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IS DOWNSIDE RISK PRICED IN CRYPTOCURRENCY MARKET?

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Abstract

I look at the cryptocurrency market through the prism of standard multifactor asset-pricing models with particular attention to the downside market risk. The analysis for 1,700 coins reveals that there is a significant heterogeneity in the exposure to the downside market risk, and that a higher downside risk exposure is associated with higher average returns. The extra downside risk is priced with a statistically significant premium in cross-sectional regressions. Adding the downside risk component to the CAPM and the 3-factor model for cryptocurrencies improves the explanatory power of the models significantly. The downside risk is orthogonal to the size and momentum risks and constitutes an important forth component in the multifactor cryptocurrency pricing model.

JEL classification: D14, G12, G15

Keywords: cryptocurrency, coins, cryptofinance, alternative investments, downside risk, DR-CAPM

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1. INTRODUCTION

Cryptocurrencies have burst into our lives as alien alternative investment assets with outrageous potential returns and severe crashes. In 7 years 2013-2019, the total capitalization of the crypto market increased from 1 to 250 billion dollars with over 5,000 cryptocurrencies traded. Individual coin returns have been as high as 20,000% and as low as -99% in one week. Of course, such weird return dynamics have received a lot of attention from academia and media. As Jamie Dimon, a JP Morgan CEO, said, cryptocurrency is "a fraud, worse than tulip bulbs". Warren Buffet expressed his opinion: "Probably rat poison squared. If I could buy a five-year put on every one of the cryptocurrencies, I'd be glad to do it but I would never short a dime's worth". The title of Nouriel Roubini's congressional testimony in October 2018 was "Crypto is the mother of all scams and (now busted) bubbles…"[1] Numerous academic papers also have claimed fraud and bubbles in the cryptocurrency market (Cheah and Fry, 2015; Henry and Irrera, 2017; Corbet et al., 2018; Geuder et al., 2018; Foley et al., 2019; Xiong et al., 2020). Others are more optimistic in the future of blockchain technology and provide fundamental theories of cryptocurrency pricing (Cong et al., 2018; Pagnotta and Burashi, 2018; Biais et al., 2018). Authors agree that cryptocurrency returns are generally unrelated to equity, currency and commodity returns and macroeconomic factors (Liu and Tsyvinski, 2018; Liu et al., 2019; Corbet et al., 2018; Bianchi, 2020), and point to diversification, hedging or even 'safe haven' properties of major cryptocurrencies (Bouri et al., 2017; Bouri et al., 2019a; Bouri et al., 2019b; Urquhart and Zhang, 2019; Shahzad et al., 2019).

On the other hand, the financial and academic press is flooded with articles about the crash risk of cryptocurrencies (e.g. Borri, 2018; Kalyvas et al., 2019; the Daily HODL, 2020). This is not surprising given that the whole cryptocurrency market experienced a series of significant crashes in 2018, when the overall market capitalization plunged by about 90% from 800 billion to 100 billion during the year. These articles talk about the *idiosyncratic* crash risk of particular cryptocurrencies, however, for an investor, who invests in a diversified portfolio of cryptocurrencies, the downside *market* risk plays a key role. Consider a recent episode of Black Thursday – March 12th, 2020 – the global stock market crash, when we observed the percentage drop in CRSP index by about 10%, the largest single-day drop since Black Monday of 1987. Bitcoin crashed by 40% on this single day, and other cryptocurrencies followed this path too. It is important to understand how various cryptocurrencies are exposed to the overall crypto-market losses, and whether a higher exposure is compensated by higher average returns. In other words, we ask the question, how (and whether) the downside market risk is priced in the cryptocurrency market.

[1] The citations are borrowed from Coursera course "Cryptocurrency and Blockchain: An Introduction to Digital Currencies" by Jessica Wachter.

This paper sheds light on this issue. It documents a significant heterogeneity in the exposure to downside market risk across various coins, where a higher downside risk exposure is associated with higher subsequent returns, indeed. This conclusion is drawn from a thorough cross-sectional analysis of all major cryptocurrencies with the market capitalization above $1 million traded in 2014-2018 (about 1,700 coins). I show that the cryptocurrency market is not different from traditional asset markets in terms of downside risk pricing, despite a prevailing view that cryptocurrency market is characterized by weird return dynamics, bubbles and idiosyncratic risk.

First, I adopt a portfolio approach, i.e. I sort cryptocurrencies into quintile portfolios by their trailing market betas, downside market betas or upside market betas and analyze the portfolios' subsequent returns. The portfolio analysis reveals that only the downside-beta sort produces a monotonically increasing pattern in the portfolio returns. Portfolios with coins with higher downside betas yield higher average returns, and the return on the zero-cost portfolio, which has a long position in the high-downside-beta coins and a short position in the low-downside-beta coins (the portfolio which loads *only* on the downside risk), yields a statistically significant premium of 2.6% per week (136% per annum). A portfolio with a long position in the high-downside-beta coins and a short position in Bitcoin yields an even higher premium of 3% per week (160% per annum).

Secondly, I perform the Fama-MacBeth (1973) cross-sectional regression analysis for the sorted portfolios, as well as for the individual cryptocurrencies, and show that the extra downside risk (on top of the overall market risk) is priced with a statistically significant premium, whereas the market risk premium is insignificant. Adding the downside risk component to the CAPM improves the explanatory power of the model significantly. These results are similar to the ones obtained for equities, currencies and several other asset classes (Ang et al., 2006; Dobrynskaya, 2014; Lettau et al., 2014; Atanasov and Nitschka, 2014).

The idea that downside and upside risks are priced differently in financial markets goes back to Roy (1952), Markowitz (1959) and Bawa and Lindenberg (1977), and was formalized and confirmed empirically by Ang et al. (2006). The intuition is that investors care about losses more than about gains because of disappointment aversion (Gul, 1991) or loss aversion (Kahneman and Tversky, 1959). Moreover, even under the standard utility assumptions, the downside market risk is of greater importance because the marginal utility of wealth is higher in times of adverse market conditions and low overall wealth. Therefore, assets which perform poorly in times of market losses are particularly unattractive and should carry a premium. The upside market risk, however, is of much lower importance due to the overall favourable market conditions, and hence it is not priced. Indeed, we observe in the cryptocurrency market that whereas the downside beta premium is positive, high and statistically significant, the upside beta premium is insignificant and even negative, in line with the original prediction of the model of Ang et al. (2006)[2]. Because the regular market beta is the weighted average of the downside beta and the upside beta, it has less explanatory power for cryptocurrency (and other assets') returns than the downside beta.

This study contributes to the recent literature on empirical multifactor pricing models for cryptocurrencies. Liu, Tsyvinski and Wu (2020) (subsequently referred to as LTW) and Liu et al. (2019) were the first to show that a conventional asset-pricing model (namely, a 3-factor model with the market, size and momentum factors for cryptocurrencies in the spirit of Fama and French, 1993) is able to explain cryptocurrency returns. LTW further show that the size factor is related to liquidity, and that the momentum factor is consistent with the investor overreaction theory (Barberis et al., 1998, Daniel et al., 1998). LTW were also the first to analyze the whole cross-section of cryptocurrencies rather than just the most popular coins. I extend their analysis by separating the market beta into the upside beta and the downside beta and show that using the downside beta improves the explanatory power of their 3-factor model for cryptocurrencies significantly. The alpha of the downside-beta-sorted zero-cost portfolio remains statistically significant and economically high, even after controlling for LTW's size and momentum factors. Therefore, the downside risk is orthogonal to the size and momentum risks and constitutes an important forth component in the multifactor cryptocurrency pricing model. The premium on the downside beta-sorted zero-cost portfolio (2.6% per week) is quantitatively similar to the premium on the zero-cost size-sorted portfolios (3.4-4% per week) and zero-cost momentum-sorted portfolios (2-3.9% per week), obtained by LTW.

As the cryptocurrency market grows and develops, as more cryptocurrencies are issued and become liquid, a thorough analysis of the whole market uncovers surprising similarities to conventional asset markets. I look at the cryptocurrency market through the prism of standard asset-pricing models, which have been successful in explaining returns in other financial markets, and similar risk and return relationships are observed. This paper claims that the Downside-Risk CAPM (DR-CAPM), which has been proposed to explain stock returns (Ang et al., 2006) and has also been successful in explaining currency, bond and commodity returns (Dobrynskaya, 2014; Lettau et al., 2014), is also valid for cryptocurrency returns. Coupled with LTW's findings on the size and momentum risk factors, we can conclude that cryptocurrencies are not wild animals, in general, and they are priced rather similarly as traditional assets, although the magnitudes of the risk premiums are higher.

This paper proceeds as follows. Section 2 lays out an illustrative model of how downside risk is priced. Section 3 describes the data and some basic statistics of the cryptocurrency market. Section 4 is devoted to the analysis of portfolios, sorted by downside, upside and regular market

[2] The estimates of the downside and upside beta premiums are not reported in the paper and are available upon request.

betas. Section 5 presents the cross-sectional regression analysis for individual cryptocurrencies. Section 6 contains robustness checks and section 7 concludes.

2. DOWNSIDE RISK PRICING

The importance of upside and downside risks was recognized as early as the first theoretical asset-pricing models were developed. Roy (1952) suggests that economic agents care particularly about the downside risk. Markowitz (1959) proposes using semi-variance as a proper measure of risk. Bawa and Lindenberg (1977) provide an extended version of the CAPM where the market beta is separated into the upside beta and the downside beta.

Ang et al. (2006) show how upside and downside risks may be priced cross-sectionally in a theoretical model with disappointment aversion in the representative investor's utility function.[3] They show numerically that, in equilibrium, the traditional CAPM alpha is increasing in the relative downside beta and decreasing in the relative upside beta. Assets should have higher expected returns if they have higher relative downside betas because such assets perform particularly badly when the overall market and investors' wealth are falling, the marginal utility of wealth is high and asset returns are particularly important. In other words, the extra downside risk (on top of the regular beta risk) requires an additional positive risk premium. Assets with higher relative upside betas, on the contrary, carry a negative additional risk premium because the upside potential is, in fact, attractive for investors.

Ang et al. (2006) also show that these relationships hold empirically. Sorting US stocks into portfolios in order of increasing downside betas produces a monotonically increasing pattern of portfolio average returns, whereas sorting stocks in order of increasing upside betas produces a monotonically decreasing pattern of returns. They also estimate the Fama-MacBeth (1973) cross-sectional regression for the two-beta CAPM for individual stocks in the US:

$$r_i - r_f = \beta_i^+ \chi^+ + \beta_i^- \chi^- + \mu + \varepsilon_i \tag{1}$$

where β_i^+ and β_i^- are the upside and downside betas, respectively, which are conditional on the market state, χ^+ and χ^- are the upside and downside beta premiums, respectively, and μ is the common pricing error, which can be restricted to zero. The authors confirm that the upside and downside risks are priced differently, and that the two-beta CAPM has a much higher explanatory power than the traditional CAPM. Even after controlling for other risk factors (size, book-to-market, momentum, liquidity and volatility), the estimates of the downside risk premium are high and statistically significant, whereas the estimates of the upside risk premium are not.

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[3] In fact, there are several alternative explanations for different investor aversion to upside and downside risks, e.g. disappointment aversion (Gul, 1991), investor sentiment (Shleifer and Vishny, 1997), funding risk (Filipe and Suominen, 2014).

More recently, asset pricing models with the downside risk also proved to be successful in explaining returns in the currency, commodity, bond and other markets (Lettau et al., 2014; Dobrynskaya, 2014, Atanasov and Nitschka, 2014). Lettau et al. (2014) estimate an alternative version of the two-beta CAPM, which they call Downside-Risk CAPM (DR-CAPM):

$$r_i - r_f = \beta_i \lambda + \left(\beta_i^- - \beta_i\right)\lambda^- + \mu + \varepsilon_i \tag{2}$$

where λ is the traditional beta premium and λ^- is the *relative* downside beta premium. Specification (2) is more convenient because it nests the traditional CAPM if the extra downside risk is not priced (λ^- is zero) or if there is no risk asymmetry (i.e. the downside beta is equal to the traditional beta and, hence, to the upside beta). The authors show that the second term is highly statistically significant, and that the downside risk is priced similarly across different asset classes.

In order to reconcile version (2) with version (1), recall that the regular market beta is the weighted average of the upside and downside betas:

$$\beta_i = \gamma\beta_i^- + (1-\gamma)\beta_i^+ \tag{3}$$

where γ is the relative frequency of down-markets in the sample period. If the upside and downside risks are similar (no risk asymmetry), $\beta_i^- \approx \beta_i^+ \approx \beta_i$. However, there may be a significant asymmetry in the upside and downside risks, which can only be identified after separating the regular market beta into the upside and downside components. The regular beta, being the average of β_i^- and β_i^+, is not a sufficient measure of risks. Since the three betas are linked by equation (3), we can use *any* two betas of the three to fully specify the two-beta CAPM. For example, deriving the expression for β_i^+ from equation (3) and substituting it into equation (1), we can derive the following version of the two-beta CAPM:

$$r_i - r_f = \beta_i \frac{\chi^+}{1-\gamma} + \beta_i^- \left(\chi^- - \frac{\gamma\chi^+}{1-\gamma}\right) + \mu + \varepsilon_i \tag{4}$$

Equation (4) can be re-written in terms of the regular beta and the *relative* downside beta as follows:

$$r_i - r_f = \beta_i\left(\chi^+ + \chi^-\right) + \left(\beta_i^- - \beta_i\right)\left(\frac{\chi^- - \gamma(\chi^+ + \chi^-)}{1-\gamma}\right) + \mu + \varepsilon_i$$

Noting that the sum of the upside and downside beta premiums equals the regular beta premium, we can derive the expression for the DR-CAPM, which is similar to equation (2):

$$r_i - r_f = \beta_i \lambda + \left(\beta_i^- - \beta_i\right)\underbrace{\left(\frac{\chi^- - \gamma\lambda}{1-\gamma}\right)}_{\lambda^-} + \mu + \varepsilon_i \tag{5}$$

The relative downside beta $\left(\beta_i^- - \beta_i\right)$ measures the degree of asymmetry in the upside and downside risks. If the asymmetry is insignificant, $\beta_i^- \approx \beta_i^+ \approx \beta_i$ and $\beta_i^- - \beta_i \approx 0$. The greater the difference in the upside and downside betas, the greater the absolute level of the relative downside beta. The relative downside beta premium λ^- shows how this extra downside risk is priced. The positive premium essentially means that the downside beta premium is higher than the upside beta premium, i.e. that the downside risk is more important to investors.

Specification (5) (or (2)) of the two-beta CAPM is more convenient than specification (1) because we can easily compare it with the traditional CAPM specification by testing the significance of the second term, and we can see the contribution of the relative downside risk to explaining excess returns. Therefore, in the subsequent cross-sectional regression analysis, I use this specification of the DR-CAPM.

3. DATA AND DESCRIPTIVE STATISTICS

I use cryptocurrency return data, kindly shared by LTW, which are described in detail in the respective paper. The initial data source is coinmarketcap.com. The authors collect daily returns and transform them to a weekly frequency (52 weeks per year). The sample contains 1,711 cryptocurrencies with market capitalization above $1 million, traded between 2014 and 2018. However, only up to one thousand coins are simultaneously traded at any point in time. The total number of traded cryptocurrencies grew exponentially during this period from 26 to 956 coins, as illustrated in figure 1.

Because I need to estimate betas on half-year horizons and study the subsequent returns, I pick currencies, which have at least 27 consecutive observations. This leaves me with 15 currencies at the beginning of the sample period and up to 516 currencies at the end.

There are only 6 cryptocurrencies, which existed during the whole period of study: Bitcoin, Ripple, Litecoin, Dogecoin, Peercoin, NXT and Namecoin. These currencies look quite "normal": they have moderate returns, moderate volatility and close to one market betas. Many other coins, however, are wild animals. Weekly returns vary from -99.99% to 30,000% per week![4] To avoid biases due to such extreme returns, I windzorize the data at a 0.05% level from the top. Even after windzorization, the cryptocurrency market is characterized by huge volatility, high positive skewness and high kurtosis of individual currency returns.

LTW also construct and share their cryptocurrency market index, which is the capitalization-weighted average of coin returns. This index had an average return of 65% per annum, a return standard deviation of 610% per annum, skewness of 0.27 and kurtosis of 1.53 in 2014-2018. I use this index to estimate the market betas of cryptocurrencies.

[4] Such outrageous behavior is usually observed in the beginning of a coin's life.

I also use LTW's size and momentum risk factors, which are constructed by sorting currencies by market capitalization and past returns, respectively, and forming long-short portfolios with exposure to these risks, following a common procedure, as in Fama and French (1993).

4. PORTFOLIO APPROACH

4.1. DESCRIPTIVE STATISTICS OF SORTED PORTFOLIOS

To test whether the downside risk is priced in the cryptocurrency market, I adopt the portfolio approach, which is common in similar tests for stock and other markets (e.g. Fama and French, 1993; Ang et al., 2006): assets are sorted by their risk exposure into portfolios, and the portfolios' subsequent returns are compared. This two-step procedure is described in detail below.

In the first step, I estimate regular betas, downside betas and upside betas for each cryptocurrency on a 26-week (half-year) rolling window. Such a rather short window is chosen for two reasons. First, the whole sample period is quite short – only four years – due to the short overall history of the cryptocurrency market, where the great majority of coins appeared only after 2017 (figure 1). Second, as LTW document, the cryptocurrency market is much quicker, compared to the stock market, where similar processes take place with greater speed.[5]

The regular betas are estimated in the classical CAPM regression:

$$R_{i,t} = \alpha_i + \beta_i * R_{CMKT,t} + \varepsilon_{i,t} \tag{6}$$

where $R_{i,t}$ is the excess return of cryptocurrency i and R_{CMKT} is the excess return of LTW's cryptocurrency market index.

The downside and upside betas are estimated in the two-beta CAPM regression (Ang et al., 2006):

$$R_{i,t} = \alpha_i + \beta_i^- * R_{CMKT,t} + \gamma_i * R_{CMKT,t} * dummy_t + \varepsilon_{i,t} \tag{7}$$

where $dummy_t = \begin{cases} 0, if\ R_{CMKT,t} > 0 \\ 1, otherwise \end{cases}$, and hence, β_i^- is the estimate of the downside beta and $\beta_i^- + \gamma_i \equiv \beta_i^+$ is the estimate of the upside beta.[6] The downside beta is interpreted as the market beta conditional on adverse market performance (negative market returns), whereas the upside beta is conditional on favorable market performance. The weighted average of the downside beta and the upside beta make up the regular market beta, estimated in regression (6).

In the second step, I sort cryptocurrencies by their trailing 26-week betas in increasing order and allocate the first 20% of currencies to portfolio 1, the next 20% of currencies to portfolio 2, and so on. As a result, I obtain 5 equally-weighted portfolios, calculate their returns

[5] This is also one of the reasons for using weekly data instead of monthly data.

[6] A common way to estimate downside betas in the stock market is to condition on the market return being below its mean, rather than zero, because of the disappointment aversion of investors. However, the mean cryptocurrency return is huge (65% per annum) and varies significantly depending on the time window. Therefore, to be consistent throughout the sample, I stick to the zero boundary, which is motivated by the absolute loss aversion.

in the subsequent week, and repeat the allocation of currencies to the portfolios at the end of the week in accordance with their new betas, estimated over the 26-week window, shifted by 1 week forward. Following this procedure, the portfolios are rebalanced weekly, and the portfolio returns are measured after the portfolio formation. This is a common portfolio rebalancing procedure, which is implementable in real time using only past information. If betas are persistent, and if higher betas are associated with higher expected returns, we should obtain a monotonic pattern of increasing returns from portfolio 1 to 5.

Following the above procedure, I obtain 3 sets of quintile portfolios sorted by regular betas, downside betas and upside betas. The returns and risk characteristics of these portfolios are reported in table 1.

In the first panel, the portfolios are sorted by downside betas. Portfolios with a higher rank have higher downside betas and yield higher average returns (columns 1 and 2). The return pattern is monotonic, and the return of the zero-cost high-minus-low portfolio "5-1" is positive, high (2.6% per week or 136% per annum) and statistically significant. Other columns in table 1 report other risk characteristics of these portfolios (regular betas, upside betas, size and momentum betas, return standard deviation, skewness and kurtosis), and we do not see a monotonic and significantly increasing pattern in any of them. Out of all the risk measures of portfolio "5-1", only the downside beta is statistically significant (0.32 with t-statistics of 2.13). Hence, we may conclude that a higher return on a cryptocurrency is a compensation for its higher downside beta. In other words, the downside risk is priced in the cryptocurrency market, as in other asset markets (Lettau et al., 2015). However, the downside risk premium is much higher compared to the stock and currency markets (Dobrynskaya, 2015).[7]

Panel B of table 1 reports the portfolios, sorted by regular CAPM betas. We also obtain an almost monotonically increasing pattern of average returns from portfolio 1 to 5, but the return on the high-minus-low portfolios “5-1” is statistically insignificant. Moreover, this return (69% per annum) is approximately 50% lower than the return on the downside-beta-sorted portfolio “5-1” in panel A (136% per annum), despite a higher benchmark beta (0.40 compared to 0.32). Therefore, the regular market risk premium is significantly lower than the downside market risk premium. The overall market risk is of much lower importance than the downside market risk, as in other asset markets.

We should notice that when we sort cryptocurrencies by regular betas, we also obtain monotonically increasing patterns of downside and upside betas (unlike in the cases of sorting by downside betas or upside betas). All three betas of portfolio “5-1” in panel B are similar in magnitude (0.36-0.43) and highly statistically significant. Therefore, it is difficult to disentangle which beta is compensated in this case.

[7] LTW also find higher risk premiums for size and momentum factors in cryptocurrency market compared to the stock market.

Panel C is devoted to the upside-beta-sorted portfolios. There is no monotonicity in the portfolio returns at all. The "5-1" portfolio return is insignificant and even negative (-11% per annum), despite its even higher upside beta (0.43) compared to the regular beta of portfolio "5-1" in panel B (0.40) and the downside beta of portfolio "5-1" in panel A (0.32). We may conclude that although there is a greater heterogeneity in the upside betas of cryptocurrencies, the upside risk is not priced; it even carries a small negative risk premium. A similar result was obtained by Ang et al. (2006) for the stock market and Dobrynskaya (2015) for the currency market.

The last two columns of table 1 report size and momentum betas because LTW name these two factors as the main common risk factors in the cryptocurrency market. Since I sort my portfolios differently, there is no monotonic pattern between portfolio rank and size beta or portfolio rank and momentum beta in any of the panels. Hence, these factors do not explain my portfolio returns in the cross-section. The downside risk factor is orthogonal to the size and momentum factors and can be considered as the third common factor in the cryptocurrency market.

We should notice, though, that all beta-sorted portfolios load similarly, positively and significantly on the size factor and do not load on the momentum factor. The exception is the "5-1" portfolio sorted by beta and upside beta, which is negatively related to the momentum factor. This echoes numerous findings of the negative beta of equity momentum portfolios.

Overall, table 1 suggests that cryptocurrency returns can be explained by similar risk factors as traditional asset returns, but generally carry higher risk premiums.

4.2. CROSS-SECTIONAL ANALYSIS FOR PORTFOLIOS

To test how the downside risk is priced in the cryptocurrency market more formally, I run cross-sectional regressions on the downside- and upside-beta sorted portfolios. The portfolio excess returns are regressed on their betas with respect to various risk factors: the market beta, the relative downside beta (defined as the downside beta minus the regular market beta), the size and momentum betas (with respect to the LTW factors for the cryptocurrency market). Table 2 reports the Fama-MacBeth estimates of the risk premiums in five alternative specifications.

In the first column, the regular CAPM is rejected, as the market risk premium is statistically insignificant and the regression's adjusted R^2 is even negative. Adding the relative downside beta (column 2) improves the explanatory power of the CAPM dramatically, and its premium is highly statistically significant, while the regular beta remains insignificant. Controlling for the size and momentum factors (columns 3-5), which have been proposed by LTW as the common explanatory factors in the cryptocurrency market, the downside risk premium remains significant and its estimates are rather stable in the alternative specifications. The size factor adds more explanatory power to the model, whereas the momentum factor does not (compare column 2 to columns 4 and 5).[8] From another angle, adding the relative downside beta to the LTW model also improves the explanatory power significantly, as the adjusted R^2 increases twice from 41% to 81%. The intercepts (pricing errors) are close to zero in all specifications. We can conclude, that the downside risk is an extra important explanatory factor in the cryptocurrency market, which is orthogonal to the previously used size and momentum factors. In general, table 2 suggests that cryptocurrencies are priced surprisingly similarly to traditional assets.

The risk premiums, however, are significantly higher compared to the equity market. The estimates of about 400% per annum seem to be huge. But since the long-short downside-beta sorted portfolio yields an average excess return of 136% per annum, and its downside beta is 0.32 (table 1), a portfolio with the unit exposure to the downside risk should yield an excess return of about 410% (136%*3). Hence, the estimates of the risk premiums are economically meaningful for the cryptocurrency portfolios.

4.3. TIME-SERIES ANALYSIS FOR PORTFOLIOS

Crypto-portfolios with a higher downside risk yield higher excess returns systematically. Perhaps, this relationship can be explained by their greater exposure to other risk factors. Apparently, not! Table 3 reports alphas of the beta-sorted crypto-portfolios, estimated in alternative multifactor specifications. Even after controlling for the size and momentum factors, the "5-1" zero-cost portfolio, sorted by the downside betas, yields a significant alpha of 2-4 percent per week (panel A). The size and momentum factors add some explanatory power for portfolios 1 to 5[9], but not for the long-short portfolio.

Portfolios sorted by regular betas (panel B) and upside betas (panel C) do not yield significant alphas in any specification. This confirms the previous findings that the overall market and the upside market risks are not as important as the downside risk.

4.4. USING BITCOIN IN THE SHORT POSITION

One may argue that some small cryptocurrencies are not easy to short, and hence these long-short strategies are not implementable. To address this concern, I follow LTW and take a short position in Bitcoin instead of portfolio 1. The results are qualitatively similar. The portfolio, which is long in high-downside-beta coins and short in Bitcoin, yields an even higher average return of 160% per annum (3.1% per week) with a t-statistics of 2.89. The portfolio also yields a statistically significant alpha of 3.4% per week after controlling for the market risk. However, the alpha reduces to 2% and becomes insignificant after controlling for the size and momentum

[8] These beta-sorted portfolios are unrelated to momentum, but it does not preclude that the momentum factor is highly important for other types of portfolios or for individual cryptocurrencies.
[9] The size factor is particularly important in addition to the market factor (see table 1).

factors. The reason is the high exposure to the size factor since the portfolio is long in small coins and short in Bitcoin. The downside beta of this zero-cost portfolio is a little lower (0.24 compared to the downside beta of “5-1” portfolio of 0.32), but remains statistically significant even after controlling for the size and momentum factors.

5. ROBUSTNESS TESTS

5.1. CROSS-SECTIONAL ANALYSIS FOR INDIVIDUAL CRYPTOCURRENCIES

The cross-sectional regressions on beta-sorted portfolios in section 4.2 provide a good illustration of how the downside risk is priced in the cryptocurrency market. However, they may be criticized for the low number of cross-sectional observations (10 portfolios) and a weak power of the test. To check the robustness of the results, I also run similar cross-sectional regressions on individual cryptocurrencies (up to 516 coins traded simultaneously).

Because the number of cryptocurrencies changes over time, I use rolling betas instead of constant betas and perform the analysis for only those cryptocurrencies which existed at each point in time. The Fama-MacBeth procedure then looks as follows. In the first step, I estimate betas with respect to various risk factors for each cryptocurrency on a half-year horizon (e.g. weeks 1-26). In the second step, the cross-section of cryptocurrency excess returns in week 27 are regressed on these betas to estimate the risk premiums. Then the rolling window is moved by 1 week forward, and the two steps are repeated. And so on.

Table 4 reports the estimates of the risk premiums in four alternative specifications. Because individual cryptocurrency returns are very noisy, their betas are estimated with errors[10]. Nevertheless, the results are similar to the portfolio results in terms of statistical significance.

As for the portfolios, the regular market factor does not have explanatory power for individual cryptocurrencies as its premium is statistically insignificant and even negative (columns 1 and 3). Separating the market factor into the downside and upside components improves the explanatory power significantly, and only the extra downside risk is priced (column 2). The LTW size and momentum factors are also highly important, and the DR-CAPM with the size and momentum factors explains 54% of cross-sectional variation of cryptocurrency average returns (column 4). Moreover, the intercept becomes insignificant in the four-factor specification. The downside market factor, the size factor and the momentum factor are all orthogonal and add extra explanatory power to the CAPM. We can conclude that the four-factor asset-pricing model explains cryptocurrency returns well, similarly to equity returns.

[10] I use Shanken correction of standard errors to address this issue.

5.2. THE RECENT PERIOD 2017-2018

The year 2017 was characterized by a burst in ICO (initial cryptocurrency offerings), due to which the market has become much more diversified (figure 1). Therefore, I look at the characteristics of the beta-sorted portfolios in the recent period 2017-2018 as a robustness check. Whereas each portfolio contained only 5 cryptocurrencies in the beginning of 2014, the number of cryptocurrencies in each portfolio varies between 15 and 163 in the recent period - a significant improvement in diversification. Table 5 reports the recent average returns and risks of the crypto-portfolios, sorted by the downside betas, regular betas and upside betas. We see that the results are almost unchanged compared to the whole period of study. The downside-beta sort (panel A) is the only one to produce an (almost) monotonically increasing pattern of returns and a statistically significant premium of the "5-1" zero-cost portfolio. All returns, return volatilities and betas are generally higher in the recent period.

6. CONCLUSION

The cryptocurrency market has been developing at a tremendous pace, with over 5,000 coins traded nowadays. The creation of derivatives on cryptocurrencies, the increasing role of institutional investors, the adoption of trading strategies (such as momentum) by investors – all these symptoms suggest that the cryptocurrency market is not much different from a conventional financial market (e.g. the stock market). Therefore, it is no surprise that conventional asset-pricing models, based on utility maximization of investors and covariance of asset's returns with the stochastic discount factor, succeed in explaining cryptocurrency returns.

In this paper, I show that the Downside-Risk CAPM, which takes into account the asymmetry of downside and upside market risks and articulates the importance of extra downside risk for investors, explains coin returns much better than the regular CAPM, similarly as in the stock and currency markets (Ang et al., 2006; Dobrynskaya, 2014). Together with the LTW size and momentum factors for cryptocurrencies, the downside market factor explains 54% of the cross-sectional variation of returns in the cryptocurrency market.

This paper, as well as LTW, looks at the cryptocurrency market in isolation, i.e. cryptocurrency returns are explained by the risk factors, which are themselves constructed as traded portfolios of cryptocurrencies. Such an approach to study an asset market in isolation is a common first step in understanding the returns (e.g. Fama and French, 1993, for equities; Bai et al., 2019, for bonds, Lustig et al., 2011, for currencies). However, as the cryptocurrency market grows and develops, as the role of institutional investors increases, as cryptocurrencies become more and more popular in multi-asset investment strategies for the sake of portfolio diversification, the cryptocurrency market becomes more integrated in the global financial market. Therefore, an avenue for further research is to study cryptocurrency pricing in a more general, multi-asset setting, in the spirit of recent studies of various asset classes by Asness et al. (2013) and Lettau et al. (2015).

It is interesting to know how cryptocurrencies are exposed to the equity downside risk factor, and whether this factor can explain coin returns *together* with returns on other assets. The recent market crash in March 2020, when cryptocurrencies crashed simultaneously, suggests that such interrelationships exist. However, we failed to observe such robust relationships in the studied period, which covers relatively calm years without significant market losses. Our sample period is also quite short due to the short history of the cryptocurrency market, and the early years of cryptocurrency trading are characterized by high idiosyncratic volatility. We need to wait more to observe the likely convergence of these markets and asset-pricing relationships.

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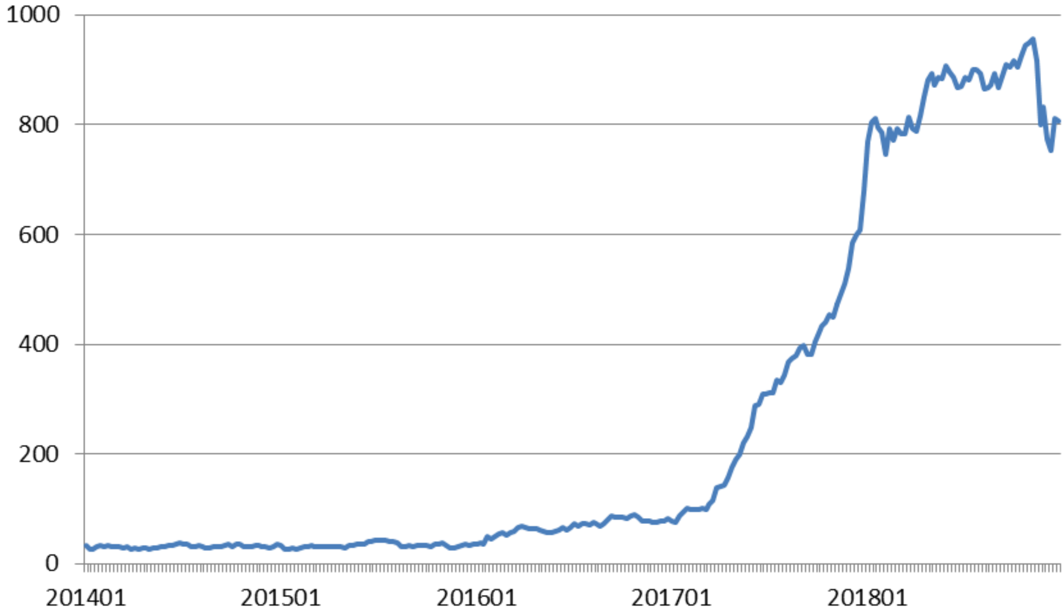
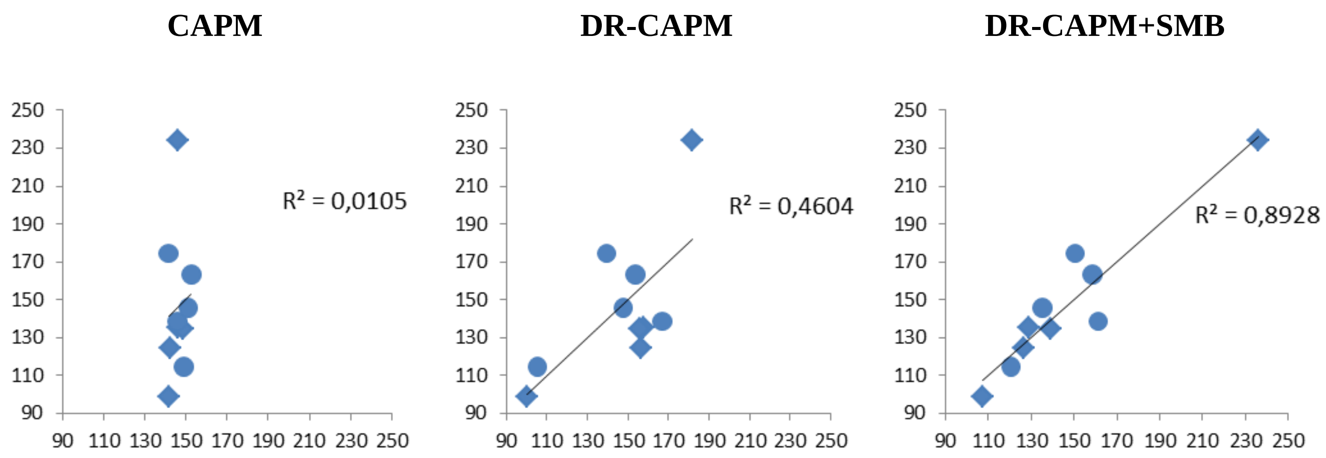
Figure 1. The growth of the cryptocurrency market over time



The figure shows the total number of traded cryptocurrencies with market capitalization above $1 million.

Figure 2. Predicted and realized returns on cryptocurrency portfolios using alternative models.



The figure plots predicted (on the horizontal axis) and actual (on the vertical axis) excess returns (in % pa) on cryptocurrency portfolios sorted by downside and upside betas. The circles represent the five upside-beta-sorted portfolios, and the squares represent the five downside-beta-sorted portfolios. Sample period: 2014-2018.

Table 1. Return and risk characteristics of beta-sorted portfolios

	Annualized return	SD (pa)	Downside beta	Beta	Upside beta	Skewness	Kurtosis	SMB beta	MOM beta
	Panel A: Portfolios sorted by downside betas								
Portfolio 1	0.99	8.05	0.81	0.91	0.98	1.55	6.38	0.21	-0.01
	[1.54]		[8.16]	[8.76]	[5.09]			[2.93]	[-0.14]
Portfolio 2	1.24	7.69	0.95	0.92	0.90	0.80	2.01	0.14	0.00
	[1.85]		[15.24]	[14.96]	[8.27]			[2.84]	[0.00]
Portfolio 3	1.35	8.81	1.10	1.08	1.07	1.00	2.76	0.14	-0.06
	[1.94]		[10.61]	[12.37]	[6.73]			[2.88]	[-1.25]
Portfolio 4	1.35	9.05	1.16	1.16	1.15	1.13	3.15	0.15	-0.01
	[1.89]		[19.10]	[12.36]	[6.76]			[2.98]	[-0.12]
Portfolio 5	2.34	10.07	1.14	1.06	1.01	1.48	4.64	0.31	-0.01
	[2.85]		[10.13]	[11.21]	[5.81]			[3.62]	[-0.17]
Portfolio 5-1	1.36	8.44	0.32	0.15	0.03	1.43	6.51	0.10	0.00
	[2.53]		[2.13]	[1.39]	[0.16]			[0.82]	[-0.06]
	Panel B: Portfolios sorted by regular betas								
Portfolio 1	1.17	7.39	0.82	0.83	0.84	1.00	2.27	0.16	0.06
	[1.95]		[9.85]	[12.12]	[7.87]			[2.14]	[1.57]
Portfolio 2	1.28	8.64	1.02	0.96	0.91	1.80	7.80	0.18	-0.07
	[2.01]		[12.17]	[13.19]	[7.70]			[5.11]	[-1.64]
Portfolio 3	1.60	8.64	1.01	1.04	1.06	0.81	1.81	0.28	-0.02
	[2.10]		[12.73]	[14.03]	[8.59]			[5.82]	[-0.52]
Portfolio 4	1.50	8.82	1.12	1.06	1.02	1.08	3.30	0.15	0.00
	[2.19]		[13.35]	[10.23]	[5.37]			[3.19]	[0.08]
Portfolio 5	1.86	10.09	1.18	1.23	1.27	1.16	3.51	0.20	-0.06
	[2.26]		[10.65]	[10.85]	[5.97]			[2.96]	[-1.10]
Portfolio 5-1	0.69	7.25	0.36	0.40	0.43	0.75	2.53	0.04	-0.12
	[1.50]		[2.64]	[4.07]	[2.38]			[1.01]	[-2.29]
	Panel C: Portfolios sorted by upside betas								
Portfolio 1	1.74	8.68	0.91	0.90	0.90	1.47	3.84	0.23	0.01
	[2.46]		[9.76]	[11.17]	[6.55]			[2.97]	[0.32]
Portfolio 2	1.39	8.21	1.07	0.98	0.92	1.25	5.58	0.19	-0.02
	[2.12]		[12.41]	[14.27]	[8.55]			[5.19]	[-0.63]
Portfolio 3	1.15	8.64	0.99	1.03	1.06	1.35	4.52	0.21	0.03
	[1.63]		[11.81]	[10.84]	[6.17]			[3.25]	[0.46]
Portfolio 4	1.46	8.25	1.19	1.13	1.10	0.37	1.19	0.15	-0.02
	[2.25]		[15.95]	[13.41]	[7.60]			[3.19]	[-0.55]
Portfolio 5	1.63	9.80	0.99	1.18	1.32	1.58	5.64	0.19	-0.07
	[2.00]		[9.26]	[9.31]	[5.56]			[2.87]	[-1.42]
Portfolio 5-1	-0.11	9.80	0.08	0.28	0.43	0.14	5.19	-0.04	-0.08
	[-0.21]		[0.58]	[2.30]	[1.77]			[-1.00]	[-2.07]

The table reports average returns (in absolute values) and various risk characteristics of cryptocurrency portfolios, sorted by trailing downside betas, regular betas and upside betas. Newey-West t-statistics are reported in brackets. Sample period: 2014-2018.

Table 2. Cross-sectional regressions for beta-sorted portfolios

	CAPM	DR-CAPM	CAPM+ SMB+MOM	DR-CAPM +SMB	DR-CAPM +SMB+MOM
Market risk premium	0.27	0.45	0.25	0.78	0.75
	[0.40]	[0.69]	[0.42]	[1.26]	[1.19]
Relative downside beta premium		4.44		4.08	4.01
		[2.66]		[2.54]	[2.07]
Size premium			5.84	4.90	4.95
			[2.38]	[2.04]	[2.10]
Momentum premium			-4.47		-0.38
			[-1.19]		[-0.08]
Constant	1.17	1.02	0.01	-0.29	-0.26
	[1.43]	[1.28]	[0.01]	[-0.39]	[-0.35]
Adjusted R^2	-0.11	0.31	0.41	0.84	0.81
SSE	1.27	0.69	0.51	0.14	0.14

The table reports the Fama-MacBeth annualized risk premiums (in absolute values), estimated in cross-sectional regressions for 5 downside-beta-sorted portfolios and 5 upside-beta-sorted portfolios. Newey-West t-statistics are reported in brackets. Sample period: 2014-2018.

Table 3. Time-series regressions for beta-sorted portfolios

	DR-CAPM		CAPM +SMB+MOM		DR-CAPM+SMB+MOM	
	alpha	*R2 adj*	*alpha*	*R2 adj*	*alpha*	*R2 adj*
	Panel A: Portfolios sorted by downside betas					
Portfolio 1	0.00	0.48	0.00	0.55	-0.01	0.55
	[-0.14]		[-0.53]		[-0.84]	
Portfolio 2	0.01	0.54	0.00	0.57	0.01	0.57
	[1.13]		[0.57]		[0.69]	
Portfolio 3	0.01	0.56	0.01	0.59	0.01	0.59
	[1.04]		[0.85]		[0.76]	
Portfolio 4	0.01	0.61	0.00	0.64	0.00	0.64
	[0.93]		[0.38]		[0.46]	
Portfolio 5	0.03	0.42	0.02	0.51	0.02	0.51
	[2.21]		[1.99]		[1.68]	
Portfolio 5-1	0.04	0.01	0.02	0.01	0.03	0.02
	[2.35]		[2.22]		[2.09]	
	Panel B: Portfolios sorted by regular betas					
Portfolio 1	0.01	0.47	0.00	0.53	0.00	0.52
	[1.00]		[0.18]		[0.28]	
Portfolio 2	0.01	0.46	0.01	0.51	0.01	0.51
	[1.31]		[0.64]		[0.93]	
Portfolio 3	0.01	0.54	0.00	0.65	0.00	0.65
	[1.22]		[0.66]		[0.57]	
Portfolio 4	0.02	0.55	0.01	0.57	0.01	0.57
	[1.41]		[0.90]		[0.95]	
Portfolio 5	0.01	0.56	0.01	0.60	0.01	0.60
	[1.14]		[1.58]		[0.73]	
Portfolio 5-1	0.00	0.11	0.01	0.13	0.01	0.13
	[0.35]		[1.46]		[0.60]	
	Panel C: Portfolios sorted by upside betas					
Portfolio 1	0.02	0.40	0.01	0.47	0.01	0.47
	[1.51]		[1.30]		[1.06]	
Portfolio 2	0.02	0.54	0.00	0.59	0.01	0.59
	[1.99]		[0.75]		[1.45]	
Portfolio 3	0.00	0.53	0.00	0.59	0.00	0.59
	[0.32]		[-0.52]		[-0.41]	
Portfolio 4	0.02	0.60	0.01	0.63	0.02	0.63
	[2.37]		[1.04]		[1.98]	
Portfolio 5	0.00	0.55	0.01	0.59	0.00	0.59
	[-0.01]		[1.19]		[-0.29]	
Portfolio 5-1	-0.02	0.05	0.00	0.05	-0.02	0.06
	-1.33		[-0.17]		[-1.06]	

The table reports weekly alphas and adjusted R^2 of the cryptocurrency portfolios in alternative multifactor specifications. Newey-West t-statistics are reported in brackets. Sample period: 2014-2018.

Table 4. Cross-sectional regressions for individual cryptocurrencies

	CAPM	DR-CAPM	CAPM+ SMB+MOM	DR-CAPM +SMB+MOM
Market risk premium	-0.03	0.14	-0.33	0.11
	[-0.10]	[0.44]	[-1.22]	[0.33]
	(-0.096)	(0.40)	(-1.19)	(0.29)
Relative downside beta premium		0.51		0.69
		[2.00]		[2.00]
		(1.99)		(1.99)
Size premium			0.79	0.87
			[2.04]	[1.99]
			(2.00)	(1.99)
Momentum premium			1.07	1.14
			[2.08]	[2.26]
			(2.04)	(2.20)
Constant	1.58	1.36	1.54	0.92
	[3.21]	[2.83]	[3.22]	[1.89]
	(3.06)	(2.72)	(3.19)	(1.82)
Adjusted R^2	0.12	0.21	0.45	0.54

The table reports the Fama-MacBeth annualized risk premiums (in absolute values), estimated in cross-sectional regressions for individual cryptocurrencies using rolling betas. Newey-West t-statistics are reported in brackets. Shanken-corrected t-statistics are reported in parentheses. Sample period: 2014-2018.

Table 5. Return and risk characteristics of beta-sorted portfolios in the recent period: 2017-18

	Annualized return	SD (pa)	Downside beta	Beta	Upside beta
	Panel A: Portfolios. sorted by downside beta				
Portfolio 1	1.70	10.05	0.75	0.99	1.15
	[1.34]		[6.10]	[7.90]	[4.97]
Portfolio 2	2.47	9.30	1.13	0.99	0.90
	[1.91]		[11.63]	[14.05]	[6.01]
Portfolio 3	2.02	10.66	1.19	1.17	1.16
	[1.51]		[12.55]	[14.59]	[7.28]
Portfolio 4	2.12	11.37	1.19	1.28	1.34
	[1.49]		[12.73]	[15.25]	[8.58]
Portfolio 5	3.18	11.70	1.31	1.26	1.22
	[2.03]		[11.26]	[14.47]	[7.14]
Portfolio 5-1	1.48	8.52	0.56	0.27	0.08
	[2.29]		[3.26]	[1.98]	[0.28]
	Panel B: Portfolios. sorted by regular beta				
Portfolio 1	1.96	8.25	0.89	0.90	0.90
	[1.78]		[9.77]	[14.32]	[8.29]
Portfolio 2	1.95	9.47	1.09	1.05	1.02
	[1.67]		[13.29]	[16.41]	[8.49]
Portfolio 3	2.52	10.90	1.07	1.18	1.26
	[1.64]		[9.61]	[19.94]	[13.35]
Portfolio 4	2.28	11.42	1.23	1.25	1.27
	[1.66]		[10.91]	[11.68]	[5.84]
Portfolio 5	2.78	12.39	1.29	1.31	1.32
	[1.69]		[10.06]	[8.77]	[4.69]
Portfolio 5-1	0.82	7.27	0.40	0.41	0.42
	[1.05]		[2.60]	[3.31]	[1.88]
	Panel C: Portfolios. sorted by upside beta				
Portfolio 1	2.58	9.73	0.95	1.06	1.14
	[1.99]		[9.39]	[17.38]	[12.56]
Portfolio 2	2.31	9.48	1.27	1.03	0.87
	[1.86]		[15.18]	[16.05]	[7.56]
Portfolio 3	1.88	10.65	0.96	1.17	1.32
	[1.40]		[10.39]	[12.01]	[7.07]
Portfolio 4	1.96	10.43	1.32	1.16	1.05
	[1.50]		[13.33]	[15.35]	[7.09]
Portfolio 5	2.76	12.43	1.06	1.26	1.40
	[1.65]		[7.95]	[7.31]	[4.24]
Portfolio 5-1	0.18	7.85	0.11	0.20	0.26
	[0.28]		[0.74]	[1.20]	[0.78]

The table reports average returns (in absolute values) and various risk characteristics of cryptocurrency portfolios, sorted by trailing downside betas, regular betas and upside betas. Newey-West t-statistics are reported in brackets. Sample period: 2017-2018.