t-stat of 8.06 (7.38). For TSKEW (ISKEW), the three-factor alpha difference is 2.67% (2.37%)

with a t-stat of 6.41 (6.10). The high degree of positive significance in return and alpha differences indicate that neither total skewness nor idiosyncratic skewness explains the link between extreme positive returns and future returns.

**INSERT TABLE 4.12 HERE**

Boyer et al. (2010) state that among other characteristics, lagged skewness might be a weak predictor for future skewness, which we wish to consider. Therefore, we perform coin-level cross-sectional regressions of TSKEW and ISKEW on lagged values of skewness and six other control variables. Rules on winsorization still apply. The results are shown in Table 4.13. The univariate and multivariate regressions of both TSKEW and ISKEW indicate that skewness is extremely significant to predict subsequent skewness. Nevertheless, in our next analysis, we additionally consider expected total skewness ($E$(TSKEW)) as a control variable that is fitted each week throughout the cross-sectional regressions. Table 4.14 reports the coefficients and corresponding Newey-West adjusted t-statistics from cross-sectional regressions of subsequent weekly returns on MAX and nine other control variables, including TSKEW, ISKEW, $E$(TSKEW).

**INSERT TABLES 4.13 and 4.14 HERE**

The time-series average coefficients of extreme positive returns are all statistically and economically significant in all the specifications. In univariate regressions, coefficients of skewness measures (TSKEW, ISKEW and $E$(TSKEW)) are all positive and statistically significant. TSKEW is significant at 5%, and ISKEW and $E$(TSKEW) are significant at 10% levels. However, in the full specifications, each of these variables are statistically insignificant. Consequently, the empirically indicated positive skewness is consistent with the findings of Wei (2018). Nevertheless, contrary to the findings of Jia et al. (2020), the results show that the skewness remains insignificant to predict subsequent returns. In addition, extreme positive return impact is significantly persistent and robust to controls for skewness measures.

### 4.5. Extreme Positive Returns and Investor Sentiment

The empirical literature documents that a significant relationship exists between the investor sentiment and expected stock returns (Baker and Wurgler, 2007; Yang and Zhou, 2015; He et al., 2019). Baker and Wurgler (2006) present lower subsequent returns, and Stambaugh et al. (2012) report common mispricing in stocks during high sentiment periods. When investors are optimistic about the subsequent returns, they might be inclined to invest in stocks with lottery-like features. This gambling tendency originates from the expectation of high-performing stocks to continue winning in the future. However, as in the theoretical model of Brunnermeier and Gollier (2007), overoptimism might result in underperforming stock investments. While Bali et al. (2011) explains this phenomenon by MAX effect, Fong and Toh (2014) indicate the dependency of MAX effect on investor sentiment. Next, if the MAX effect is induced by investor optimism, the significance will vanish when we control for the cryptocurrency market sentiment. Hence, the aim of this section is to understand the relationship between the investor sentiment and extreme positive returns.

We perform the univariate portfolio analysis to test the effect of investor sentiment on subsequent returns. We define two periods: low sentiment and high sentiment. As a proxy for market sentiment, we use Bitcoin Sentiment Index, which is constructed with regards to the Bitcoin conversations collected from Twitter, Reddit, and Bitcointalk. The value changes between 0 and 1, where 0 refers to extreme bearish and 1 refers to extreme bullish.[17] We categorize weekly data into bins of *low sentiment* whenever the sentiment index is below the sample median value and *high sentiment* whenever the sentiment index is above the sample median value. We report the value-weighted average raw return and three-factor alpha differences in Table 4.15, with the corresponding t-statistics. For low (high) sentiment periods, the mean return difference between decile 10 (high MAX) and decile 1 (low MAX) is 2.80% (3.25%) with an adjusted t-stat of 3.16 (1.98). These magnitudes are very similar with those reported in Table 4.2, which supports the significance of extreme positive returns to explain subsequent returns. The results are consistent with the positive MAX effect reported in our analyses. Fong and Toh (2014) claim that the high investor sentiment periods

[17] Further information is available at https://www.augmento.ai/bitcoin-sentiment/.

drive the MAX effect in stock markets; however, we report similar magnitudes and significance levels in both states. This indicates investor preference over lottery-like assets both following low and high sentiment periods for the cryptocurrency market, contrary to the findings of Fong and Toh (2014) in the stock market.

Furthermore, we perform long-short portfolio analysis with regards to the low MAX and high MAX decile performances. We calculate the subsequent long-short portfolio returns (high MAX decile – low MAX decile) to control whether MAX effect is driven by low or high sentiment periods. We plot the time-series of cumulative return performance and sentiment index in Figure 4.1.[18] The figure supports the findings in Table 4.15 that the performance of long-short hedge portfolio based on MAX is slightly higher following high sentiment states. In addition, the cumulative return of the long-short portfolio decreases in the early sample period before moving upwards until the end. This might be interpreted as the investors acting pessimistic and taking short position whenever the sentiment index is at low levels in the beginning. Immediately after the sentiment index begins to increase, the investors in the cryptocurrency market embrace an optimistic behavior and take a long position until the end of the sample period. Nevertheless, the MAX effect is statistically significant for both high and low sentiment periods, indicating that MAX effect is also robust after controlling for investor sentiment.

————————**INSERT TABLE 4.15 and FIGURE 4.1 HERE**————————

### 4.6. Conclusion

Investor preference for lottery-like assets is a novel phenomenon for the cryptocurrency market. Within this context, we follow Bali et al. (2011) and investigate the impact of the maximum daily return within the past month (MAX effect) on next week returns for the period from January 2014 to

[18] The reason that we consider the long-short portfolio return along with the sentiment analysis is to understand whether cycles exist within our sample period following the sentiment index. Therefore, we perform autocorrelation tests for the sentiment index to analyze whether sentiment is persistent. The results of both Durbin Watson Test and Ljung-Box Q Test show that there is no evidence of residuals of sentiment returns being positively correlated. The results are available upon request.

September 2020. The univariate and bivariate portfolio analyses show that MAX effect is present and persistent in the cryptocurrency market. The positive impact of extreme positive returns remains statistically significant when we use the averages of $N$ ($N = 2, 3, 4,$ *and* $5$) highest daily returns within the previous month. In addition to the lottery-like features of stocks documented in the literature, weekly regression analyses provide strong evidence that a significant positive relation exists between extreme positive returns and expected returns in the cryptocurrency market. We further show that these results are robust after controlling for size, price, momentum, short-term reversal, and liquidity.

Moreover, we analyze the possibility of extreme positive returns acting as a substitute for either volatility or skewness. To check this, we utilize different measures for volatility and skewness and report that the explanatory power of extreme positive returns over subsequent returns continues to exist. Finally, to understand the link between extreme positive returns and investor sentiment, we categorize our data into bins of low sentiment and high sentiment, and we conduct portfolio analysis. Additionally, we investigate the time series of the long-short portfolio return to check whether cycles exist, and we control whether investor sentiment is persistent. We report that the MAX effect is also robust to controls for investor sentiment. Our results signal lack of efficiency in the cryptocurrency market by which, investors might gain an advantage while forming their portfolios. It would be prudent for market participants and fund managers to consider the effect of extreme positive returns. However, further research is necessary to make interpretations and exploit this potentially fruitful anomaly.

*Table 4.1:* Descriptive statistics of the main variables

Table reports summary statistics of the main variables used in the study. Mean, median, standard deviation, skewness, kurtosis, 25th and 75th quartiles of weekly calculations are shown. MAX refers to the maximum daily return within a month. BETA is the market beta calculated as the sum of coefficients on lag, current and lead returns on market portfolio. SIZE equals the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. PRICE is the natural logarithm of one plus the cryptocurrency's price. MOM stands for momentum that equals the cumulative return over the previous three weeks skipping past week. REV stands for short-term reversal and equals the return in the past week. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. VOL refers to Garman-Klass volatility measure, which takes into account the highest, lowest, opening and closing prices.

| | Mean | Median | SD | Skewness | Kurtosis | 25th Quartile | 75th Quartile |
|---|---|---|---|---|---|---|---|
| MAX | 0.22 | 0.16 | 0.20 | 2.92 | 16.51 | 0.10 | 0.26 |
| BETA | 0.86 | 0.93 | 0.71 | -0.70 | 19.87 | 0.51 | 1.21 |
| SIZE | 17.12 | 16.72 | 1.44 | 1.07 | 3.51 | 15.99 | 17.90 |
| PRICE | 0.55 | 0.12 | 0.91 | 2.31 | 8.60 | 0.02 | 0.67 |
| MOM | 0.07 | 0.00 | 0.43 | 4.18 | 42.77 | -0.16 | 0.19 |
| REV | 0.02 | 0.00 | 0.20 | 2.37 | 23.23 | -0.09 | 0.09 |
| ILLIQ | 0.00 | 0.00 | 0.00 | 6.12 | 57.71 | 0.00 | 0.00 |
| VOL | 0.91 | 0.77 | 0.50 | 1.25 | 4.44 | 0.55 | 1.14 |

*Table 4.2:* Returns and alphas on portfolios of cryptocurrencies sorted by MAX
Decile portfolios are formed every week from January 2014 to September 2020 by ranking cryptocurrencies based on the maximum daily return (MAX) within the past month. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily return over the previous month. Table presents the value-weighted (VW) and equal-weighted (EW) average weekly returns, three-factor alphas on the value-weighted and equal weighted portfolios, and average maximum daily returns of cryptocurrencies within the past month. The bottom two rows report the differences in weekly returns and the differences in alphas between portfolios 10 and 1, and the corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| | **VW Portfolios** | | **EW Portfolios** | | |
|---|---|---|---|---|---|
| Decile | Average Return | Alpha | Average Return | Alpha | Average MAX |
| Low MAX | -0.009 | -0.009 | 0.006 | 0.003 | 0.056 |
| 2 | -0.007 | -0.008 | 0.016 | 0.016 | 0.083 |
| 3 | -0.007 | -0.008 | 0.012 | 0.013 | 0.099 |
| 4 | -0.007 | -0.008 | 0.013 | 0.011 | 0.126 |
| 5 | 0.002 | 0.001 | 0.024 | 0.021 | 0.132 |
| 6 | 0.000 | 0.000 | 0.016 | 0.015 | 0.169 |
| 7 | 0.010 | 0.008 | 0.017 | 0.013 | 0.200 |
| 8 | 0.007 | 0.007 | 0.027 | 0.024 | 0.241 |
| 9 | 0.020 | 0.014 | 0.022 | 0.021 | 0.317 |
| High MAX | 0.021 | 0.011 | 0.031 | 0.027 | 0.555 |
| 10-1 difference | 0.030 | 0.020 | 0.025 | 0.024 | |
| | (4.102)*** | (3.724)*** | (3.217)*** | (3.342)*** | |

*Table 4.3:* Returns on portfolios of cryptocurrencies sorted by multi-day MAX

Decile portfolios are formed every week from January 2014 to September 2020 by sorting cryptocurrencies based on the average of $N$ highest daily returns (MAX($N$)) within the past month. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum multi-day returns over the previous month. Table presents the value-weighted (VW) (in Panel A) and equal-weighted (EW) (in Panel B) average weekly returns for $N$=1, 2, 3, 4, and 5. The bottom two rows report the differences in weekly returns and the differences in three-factor alphas between portfolios 10 and 1, and the corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| *Panel A. Value-weighted returns on MAX(N) portfolios* | | | | | |
|---|---|---|---|---|---|
| Decile | N=1 | N=2 | N=3 | N=4 | N=5 |
| Low MAX(N) | -0.009 | -0.003 | -0.004 | -0.003 | -0.002 |
| 2 | -0.007 | 0.002 | -0.001 | 0.000 | 0.001 |
| 3 | -0.007 | -0.001 | -0.001 | -0.001 | -0.001 |
| 4 | -0.007 | -0.001 | 0.006 | 0.008 | 0.002 |
| 5 | 0.002 | 0.006 | 0.006 | 0.006 | 0.011 |
| 6 | 0.000 | 0.002 | -0.001 | -0.002 | -0.003 |
| 7 | 0.010 | 0.008 | 0.004 | 0.006 | 0.010 |
| 8 | 0.007 | 0.009 | 0.011 | 0.007 | 0.006 |
| 9 | 0.020 | 0.017 | 0.017 | 0.007 | 0.006 |
| High MAX(N) | 0.021 | 0.022 | 0.014 | 0.020 | 0.023 |
| Return difference | 0.030 | 0.026 | 0.018 | 0.023 | 0.025 |
| | (4.102)*** | (3.235)*** | (3.040)*** | (2.212)** | (2.447)*** |
| Alpha difference | 0.020 | 0.024 | 0.023 | 0.019 | 0.016 |
| | (3.724)*** | (3.525)*** | (2.773)*** | (2.431)*** | (2.364)*** |
| *Panel B. Equal-weighted returns on MAX(N) portfolios* | | | | | |
| Decile | N=1 | N=2 | N=3 | N=4 | N=5 |
| Low MAX(N) | 0.006 | 0.005 | 0.005 | 0.006 | 0.007 |
| 2 | 0.016 | 0.017 | 0.014 | 0.015 | 0.016 |
| 3 | 0.012 | 0.014 | 0.013 | 0.013 | 0.011 |
| 4 | 0.013 | 0.013 | 0.021 | 0.023 | 0.016 |
| 5 | 0.024 | 0.017 | 0.016 | 0.017 | 0.024 |
| 6 | 0.016 | 0.019 | 0.016 | 0.015 | 0.013 |
| 7 | 0.017 | 0.024 | 0.021 | 0.023 | 0.026 |
| 8 | 0.027 | 0.028 | 0.029 | 0.023 | 0.022 |
| 9 | 0.022 | 0.021 | 0.021 | 0.021 | 0.020 |
| High MAX(N) | 0.031 | 0.027 | 0.026 | 0.029 | 0.032 |
| Return difference | 0.025 | 0.022 | 0.021 | 0.023 | 0.025 |
| | (3.217)*** | (2.903)*** | (2.857)*** | (3.051)*** | (3.176)*** |
| Alpha difference | 0.024 | 0.018 | 0.017 | 0.020 | 0.021 |
| | (3.342)*** | (2.543)*** | (2.484)*** | (2.795)*** | (2.822)*** |

*Table 4.4:* Cross-sectional predictability of MAX
Each week, we conduct a cryptocurrency-level cross-sectional regression of the MAX on lagged explanatory variables, which are lagged MAX, BETA, SIZE, PRICE, MOM, REV, ILLIQ and VOL. MAX refers to the maximum daily return within a month. BETA is the market beta calculated as the sum of coefficients on lag, current and lead returns on market portfolio. SIZE equals the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. PRICE is the natural logarithm of one plus the cryptocurrency's price. MOM stands for momentum that equals the cumulative return over the previous three weeks skipping past week. REV stands for short-term reversal and equals the return in the past week. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. VOL refers to Garman-Klass volatility measure, which takes into account the highest, lowest, opening and closing prices. Both dependent and independent variables are winsorized at 5% level from upper and lower tails. Table reports the time-series averages of the cross-sectional regression coefficients and corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| MAX | BETA | SIZE | PRICE | MOM | REV | ILLIQ | VOL | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 0.957 | | | | | | | | 68.57% |
| (90.128)*** | | | | | | | | |
| | 0.413 | | | | | | | 11.37% |
| | (1.255) | | | | | | | |
| | | -0.012 | | | | | | 8.22% |
| | | (-2.228)** | | | | | | |
| | | | 0.083 | | | | | 6.98% |
| | | | (3.915)*** | | | | | |
| | | | | 0.084 | | | | 11.11% |
| | | | | (3.371)*** | | | | |
| | | | | | 0.109 | | | 13.36% |
| | | | | | (2.218)** | | | |
| | | | | | | 1.540 | | 15.62% |
| | | | | | | (2.315)** | | |
| | | | | | | | 0.242 | 36.27% |
| | | | | | | | (5.953)*** | |
| 1.339 | 0.377 | -0.025 | 0.034 | -0.097 | 0.731 | 1.277 | 0.087 | 75.47% |
| (24.122)*** | (0.907) | (-1.014) | (1.106) | (-0.818) | (1.179) | (0.201) | (1.586) | |

*Table 4.5:* Distribution of weekly returns for cryptocurrencies in high and low MAX portfolios Decile portfolios are formed every week from January 2014 to September 2020 by sorting cryptocurrencies according to maximum daily return (MAX) within the previous month. The table presents descriptive statistics for the approximately 55.000 weekly returns on the coins in decile 1 (low MAX) and decile 10 (high MAX) in the subsequent week.

| | Low MAX | High MAX |
|---|---|---|
| Mean | 0.005 | 0.038 |
| Median | -0.001 | -0.003 |
| Std Dev | 0.155 | 0.251 |
| Skewness | 2.570 | 2.919 |
| Percentiles | | |
| 1% | -0.352 | -0.371 |
| 5% | -0.213 | -0.262 |
| 10% | -0.154 | -0.199 |
| 25% | -0.061 | -0.126 |
| 50% | -0.001 | -0.003 |
| 75% | 0.050 | 0.155 |
| 90% | 0.159 | 0.337 |
| 95% | 0.256 | 0.430 |
| 99% | 0.505 | 0.722 |

*Table 4.6:* Summary statistics for decile portfolios of stocks sorted by MAX
Decile portfolios are formed every week from January 2014 to September 2020 by ranking cryptocurrencies based on the maximum daily return (MAX) within the past month. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily return over the previous month. Table presents the averages of weekly median values of each decile for various characteristics of cryptocurrencies – the maximum daily return (MAX), the cryptocurrency market beta, the market capitalization (in millions of dollars), the price (in dollars), the cumulative return over the previous three weeks prior to the week before (MOM), the cumulative return over the past week (REV), the Amihud illiquidity measure (scaled by $10^{-5}$), and the Garman-Klass volatility measure.

| Decile | MAX | BETA | SIZE ($\$10^6$) | PRICE (\$) | MOM | REV | ILLIQ ($10^{-5}$) | VOL |
|---|---|---|---|---|---|---|---|---|
| Low MAX | 0.054 | 0.693 | 426.752 | 0.982 | -0.030 | -0.019 | 0.027 | 0.376 |
| 2 | 0.083 | 0.871 | 354.295 | 0.762 | -0.036 | -0.015 | 0.033 | 0.546 |
| 3 | 0.100 | 0.868 | 150.015 | 0.558 | -0.021 | -0.014 | 0.042 | 0.605 |
| 4 | 0.126 | 0.908 | 251.399 | 0.668 | -0.011 | -0.006 | 0.066 | 0.680 |
| 5 | 0.132 | 0.801 | 129.025 | 0.427 | 0.022 | 0.000 | 0.061 | 0.657 |
| 6 | 0.169 | 0.905 | 174.171 | 0.518 | 0.025 | 0.009 | 0.070 | 0.776 |
| 7 | 0.199 | 0.916 | 135.694 | 0.532 | 0.059 | 0.012 | 0.088 | 0.852 |
| 8 | 0.241 | 0.889 | 27.440 | 0.367 | 0.076 | 0.021 | 0.078 | 0.896 |
| 9 | 0.314 | 0.839 | 35.708 | 0.313 | 0.128 | 0.042 | 0.129 | 0.961 |
| High MAX | 0.596 | 0.942 | 21.916 | 0.350 | 0.245 | 0.077 | 0.285 | 1.389 |

*Table 4.7:* Returns on portfolios of cryptocurrencies sorted by MAX after controlling for SIZE, PRICE, MOM, REV, and ILLIQ

Decile portfolios are formed every week from January 2014 to September 2020 by sorting cryptocurrencies based on the maximum daily returns after controlling for size, price, momentum, short-term reversal, and illiquidity. In each column, we first rank cryptocurrencies based on the control variable, then within each decile, we sort cryptocurrencies into decile portfolios of MAX. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily return over the previous month. Table presents the value-weighted (VW) (in Panel A) and equal-weighted (EW) (in Panel B) average weekly returns. The bottom two rows report the differences in weekly returns and the differences in three-factor alphas between portfolios 10 and 1, and the corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. Value-weighted portfolio returns*

| **Decile** | SIZE | PRICE | MOM | REV | ILLIQ |
|---|---|---|---|---|---|
| Low MAX | 0.010 | 0.009 | 0.007 | 0.010 | 0.010 |
| 2 | 0.018 | 0.014 | 0.016 | 0.012 | 0.017 |
| 3 | 0.013 | 0.013 | 0.014 | 0.010 | 0.012 |
| 4 | 0.016 | 0.014 | 0.010 | 0.014 | 0.011 |
| 5 | 0.012 | 0.010 | 0.011 | 0.013 | 0.010 |
| 6 | 0.021 | 0.016 | 0.016 | 0.016 | 0.019 |
| 7 | 0.020 | 0.014 | 0.013 | 0.012 | 0.014 |
| 8 | 0.018 | 0.013 | 0.016 | 0.013 | 0.015 |
| 9 | 0.016 | 0.010 | 0.011 | 0.010 | 0.008 |
| High MAX | 0.038 | 0.027 | 0.024 | 0.025 | 0.028 |
| | | | | | |
| Return difference | 0.027 | 0.017 | 0.017 | 0.015 | 0.018 |
| | (7.702)*** | (5.555)*** | (5.188)*** | (4.344)*** | (5.244)*** |
| Alpha difference | 0.025 | 0.015 | 0.014 | 0.012 | 0.014 |
| | (2.713)*** | (2.859)*** | (5.246)*** | (3.743)*** | (2.867)*** |

| *Panel B. Equal-weighted portfolio returns* | | | | | |
|---|---|---|---|---|---|
| Decile | SIZE | PRICE | MOM | REV | ILLIQ |
| Low MAX | 0.007 | 0.009 | 0.007 | 0.009 | 0.009 |
| 2 | 0.015 | 0.013 | 0.014 | 0.011 | 0.014 |
| 3 | 0.010 | 0.013 | 0.012 | 0.010 | 0.010 |
| 4 | 0.012 | 0.013 | 0.009 | 0.013 | 0.011 |
| 5 | 0.009 | 0.009 | 0.009 | 0.012 | 0.009 |
| 6 | 0.016 | 0.014 | 0.014 | 0.015 | 0.016 |
| 7 | 0.015 | 0.013 | 0.012 | 0.011 | 0.011 |
| 8 | 0.012 | 0.011 | 0.015 | 0.011 | 0.013 |
| 9 | 0.009 | 0.009 | 0.010 | 0.008 | 0.006 |
| High MAX | 0.028 | 0.027 | 0.025 | 0.026 | 0.025 |
| | | | | | |
| Return difference | 0.021 | 0.018 | 0.018 | 0.017 | 0.016 |
| | (6.197)*** | (6.072)*** | (5.772)*** | (5.310)*** | (4.839)*** |
| Alpha difference | 0.019 | 0.016 | 0.016 | 0.015 | 0.013 |
| | (2.043)** | (2.813)*** | (4.807)*** | (3.775)*** | (2.592)*** |

*Table 4.8:* Cross-sectional return regressions

Each week from January 2014 to September 2020, we conduct a cryptocurrency-level cross-sectional regression of the return in that week on lagged explanatory variables, which are lagged MAX, BETA, SIZE, PRICE, MOM, REV, and ILLIQ. MAX refers to the maximum daily return within a month. BETA is the market beta calculated as the sum of coefficients on lag, current and lead returns on market portfolio. SIZE equals the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. PRICE is the natural logarithm of one plus the cryptocurrency's price. MOM stands for momentum that equals the cumulative return over the previous three weeks skipping past week. REV stands for short-term reversal and equals the return in the past week. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. Both dependent and independent variables are winsorized at 5% level from upper and lower tails. Table reports the time-series averages of the cross-sectional regression coefficients and corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| MAX | BETA | SIZE | PRICE | MOM | REV | ILLIQ |
|---|---|---|---|---|---|---|
| 0.082 | | | | | | |
| (3.135)*** | | | | | | |
| | 0.016 | | | | | |
| | (0.200) | | | | | |
| | | -0.001 | | | | |
| | | (-2.730)*** | | | | |
| | | | 0.008 | | | |
| | | | (2.624)*** | | | |
| | | | | 0.039 | | |
| | | | | (2.315)** | | |
| | | | | | 0.096 | |
| | | | | | (2.634)*** | |
| | | | | | | 1.586 |
| | | | | | | (0.970) |
| | 0.049 | -0.002 | 0.003 | 0.022 | -0.005 | 0.847 |
| | (1.170) | (-0.763) | (0.868) | (0.734) | (-0.122) | (0.228) |
| 0.284 | 0.012 | -0.006 | 0.007 | 0.015 | 0.013 | 3.538 |
| (6.136)*** | (0.314) | (-1.022) | (1.257) | (0.209) | (0.334) | (0.524) |

*Table 4.9:* Time-series averages of cross-sectional correlations

Table reports the averages of the weekly cross-sectional correlations of the maximum daily return in a month (MAX), the average of the highest five daily returns in a month (MAX(5)), the minimum daily return in a month (MIN), total volatility (TVOL), idiosyncratic volatility (IVOL), and Garman-Klass volatility (VOL).

| | MAX | MAX(5) | MIN | TVOL | IVOL | VOL |
|---|---|---|---|---|---|---|
| MAX | 1 | | | | | |
| MAX(5) | 0.9978 | 1 | | | | |
| MIN | -0.0354 | 0.0107 | 1 | | | |
| TVOL | 0.7695 | 0.7716 | -0.0219 | 1 | | |
| IVOL | 0.7957 | 0.7525 | 0.6506 | 0.9881 | 1 | |
| VOL | 0.0028 | 0.0036 | 0.5538 | 0.0042 | 0.0013 | 1 |

*Table 4.10:* Returns on portfolios of cryptocurrencies sorted by MAX and volatility after controlling for volatility and MAX
Double-sorted, value-weighted (VW) and equal-weighted (EW) decile portfolios are formed every week from January 2014 to September 2020. In Panel A, cryptocurrencies are sorted based on the maximum daily returns after controlling for volatility (VOL and IVOL). In Panel B, cryptocurrencies are sorted based on the volatility (VOL and IVOL) after controlling for the maximum daily returns. VOL refers to Garman-Klass volatility and IVOL refers to the idiosyncratic volatility. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily return over the previous month. Table presents the value-weighted (VW) and equal-weighted (EW) average weekly returns. The bottom two rows report the differences in weekly returns and the differences in three-factor alphas between portfolios 10 and 1, and the corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. Sorted by MAX controlling for VOL and IVOL*

| | **VOL** | | **IVOL** | |
|---|---|---|---|---|
| Decile | VW | EW | VW | EW |
| Low MAX | 0.009 | 0.008 | 0.015 | 0.014 |
| 2 | 0.014 | 0.012 | 0.018 | 0.016 |
| 3 | 0.012 | 0.011 | 0.012 | 0.011 |
| 4 | 0.011 | 0.010 | 0.013 | 0.011 |
| 5 | 0.009 | 0.008 | 0.012 | 0.010 |
| 6 | 0.013 | 0.012 | 0.013 | 0.013 |
| 7 | 0.017 | 0.015 | 0.008 | 0.007 |
| 8 | 0.014 | 0.012 | 0.008 | 0.007 |
| 9 | 0.007 | 0.008 | 0.008 | 0.006 |
| High MAX | 0.025 | 0.028 | 0.024 | 0.024 |
| | | | | |
| Return difference | 0.016 | 0.020 | 0.009 | 0.010 |
| | (5.173)*** | (6.762)*** | (2.720)*** | (2.982)*** |
| Alpha difference | 0.013 | 0.018 | 0.006 | 0.007 |
| | (2.644)*** | (3.455)*** | (2.128)** | (2.031)** |

| *Panel B. Sorted by VOL and IVOL controlling for MAX* | | | | |
|---|---|---|---|---|
| | **VOL** | | **IVOL** | |
| Decile | VW | EW | VW | EW |
| Low Volatility | 0.016 | 0.019 | 0.014 | 0.016 |
| 2 | 0.014 | 0.014 | 0.008 | 0.008 |
| 3 | 0.010 | 0.011 | 0.013 | 0.011 |
| 4 | 0.013 | 0.011 | 0.013 | 0.012 |
| 5 | 0.007 | 0.006 | 0.007 | 0.006 |
| 6 | 0.016 | 0.015 | 0.014 | 0.012 |
| 7 | 0.011 | 0.010 | 0.011 | 0.009 |
| 8 | 0.013 | 0.011 | 0.010 | 0.010 |
| 9 | 0.007 | 0.006 | 0.008 | 0.008 |
| High Volatility | 0.020 | 0.019 | 0.028 | 0.028 |
| | | | | |
| Return difference | 0.004 | 0.001 | 0.014 | 0.012 |
| | (1.417) | (0.239) | (1.287) | (1.112) |
| Alpha difference | 0.002 | 0.002 | 0.011 | 0.010 |
| | (0.641) | (0.621) | (0.647) | (0.741) |

*Table 4.11:* Cross-sectional return regressions with MAX, MIN and VOL

Each week from January 2014 to September 2020, we conduct a cryptocurrency-level cross-sectional regression of the return in that week on lagged explanatory variables, which are lagged MAX, MIN and VOL as well as six other control variables - BETA, SIZE, PRICE, MOM, REV and ILLIQ. MAX refers to the maximum daily return within a month. MIN refers to the minimum daily return within a month. VOL refers to Garman-Klass volatility measure, which takes into account the highest, lowest, opening and closing prices. BETA is the market beta calculated as the sum of coefficients on lag, current and lead returns on market portfolio. SIZE equals the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. PRICE is the natural logarithm of one plus the cryptocurrency's price. MOM stands for momentum that equals the cumulative return over the previous three weeks skipping past week. REV stands for short-term reversal and equals the return in the past week. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. Both dependent and independent variables are winsorized at 5% level from upper and lower tails. Table reports the time-series averages of the cross-sectional regression coefficients and corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| MAX | VOL | MIN | BETA | SIZE | PRICE | MOM | REV | ILLIQ |
|---|---|---|---|---|---|---|---|---|
| 0.082 | | | | | | | | |
| (3.135)*** | | | | | | | | |
| | 0.017 | | | | | | | |
| | (1.510) | | | | | | | |
| 0.331 | -0.010 | | | | | | | |
| (9.794)*** | -0.909 | | | | | | | |
| 0.447 | 0.005 | | 0.046 | -0.005 | 0.009 | 0.062 | 0.046 | 1.545 |
| (3.828)*** | (0.125) | | (0.704) | (-1.041) | (0.984) | (1.850)* | (2.514)*** | (0.924) |
| | | 0.094 | | | | | | |
| | | (2.312)** | | | | | | |
| 0.325 | | -0.024 | | | | | | |
| (9.917)*** | | (-0.423) | | | | | | |
| 0.363 | | -0.889 | -0.012 | 0.010 | -0.017 | 0.367 | 0.078 | 1.146 |
| (3.964)*** | | (-1.055) | (-0.233) | (1.217) | (-1.071) | (1.957)* | (2.051)** | (0.531) |
| 0.388 | 0.023 | -0.105 | | | | | | |
| (10.178)*** | (1.017) | (-1.383) | | | | | | |
| 0.441 | 0.045 | 0.225 | 0.018 | -0.001 | -0.002 | 0.046 | 0.148 | 0.597 |
| (3.475)*** | (0.515) | (0.885) | (0.206) | (-0.217) | (-0.236) | (1.881)* | (2.130)** | (0.255) |

*Table 4.12:* Returns on portfolios of cryptocurrencies sorted by MAX after controlling for skewness

Decile portfolios are formed every week from January 2014 to September 2020 by sorting cryptocurrencies based on the maximum daily returns after controlling for total (TSKEW) and idiosyncratic (ISKEW). In each column, we first rank cryptocurrencies based on the skewness variable (TSKEW and ISKEW), then within each decile, we sort cryptocurrencies into decile portfolios of MAX. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily return over the previous month. Table presents the value-weighted (VW) average weekly returns. The bottom two rows report the differences in weekly returns and the differences in three-factor alphas between portfolios 10 and 1, and the corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| Decile | TSKEW | ISKEW |
|---|---|---|
| Low MAX | 0.008 | 0.009 |
| 2 | 0.012 | 0.012 |
| 3 | 0.012 | 0.010 |
| 4 | 0.013 | 0.015 |
| 5 | 0.009 | 0.009 |
| 6 | 0.017 | 0.012 |
| 7 | 0.013 | 0.009 |
| 8 | 0.012 | 0.012 |
| 9 | 0.011 | 0.012 |
| High MAX | 0.038 | 0.035 |
| Return difference | 0.029 | 0.027 |
| | (8.064)*** | (7.375)*** |
| Alpha difference | 0.027 | 0.024 |
| | (6.413)*** | (6.102)*** |

*Table 4.13:* Cross-sectional predictability of skewness

Each week from January 2014 to September 2020, we conduct a cryptocurrency-level cross-sectional regression of the skewness measures on lagged explanatory variables, including total skewness (TSKEW) and idiosyncratic skewness (ISKEW) as well as six other control variables - BETA, SIZE, PRICE, MOM, REV and ILLIQ. TSKEW refers to the total skewness measured for past month using daily returns. ISKEW is the skewness of regression residuals. BETA is the market beta calculated as the sum of coefficients on lag, current and lead returns on market portfolio. SIZE equals the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. PRICE is the natural logarithm of one plus the cryptocurrency's price. MOM stands for momentum that equals the cumulative return over the previous three weeks skipping past week. REV stands for short-term reversal and equals the return in the past week. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. Both dependent and independent variables are winsorized at 5% level from upper and lower tails. Table reports the time-series averages of the cross-sectional regression coefficients and corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| TSKEW | ISKEW | BETA | SIZE | PRICE | MOM | REV | ILLIQ | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 0.757 | | | | | | | | 50.25% |
| (51.531)*** | | | | | | | | |
| 0.588 | | -1.611 | 0.108 | -0.131 | 1.369 | 0.068 | 23.819 | 62.35% |
| (5.046)*** | | (-0.876) | (0.910) | (-0.964) | (1.110) | (0.231) | (1.529) | |
| | 0.744 | | | | | | | 43.57% |
| | (49.266)*** | | | | | | | |
| | 0.666 | 0.075 | -0.001 | -0.005 | 0.042 | -1.643 | -14.620 | 56.82% |
| | (13.213)*** | (0.158) | (-0.044) | (-0.128) | (0.135) | (-0.942) | (-0.780) | |

*Table 4.14:* Cross-sectional return regressions with MAX and skewness

Each week from January 2014 to September 2020, we conduct a cryptocurrency-level cross-sectional regression of the return in that week on lagged explanatory variables, which are lagged TSKEW, ISKEW, $E$(TSKEW), and MAX as well as six other control variables - BETA, SIZE, PRICE, MOM, REV and ILLIQ. TSKEW refers to the total skewness measured for past month using daily returns. ISKEW is the skewness of regression residuals. $E$(TSKEW) refers to the expected total skewness fitted each week throughout the cross-sectional regressions. MAX refers to the maximum daily return within a month. BETA is the market beta calculated as the sum of coefficients on lag, current and lead returns on market portfolio. SIZE equals the natural logarithm of the cryptocurrency's market capitalization by the end of previous week. PRICE is the natural logarithm of one plus the cryptocurrency's price. MOM stands for momentum that equals the cumulative return over the previous three weeks skipping past week. REV stands for short-term reversal and equals the return in the past week. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. Both dependent and independent variables are winsorized at 5% level from upper and lower tails. Table reports the time-series averages of the cross-sectional regression coefficients and corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| MAX | BETA | SIZE | PRICE | MOM | REV | ILLIQ | TSKEW | ISKEW | $E$(TSKEW) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | 0.009 | | |
| | | | | | | | (2.004)** | | |
| | | | | | | | | 0.008 | |
| | | | | | | | | (1.874)* | |
| 0.424 | 0.064 | -0.003 | 0.005 | 0.035 | 0.031 | 1.612 | -0.006 | | |
| (7.298)*** | (1.710)* | (-1.226) | (1.160) | (1.841)* | (2.696)*** | (0.186) | (-0.635) | | |
| 0.452 | 0.049 | -0.002 | 0.003 | 0.089 | 0.071 | -0.729 | | -0.009 | |
| (6.069)*** | (1.249) | (-0.716) | (0.802) | (1.978)** | (2.552)*** | (-0.265) | | (-0.894) | |
| | | | | | | | | | 0.038 |
| | | | | | | | | | (1.747)* |
| 0.411 | 0.053 | -0.004 | 0.009 | 0.026 | 0.025 | 1.145 | | | 0.031 |
| (6.973)*** | (1.265) | (-1.410) | (1.586) | (2.587)*** | (2.650)*** | (0.850) | | | (1.375) |

*Table 4.15:* Returns on portfolios of cryptocurrencies sorted by MAX after controlling for investor sentiment

Decile portfolios are formed every week from January 2014 to September 2020 by ranking cryptocurrencies based on the maximum daily return (MAX) within the past month. Decile 1 (10) is the portfolio of cryptocurrencies with the lowest (highest) maximum daily return over the previous month. Table presents the value-weighted (VW) average weekly returns on low sentiment and high sentiment bins. The bottom two rows report the differences in weekly returns and the differences in alphas between portfolios 10 and 1, and the corresponding t-statistics. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| Decile | Low Sentiment | High Sentiment |
|---|---|---|
| Low MAX | 0.010 | 0.008 |
| 2 | 0.021 | 0.021 |
| 3 | 0.013 | 0.018 |
| 4 | 0.021 | 0.011 |
| 5 | 0.015 | 0.035 |
| 6 | 0.011 | 0.028 |
| 7 | 0.027 | 0.011 |
| 8 | 0.029 | 0.040 |
| 9 | 0.023 | 0.030 |
| High MAX | 0.038 | 0.041 |
| | | |
| Return difference | 0.028 | 0.033 |
| | (3.157)*** | (1.979)** |
| Alpha difference | 0.025 | 0.030 |
| | (3.040)*** | (2.438)*** |

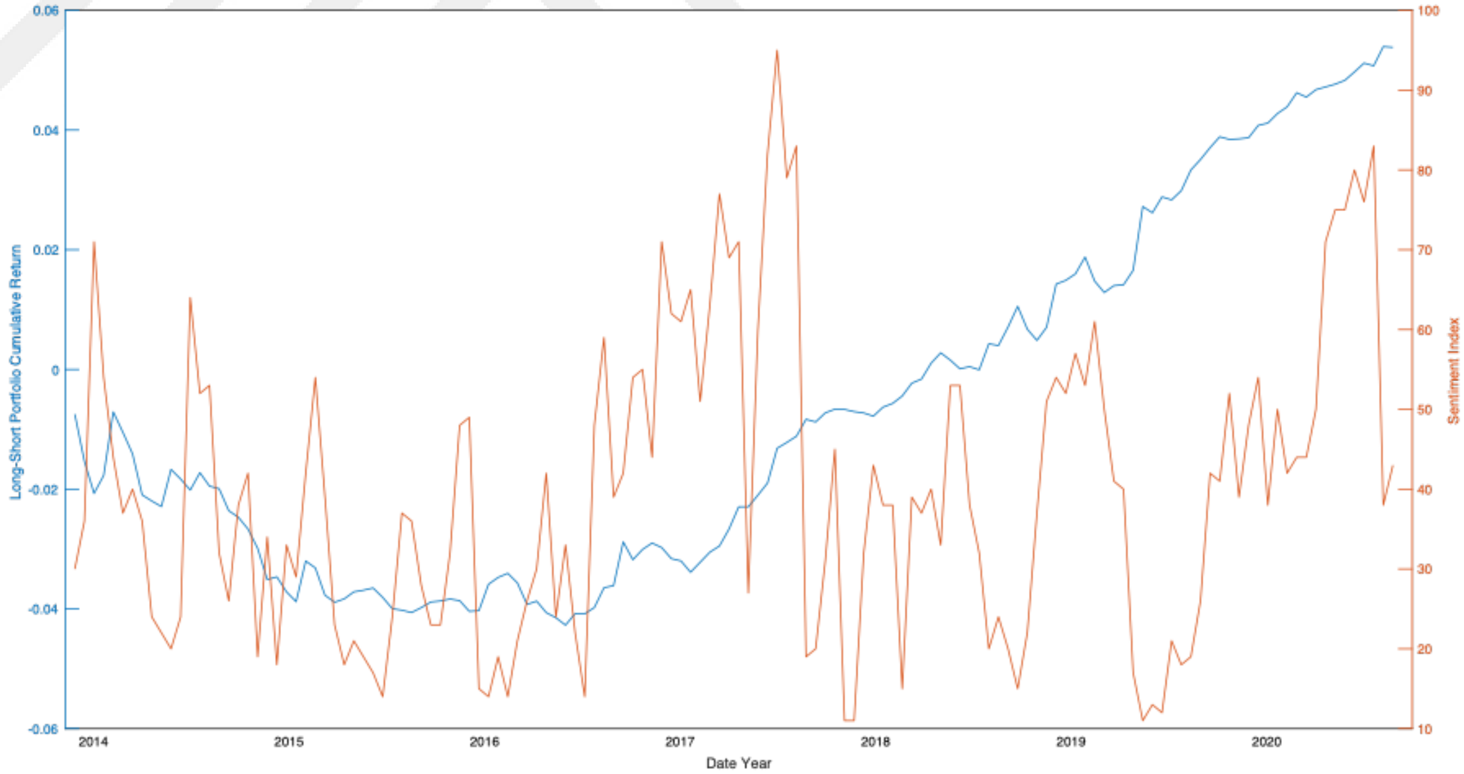



*Figure 4.1:* Long-Short Portfolio Cumulative Return and Sentiment Index

# CHAPTER 5

# RETAIL VS INSTITUTIONAL INVESTOR ATTENTION IN THE CRYPTOCURRENCY MARKET

## 5.1. Introduction

Cryptocurrency market has drawn significant investor attention recently since it offers an online trading algorithm based on electronic cash payment system, which brings a brand new investment opportunity. Latest studies show that investor attention associates with the cryptocurrency market dynamics such as prices, volatility and liquidity (Shen et al., 2019; Philippas et al., 2019; Subramaniam and Chakraborty, 2020; Choi, 2021; Al Guindy, 2021; Smales, 2022). These studies mainly focus on the individual side of investor attention. Different from the investor attention literature, this paper investigates the role of retail and institutional investor attention on cryptocurrency returns, idiosyncratic volatility and liquidity of the cryptocurrency market. To our knowledge, this is the first paper that introduces the institutional investor side into the picture to explore the similarities and differences between the effect of these two investor attention indices on the cryptocurrency market.

Efficient market hypothesis emphasizes that asset prices instantaneously reflect all relevant information available. Today, the rapidly developing technology enables investors to access information easily and quickly. However, behavioral finance theory underlines the fact that attention is a limited resource since investors are only capable of paying attention to those assets, whichever grab their attention (Kahneman, 1973; Grossman and Stiglitz, 1980). Besides, Barber and Odean (2008) show that retail investor attention induces substantial price reactions due to increased buying pressure. Similarly, Da et al. (2011) report that increase in retail investor attention anticipates raise in future prices. Due to speculative nature of cryptocurrencies, Lucey et al. (2021) discuss that individual investors could pay higher attention to the new released information than institutional investors whereas Białkowski (2020) suggests that cryptocurrencies might be unfavorable candidates for institutional investors. However, high degree of investor attention can influence how quickly and steadily information is reflected in the asset prices depending on the investor responses and trading activities (DellaVigna and Pollet, 2009; Vozlyublennaia, 2014; Yuan, 2015).

A group of recent papers explore the significant impact of investor attention in the cryptocurrency market utilizing various medias as the measure of investor attention. For example, Urquhart (2018) uses Google trends search queries and reports that investor attention does not have the predictive power to explain Bitcoin returns, volume and realized volatility. Contrarily, Dastgir et al. (2019) point out a bi-directional causal relationship between investor attention and Bitcoin returns. Zhang and Wang (2020) show that high investor attention predicts cryptocurrency returns and return volatility. Besides, employing Wikipedia daily views as the investor attention measure, Kristoufek (2013) finds evidence for the relationship between attention and Bitcoin prices with the distinction of positive and negative news. Shen et al. (2019) suggest that tweets data from Twitter is a better measure of investor attention since it reflects more informed trader information, and they indicate that the number of tweets is a significant indicator of realized volatility and trading volume, but not returns. Philippas et al. (2019) additionally indicate that investor attention partially effective on cryptocurrency prices, especially for periods with higher uncertainty. Considering the 23 largest coins, Al Guindy (2021) provides evidence for the causal relationship between investor attention and future price volatility.

The rapid development of the cryptocurrency market not only allows investors for new investment opportunities but also exacerbates the information asymmetry and thus, imperfect information transparency. The quality of information disclosure is crucial for a standardized, stable and transparent financial market. Despite the difficulty of rendering a perfect degree of investor attention (Kahneman and Tversky, 1973; Huberman and Regev, 2001), empirical studies on idiosyncratic risk in the cryptocurrency market might help investors to construct diversified portfolio investment strategies. Although there exists an extensive literature on the volatility of the cryptocurrency market (Katsiampa, 2017; Urquhart, 2017b; Baur and Dimpfl, 2018; Yi et al., 2018; Katsiampa, 2019; Sabah, 2020), research regarding the role of idiosyncratic volatility is quite scarce. Zhang and Li (2020) focus on the pricing impact of idiosyncratic risk in the cross-section of cryptocurrency returns and report a positive relation between the idiosyncratic volatility and expected returns. Furthermore, Yao et al. (2021a) document that investor attention has a constraining effect on the idiosyncratic risk by increasing the liquidity of the cryptocurrency market.

The pursuit of efficiency in the financial markets brings along the question of liquidity to determine the price levels. An increase in the investor attention towards particular cryptocurrencies might result in high number of buy orders. However, there is no market maker for cryptocurrencies to provide stability and smoothness into the market by balancing with the sell orders (Yao et al., 2021b). Therefore, the cryptocurrency market is still prone to suffer from illiquidity. Brauneis and Mestel (2018) suggest that efficiency of the cryptocurrency market is positively related to liquidity. Wei (2018) indicates that higher the market liquidity, lower the return predictability. Although the study reports signs of efficiency enhancement for Bitcoin, other cryptocurrencies remain inefficient. Choi (2021) documents that investor attention significantly increases the liquidity of Bitcoin. However, Koutmos (2018) and Choi (2021) argue that relative to few popular cryptocurrencies, the market as a whole remins illiquid and inefficient. Besides, Smales (2022) shows that an increase in the investor attention causes higher levels of market illiquidity.

Motivated by these lines of literature, we explore whether and how retail and institutional investor attention affect the cryptocurrency returns, idiosyncratic risk and market liquidity. Following Shen et al. (2019), Choi (2021) and Al Guindy (2021), we employ number of tweets as the measure of retail investor attention. For institutional investor attention, we utilize story search counts from the new trends function of Bloomberg terminal. This unique data enables us to measure the institutional side of investor attention since Bloomberg terminal is for corporate use by nature. By this way, our study gains a new insight within the empirical literature by analyzing the similarities and differences between the impact of retail and institutional investor attention in terms of expected return, idiosyncratic volatility and liquidity in the cryptocurrency market. We collect our sample data for 10 main cryptocurrencies spanning the period from the beginning of January 2018 through the end of December 2020. We conduct weekly panel regression models using retail and institutional investor attention as well as a set of control variables as the independent variables.[1] We first examine the effect of investor attention on cryptocurrency returns. The univariate and multivariate regression analyses give significantly negative coefficients for retail and significantly positive coefficients for institutional investor attention. The findings indicate that, an increase in retail investor attention results in a decrease in expected returns whereas, in line with the findings of Subramaniam and Chakraborty (2020) and Smales (2022), there exists a positive relationship between institutional investor attention and expected coin returns. The two-way fixed effects regression document that retail (institutional) investor attention impact lasts until t+5 (t+4) to explain future returns. The significance over longer time horizons show that the contrary effects of the individual and institutional investor attention on returns are valid and consistent.

Moreover, we analyze the relationship between investor attention and idiosyncratic volatility. Employing a similar panel regression model, we report a significantly positive (negative) relation between retail (institutional) investor attention and future idiosyncratic risk for the univariate and all multivariate regressions. The constraining impact of institutional investor attention on idiosyncratic volatility is in line with the findings of Yao et al. (2021a). The two-way regressions show that these impacts last for another four weeks (until t+5). The results are persistent after series of robustness tests. For example, as an alternative measure of idiosyncratic volatility, we use the standard deviation of the residual term from the three factor regression model (Fama and French, 1993; Carhart, 1997), and report similar coefficients for investor attention variables. Besides, we perform two-step regression approach (Kim et al., 2016; Feng et al., 2021) to explore a potential channel, which links investor attention

[1] We employ weekly returns since in the cryptocurrency market, trading and investor reactions to market attention is faster when compared to the traditional financial markets (Dyhrberg, 2016; Hong, 2017).

and idiosyncratic volatility. The results show that higher liquidity levels arising from either retail or institutional investor attention lower down the idiosyncratic risk in the cryptocurrency market, emphasizing the substantial effect of liquidity. Finally, we search potential cross-sectional variability of investor attentions in terms of coin-level characteristics and market conditions. We find empirical evidence on the notable effect of retail investor attention on idiosyncratic risk in case of higher capitalized cryptocurrencies with lower liquidity as well as in relatively low and unstable economic conditions. Contrarily, the impact of institutional investor attention is more pronounced for small-cap and liquid coins in states of good market conditions and stable environment.

Finally, we investigate the impact of retail and institutional investor attention on the cryptocurrency market liquidity. By using Amihud (2002) illiquidity measure, we test the relationship between investor attention and liquidity. In line with the findings of Cheng et al. (2021), Choi (2021) and Yao et al. (2021b), two-way fixed effect regressions report negative and statistically significant coefficients for both retail and institutional investor attention to explain subsequent illiquidity in the short-term. For both types of investors, the coefficients of attention are relatively very high, signaling that the significant impact on liquidity in the short-run might persist in the long-run. To explore that, we again perform two-way regressions by utilizing monthly data. The analyses conducted for the next six months indicate that the impact of retail investor attention on the cryptocurrency liquidity lasts within the next four months and remain insignificant thereafter. However, the effect of institutional investor attention on subsequent illiquidity continues to remain highly significant for the next six months. The results show that the investor attention impact is robust and significantly improves the liquidity of cryptocurrency market, which signals that both type of investors are considerable market participants. Furthermore, we conduct conditional analyses to control the cross-sectional variations of investor attention regarding coin-level characteristics and market conditions. All reported coefficients except small-cap coins for retail investor attention, are negative and statistically significant. Looking at the absolute value of coefficients, the impact of retail investor attention on the enhancement of liquidity is higher for coins with higher market capitalization and idiosyncratic volatility. Conversely, small coins with lower idiosyncratic risk show higher liquidity improvement by means of institutional investor attention. Regarding aggregate states, both retail and institutional investor attention is more effective for liquidity augmentation at times of positive market state and economic stability.

The main contributions of this paper is threefold. As well as the remaining fields of recent empirical literature in the cryptocurrency market, most of the research conducted on the investor attention focuses on Bitcoin solely, since it is the best-known coin with the highest market capitalization. However, substantial development has occurred with the introduction of numerous coins that rapidly earns significant trading volume. First, this study contributes to the literature by considering 10 main cryptocurrencies to investigate the effect of investor attention and obtain relatively significant and reliable results.[2] Second, to our knowledge, this is the first paper to investigate the impact of institutional investor attention on the cryptocurrency market. This study adds another angle to the literature in terms of documenting the discrepancies between individual and institutional investor attention influence on the market dynamics of coins. Although the market is quite volatile in terms of price and efficiency, institutional investors are shown to be more informed and confident such that the volatility of price does not affect their confidence or market participation (Sun et al., 2021). And finally, this study enriches the empirical research on the impact of investor attention on cryptocurrency returns, idiosyncratic risk and liquidity. The empirical studies remain limited to explore the relationship between investor attention and idiosyncratic volatility as well as liquidity. The findings of this study provide consequential results for a more comprehensive understanding of the cryptocurrency market risk and liquidity. Moreover, institutional investor attention aspect has not been elaborated in any of the studies before.

The remainder of the paper is organized as follows. Section 5.2 introduces the data source, sample selection and variable descriptions. Section 5.3 discusses the empirical analyses and results. Section 5.4 provides robustness checks. Finally, Section 5.5 concludes.

[2]The reason why we focus on the ten cryptocurrencies specifically is because of the limited data availability on institutional investor attention collected from Bloomberg search counts.

### 5.2. Data and variable description

#### 5.2.1. Data source and sample selection

We use daily closing prices of 10 cryptocurrencies that attract most attention by the investors (Naeem et al., 2021), namely Bitcoin, Bitcoin Cash, Dash, EOS Tokens, Ethereum, Ethereum Classic, Litecoin, Monero, Ripple, and Zcash. The data source is CoinMarketCap (https://coinmarketcap.com/coins/) and our sample spans the period from the beginning of January 2018 through the end of December 2020. To capture investor attention, we utilize two different datasets. First, we collect Twitter data containing the names of the 10 coins we consider for our sample to construct a Cryptocurrency Retail Investor Attention Index. Specifically, we obtain the data using Twitter API, which represents the Twitter discussions about a specific cryptocurrency within the sample period. By the help of Phyton programming language, we daily collect detailed information about each tweet. By this way, we obtain the count of tweets by keyword searches used for each of 10 coins, i.e. "bitcoin" and "btc" for Bitcoin. Our dataset represents the Twitter discussions on the specific cryptocurrency within the sample period.[3] Second, we collect the story search counts data using the new trends function of Bloomberg terminal. We search the count of stories including the terms "bitcoin" etc. to construct a Cryptocurrency Institutional Investor Attention Index for the same 10 cryptocurrencies.

**INSERT FIGURE 5.1 HERE**

Figure 5.1 presents the time-series graphs of the Cryptocurrency Retail Investor Attention Index and Cryptocurrency Institutional Investor Attention Index on the left side and the closing prices on the right side for Bitcoin, Ethereum, Ripple and Litecoin.[4] Figure 5.1 shows that our sample time span covers different periods where the coin prices experience large variations. Similarly, retail and institutional investor attention indices indicate huge ups and downs.

[3]Recent studies present the connection between financial markets and investor attention analysis based on Twitter discussions (refer to Yang et al. (2015); Nisar and Yeung (2018), among others).

[4]We report the findings of 4 main cryptocurrencies for brevity, however, the time-series graphs of 6 other cryptocurrencies are available upon request.

The time-series concurrence between attention indices and coin prices motivates this study to investigate the explanatory power of investor attention over the cryptocurrency returns, market liquidity and idiosyncratic volatility.

### 5.2.2. Variable construction

Following Shen et al. (2019); Philippas et al. (2019); Choi (2021), we use the number of tweets as a measure for retail investor attention and we construct a Retail Investor Attention Index *(ATT_RET)* by the natural logarithm of one plus the daily number of tweets for each coin. Similarly, we construct an Institutional Investor Attention Index *(ATT_INST)* by the natural logarithm of one plus the daily count of Bloomberg story searches for each coin.

To estimate idiosyncratic volatility ($IVOL$), we revisit the classical capital asset pricing model (CAPM) and consider a single-factor return generating process as shown in equation (5.1):

$$\mathrm{R}_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \epsilon_{i,d} \tag{5.1}$$

where $\mathrm{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$, $\mathrm{R}_{m,d}$ is the cryptocurrency market portfolio return on day $d$, and $\mathrm{r}_{f,d}$ is the risk-free rate on day $d$ and, $\epsilon_{i,d}$ is the idiosyncratic return on day $d$.[5] The weekly idiosyncratic volatility ($IVOL$) of cryptocurrency $i$ in month $t$ is defined as the standard deviation of daily residuals in month t:

$$\mathrm{IVOL}_{i,t} = \sqrt{var(\epsilon_{i,d})} \tag{5.2}$$

We measure cryptocurrency liquidity by Amihud illiquidity ratio (Amihud, 2002) since it considers three-dimensional composite liquidity with the speed, width and depth and it is a common proxy of liquidity in cryptocurrency studies (Loi, 2018; Smales, 2022). To measure illiquidity ($ILLIQ$), we calculate the ratio of absolute daily cryptocurrency return to its mean dollar trading volume each

[5] Risk-free rate is the one-month T-bill return. As the cryptocurrency market index, we use Crescent Crypto Market Index (CCMIX), which is a value-weighted cryptocurrency market index constructed using the largest and most liquid cryptocurrencies. For more information, please refer to https://www.crescentcrypto.com/cryptocurrency-market-index/.

week as shown in equation (5.3):

$$\text{ILLIQ}_{i,t} = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{VOLD_{i,d}/10^6} \tag{5.3}$$

where $\text{VOLD}_{i,d}$ is the respective trading volume in dollars scaled by $10^{-6}$ and D is the total number of trading days in a week.

Following Yao et al. (2019), Ibikunle et al. (2020) and Yao et al. (2021b), we incorporate nine control variables that might have an effect over the liquidity of cryptocurrency market. We measure *SIZE* by the natural logarithm of the cryptocurrency's average market capitalization over the week. As another size variable, we measure *PRICE* by the natural logarithm of one plus the cryptocurrency's average price over the week. The volume variable ($VOL$) is calculated as the natural logarithm of average trading volume of each coin over the week. The momentum variable ($MOM$) is calculated weekly for each coin as the cumulative return over the previous three months starting one month ago, i.e., the cumulative return from week t-16 to week t-5. Short-term reversal ($REV$) is defined as the cumulative return on cryptocurrency $i$ within the past month, i.e. the cumulative return from week t-4 to week t-1. Following Harvey and Siddique (2000), we separate total skewness into idiosyncratic and systematic components by considering the regression in equation (5.4):

$$\text{R}_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \theta_i(R_{m,d} - r_{f,d})^2 + \epsilon_{i,d} \tag{5.4}$$

where as usual $\text{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$, $\text{R}_{m,d}$ is the cryptocurrency market portfolio return on day $d$, and $\text{r}_{f,d}$ is the risk-free rate on day $d$ and, $\epsilon_{i,d}$ is the idiosyncratic return on day $d$. The weekly idiosyncratic skewness ($ISKEW$) of cryptocurrency $i$ in month $t$ equals the skewness of daily residuals $\epsilon_{i,d}$ in month $t$. The weekly systematic skewness ($SSKEW$) or co-skewness of cryptocurrency $i$ in month $t$ equals the slope coefficient $\theta_{i,d}$. Our final control variable is the maximum daily return within the past month ($MAX$). Following Bali et al. (2011), we calculate ($MAX$) variable weekly for each coin, as described in equation (5.5).

$$\text{MAX}_{i,t} = max(R_{i,d}), \quad d = 1, ..., D_m \tag{5.5}$$

where $R_{i,d}$ is the return on cryptocurrency $i$ on day $d$ and $D_m$ is the number of trading days in month m.[6] For each of the 154 sample weeks, we winsorize all variables at 1% level from both upper and lower tails to get rid of the outlier effect without removing any observation.

### 5.3. Empirical Analyses and Results

#### 5.3.1. Descriptive statistics and correlations

Table 5.1 shows descriptive statistics of all variables used in the weekly panel regression models of retail and institutional investor attention. The mean and median of retail investor attention are 7.419 and 7.906, respectively, with a left-skewed distribution. The mean and median of institutional investor attention are 4.384 and 4.043, respectively, with a right-skewed distribution. The mean values show that average weekly retail attention is higher than institutional attention. The mean of illiquidity and idiosyncratic risk of cryptocurrencies are 0.013 and 0.062, respectively, with standard deviations of 0.315 and 0.352, respectively. This indicates that the liquidity and volatility of our sample cryptocurrencies substantially vary.

**———————INSERT TABLES 5.1 and 5.2 HERE———————**

Table 5.2 presents the coefficients of Pearson correlation analysis. The analysis shows that a negative correlation exists between illiquidity and retail investor attention whereas a positive correlation exists between idiosyncratic volatility and retail investor attention. Besides, institutional investor attention is negatively correlated with illiquidity as well as idiosyncratic volatility. Most of the correlation coefficients among the weekly regression variables are lower than 0.5, which eliminates the risk of a serious multicollinearity problem.[7]

[6] The meaning of *trading days* in cryptocurrency market is different from traditional stock market since coin market is always active. In our analysis, we assume a week and a month to be 7 and 28 trading days, respectively.

[7] The variance inflation factor (VIF) for most of the variables are less than 2.0, which is considerably lower than the critical value of 15. Therefore, we do not suspect a serious multicollinearity issue in the regression model.

### 5.3.2. Investor attention and cryptocurrency returns

Our aim is to understand the effect of investor attention on the cryptocurrency market. By constructing a panel data, we first investigate the weekly impact of retail and institutional investor attention on cryptocurrency returns as shown in equation (5.6) and equation (5.7), respectively.

$$\begin{aligned}\text{Return}_{i,t+1} = \beta_0 + \beta_1 ATT\_RET_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1}\end{aligned} \tag{5.6}$$

where $\text{Return}_{i,t+1}$ is the realized return of cryptocurrency $i$ in week $t+1$ and $\text{ATT\_RET}_{i,t}$ is the retail investor attention of cryptocurrency $i$ in week $t$. $\text{CONTROL}_{k,i,t}$ is the set of nine control variables, which are *SIZE*, *PRICE*, *VOL*, *MOM*, *REV*, *IVOL*, *ISKEW*, *SSKEW* and *MAX*. $\sum$ COIN and $\sum$ TIME shows that we also control for cryptocurrency fixed effects and time fixed effects.

$$\begin{aligned}\text{Return}_{i,t+1} = \beta_0 + \beta_1 ATT\_INST_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1}\end{aligned} \tag{5.7}$$

where $\text{ATT\_INST}_{i,t}$ is the institutional investor attention of cryptocurrency $i$ in week $t$ and other variables are the same as described for equation (5.6). The standard errors are clustered at the cryptocurrency level, as discussed by Petersen (2009).

Table 5.3 presents the regression coefficients from fixed-effect panel regressions and t-statistics of equation (5.6) in Panel A and equation (5.7) in Panel B. The first column of Panel A (Panel B) reports a significantly negative (positive) coefficient for ATT_RET (ATT_INST). To confirm the robustness of our empirical results, we perform panel data analysis with controls as described in Section (5.2.2). In the second column, we consider SIZE, PRICE and VOL along with investor attention. Then, we add MOM, REV, IVOL, SSKEW, ISKEW, and MAX variables, respectively, in Columns 3-8. Finally, Column 9 considers all control variables in a multivariate regression framework. The coefficients of all regressions verify the constraining effect of retail investor attention on cryprocurrency returns in Panel A as well as the aggravating impact of institutional investor attention on cryptocurrency returns in Panel B.

——————————INSERT TABLE 5.3 HERE——————————

The retail investor attention shows a negative effect on expected cryptocurrency returns. Contrarily, as the institutional investor attention increases, the expected coin returns increase, as well. To understand the persistence of these effects over longer time horizons, we perform two-way fixed effects regression analyses following Cheng et al. (2021). We examine the impact of investor attention on future returns from t+2 to t+6 and Table 5.4 indicates the regression results. ATT_RET impact still exists between t+2 and t+5, however, the absolute value of this negative effect demonstrates a downward trend. Therefore, the power of retail investor attention to explain future returns diminishes in time. No significance is observed in t+6 period. Besides, the positive effect of ATT_INST continues until t+4 period and the significance disappears after t+5. The results confirm that the negative impact of retail investor attention and the positive impact of institutional investor attention in the short term persist until a certain period of time to predict future returns in the cryptocurrency market. The opposite effects of investor attention variables draw our attention to elaborate more on the possible cross-sectional variations of the attention impact.

——————————INSERT TABLE 5.4 HERE——————————

### 5.3.3. Investor attention and idiosyncratic risk

Second, we examine the weekly impact of retail and institutional investor attention on idiosyncratic volatility as shown in equation (5.8) and equation (5.9), respectively.

$$\begin{aligned}\mathrm{IVOL}_{i,t+1} = \beta_0 + \beta_1 ATT\_RET_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1}\end{aligned} \tag{5.8}$$

where $\mathrm{IVOL}_{i,t+1}$ is the idiosyncratic volatility of cryptocurrency $i$ in week *t+1* and $\mathrm{ATT\_RET}_{i,t}$ is the retail investor attention of cryptocurrency $i$ in week $t$.

$\text{CONTROL}_{k,i,t}$ is the set of eight control variables, which are *SIZE*, *PRICE*, *VOL*, *MOM*, *REV*, *ISKEW*, *SSKEW* and *MAX*. $\sum$COIN and $\sum$TIME shows that we also control for cryptocurrency fixed effects and time fixed effects.

$$\begin{aligned} \text{IVOL}_{i,t+1} = \beta_0 + \beta_1 ATT\_INST_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1} \end{aligned} \tag{5.9}$$

where $\text{ATT\_INST}_{i,t}$ is the institutional investor attention of cryptocurrency $i$ in week $t$ and other variables are the same as described in equation (5.8). The standard errors are clustered at the cryptocurrency level, following Petersen (2009).

Table 5.5 shows the baseline regression results of equation (5.8) in Panel A and equation (5.9) in Panel B. Contrary to the results of return regressions, univariate regressions indicate a significantly positive coefficient for retail investor attention and a significantly negative coefficient for institutional investor attention to explain idiosyncratic risk of cryptocurrencies. When we control for the well-known determinants of idiosyncratic risk, i.e. SIZE, PRICE, VOL, MOM, REV, SSKEW, ISKEW, and MAX, the multivariate regressions confirm the positive (negative) explanatory power of ATT_RET (ATT_INST) on idiosyncratic volatility.

**INSERT TABLE 5.5 HERE**

Following Yao et al. (2021a), we conduct a two-way fixed effect model to understand the durability of retail and institutional investor attention impact on cryptocurrency risk. We investigate the persistence of attention effect over longer time horizons from t+2 to t+6 as shown in Table 5.6. The short-term positive power of retail investor attention on idiosyncratic volatility continues between periods t+2 and t+5. The significance of the positive coefficients weakens over time and disappears at t+6 period. Furthermore, the negative effect of institutional investor attention on idiosyncratic risk, which is in line with the findings of Yao et al. (2021a), persist until t+4. After t+5, the coefficients are no longer significant. The results show that institutional investor attention helps stabilizing the cryptocurrency market to reduce market volatility, however, retail investor attention signals the contrarian impact. We may interpret these results by considering the institutional investor side as more informed. The positive attention of informed traders benefit the stabilization of cryptocurrency market by lowering down the idiosyncratic risk (O'Hara, 2003; Ferreira and Laux, 2007; Kang and Nam, 2015). On the other hand, retail investors, who are less informed than institutional investors, are inclined to act more incautious against speculations. Increased trading activity might increase the price of a coin transiently and hardly causing an ascent in the volatility. These results are in line with the contrary relationship between retail investor attention and expected cryptocurrency returns reported in Section (5.3.2). Thus, investor attention does not necessarily act as a cure for market volatility if the traders are uninformed. Our next step is to examine the market participation of these two different kinds of investors to understand whether investor attention affects liquidity of the cryptocurrency market.

**INSERT TABLE 5.6 HERE**

#### 5.3.4. Investor attention and cryptocurrency liquidity

Third, we investigate the weekly impact of retail investor attention on Amihud illiquidity as shown in equation (5.10) and of institutional investor attention on Amihud illiquidity as shown in equation (5.11).

$$\begin{aligned}\mathrm{ILLIQ}_{i,t+n} &= \beta_0 + \beta_1 ATT\_RET_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ &\quad + \sum COIN + \sum TIME + \epsilon_{i,t+n}\end{aligned} \tag{5.10}$$

where $\mathrm{ILLIQ}_{i,t+n}$ is the Amihud illiquidity ratio of cryptocurrency $i$ in week $t{+}n$ $(n = 0, 1, 2, \ldots)$ and $\mathrm{ATT\_RET}_{i,t}$ is the retail investor attention of cryptocurrency $i$ in week $t$. $\mathrm{CONTROL}_{k,i,t}$ is the set of nine control variables, which are *SIZE*, *PRICE*, *VOL*, *MOM*, *REV*, *IVOL*, *ISKEW*, *SSKEW* and *MAX*. $\sum$ COIN and $\sum$ TIME shows that we also control for cryptocurrency fixed effects and time fixed effects.

$$\begin{aligned}\text{ILLIQ}_{i,t+n} = \beta_0 + \beta_1 ATT\_INST_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+n}\end{aligned} \tag{5.11}$$

where $\text{ATT\_INST}_{i,t}$ is the institutional investor attention of cryptocurrency $i$ in week $t$ and other variables are the same as described in equation (5.10). Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. All independent variables are lagged n *(n = 0, 1, 2, ...)* weeks to avoid any possible causality and endogeneity problems.

Following Yao et al. (2021b), we perform a two-way fixed effect model to understand the effect of retail and institutional investor attention on cryptocurrency liquidity. Table 5.7 reports weekly regression results of equation (5.10) in Panel A and equation (5.11) in Panel B for the current and next 6 weeks.[8] In line with the findings of Yao et al. (2021b), the coefficients of ATT_RET and ATT_INST are significantly negative at 1% significance level. Results signify that both retail investor attention and institutional investor attention significantly enhance the current and future liquidity of the cryptocurrency market, in addition to the findings of Cheng et al. (2021) and Choi (2021).

**INSERT TABLE 5.7 HERE**

The analyses thus far uncover some evidence against the divergent impact of retail and institutional investor attention on the cryptocurrency market. The results reveal that although retail and institutional investor attention indicate contrarian results to explain future returns and idiosynratic risk of the cryptocurrency market, both type of investors are market participants since their attention significantly and substantially increase market liquidity. In order to further explore the long-term effect of investor attention on market liquidity, we perform a similar two-way fixed effect regression model on a monthly basis. Table 5.8 shows monthly regression results of equation (5.10) in Panel A and

[8]We report the regression results for the current and next 6 weeks for brevity, however, further results are available upon request.

equation (5.11) in Panel B for the current and next 6 months.[9] The regression results of ATT_RET indicate significantly negative coefficients in the cases where $n$ = *0, 1, 2, 3, and 4*, however, the significance no longer exists persists after $n$ = *5*. This supports the improving impact of retail investor attention on market liquidity for the next four months. Moreover, the coefficients of ATT_INST are highly significant for the next six months.[10] The long-term results verify the short-term outcomes and signifies a persistent and significant positive effect of institutional investor attention on liquidity of the cryptocurrency market.

**INSERT TABLE 5.8 HERE**

## 5.4. Robustness Checks

### 5.4.1. Alternative measure of idiosyncratic volatility

We consider a single-factor return generating process to calculate the idiosyncratic volatility. In this section, we utilize an alternative measure of idiosyncratic risk, following Liu et al. (2020), Zhang and Li (2020) and Yao et al. (2021a). We conduct the regression equation (5.12) of the three factor model that takes into consideration the excess market return, a size factor, and a momentum factor, following Fama and French (1993) and Carhart (1997).[11]

$$\mathrm{R}_{i,d} - r_{f,d} = \alpha_i + \beta_i^{MKT}(R_{m,d} - r_{f,d}) + \beta_i^{SMB} SMB_d + \beta_i^{MOM} MOM_d + \epsilon_{i,d} \quad (5.12)$$

where $\mathrm{R}_{i,d}$ is the return on cryptocurrency $i$ on day $d$, $\mathrm{R}_{m,d}$ is the cryptocurrency market portfolio return on day $d$, and $\mathrm{r}_{f,d}$ is the risk-free rate on day $d$, $\mathrm{SMB}_d$ is the size factor, $\mathrm{MOM}_d$ is the momentum factor and, $\epsilon_{i,d}$ is the idiosyncratic return on day $d$. The excess cryptocurrency market return represents the difference between cryptocurrency market index return and the risk-free rate.

[9] All variables used in this analysis are calculated monthly, similar to the control variables used in the weekly regression models, and all independent variables are lagged n *(n = 0, 1, 2, ...)* months to refrain any causality and endogeneity issues.

[10] The results of monthly regressions, which are not shown in the paper, indicate that the significance of institutional investor attention coefficient lasts for another three months. This implies that institutional investor attention is likely to reinforce the cryptocurrency liquidity for up to 9 months.

[11] The classical Fama-French approach additionally include High Minus Low (HML) factor in the equation, however, our equation lacks this variable since book values for most of the cryptocurrencies do not exist.

For the size factor, we split cryptocurrencies per week into three groups by market capitalization. We form value-weighted portfolios for each size group and calculate the difference between average returns of small and big size portfolios. Similarly, for the momentum factor, we split cryptocurrencies per week into three groups by momentum. We construct value-weighted portfolios for each momentum group, and we calculate the difference between average returns of the highest and lowest momentum portfolios. Finally, we use the standard deviation of the residual term, estimated from the regression equation (5.12), to calculate the alternative measure of weekly idiosyncratic volatility as shown in equation (5.13).

$$\text{IVOL\_FF3}_{i,t} = \sqrt{var(\epsilon_{i,d})} \tag{5.13}$$

Table 5.9 reports the regression results for retail investor attention (in Panel A) and institutional investor attention (in Panel B) along with the control variables. Results indicate very similar coefficients to those reported in Table 5.5, i.e. a significant positive effect of ATT_RET and a significant negative effect of ATT_INST on idiosyncratic risk of cryptocurrencies. Therefore, the panel regression results are not contingent and are indeed robust to different measures of idiosyncratic volatility.

———————————**INSERT TABLE 5.9 HERE**———————————

### 5.4.2. Channel analysis

We perform panel regression analyses to test the impact of investor attention on idiosyncratic risk and illiquidity separately. In this section, our aim is to explore whether and how idiosyncratic volatility affects investor attention through the channel of liquidity. The analysis consists of two-step regression approach following Kim et al. (2016) and Feng et al. (2021). The first step tests the explanatory power of investor attention on the cryptocurrency liquidity measured by Amihud illiquidity, as described in equation (5.14) for retail investor attention and equation (5.15) for institutional investor attention. The second step conducts a similar regression analysis to investigate the effect of cryptocurrency liquidity on idiosyncratic risk based on equation (5.16).

$$\begin{aligned}\text{ILLIQ}_{i,t} = \beta_0 + \beta_1 ATT\_RET_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1}\end{aligned} \tag{5.14}$$

$$\begin{aligned}\text{ILLIQ}_{i,t} = \beta_0 + \beta_1 ATT\_INST_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1}\end{aligned} \tag{5.15}$$

$$\begin{aligned}\text{IVOL}_{i,t+1} = \beta_0 + \beta_1 ILLIQ_{i,t} + \sum_k \gamma_k CONTROL_{k,i,t} \\ + \sum COIN + \sum TIME + \epsilon_{i,t+1}\end{aligned} \tag{5.16}$$

where $\text{ILLIQ}_{i,t}$ is the Amihud illiquidity ratio of cryptocurrency $i$ in week $t$, $\text{ATT\_RET}_{i,t}$ is the retail investor attention of cryptocurrency $i$ in week $t$, $\text{ATT\_INST}_{i,t}$ is the institutional investor attention of cryptocurrency $i$ in week $t$, and $\text{IVOL}_{i,t+1}$ is the idiosyncratic volatility of cryptocurrency $i$ in week *t+1*. $\text{CONTROL}_{k,i,t}$ is the set of eight control variables, which are *SIZE*, *PRICE*, *VOL*, *MOM*, *REV*, *ISKEW*, *SSKEW* and *MAX*. $\sum$ COIN and $\sum$ TIME shows that we also control for cryptocurrency fixed effects and time fixed effects. The standard errors are clustered at the cryptocurrency level, as discussed by Petersen (2009).

The results of the channel analysis are shown in Table 5.10. The first and second columns of the table report the first stage regression of retail and institutional investor attention, respectively. The coefficients of both ATT_RET (-0.034) and ATT_INST (-0.024) are negative and statistically significant at 1% confidence level. The results are conformable to those reported in Section (5.3.4), which indicates that higher the investor attention, lower the cryptocurrency Amihud illiquidity. The third and fourth columns of Table 5.10 reports the second step regression results. Independent of the idiosyncratic risk measure, the coefficient of ILLIQ is positive and statistically significant at 1% confidence level. The results suggest that low levels of liquidity exacerbate the idiosyncratic risk. Therefore, the channel analysis further sheds light on the fact that the liquidity derived from investor attention substantially decrease the idiosyncratic volatility in the cryptocurrency market.

INSERT TABLE 5.10 HERE

### 5.4.3. Conditional analysis

The literature on investor attention documents that the asymmetry of asset characteristics and market conditions play a significant role on the impact of investor attention. Takeda and Wakao (2014) and Tantaopas et al. (2016) indicate that the relationships between investor attention and market return, trading volume and volatility are asymmetric. Similarly, Cooper et al. (2004), Baker and Wurgler (2006) and Avramov et al. (2016) show that aggregate market states effect the investor overconfidence. Therefore, positive conditions encourage unsophisticated investors to make optimistic investment decisions, which produce ascending investor sentiment. Alongside of the stock market findings, it is noteworthy to understand whether and how the cryptocurrency market is sensitive to different characteristics and aggregate changes. Following Cheng et al. (2021) and Yao et al. (2021a), this section aims to discuss the conditional impact of investor attention on coin-level characteristics and market conditions.

We first conditionally analyze the impact of investor attention on idiosyncratic risk. Considering the effect of different coin characteristics and aggregate states on investor attention, we divide our sample into four distinct groups by: Market capitalization, liquidity, market return and global economic policy uncertainty. We divide all sample into two groups based on median size value (Small Cap and Large Cap) and median Amihud illiquidity value (More Liquid and Less Liquid). Following Fabozzi and Francis (1977), we form two subgroups of Up Market, where excess market returns are positive, and Down Market, where excess market returns are negative. Lastly, following Baker et al. (2016), we categorize our sample into High GEPU and Low GEPU groups based on the median value of global economic policy uncertainty (GEPU) within sample period. For each group, we conduct panel regressions. Table 5.11 shows the results of conditional regression analyses for retail investor attention in Panel A (by coin-level characteristics) and Panel B (by market conditions), and institutional investor attention in Panel C (by coin-level characteristics) and Panel D (by market conditions).

The results of retail investor attention are contrary to the results of institutional investor attention. The coefficients of ATT_RET are positive and statistically significant for cryptocurrencies with higher market capitalization and lower liquidity. This shows that investor attention aggravates the idiosyncratic risk of large cap and illiquid coins whenever the market state is low (because of the significantly positive coefficient for down market group). Besides, retail investor attention exacerbates idiosyncratic volatility in both high GEPU and low GEPU states although the significance is much higher for unstable economic conditions. On the other hand, the coefficients of ATT_INST are negative and statistically significant in all characteristic subgroups. However, for cryptocurrencies with lower market capitalization and higher liquidity, the significance is higher, indicating a constraining impact of investor attention on the idiosyncratic risk. The table reports significantly negative coefficients for up market and low GEPU groups. In line with the findings of Yao et al. (2021a), when market is in a good state with a stable external environment, investor attention substantially lower the idiosyncratic volatility.

**INSERT TABLE 5.11 HERE**

Next, we conditionally analyze the effect of investor attention on Amihud illiquidity. Regarding the effect of different coin characteristics and aggregate states on investor attention, we divide our sample into four distinct groups: Market capitalization, idiosyncratic volatility, market return and global economic policy uncertainty. All subgroups except idiosyncratic volatility are formed as described above. For that, we divide all sample into two groups based on median idiosyncratic volatility value (Low IVOL and High IVOL). Table 5.12 reports the results of conditional regression analyses of Amihud illiquidity for retail investor attention in Panel A (by coin-level characteristics) and Panel B (by market conditions), and institutional investor attention in Panel C (by coin-level characteristics) and Panel D (by market conditions). For retail investor attention, all coefficients are statistically significant except for cryptocurrencies with low market capitalization. In terms of the absolute value of the coefficients, the impact of investor attention is more constructive to the cryptocurrency liquidity for higher capitalized coins with higher idiosyncratic risk whenever there is positive market state and economic stability. Similarly, all coefficients for institutional investor attention are negative and statistically significant. Looking at the absolute values, for the samples with small market capitalization and low idiosyncratic volatility as well as low global economic policy uncertainty and favorable market conditions, the investor attention impact is more considerable on the improvement of the cryptocurrency market liquidity.

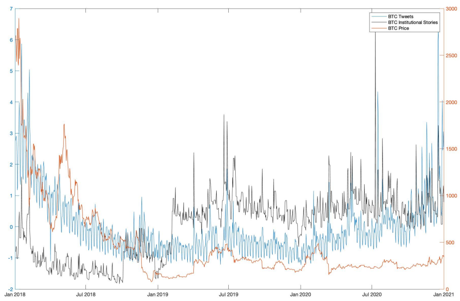
**INSERT TABLE 5.12 HERE**

### 5.5. Conclusion

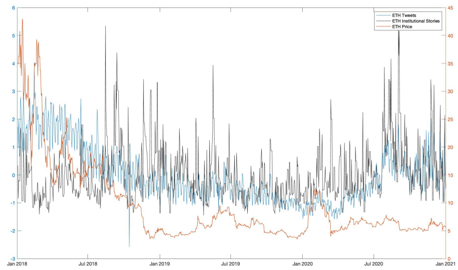
In this rapidly-growing era of technology, investor attention has become a popular field of research in the cryptocurrency market. Empirical evidence shows that information generation and transfer as a result of active investor attention substantially increase cryptocurrency trading activity (Lammer et al., 2020; Choi, 2020). However, trading behaviors of informed and uninformed investors seriously differ, affecting the efficiency of the financial markets (Cheng et al., 2021). Therefore, it is important to distinguish between individual and institutional traders and the impact of these investors' attentions on the cryptocurrency market. Specifically, the aim of this paper is to investigate the role of investor attention on cryptocurrency returns, idiosyncratic risk and liquidity in terms of informed and uninformed investors.

By collecting tweets data as a measure of retail investor attention and Bloomberg story search counts as a measure of institutional investor attention, we conduct panel regressions for 10 main cryptocurrencies for the period between January 2018 and December 2020. The results show that retail investor attention has a negative impact on cryptocurrency returns whereas institutional investor attention has a positive impact. Furthermore, retail investor attention aggravates idiosyncratic risk although institutional investor attention is found to have a constraining effect. Besides, liquidity is documented to be positively affected by an increase in either retail or institutional investor attention. The results are robust to controls for main characteristics of cryptocurrencies, two-way fixed effect regressions, alternative measure of idiosyncratic risk, and channel analysis. Finally, conditional tests indicate that retail investor attention exacerbates idiosyncratic risk for high capitalized and less liquid coins within down and unstable market conditions although it has a constructive influence on liquidity in good and stable environmental states. On the other hand, although institutional investor attention is significantly effective throughout all conditions, the absolute value of coefficients underline its lowering impact on idiosyncratic risk and boosting impact on liquidity for smaller cryptocurrencies when the market is up and the economy is less uncertain.

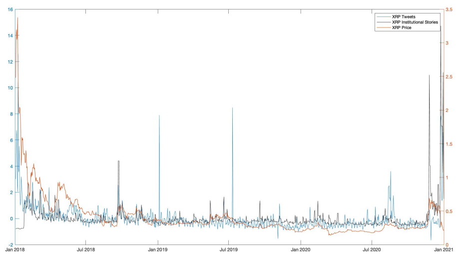
The conclusions of this paper provide an enlightening picture of the roles of retail and institutional investors in the cryptocurrency market. We show that they are both active participants of the market since their attention substantially and significantly increase market liquidity. However, the results of the investor attention impact on returns and idiosyncratic volatility reveal that individual investors are less informed and less cautious while institutional investors are more informed and confident. Besides, the effect of institutional investor attention on the cryptocurrency market risk and liquidity lasts longer than that of retail investor attention. These varying impacts of investor attention in both time and cross-section might offer some practical implications for both market participants and policy makers since creating sources of liquidity alone is neither adequate nor effective.



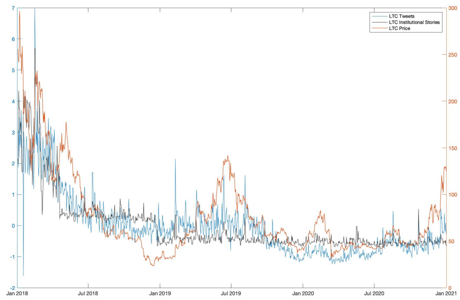
*(a)* Bitcoin



*(b)* Ethereum



*(c)* Ripple



*(d)* Litecoin

*Figure 5.1:* Time-series graphs of Cryptocurrency Retail Investor Attention Index and Cryptocurrency Institutional Investor Attention Index versus Closing Prices of Bitcoin, Ethereum, Ripple and Litecoin

This figure presents the prices of Bitcoin, Ethereum, Ripple and Litecoin along with the media attention flows of tweets and institutional stories. Cryptocurrency Retail Investor Attention Index indicates the number of Twitter discussions on cryptocurrencies normalized with center 0 and standard deviation 1. Cryptocurrency Institutional Investor Attention Index indicates the number of Bloomberg story searches on cryptocurrencies normalized with center 0 and standard deviation 1. The time span covers the period from the beginning of January 2018 to the end of December 2020.

*Table 5.1:* Descriptive statistics

Table reports summary statistics of the main variables used in the study for 1540 observations. Mean, standard deviation, minimum, median, maximum, skewness, and kurtosis of weekly calculations are shown. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. IVOL refers to the weekly idiosyncratic volatility, which equals the standard deviation of daily residuals over the month. ATT_RET is the retail investor attention, representing the weekly average of the natural logarithm of one plus the daily number of Twitter discussions on cryptocurrencies. ATT_INST is the institutional investor attention, representing the weekly average of the natural logarithm of one plus the daily number of Bloomberg story searches on cryptocurrencies. SIZE equals the natural logarithm of the cryptocurrency's market capitalization over the week. PRICE is the natural logarithm of one plus the cryptocurrency's price. VOL equals the natural logarithm of average trading volume. MOM stands for momentum that equals the cumulative return over the previous three months skipping past month. REV stands for short-term reversal and equals the cumulative return in the past month. SSKEW refers to systematic skewness and equals the slope coefficient $\theta_{i,d}$ in equation (5.4). ISKEW refers to idiosyncratic skewness and equals the skewness of daily residuals $\epsilon_{i,d}$ of equation (5.4). MAX refers to the maximum daily return within a month.

| | Mean | St Dev | Min | Median | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| ILLIQ | 0.013 | 0.315 | 0.000 | 0.003 | 0.403 | 3.389 | 16.627 |
| IVOL | 0.062 | 0.352 | 0.011 | 0.054 | 0.281 | 2.439 | 11.880 |
| ATT_RET | 7.419 | 1.807 | 2.608 | 7.906 | 11.061 | -0.345 | 2.414 |
| ATT_INST | 4.384 | 1.828 | 0.134 | 4.043 | 8.380 | 0.471 | 2.276 |
| SIZE | 22.259 | 1.733 | 19.206 | 22.037 | 26.801 | 0.245 | 2.028 |
| PRICE | 4.267 | 2.379 | 0.140 | 4.342 | 10.064 | -0.272 | 1.985 |
| VOL | 20.562 | 1.704 | 16.152 | 20.591 | 24.989 | 0.141 | 2.250 |
| MOM | 0.238 | 1.487 | -0.856 | -0.079 | 24.939 | 4.956 | 39.043 |
| REV | 0.036 | 0.519 | -0.794 | -0.013 | 13.232 | 1.575 | 9.700 |
| SSKEW | -0.157 | 1.085 | -9.493 | -0.055 | 11.759 | 0.099 | 21.152 |
| ISKEW | 0.074 | 0.811 | -2.503 | 0.028 | 3.427 | 0.343 | 3.891 |
| MAX | 0.119 | 0.074 | 0.012 | 0.102 | 0.512 | 1.328 | 5.066 |

*Table 5.2:* Pearson correlation coefficiens

Table reports the Pearson correlations between all variables used in the weekly regression models of retail and institutional investor attention. ILLIQ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. IVOL refers to the weekly idiosyncratic volatility, which equals the standard deviation of daily residuals over the month. ATT_RET is the retail investor attention, representing the weekly average of the natural logarithm of one plus the daily number of Twitter discussions on cryptocurrencies. ATT_INST is the institutional investor attention, representing the weekly average of the natural logarithm of one plus the daily number of Bloomberg story searches on cryptocurrencies. SIZE equals the natural logarithm of the cryptocurrency's market capitalization over the week. PRICE is the natural logarithm of one plus the cryptocurrency's price. VOL equals the natural logarithm of average trading volume. MOM stands for momentum that equals the cumulative return over the previous three months skipping past month. REV stands for short-term reversal and equals the cumulative return in the past month. SSKEW refers to systematic skewness and equals the slope coefficient $\theta_{i,d}$ in equation (5.4). ISKEW refers to idiosyncratic skewness and equals the skewness of daily residuals $\epsilon_{i,d}$ of equation (5.4). MAX refers to the maximum daily return within a month.

| | ILLIQ | IVOL | ATT_RET | ATT_INST | SIZE | PRICE | VOL | MOM | REV | SSKEW | ISKEW |
|---|---|---|---|---|---|---|---|---|---|---|---|
| IVOL | 0.011 | | | | | | | | | | |
| ATT_RET | -0.018 | 0.056 | | | | | | | | | |
| ATT_INST | -0.342 | -0.005 | 0.503 | | | | | | | | |
| SIZE | -0.284 | -0.016 | -0.018 | 0.029 | | | | | | | |
| PRICE | 0.154 | -0.026 | -0.028 | -0.027 | 0.258 | | | | | | |
| VOL | -0.447 | 0.166 | -0.023 | 0.186 | 0.226 | 0.114 | | | | | |
| MOM | 0.061 | 0.031 | 0.077 | -0.015 | 0.090 | 0.085 | 0.043 | | | | |
| REV | -0.174 | -0.010 | -0.012 | 0.025 | 0.078 | 0.069 | 0.023 | -0.077 | | | |
| SSKEW | 0.053 | 0.051 | -0.016 | -0.072 | 0.004 | 0.018 | -0.055 | 0.016 | 0.004 | | |
| ISKEW | -0.085 | -0.031 | 0.019 | 0.093 | -0.021 | -0.028 | 0.079 | -0.069 | 0.015 | -0.037 | |
| MAX | 0.075 | 0.040 | 0.017 | -0.005 | 0.055 | 0.048 | 0.000 | 0.030 | 0.024 | 0.011 | 0.044 |

*Table 5.3:* The weekly effect of retail and institutional investor attention on cryptocurrency returns

Table reports the fixed-effect panel regression results of retail (Panel A) and institutional (Panel B) investor attention effect on cryptocurrency returns. $\text{Return}_{t+1}$ refers to the cryptocurrency return in $\text{week}_{t+1}$. The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. The impact of retail investor attention on cryptocurrency returns*

| | Dependent Variable = Cryptocurrency $\text{Return}_{t+1}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ATT_RET | -0.002*** | -0.009** | -0.009** | -0.006*** | -0.010** | -0.009** | -0.009** | -0.009** | -0.007*** |
| | (-4.404) | (-2.279) | (-2.234) | (-2.616) | (-2.411) | (-2.356) | (-2.278) | (-2.206) | (-2.866) |
| SIZE | | -0.001 | -0.001 | -0.002 | -0.001 | -0.002 | -0.001 | -0.002 | -0.001 |
| | | (-0.360) | (-0.340) | (-0.391) | (-0.269) | (-0.404) | (-0.336) | (-0.396) | (-0.185) |
| PRICE | | -0.005* | -0.005* | -0.004 | -0.005** | -0.005* | -0.005* | -0.005* | -0.005* |
| | | (-1.914) | (-1.921) | (-1.548) | (-1.976) | (-1.899) | (-1.915) | (-1.887) | (-1.676) |
| VOLUME | | -0.004 | -0.004 | -0.001 | -0.005 | -0.004 | -0.004 | -0.004 | -0.002 |
| | | (-0.839) | (-0.801) | (-0.199) | (-0.949) | (-0.842) | (-0.884) | (-0.772) | (-0.381) |
| MOM | | | -0.002 | | | | | | -0.004** |
| | | | (-0.530) | | | | | | (-2.206) |
| REV | | | | -0.033** | | | | | -0.034** |
| | | | | (-2.506) | | | | | (-2.423) |
| IVOL | | | | | 0.112 | | | | 0.207 |
| | | | | | (1.106) | | | | (1.594) |
| SSKEW | | | | | | -0.010** | | | -0.010** |
| | | | | | | (-1.990) | | | (-1.979) |
| ISKEW | | | | | | | 0.001 | | 0.002 |
| | | | | | | | (0.198) | | (0.364) |
| MAX | | | | | | | | -0.014 | -0.005 |
| | | | | | | | | (-0.220) | (-0.051) |
| Constant | -0.375 | -0.280 | -0.960 | -0.392 | -0.195 | -0.866 | -0.441 | -0.973 | -1.577 |
| | (-0.705) | (-0.966) | (-0.872) | (-0.663) | (-0.797) | (-0.703) | (-0.823) | (-0.821) | (-1.294) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.015 | 0.019 | 0.020 | 0.032 | 0.020 | 0.025 | 0.019 | 0.019 | 0.040 |

| *Panel B. The impact of institutional investor attention on cryptocurrency returns* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Dependent Variable = Cryptocurrency Return$_{t+1}$ | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ATT_INST | 0.001*** | 0.001*** | 0.002*** | 0.002*** | 0.001*** | 0.003*** | 0.002*** | 0.001*** | 0.004** |
| | (4.266) | (3.485) | (3.157) | (3.240) | (3.100) | (3.052) | (3.278) | (2.897) | (2.381) |
| SIZE | | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.002 |
| | | (-0.669) | (-0.634) | (-0.635) | (-0.622) | (-0.703) | (-0.672) | (-0.764) | (-0.469) |
| PRICE | | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | | (-0.268) | (-0.332) | (-0.372) | (-0.236) | (-0.245) | (-0.268) | (-0.327) | (-0.419) |
| VOLUME | | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.001 | 0.002 |
| | | (0.044) | (0.073) | (0.503) | (-0.003) | (0.069) | (0.047) | (0.177) | (0.464) |
| MOM | | | -0.002 | | | | | | -0.004 |
| | | | (-0.653) | | | | | | (-1.265) |
| REV | | | | -0.035*** | | | | | -0.036** |
| | | | | (-2.612) | | | | | (-2.512) |
| IVOL | | | | | 0.069 | | | | 0.189 |
| | | | | | (0.669) | | | | (1.439) |
| SSKEW | | | | | | -0.010* | | | -0.010* |
| | | | | | | (-1.923) | | | (-1.909) |
| ISKEW | | | | | | | -0.006 | | 0.002 |
| | | | | | | | (-0.012) | | (0.321) |
| MAX | | | | | | | | -0.040 | -0.016 |
| | | | | | | | | (-0.612) | (-0.165) |
| Constant | -0.236 | -0.789 | -1.096 | -0.158 | -0.214 | -0.044 | -0.178 | -0.120 | -1.660 |
| | (-0.646) | (-1.288) | (-0.316) | (-0.397) | (-0.173) | (-0.557) | (-0.284) | (-0.273) | (-1.115) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.015 | 0.016 | 0.016 | 0.031 | 0.016 | 0.021 | 0.016 | 0.016 | 0.037 |

*Table 5.4:* The weekly effect of retail and institutional investor attention on cryptocurrency returns in the long-term

Table reports the fixed-effect panel regression results of retail (Panel A) and institutional (Panel B) investor attention effect on cryptocurrency returns from $t$+2 to $t$+6. Return$_{t+n}$ refers to the cryptocurrency return in week$_{t+n}$ (n=2-6). The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| *Panel A. The impact of retail investor attention on cryptocurrency returns* | | | | | |
|---|---|---|---|---|---|
| Dependent variable = | Return$_{t+2}$ | Return$_{t+3}$ | Return$_{t+4}$ | Return$_{t+5}$ | Return$_{t+6}$ |
| | n=2 | n=3 | n=4 | n=5 | n=6 |
| ATT_RET | -0.013** | -0.011*** | -0.011*** | -0.006* | -0.003 |
| | (-2.366) | (-2.741) | (-2.763) | (-1.682) | (-0.678) |
| SIZE | 0.004 | 0.005 | -0.002 | -0.002 | -0.004 |
| | (0.926) | (1.082) | (-0.449) | (-0.388) | (-1.031) |
| PRICE | -0.007* | -0.006** | -0.006** | -0.003 | -0.001 |
| | (-1.650) | (-2.210) | (-2.141) | (-1.271) | (-0.525) |
| VOLUME | -0.010** | -0.010* | -0.004 | -0.002 | 0.003 |
| | (-2.034) | (-1.844) | (-0.663) | (-0.419) | (0.647) |
| MOM | -0.006* | -0.002 | -0.001 | 0.003 | 0.006 |
| | (-1.786) | (-0.702) | (-0.253) | (0.760) | (1.504) |
| REV | -0.024* | -0.039* | -0.006 | 0.011 | -0.004 |
| | (-1.723) | (-1.667) | (-0.375) | (1.503) | (-0.590) |
| IVOL | 0.356* | 0.196* | 0.368* | 0.062 | -0.184 |
| | (1.891) | (1.721) | (1.957) | (0.535) | (-1.547) |
| SSKEW | -0.002 | 0.003 | 0.007 | 0.002 | -0.004 |
| | (-0.524) | (0.802) | (0.246) | (0.786) | (-1.116) |
| ISKEW | 0.010 | 0.015 | 0.023* | 0.022*** | 0.025* |
| | (0.958) | (1.314) | (1.802) | (2.588) | (1.923) |
| MAX | -0.035 | 0.009 | -0.232** | -0.261*** | -0.252*** |
| | (-0.364) | (1.052) | (-2.400) | (-2.799) | (-2.661) |
| Constant | -1.728 | -1.189 | -0.637 | -0.528 | -0.625 |
| | (-1.034) | (-1.265) | (-0.749) | (-0.654) | (-0.717) |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.037 | 0.043 | 0.032 | 0.021 | 0.032 |

| *Panel B. The impact of institutional investor attention on cryptocurrency returns* | | | | | |
|---|---|---|---|---|---|
| Dependent variable = | $\text{Return}_{t+2}$ | $\text{Return}_{t+3}$ | $\text{Return}_{t+4}$ | $\text{Return}_{t+5}$ | $\text{Return}_{t+6}$ |
| | n=2 | n=3 | n=4 | n=5 | n=6 |
| ATT_INST | 0.005** | 0.004** | 0.003** | 0.001 | 0.001 |
| | (2.329) | (2.041) | (1.968) | (1.358) | (1.154) |
| SIZE | 0.003 | 0.004 | -0.003 | -0.002 | -0.004 |
| | (0.608) | (0.852) | (-0.732) | (-0.531) | (-1.043) |
| PRICE | -0.002 | -0.002 | -0.001 | -0.001 | -0.001 |
| | (-0.884) | (-0.821) | (-0.662) | (-0.429) | (-0.303) |
| VOLUME | -0.004 | -0.005 | 0.002 | 0.001 | 0.004 |
| | (-0.788) | (-0.951) | (0.422) | (0.257) | (0.988) |
| MOM | -0.006* | -0.003* | -0.001 | 0.003 | 0.006 |
| | (-1.881) | (-0.815) | (-0.326) | (0.713) | (1.492) |
| REV | -0.028* | -0.042* | -0.008 | 0.009 | -0.004 |
| | (-1.881) | (-1.853) | (-0.549) | (1.253) | (-0.718) |
| IVOL | 0.317 | 0.163 | 0.336* | 0.041 | -0.195 |
| | (1.527) | (1.408) | (1.684) | (0.345) | (-1.627) |
| SSKEW | -0.002 | 0.003 | 0.007* | 0.002 | -0.004 |
| | (-0.430) | (0.891) | (1.758) | (0.839) | (-1.113) |
| ISKEW | 0.010* | 0.014* | 0.023* | 0.022** | 0.025*** |
| | (1.907) | (1.683) | (1.735) | (2.561) | (3.184) |
| MAX | -0.049 | -0.001 | -0.242* | -0.265* | -0.253** |
| | (-0.504) | (-0.017) | (-1.854) | (-1.829) | (-2.267) |
| Constant | -1.025 | -1.239 | -0.886 | -0.715 | -0.745 |
| | (-1.039) | (-1.007) | (-1.057) | (-0.886) | (-0.860) |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.030 | 0.039 | 0.027 | 0.019 | 0.031 |

*Table 5.5:* The weekly effect of retail and institutional investor attention on idiosyncratic risk Table reports the fixed-effect panel regression results of retail (Panel A) and institutional (Panle B) investor attention effect on cryptocurrency idiosyncratic risk. $\text{IVOL}_{t+1}$ refers to the idiosyncratic volatility, which equals the standard deviation of daily residuals over the month in $\text{week}_{t+1}$. The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. The impact of retail investor attention on idiosyncratic risk*

| | Dependent Variable = $\text{IVOL}_{t+1}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ATT_RET | 0.003*** | 0.006*** | 0.005*** | 0.005*** | 0.006*** | 0.006*** | 0.002** | 0.002*** |
| | (4.780) | (6.359) | (5.605) | (6.164) | (6.490) | (6.260) | (2.476) | (2.791) |
| SIZE | | -0.003*** | -0.004*** | -0.003*** | -0.003*** | -0.003*** | 0.001 | -0.001 |
| | | (-3.402) | (-3.984) | (-3.394) | (-3.359) | (-3.375) | (0.830) | (-0.002) |
| PRICE | | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.001** | 0.001** |
| | | (3.333) | (3.660) | (3.217) | (3.326) | (3.316) | (2.447) | (2.146) |
| VOLUME | | 0.006*** | 0.005*** | 0.006*** | 0.006*** | 0.006*** | 0.000 | 0.001 |
| | | (5.745) | (5.036) | (5.316) | (5.772) | (5.586) | (-0.233) | (0.933) |
| MOM | | | 0.007*** | | | | | 0.003*** |
| | | | (6.449) | | | | | (2.615) |
| REV | | | | 0.002 | | | | -0.007 |
| | | | | (0.722) | | | | (-1.365) |
| SSKEW | | | | | 0.003*** | | | 0.001*** |
| | | | | | (3.912) | | | (2.649) |
| ISKEW | | | | | | 0.001 | | -0.013 |
| | | | | | | (0.507) | | (-1.602) |
| MAX | | | | | | | 0.277* | 0.349* |
| | | | | | | | (1.934) | (1.959) |
| Constant | -1.077 | -0.709 | -1.025 | -0.708 | -0.755 | -0.717 | -1.774 | -0.179 |
| | (-0.859) | (-0.459) | (-1.489) | (-1.461) | (-1.489) | (-1.457) | (-1.333) | (-1.539) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.059 | 0.078 | 0.165 | 0.079 | 0.086 | 0.078 | 0.373 | 0.490 |

*Panel B. The impact of institutional investor attention on idiosyncratic risk*

| | Dependent Variable = $IVOL_{t+1}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ATT_INST | -0.005** | -0.001** | -0.002** | -0.001** | -0.003* | -0.001** | -0.001*** | -0.006** |
| | (-2.225) | (-2.026) | (-2.363) | (-2.059) | (-1.855) | (-2.100) | (-3.493) | (-2.483) |
| SIZE | | -0.002** | -0.003*** | -0.002** | -0.002** | -0.002** | 0.001 | 0.004 |
| | | (-2.516) | (-3.235) | (-2.546) | (-2.485) | (-2.392) | (1.552) | (0.599) |
| PRICE | | -0.001** | 0.000 | -0.001** | -0.001** | -0.001** | 0.000 | 0.002 |
| | | (-2.138) | (-1.024) | (-2.120) | (-2.171) | (-2.136) | (-0.468) | (0.697) |
| VOLUME | | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | -0.001 | 0.000 |
| | | (3.172) | (2.789) | (2.864) | (3.154) | (2.970) | (-1.549) | (-0.403) |
| MOM | | | 0.007*** | | | | | 0.003** |
| | | | (3.932) | | | | | (2.307) |
| REV | | | | 0.003* | | | | -0.006 |
| | | | | (1.744) | | | | (-1.294) |
| SSKEW | | | | | 0.003*** | | | 0.001*** |
| | | | | | (3.503) | | | (2.684) |
| ISKEW | | | | | | 0.001 | | -0.013** |
| | | | | | | (1.150) | | (-2.572) |
| MAX | | | | | | | 0.283** | 0.354** |
| | | | | | | | (2.044) | (1.995) |
| Constant | -0.994 | -0.625 | -0.949 | -0.631 | -0.661 | -0.648 | -1.816 | -0.235 |
| | (-1.643) | (-0.970) | (-1.641) | (-1.405) | (-1.421) | (-1.401) | (-1.331) | (-1.526) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.045 | 0.055 | 0.147 | 0.057 | 0.061 | 0.056 | 0.375 | 0.489 |

*Table 5.6:* The weekly effect of retail and institutional investor attention on idiosyncratic risk in the long-term

Table reports the fixed-effect panel regression results of retail (Panel A) and institutional (Panel B) investor attention effect on idiosyncratic risk from $t$+2 to $t$+6. $\text{IVOL}_{t+n}$ refers to the idiosyncratic volatility, which equals the standard deviation of daily residuals over the month in $\text{week}_{t+n}$ (n=2-6). The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| *Panel A. The impact of retail investor attention on idiosyncratic risk* | | | | | |
|---|---|---|---|---|---|
| Dependent variable = | $\text{IVOL}_{t+2}$ | $\text{IVOL}_{t+3}$ | $\text{IVOL}_{t+4}$ | $\text{IVOL}_{t+5}$ | $\text{IVOL}_{t+6}$ |
| | n=2 | n=3 | n=4 | n=5 | n=6 |
| ATT_RET | 0.003*** | 0.003*** | 0.003** | 0.003* | 0.003 |
| | (3.038) | (2.599) | (2.147) | (1.955) | (1.496) |
| SIZE | -0.002** | -0.002** | -0.001 | -0.001 | 0.000 |
| | (-2.375) | (-2.191) | (-1.303) | (-0.881) | (-0.349) |
| PRICE | 0.002*** | 0.002*** | 0.001** | 0.001** | 0.001** |
| | (3.325) | (3.047) | (2.544) | (2.556) | (2.464) |
| VOLUME | 0.003*** | 0.003*** | 0.002 | 0.001 | 0.000 |
| | (3.281) | (2.821) | (1.498) | (0.999) | (0.305) |
| MOM | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (3.686) | (3.364) | (3.592) | (4.776) | (5.146) |
| REV | -0.002 | 0.001 | 0.007** | 0.010*** | 0.011*** |
| | (-0.646) | (0.446) | (2.448) | (3.427) | (3.019) |
| SSKEW | 0.000 | -0.001*** | -0.001 | 0.000 | 0.000 |
| | (-0.641) | (-2.586) | (-1.594) | (0.786) | (0.446) |
| ISKEW | -0.009*** | -0.008*** | -0.007** | -0.005*** | -0.002* |
| | (-2.736) | (-2.734) | (-2.246) | (-3.838) | (-1.915) |
| MAX | 0.209** | 0.139*** | 0.082** | 0.068*** | 0.075*** |
| | (2.410) | (2.703) | (2.562) | (2.748) | (3.490) |
| Constant | -0.166 | -0.159 | -0.169 | -0.185 | -0.411 |
| | (-1.218) | (-1.125) | (-1.130) | (-1.196) | (-1.268) |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.272 | 0.201 | 0.171 | 0.177 | 0.197 |

| *Panel B. The impact of institutional investor attention on idiosyncratic risk* | | | | | |
|---|---|---|---|---|---|
| Dependent variable = | $IVOL_{t+2}$ | $IVOL_{t+3}$ | $IVOL_{t+4}$ | $IVOL_{t+5}$ | $IVOL_{t+6}$ |
| | n=2 | n=3 | n=4 | n=5 | n=6 |
| ATT_INST | -0.003* | -0.003* | -0.002* | -0.002 | 0.000 |
| | (-1.904) | (-1.832) | (-1.759) | (-1.629) | (-1.332) |
| SIZE | -0.001* | -0.001 | -0.001 | 0.000 | 0.000 |
| | (-1.783) | (-1.641) | (-0.774) | (-0.341) | (0.154) |
| PRICE | 0.000 | -0.003 | 0.000 | 0.000 | 0.000 |
| | (0.201) | (-0.142) | (-0.451) | (-0.382) | (-0.240) |
| VOLUME | 0.002* | 0.001 | 0.000 | -0.001 | -0.001 |
| | (1.697) | (1.313) | (-0.044) | (-0.572) | (-1.183) |
| MOM | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (3.492) | (3.212) | (3.439) | (4.499) | (5.797) |
| REV | -0.002 | 0.002 | 0.008* | 0.010*** | 0.012*** |
| | (-0.438) | (0.862) | (1.899) | (3.570) | (3.134) |
| SSKEW | 0.000 | -0.002*** | -0.001* | 0.000 | 0.000 |
| | (-0.901) | (-2.821) | (-1.845) | (0.515) | (0.193) |
| ISKEW | -0.009*** | -0.008** | -0.007** | -0.004*** | -0.002* |
| | (-2.871) | (-2.500) | (-2.087) | (-2.732) | (-1.832) |
| MAX | 0.216 | 0.147* | 0.089** | 0.074** | 0.080** |
| | (1.279) | (1.908) | (2.030) | (2.141) | (2.475) |
| Constant | -0.163 | -0.156 | -0.165 | -0.181 | -0.086 |
| | (-1.170) | (-1.074) | (-1.090) | (-1.159) | (-1.238) |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.265 | 0.192 | 0.163 | 0.169 | 0.191 |

*Table 5.7:* The weekly effect of retail and institutional investor attention on cryptocurrency liquidity

Table reports the regression results of retail (Panel A) and institutional (Panel B) investor attention effect on cryptocurrency liquidity. $ILLIQ_{t+n}$ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume, in $week_{t+n}$ (n=0,1,2,...). The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. The impact of retail investor attention on cryptocurrency liquidity*

| | Dependent Variable = $ILLIQ_{t+n}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (0) | (1) | (2) | (3) | (4) | (5) | (6) |
| ATT_RET | -0.036*** | -0.034*** | -0.030*** | -0.027*** | -0.021*** | -0.019*** | -0.020*** |
| | (-5.082) | (-6.924) | (-4.427) | (-4.158) | (-3.535) | (-3.301) | (-3.569) |
| SIZE | 0.050*** | 0.050*** | 0.048*** | 0.045*** | 0.043*** | 0.044*** | 0.045*** |
| | (4.961) | (7.101) | (4.880) | (4.446) | (4.234) | (4.296) | (4.277) |
| PRICE | 0.015*** | 0.016*** | 0.019*** | 0.021*** | 0.025*** | 0.026*** | 0.025*** |
| | (4.807) | (7.180) | (5.958) | (6.869) | (8.012) | (8.204) | (8.763) |
| VOLUME | -0.166*** | -0.165*** | -0.159*** | -0.154*** | -0.147*** | -0.145*** | -0.146*** |
| | (-8.809) | (-12.525) | (-8.696) | (-8.315) | (-8.155) | (-8.099) | (-7.823) |
| MOM | -0.006*** | -0.005*** | -0.001 | 0.000 | -0.005 | 0.000 | -0.001 |
| | (-2.606) | (-2.898) | (-0.271) | (-0.166) | (-0.022) | (-0.132) | (-0.483) |
| REV | -0.025* | -0.018** | -0.003 | 0.015 | 0.028* | 0.024* | 0.024* |
| | (-1.809) | (-2.269) | (-0.499) | (1.616) | (1.912) | (1.807) | (1.916) |
| IVOL | 0.731*** | 0.671*** | 0.566*** | 0.520*** | 0.359* | 0.192 | 0.239 |
| | (4.490) | (5.677) | (3.487) | (2.978) | (1.885) | (0.962) | (1.232) |
| SSKEW | 0.003 | 0.002 | -0.009* | -0.016*** | -0.014** | -0.012** | -0.019*** |
| | (0.645) | (0.009) | (-1.889) | (-2.756) | (-2.517) | (-2.116) | (-3.080) |
| ISKEW | -0.008 | -0.010* | -0.009 | -0.019* | -0.024* | -0.031** | -0.030** |
| | (-1.208) | (-1.857) | (-0.880) | (-1.679) | (-1.851) | (-2.137) | (-2.109) |
| MAX | 0.327** | 0.269*** | 0.137 | 0.154 | 0.167 | 0.268* | 0.237* |
| | (2.537) | (3.070) | (1.238) | (1.275) | (1.253) | (1.909) | (1.679) |
| Constant | -0.824 | -0.716 | -0.045 | 0.235 | 0.345 | -0.391 | -0.437 |
| | (-0.598) | (-0.754) | (-0.037) | (0.177) | (0.251) | (-0.269) | (-0.306) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.426 | 0.423 | 0.408 | 0.398 | 0.386 | 0.380 | 0.381 |

| *Panel B. The impact of institutional investor attention on cryptocurrency liquidity* | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Dependent Variable = $\text{ILLIQ}_{t+n}$ | | | | | | |
| | (0) | (1) | (2) | (3) | (4) | (5) | (6) |
| ATT_INST | -0.023*** | -0.023*** | -0.023*** | -0.022*** | -0.022*** | -0.021*** | -0.021*** |
| | (-6.606) | (-9.249) | (-6.460) | (-6.342) | (-6.266) | (-6.132) | (-6.007) |
| SIZE | 0.052*** | 0.052*** | 0.050*** | 0.048*** | 0.046*** | 0.047*** | 0.048*** |
| | (5.235) | (7.507) | (5.212) | (4.759) | (4.587) | (4.637) | (4.570) |
| PRICE | 0.021*** | 0.022*** | 0.023*** | 0.024*** | 0.025*** | 0.026*** | 0.025*** |
| | (10.726) | (15.461) | (11.270) | (11.599) | (11.789) | (11.936) | (12.526) |
| VOLUME | -0.149*** | -0.149*** | -0.146*** | -0.142*** | -0.138*** | -0.137*** | -0.137*** |
| | (-9.566) | (-13.667) | (-9.556) | (-9.088) | (-8.965) | (-8.891) | (-8.478) |
| MOM | -0.009*** | -0.007*** | -0.003 | -0.003 | -0.002 | -0.002 | -0.003 |
| | (-3.407) | (-4.068) | (-1.157) | (-0.986) | (-0.765) | (-0.781) | -1.158 |
| REV | -0.036** | -0.028*** | -0.012 | 0.008 | 0.022 | 0.018 | 0.019 |
| | (-2.216) | (-2.974) | (-1.519) | (0.862) | (1.586) | (1.494) | (1.598) |
| IVOL | 0.549*** | 0.495*** | 0.406*** | 0.372 | 0.228 | 0.068 | 0.113 |
| | (3.496) | (4.322) | (2.605) | (2.138) | (1.172) | (0.328) | (0.558) |
| SSKEW | 0.002 | -0.001 | -0.010** | -0.017*** | -0.015*** | -0.014** | -0.020*** |
| | (0.479) | (-0.281) | (-2.094) | (-2.931) | (-2.738) | (-2.324) | (-3.252) |
| ISKEW | -0.006 | -0.008 | -0.007 | -0.017 | -0.022* | -0.029** | -0.028** |
| | (-0.922) | (-1.524) | (-0.695) | (-1.532) | (-1.720) | (-2.047) | (-2.015) |
| MAX | 0.311** | 0.254*** | 0.129 | 0.149 | 0.168 | 0.272** | 0.241* |
| | (2.490) | (3.012) | (1.208) | (1.279) | (1.293) | (1.980) | (1.750) |
| Constant | -2.913 | -0.753 | -2.019 | -1.671 | -1.427 | -2.088 | -2.166 |
| | (-1.601) | (-0.467) | (-1.410) | (-1.075) | (-0.903) | (-1.256) | (-1.320) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.435 | 0.432 | 0.420 | 0.410 | 0.400 | 0.394 | 0.395 |

*Table 5.8:* The monthly effect of retail and institutional investor attention on cryptocurrency liquidity

Table reports the regression results of retail (Panel A) and institutional (Panel B) investor attention effect on cryptocurrency liquidity. ILLIQ$_{t+n}$ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume, in month$_{t+n}$ (n=0,1,2,...). The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. The impact of retail investor attention on cryptocurrency liquidity*

| | Dependent Variable = ILLIQ$_{t+n}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (0) | (1) | (2) | (3) | (4) | (5) | (6) |
| ATT_RET | -0.047*** | -0.041*** | -0.026** | -0.018* | -0.011* | -0.012 | -0.015 |
| | (-2.764) | (-2.737) | (-1.975) | (-1.831) | (-1.711) | (-1.548) | (-1.420) |
| SIZE | 0.066*** | 0.068*** | 0.058** | 0.047** | 0.039** | 0.040* | 0.044** |
| | (2.834) | (3.123) | (2.479) | (2.309) | (2.283) | (1.944) | (2.283) |
| PRICE | 0.010 | 0.013** | 0.021*** | 0.024*** | 0.025*** | 0.023*** | 0.021*** |
| | (1.374) | (1.985) | (3.709) | (4.811) | (4.934) | (4.679) | (4.089) |
| VOLUME | -0.188*** | -0.185*** | -0.157*** | -0.136*** | -0.120*** | -0.119*** | -0.122*** |
| | (-4.458) | (-4.765) | (-4.019) | (-4.112) | (-4.015) | (-3.518) | (-3.721) |
| MOM | -0.011* | -0.008 | -0.010* | -0.012* | -0.008 | -0.001 | 0.000 |
| | (-1.889) | (-1.551) | (-1.884) | (-1.713) | (-1.352) | (-0.126) | (0.003) |
| REV | -0.018 | 0.014 | 0.000 | 0.020 | 0.009 | 0.004 | 0.012 |
| | (-1.324) | (1.058) | (-0.033) | (1.300) | (0.666) | (0.289) | (0.666) |
| IVOL | 0.179 | 0.155 | 0.179 | 0.268* | 0.302** | 0.344** | 0.367** |
| | (1.342) | (0.897) | (1.176) | (1.862) | (2.128) | (2.460) | (1.971) |
| SSKEW | 0.014 | 0.005 | -0.014 | 0.000 | 0.004 | 0.004 | 0.005 |
| | (1.236) | (0.564) | (-1.339) | (-0.010) | (0.696) | (0.659) | (0.736) |
| ISKEW | -0.004 | -0.020 | -0.050** | -0.024 | 0.007 | 0.015 | 0.011 |
| | (-0.325) | (-1.454) | (-2.179) | (-1.342) | (0.545) | (1.484) | (0.971) |
| MAX | 0.720*** | 0.494** | 0.555** | 0.321 | 0.112 | -0.032 | -0.058 |
| | (3.241) | (2.467) | (2.165) | (1.232) | (0.600) | (-0.187) | (-0.347) |
| Constant | -2.160 | -1.844 | -1.598 | 0.021 | 0.803 | 0.622 | -0.716 |
| | (-1.230) | (-1.145) | (-0.545) | (0.008) | (0.380) | (0.246) | (-0.311) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.489 | 0.476 | 0.428 | 0.365 | 0.316 | 0.301 | 0.287 |

| *Panel B. The impact of institutional investor attention on cryptocurrency liquidity* | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Dependent Variable = $\text{ILLIQ}_{t+n}$ | | | | | | |
| | (0) | (1) | (2) | (3) | (4) | (5) | (6) |
| ATT_INST | -0.026*** | -0.028*** | -0.025*** | -0.022*** | -0.021*** | -0.020*** | -0.019** |
| | (-3.473) | (-3.711) | (-3.316) | (-2.941) | (-2.671) | (-2.589) | (-2.523) |
| SIZE | 0.066*** | 0.069*** | 0.061*** | 0.051** | 0.044** | 0.045** | 0.049** |
| | (2.957) | (3.311) | (2.667) | (2.467) | (2.452) | (2.115) | (2.415) |
| PRICE | 0.020*** | 0.019*** | 0.022*** | 0.022*** | 0.021*** | 0.020*** | 0.019*** |
| | (4.893) | (5.053) | (5.884) | (6.090) | (6.050) | (5.734) | (5.610) |
| VOLUME | -0.165*** | -0.166*** | -0.146*** | -0.130*** | -0.117*** | -0.116*** | -0.118*** |
| | (-4.860) | (-5.242) | (-4.433) | (-4.421) | (-4.299) | (-3.819) | (-3.992) |
| MOM | -0.015** | -0.012** | -0.014** | -0.016** | -0.012* | -0.004 | -0.003 |
| | (-2.332) | (-2.160) | (-2.401) | (-2.057) | (-1.714) | (-0.483) | (-0.391) |
| REV | -0.018 | 0.015 | 0.003 | 0.024* | 0.014 | 0.008 | 0.016 |
| | (-1.140) | (1.365) | (0.266) | (1.748) | (1.059) | (0.635) | (0.902) |
| IVOL | 0.113 | 0.089 | 0.124 | 0.219 | 0.260* | 0.298** | 0.322* |
| | (0.784) | (0.512) | (0.756) | (1.506) | (1.907) | (2.160) | (1.836) |
| SSKEW | 0.014 | 0.005 | -0.014 | 0.000 | 0.004 | 0.004 | 0.004 |
| | (1.240) | (0.567) | (-1.415) | (-0.038) | (0.735) | (0.619) | (0.680) |
| ISKEW | 0.001 | -0.015 | -0.047** | -0.021 | 0.010 | 0.017* | 0.012 |
| | (0.060) | (-1.131) | (-2.097) | (-1.217) | (0.755) | (1.660) | (1.078) |
| MAX | 0.592*** | 0.383** | 0.495** | 0.282 | 0.088 | -0.049 | -0.076 |
| | (3.137) | (2.328) | (2.209) | (1.163) | (0.492) | (-0.311) | (-0.468) |
| Constant | -4.021 | -3.078 | -2.368 | -1.638 | -0.809 | -1.142 | -2.670 |
| | (-1.583) | (-1.633) | (-1.013) | (-0.545) | (-0.332) | (-0.384) | (-0.983) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.496 | 0.490 | 0.445 | 0.383 | 0.334 | 0.316 | 0.301 |

*Table 5.9:* Robustness test with alternative idiosyncratic risk measure

Table reports the fixed-effect panel regression results of retail (Panel A) and institutional investor (Panel B) attention effect on cryptocurrency idiosyncratic risk. $IVOL\_FF3_{t+1}$ refers to the idiosyncratic volatility, which equals the standard deviation of daily residuals, calculated by the three-factor model, over the month in $week_{t+1}$. The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| *Panel A. The impact of retail investor attention on idiosyncratic risk* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Dependent Variable = $IVOL\_FF3_{t+1}$ | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ATT_RET | 0.002*** | 0.004*** | 0.004*** | 0.005*** | 0.004*** | 0.006*** | 0.001** | 0.001** |
| | (3.729) | (5.492) | (5.088) | (5.973) | (5.964) | (6.125) | (2.556) | (2.467) |
| SIZE | | -0.003*** | -0.004*** | -0.003*** | -0.003*** | -0.003*** | 0.000 | -0.001 |
| | | (-3.016) | (-3.802) | (-2.912) | (-2.900) | (-2.904) | (1.116) | (-0.002) |
| PRICE | | 0.001*** | 0.002*** | 0.001*** | 0.001*** | 0.001*** | 0.001** | 0.001** |
| | | (2.608) | (3.775) | (2.690) | (2.654) | (2.602) | (2.476) | (2.346) |
| VOLUME | | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.000 | 0.001 |
| | | (4.210) | (4.921) | (4.587) | (4.621) | (5.119) | (-0.200) | (0.996) |
| MOM | | | 0.005*** | | | | | 0.003*** |
| | | | (6.231) | | | | | (2.667) |
| REV | | | | -0.005 | | | | -0.004 |
| | | | | (-0.779) | | | | (-1.303) |
| SSKEW | | | | | 0.002*** | | | 0.001*** |
| | | | | | (3.706) | | | (2.781) |
| ISKEW | | | | | | -0.018 | | -0.013 |
| | | | | | | (-0.047) | | (-1.436) |
| MAX | | | | | | | 0.249** | 0.311** |
| | | | | | | | (2.145) | (1.997) |
| Constant | -1.656 | -0.644 | -1.467 | -0.855 | -0.904 | -1.264 | -1.752 | -0.225 |
| | (-1.010) | (-0.952) | (-1.288) | (-1.277) | (-1.238) | (-1.229) | (-1.448) | (-1.480) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.113 | 0.125 | 0.172 | 0.128 | 0.128 | 0.125 | 0.351 | 0.439 |

| *Panel B. The impact of institutional investor attention on idiosyncratic risk* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Dependent Variable = IVOL_FF3$_{t+1}$ | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ATT_INST | -0.004*** | -0.001** | -0.005** | -0.001** | -0.002** | -0.001** | -0.001*** | -0.006** |
| | (-3.097) | (-2.202) | (-2.225) | (-2.385) | (-2.089) | (-2.047) | (-2.911) | (-2.509) |
| SIZE | | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.002*** | 0.001 | -0.003 |
| | | (-2.708) | (-3.135) | (-2.714) | (-2.643) | (-2.693) | (1.584) | (0.543) |
| PRICE | | -0.001** | 0.000 | -0.001** | -0.001** | -0.001** | -0.001 | 0.004 |
| | | (-2.474) | (-1.209) | (-2.465) | (-2.481) | (-2.474) | (-0.574) | (0.645) |
| VOLUME | | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | -0.001 | 0.000 |
| | | (3.275) | (2.857) | (2.753) | (3.189) | (2.702) | (-1.316) | (-0.309) |
| MOM | | | 0.006*** | | | | | 0.003** |
| | | | (3.534) | | | | | (2.185) |
| REV | | | | -0.004** | | | | -0.004 |
| | | | | (-1.977) | | | | (-1.278) |
| SSKEW | | | | | 0.002*** | | | 0.001*** |
| | | | | | (3.679) | | | (2.712) |
| ISKEW | | | | | | 0.002 | | -0.013** |
| | | | | | | (1.293) | | (-2.339) |
| MAX | | | | | | | 0.253** | 0.314** |
| | | | | | | | (2.477) | (2.157) |
| Constant | -1.597 | -0.795 | -1.442 | -1.261 | -0.723 | -1.261 | -1.223 | -0.228 |
| | (-1.343) | (-0.594) | (-1.640) | (-1.208) | (-1.230) | (-0.635) | (-1.452) | (-1.482) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.105 | 0.113 | 0.162 | 0.115 | 0.116 | 0.113 | 0.354 | 0.440 |

*Table 5.10:* Channel analysis

Table reports the weekly regression results of channel analysis. $ILLIQ_t$ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume. $IVOL_{t+1}$ refers to the idiosyncratic volatility, which equals the standard deviation of daily residuals over the month in $week_{t+1}$. $IVOL\_FF3_{t+1}$ refers to the idiosyncratic volatility, which equals the standard deviation of daily residuals, calculated by the three-factor model, over the month in $week_{t+1}$. The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

| Dependent Variable = | ILLIQ | ILLIQ | $IVOL_{t+1}$ | $IVOL\_FF3_{t+1}$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ATT_RET | -0.034*** | | | |
| | (-4.889) | | | |
| ATT_INST | | -0.024*** | | |
| | | (-6.703) | | |
| ILLIQ | | | 0.001*** | 0.002*** |
| | | | (4.185) | (3.649) |
| SIZE | 0.050*** | 0.052*** | -0.002** | -0.002*** |
| | (4.955) | (5.260) | (-2.062) | (-2.679) |
| PRICE | 0.016*** | 0.021*** | 0.001 | 0.000 |
| | (5.058) | (10.661) | (0.028) | (-0.681) |
| VOLUME | -0.165*** | -0.149*** | 0.003*** | 0.004*** |
| | (-8.775) | (-9.581) | (3.114) | (2.655) |
| MOM | -0.004 | -0.007** | 0.004*** | 0.004*** |
| | (-1.420) | (-2.448) | (3.915) | (3.592) |
| REV | -0.030* | -0.039** | -0.004 | -0.001 |
| | (-1.808) | (-2.179) | (-0.786) | (-0.287) |
| SSKEW | 0.004 | 0.003 | 0.000 | -0.001 |
| | (0.887) | (0.654) | (0.719) | (-0.994) |
| ISKEW | -0.018*** | -0.013** | -0.011*** | -0.009*** |
| | (-2.755) | (-2.086) | (-13.131) | (-9.279) |
| MAX | 0.582*** | 0.505*** | 0.289*** | 0.209*** |
| | (5.404) | (5.185) | (16.622) | (12.478) |
| Constant | -0.993 | -1.024 | -1.736 | -1.570 |
| | (-0.753) | (-1.578) | (-1.296) | (-1.150) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.423 | 0.433 | 0.389 | 0.276 |

*Table 5.11:* Conditional analysis: The weekly effect of retail and institutional investor attention on idiosyncratic risk under coin-level characteristics and market conditions

We divide the full sample into sub-samples of: Large-cap/Small-cap, More liquid/Less liquid, Down Market/Up Market, High GEPU/Low GEPU, and conduct weekly regression analysis. Table reports the regression results of retail (Panel A and B) and institutional (Panel C and D) investor attention effect on cryptocurrency idiosyncratic risk for sub-samples. $\text{IVOL}_{t+1}$ refers to the idiosyncratic volatility, which equals the standard deviation of daily residuals over the month in $\text{week}_{t+1}$. The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. The impact of retail investor attention by coin-level characteristics*

| | Dependent Variable = $\text{IVOL}_{t+1}$ | | | |
|---|---|---|---|---|
| | (1) Large Cap | (2) Small Cap | (3) More Liquid | (4) Less Liquid |
| ATT_RET | 0.003*** | 0.002 | 0.001 | 0.003** |
| | (3.170) | (0.726) | (1.003) | (2.222) |
| SIZE | 0.000 | 0.001 | -0.002 | 0.000 |
| | (-0.265) | (0.481) | (-1.590) | (0.345) |
| PRICE | 0.002*** | 0.001 | 0.000 | 0.003*** |
| | (4.483) | (0.834) | (-0.213) | (4.019) |
| VOLUME | 0.001 | 0.003*** | 0.006*** | 0.004*** |
| | (0.386) | (2.626) | (3.018) | (4.155) |
| MOM | 0.002*** | 0.020*** | 0.008*** | 0.003*** |
| | (3.627) | (7.777) | (4.287) | (3.810) |
| REV | 0.001 | -0.032*** | -0.002 | -0.016*** |
| | (0.419) | (-6.287) | (-0.390) | (-2.825) |
| SSKEW | 0.000 | 0.001 | 0.001 | 0.000 |
| | (0.483) | (0.926) | (1.602) | (-0.282) |
| ISKEW | -0.014*** | -0.008*** | -0.013*** | -0.008*** |
| | (-12.239) | (-6.104) | (-12.563) | (-6.066) |
| MAX | 0.313*** | 0.281*** | 0.317*** | 0.241*** |
| | (16.068) | (12.947) | (11.780) | (12.088) |
| Constant | -1.726 | -2.111 | -2.121 | -1.763 |
| | (-0.901) | (-1.057) | (-1.244) | (-0.795) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.445 | 0.490 | 0.444 | 0.384 |

| *Panel B. The impact of retail investor attention by market conditions* | | | | |
|---|---|---|---|---|
| | Dependent Variable = $IVOL_{t+1}$ | | | |
| | (1) Down Market | (2) Up Market | (3) High GEPU | (4) Low GEPU |
| ATT_RET | 0.003*** | 0.001 | 0.003*** | 0.002* |
| | (3.617) | (1.260) | (3.017) | (1.806) |
| SIZE | -0.002*** | 0.000 | -0.001 | -0.002** |
| | (-2.435) | (0.182) | (-0.613) | (-2.065) |
| PRICE | 0.003*** | 0.001 | 0.002*** | 0.001 |
| | (4.308) | (0.764) | (4.385) | (1.196) |
| VOLUME | 0.005*** | -0.001 | 0.002* | 0.003** |
| | (3.994) | (-1.102) | (1.949) | (2.287) |
| MOM | 0.002*** | 0.008*** | 0.002* | 0.004*** |
| | (3.046) | (3.197) | (1.803) | (3.169) |
| REV | -0.032*** | 0.002 | -0.040*** | -0.002 |
| | (-5.645) | (1.162) | (-6.470) | (-0.422) |
| SSKEW | 0.001 | 0.002** | 0.001** | 0.000 |
| | (1.149) | (1.998) | (2.322) | (-0.519) |
| ISKEW | -0.014*** | -0.007*** | -0.010*** | -0.013*** |
| | (-13.139) | (-4.457) | (-9.300) | (-9.477) |
| MAX | 0.335*** | 0.222*** | 0.334*** | 0.271*** |
| | (15.467) | (9.519) | (17.942) | (9.152) |
| Constant | -2.225 | -1.553 | -1.053 | -0.980 |
| | (-1.125) | (-0.861) | (-1.643) | (-1.473) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.450 | 0.405 | 0.566 | 0.318 |

| *Panel C. The impact of institutional investor attention by coin-level characteristics* | | | | |
|---|---|---|---|---|
| | Dependent Variable = $\text{IVOL}_{t+1}$ | | | |
| | (1) Large Cap | (2) Small Cap | (3) More Liquid | (4) Less Liquid |
| ATT_INST | 0.000* | -0.001*** | -0.001*** | -0.001** |
| | (-1.831) | (-2.738) | (-2.683) | (-2.461) |
| SIZE | 0.000 | 0.000 | -0.001 | 0.002** |
| | (0.145) | (0.209) | (-1.038) | (2.251) |
| PRICE | 0.001*** | 0.000 | -0.001 | 0.002*** |
| | (2.633) | (0.307) | (-1.275) | (4.126) |
| VOLUME | -0.002 | 0.003*** | 0.004** | 0.005*** |
| | (-1.473) | (2.738) | (1.997) | (4.532) |
| MOM | 0.002*** | 0.021*** | 0.009*** | 0.003*** |
| | (3.250) | (8.320) | (4.045) | (3.226) |
| REV | 0.002 | -0.031*** | -0.001 | -0.016*** |
| | (0.738) | (-5.887) | (-0.265) | (-3.039) |
| SSKEW | 0.000 | 0.000 | 0.001 | 0.000 |
| | (0.533) | (0.662) | (1.534) | (-0.622) |
| ISKEW | -0.014*** | -0.008*** | -0.012*** | -0.009*** |
| | (-11.694) | (-6.491) | (-11.611) | (-6.337) |
| MAX | 0.319*** | 0.282*** | 0.320*** | 0.241*** |
| | (16.673) | (13.289) | (12.091) | (11.940) |
| Constant | -1.810 | -2.001 | -1.400 | -1.760 |
| | (-1.511) | (-1.039) | (-1.312) | (-1.493) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.438 | 0.491 | 0.448 | 0.385 |

| *Panel D. The impact of institutional investor attention by market condition* | | | | |
|---|---|---|---|---|
| | Dependent Variable = $\text{IVOL}_{t+1}$ | | | |
| | (1) Down Market | (2) Up Market | (3) High GEPU | (4) Low GEPU |
| ATT_INST | -0.001 | -0.001** | 0.001 | -0.001*** |
| | (-0.237) | (-1.995) | (0.147) | (-2.596) |
| SIZE | -0.002* | 0.001 | 0.000 | -0.002 |
| | (-1.925) | (0.474) | (-0.276) | (-1.572) |
| PRICE | 0.001* | 0.000 | 0.001** | 0.000 |
| | (1.935) | (-0.677) | (2.478) | (-0.880) |
| VOLUME | 0.003*** | -0.002* | 0.001 | 0.002 |
| | (2.768) | (-1.957) | (0.757) | (1.408) |
| MOM | 0.002*** | 0.008*** | 0.002* | 0.004*** |
| | (2.838) | (3.169) | (1.677) | (2.992) |
| REV | -0.031*** | 0.003 | -0.039*** | -0.001 |
| | (-5.464) | (1.360) | (-6.395) | (-0.287) |
| SSKEW | 0.001 | 0.001* | 0.001** | 0.000 |
| | (0.792) | (1.870) | (2.082) | (-0.663) |
| ISKEW | -0.014*** | -0.007*** | -0.010*** | -0.013*** |
| | (-12.641) | (-4.432) | (-9.080) | (-9.225) |
| MAX | 0.343*** | 0.225*** | 0.340*** | 0.276*** |
| | (15.903) | (9.738) | (18.484) | (9.273) |
| Constant | -2.190 | -1.574 | -3.084 | -0.990 |
| | (-1.092) | (-0.843) | (-1.617) | (-1.459) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.442 | 0.405 | 0.561 | 0.317 |

*Table 5.12:* Conditional analysis: The weekly effect of retail and institutional investor attention on liquidity under coin-level characteristics and market conditions

We divide the full sample into sub-samples of: Large-cap/Small-cap, Low IVOL/High IVOL, Down Market/Up Market, High GEPU/Low GEPU, and conduct weekly regression analysis. Table reports the regression results of retail (Panel A and B) and institutional (Panel C and D) investor attention effect on cryptocurrency idiosyncratic risk for sub-samples. $ILLIQ_{t+1}$ refers to Amihud illiquidity measure, which is calculated by the ratio of absolute daily cryptocurrency return to its mean dollar trading volume, in $month_{t+1}$. The detailed definitions of independent variables are as described in Section 5.2.2. All variables are winsorized at 1% level from upper and lower tails. Following Petersen (2009), the standard errors are clustered at the cryptocurrency level. Cryptocurrency and time fixed effects are controlled. t-statistics are presented in the parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

*Panel A. The impact of retail investor attention by coin-level characteristics*

| | Dependent Variable = $ILLIQ_{t+1}$ | | | |
|---|---|---|---|---|
| | (1) Large Cap | (2) Small Cap | (3) Low IVOL | (4) High IVOL |
| ATT_RET | -0.006*** | -0.011 | -0.032*** | -0.035*** |
| | (-3.000) | (-0.586) | (-4.595) | (-3.171) |
| SIZE | -0.005* | 0.147*** | 0.052*** | 0.051*** |
| | (-1.716) | (8.208) | (4.575) | (3.274) |
| PRICE | 0.028*** | -0.023** | 0.019*** | 0.012** |
| | (5.941) | (-1.986) | (5.106) | (2.333) |
| VOLUME | -0.076*** | -0.216*** | -0.161*** | -0.172*** |
| | (-7.959) | (-7.647) | (-7.935) | (-5.757) |
| MOM | 0.006*** | 0.012 | 0.013 | -0.008*** |
| | (3.712) | (0.692) | (1.584) | (-3.158) |
| REV | 0.011** | -0.125** | 0.054 | -0.017 |
| | (2.108) | (-2.502) | (1.446) | (-1.550) |
| IVOL | 0.371*** | 0.623* | 1.070 | 0.372** |
| | (3.415) | (1.898) | (0.744) | (2.106) |
| SSKEW | -0.002 | -0.003 | -0.002 | -0.009 |
| | (-1.044) | (-0.693) | (-0.650) | (-0.896) |
| ISKEW | 0.006* | -0.022 | -0.008 | -0.023** |
| | (1.691) | (-1.349) | (-0.488) | (-2.002) |
| MAX | 0.059 | 0.375 | 0.315 | 0.061 |
| | (0.863) | (1.504) | (0.876) | (0.473) |
| Constant | -1.181 | 1.365 | -0.617 | 0.633 |
| | (-0.840) | (0.582) | (-0.443) | (0.866) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.476 | 0.466 | 0.433 | 0.430 |

| *Panel B. The impact of retail investor attention by market conditions* | | | | |
|---|---|---|---|---|
| | Dependent Variable = $ILLIQ_{t+1}$ | | | |
| | (1) Down Market | (2) Up Market | (3) High GEPU | (4) Low GEPU |
| ATT_RET | -0.029*** | -0.039*** | -0.022*** | -0.044*** |
| | (-3.367) | (-3.386) | (-3.901) | (-3.550) |
| SIZE | 0.045*** | 0.061*** | 0.039*** | 0.064*** |
| | (3.792) | (3.391) | (4.496) | (3.464) |
| PRICE | 0.019*** | 0.013*** | 0.022*** | 0.011** |
| | (4.788) | (2.674) | (6.297) | (2.022) |
| VOLUME | -0.153*** | -0.186*** | -0.140*** | -0.193*** |
| | (-7.008) | (-5.593) | (-9.016) | (-5.682) |
| MOM | -0.003 | -0.004 | -0.003 | -0.003 |
| | (-1.248) | (-0.532) | (-0.827) | (-0.989) |
| REV | -0.054 | 0.001 | 0.046 | -0.017 |
| | (-1.546) | (0.082) | (1.513) | (-1.439) |
| IVOL | 0.928*** | -0.044 | 0.529** | 0.991*** |
| | (3.666) | (-0.177) | (2.249) | (3.744) |
| SSKEW | -0.005 | 0.002 | -0.002 | -0.002 |
| | (-1.009) | (0.425) | (-0.632) | (-0.314) |
| ISKEW | 0.008 | -0.040** | -0.013 | -0.009 |
| | (1.023) | (-2.014) | (-0.923) | (-0.814) |
| MAX | 0.102 | 0.431** | 0.065 | 0.175 |
| | (0.564) | (2.354) | (0.447) | (0.963) |
| Constant | 0.177 | -0.304 | 1.163 | -1.520 |
| | (0.089) | (-1.380) | (0.796) | (-0.672) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.466 | 0.391 | 0.481 | 0.401 |

| *Panel C. The impact of institutional investor attention by coin-level characteristics* | | | | |
|---|---|---|---|---|
| | Dependent Variable = $ILLIQ_{t+1}$ | | | |
| | (1) Large Cap | (2) Small Cap | (3) Low IVOL | (4) High IVOL |
| ATT_INST | -0.007*** | -0.054*** | -0.025*** | -0.021*** |
| | (-4.218) | (-6.136) | (-5.241) | (-4.297) |
| SIZE | -0.003 | 0.129*** | 0.053*** | 0.055*** |
| | (-1.222) | (8.262) | (4.767) | (3.445) |
| PRICE | 0.029*** | -0.049*** | 0.023*** | 0.018*** |
| | (6.453) | (-3.328) | (8.250) | (5.755) |
| VOLUME | -0.078*** | -0.197*** | -0.145*** | -0.158*** |
| | (-8.227) | (-7.869) | (-8.480) | (-6.199) |
| MOM | 0.006*** | 0.013 | 0.009 | -0.011*** |
| | (3.330) | (0.703) | (1.004) | (-3.716) |
| REV | 0.010** | -0.105** | 0.043 | -0.026** |
| | (2.114) | (-2.290) | (1.195) | (-1.992) |
| IVOL | 0.318*** | 0.458 | 0.236 | 0.339* |
| | (3.072) | (1.447) | (0.166) | (1.918) |
| SSKEW | -0.002 | -0.012** | -0.002 | -0.012 |
| | (-0.945) | (-2.059) | (-0.519) | (-1.219) |
| ISKEW | 0.007** | -0.029* | -0.011 | -0.021* |
| | (2.204) | (-1.847) | (-0.679) | (-1.828) |
| MAX | 0.063 | 0.423* | 0.471 | 0.034 |
| | (0.946) | (1.807) | (1.305) | (0.280) |
| Constant | -1.415 | 1.316 | -0.515 | -0.343 |
| | (-0.980) | (1.436) | (-1.252) | (-0.153) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.489 | 0.502 | 0.446 | 0.436 |

| *Panel D. The impact of institutional investor attention by market condition* | | | | |
|---|---|---|---|---|
| | Dependent Variable = $ILLIQ_{t+1}$ | | | |
| | (1) Down Market | (2) Up Market | (3) High GEPU | (4) Low GEPU |
| ATT_INST | -0.022*** | -0.026*** | -0.017*** | -0.028*** |
| | (-5.507) | (-3.743) | (-4.897) | (-4.710) |
| SIZE | 0.047*** | 0.065*** | 0.040*** | 0.067*** |
| | (4.054) | (3.566) | (4.694) | (3.693) |
| PRICE | 0.023*** | 0.019*** | 0.024*** | 0.018*** |
| | (9.509) | (5.838) | (8.983) | (6.173) |
| VOLUME | -0.139*** | -0.170*** | -0.128*** | -0.175*** |
| | (-7.851) | (-5.969) | (-9.664) | (-6.149) |
| MOM | -0.006** | -0.007 | -0.004 | -0.005* |
| | (-1.976) | (-0.998) | (-1.346) | (-1.800) |
| REV | -0.059 | -0.010 | 0.040 | -0.029* |
| | (-1.617) | (-1.159) | (1.365) | (-1.944) |
| IVOL | 0.786*** | -0.230 | 0.446* | 0.685*** |
| | (3.161) | (-0.851) | (1.929) | (2.686) |
| SSKEW | -0.005 | -0.001 | -0.003 | -0.004 |
| | (-1.057) | (-0.098) | (-0.714) | (-0.690) |
| ISKEW | 0.013 | -0.044** | -0.010 | -0.008 |
| | (1.618) | (-2.156) | (-0.757) | (-0.761) |
| MAX | 0.097 | 0.392** | 0.035 | 0.204 |
| | (0.560) | (2.195) | (0.242) | (1.154) |
| Constant | -1.465 | -0.562 | 0.051 | -0.460 |
| | (-0.654) | (-1.084) | (0.034) | (-1.414) |
| Time FE | Yes | Yes | Yes | Yes |
| Crypto FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.478 | 0.400 | 0.490 | 0.412 |

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