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The fair value of a token: How do markets price cryptocurrencies?

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ABSTRACT

With the rise of cryptocurrency tokens as a new asset class, the question of the fair evaluation of a cryptocurrency token has become a question of increasing importance. We estimate the pricing kernel with which users price factors affecting their token holdings. We investigate how traditional risk factors such as market risk are evaluated, as well as how blockchain specific risk factors are priced in. In order to do so, we introduce an asset pricing model and modify its properties to make it applicable to cryptocurrency markets. We group the risk factors into market related and Bitcoin- and Ethereum blockchain specific risk factors. We find that blockchain specific risk factors are priced in. There is evidence that risk factors have moved from Bitcoin to Ethereum specific risk factors with an increasing importance of market factors, providing evidence for a decoupling of on-chain and off-chain trading activity.

1. Introduction

For the new asset class of cryptocurrencies, investigating how risk factors unique to cryptocurrencies such as transaction volume of a blockchain or number of participating nodes in a network affect their value is an important subject of exploration. In order to do so, it is necessary to understand the properties of this novel market, especially considering its rapid and erratic development. Bitcoin was the first main cryptocurrency, and Ethereum has been a platform for many other ERC-20 tokens. We thus analyse and compare factors related to the Bitcoin, Ethereum and market specific risk factors. Since the massive increase in prices, Bitcoin (Nakamoto, 2008) and other cryptocurrencies have caught increased academic attention. A large part of research conducted in the computer science community has focused on technical properties of blockchain (e.g., Poon and Dryja, 2016; Nikolić et al., 2018) as well predicting or visualizing cryptocurrency transaction patterns and price actions (McGinn et al., 2016; Reid and Harrigan, 2013). Such approaches allow for little interpretation of causality as well as potential modeling of market actions. We therefore borrow from the literature of empirical asset pricing and adopt a model for the cryptocurrency framework in order to evaluate how the market evaluates cryptocurrency tokens. We emphasize the difference between cryptocurrencies using their own underlying blockchain such as Bitcoin and ERC-20 tokens based on Ethereum smart contracts. This motivates our choice of both the Bitcoin and Ethereum network as risk factors. For the rest of the paper we use the terms cryptocurrency coin and token interchangeably and will mention ERC-20 tokens explicitly when necessary.

Economic research about cryptocurrency tokens has been increasing recently. Some authors have used mainly statistical methods to analyse cryptocurrency markets. Authors such as Kristoufek (2015) have analysed drivers of Bitcoin prices, using wavelet analysis to study correlation between a large number of time series. Symitsi et al. (2019) study the diversification benefits of cryptocurrencies in the context of commodities and stocks. Others such as Koutmos (2018) have studied Bitcoin returns using Vector Autoregressive (VAR) analysis and found evidence that higher Bitcoin transaction activity results temporarily in higher returns. An excellent review

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of further econometric techniques applied so far can be found in Fantazzini et al. (2017). A variety of authors have recently started economic modelling of cryptocurrencies (see e.g., Cong et al., 2019, Huberman et al., 2017). Other current research such as Liu and Tsyvinski (2018) work along the same line as we do, methodologically employing an empirical asset pricing model. They find that cryptocurrencies have little exposure to factors most common to stock markets and macroeconomic factors, whereas factors such as momentum within the cryptocurrency market have stronger effects. In line with this, we are one the first to adopt an empirical asset pricing approach in the style of factor models in which we specifically address network properties of Bitcoin and Ethereum as risk factor.

In particular, we are interested in estimating the pricing kernel or stochastic discount factor (SDF) for cryptocurrencies. We aim to obtain aggregate parameter estimates which give an indication of market properties and behaviour of participating agents. The estimation procedure is conducted via a Two-Stage regression approach. We assume a basic linear stochastic discount factor, as is common in financial literature and advocated by Fama and French (1993) as well its extension such as Carhart (1997).

1.1. Contribution

Our aim is to investigate what the differences in Bitcoin blockchain, Ethereum blockchain and market specific risk factors are, and if they changed over time. A plethora of network properties is available for analysis. We pick variables that proxy network utilization as well as the cost of performing transactions. We are interested in how these factors are priced by markets, since these two factors are the most commonly cited (e.g., Poon and Dryja, 2016) and publicly known hindrance for a wide-spread adoption of cryptocurrencies. These properties immediately affect users, thus studying their risk profile is of interest. We also construct factor mimicking portfolios (Breeden et al., 1989; Balduzzi and Robotti, 2008) to study their evaluation over time. The model serves as a benchmark evaluation method applicable to current and future cryptocurrencies.

Other questions we are investigating are: Do the underlying mechanics of the cryptocurrency market as a whole align with established financial markets? For individual coins, what is the fair value of tokens given their exposure to network characteristics such as transaction fees? Do these values differ by market segment under investigation, i.e., how does exposure to risk factors change if strategies are based on price stability or return patterns?

Our main contribution is therefore establishing and confirming the properties of a baseline model for cryptocurrency evaluation. We also provide evidence that the factors affecting the pricing of cryptocurrencies has moved from Bitcoin blockchain activity to Ethereum related properties.

We demonstrate how the pricing of traditional risk factors such as market risk and volatility risk differ between established financial markets and cryptocurrency markets.

1.2. Empirical findings

We form cryptocurrency portfolios based on returns, liquidity and price stability and investigate how this affects usage and pricing in our models. We find that parameter estimates of our modified framework are similar to established financial markets, making it applicable for further analysis, especially with regards to a further maturing of cryptocurrency markets (e.g., Urquhart, 2016). Our estimates also reveal key differences in both markets. The results indicate that unlike traditional financial markets, volatility is not associated with market downturns. Furthermore our analysis provides evidence that participants in cryptomarkets are pricing in risk factors given by the Bitcoin and Ethereum network status. There is further evidence that certain portfolio holders are willing to pay a premium to hedge against such risk. We find that in the early sample Bitcoin risk factors are priced in whereas results for Ethereum are insignificant. For the full sample, Ethereum risk factors are more significant than Bitcoin related ones. When only studying the end of the sample, market driven properties like volatility and liquidity gain importance. This provides evidence that with more and more cryptocurrencies based on ERC20 tokens, Ethereum related risk factors gained importance, whereas Bitcoin's network properties importance to users decreased. The emphasis on market related factors later in the sample provides evidence that after gaining wide-spread attention and with many traders entering the market, the off-chain trading activity and risk evaluation has become more decoupled from on-chain activity.

The rest of the paper is structured as follows: section two introduces the model, section three describes how we adopt it to a cryptocurrency market. Section four estimates and discusses results, whereas section five studies the risk profile of factors over time. Section six analyses and discusses a case study. Section seven concludes.

2. The model

Cryptocurrencies are publicly tradable on exchanges, we thus regard them as new asset class, as is the view of institutions such as the ECB (Bullmann et al., 2019). Common asset pricing literature such as Arbitrage Pricing Theory suggests that returns are generated by a linear factor model. We want to estimate the stochastic discount factor or pricing kernel M of the general asset pricing equation (see for example Cochrane, 2009; Munk, 2013) for an individual asset:

$$P = \mathbb{E}\mathrm{Mx} \tag{1}$$

Where P is a vector of prices for K assets and x the expected payoff. When rewritten in return form and in the absence of arbitrage the excess returns must satisfy:

$$\mathbb{E}\mathrm{RM} = 0_K \tag{2}$$

where R is a column vector of dimension K and where here the discount factors is linear

$$M = 1 - [(1 - \mathbb{E})F]'b \tag{3}$$

and F is a L-dimensional vector of factors whereas b is a column vector of factors loadings, 0_k is the K dimensional column vector of zeros. From the standard relation:

$$\mathbb{E}\mathrm{RM} = \mathbb{E}R\mathbb{E}M + \mathrm{Cov}(R, M) \tag{4}$$

the above two equations imply the linear pricing restriction:

$$\mathbb{E}R = B\lambda \tag{5}$$

where $B = Cov(R, F)[Var(F)]^{-1}$ and risk premium $\lambda = Var(F)b$. This is due to the fact that $Cov(R, M) = -Cov(R, F)b$.

The asset pricing equations (2) and (3) imply a linear factor representation for excess returns:

$$R = \alpha_0 + \mathrm{BF} + \varepsilon \tag{6}$$

where

$$\alpha = \mathbb{E}R - B\mathbb{E}F \tag{7}$$

and

$$B = \mathrm{Cov}(R, F)[\mathrm{Var}(F)]^{-1} \tag{8}$$

the error term ε is uncorrelated to the factors and has zero mean $\mathbb{E}\varepsilon F = 0$ The above relation can be estimated via GMM or a Fama-Macbeth procedure, which we outline in the following sections.

3. Adopting risk factor estimation to cryptocurrencies

3.1. Risk factor formation

Since the introduction of the single factor CAPM (Sharpe, 1964; Lintner, 1965) and the following multi-factor APT (Ross, 2013), a multitude of potential risk factors for financial markets have been discussed. Risk factors explaining the behaviour of returns usually include economic variables such as volatility (Kozhan et al., 2013; Bansal et al., 2014) and illiquidity risk (Acharya and Pedersen, 2005) as well as specific factors of interest such as Small Minus Big (SMB) or High Minus Low (HML) portfolios (Fama and French, 1993). To study which factors affect cryptocurrencies and their relationship with activity on the blockchain as well as market movements, we investigate three main sources: properties of the Bitcoin blockchain, properties of the Ethereum blockchain as well as market based measures such as volatility and liquidity. This enables us to analyse the link between on-chain and off-chain movements and investigate if the sources of risk are priced differently over time. To generate the excess returns R usually 10 year FED government bonds are used to proxy the risk-free rate r^f. To proxy the rate in cryptocurrency markets we assume that users will leave the market and convert their tokens back to fiat based assets thus we keep the returns of treasury bonds as risk free rate. An integral part for every risk factor analysis is market return R^m, since all other factors evaluated have to take into account general market risk. In real markets this is done by using a broad based index such as the S&P500 or Fama's value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ which we do include as as a robustness check in our analysis.

In order to create a cryptocurrency equivalent it is mandatory to have a large portfolio of cryptocurrencies spanning the whole market. We draw on work conducted by Trimborn and Härdle (2016) which have attempted to construct a market index for the cryptocurrency market (CRIX). The cryptocurrency index is based on a Laspeyres index: $P_{0t}^L(k) = \frac{\sum_{i=1}^k P_{it}Q_{i0}}{\sum_{i=1}^k P_{i0}Q_{i0}}$ where P_{it} is the price of token i at time t and Q_{i0} the according quantity of token i at base period 0. This represents market capitalization and is a dynamic value weighted market index with tokens entering and leaving the index, starting from 2014/07/31. The index and other major currencies such as Ethereum (Wood, 2014) are depicted in Figure 1. A more detailed description of the index composition is also available from Härdle and Trimborn (2015). We use this as market return factor for the rest of the analysis. We do use the market factor of before mentioned Fama's value weigthed return of all CRSP firms as a robustness check in the following sections.

To analyse volatility risk we use the VCRIX[1] (Kolesnikova, 2018), a volatility index based on the CRIX index which is constructed using a Heterogeneous Auto-Regressive (HAR) model (Corsi and Reno, 2009), as well as a simple realized variance proxy (Da and Schaumburg, 2011) by squaring the daily returns of the CRIX index. Since the liquidity of cryptocurrencies might play an additional important role in how they are valued by the market we sort them by liquidity. We analyse the liquidity in cryptocurrency markets following the approach of Wei (2018). The original metric is based on Amihud (2002) and is constructed the following way:

$$\mathrm{Illiquidity}_T^i = \frac{1}{D_T}\sum_{t=1}^{D_T}\frac{|R_t^i|}{P_t^i V_t^i} \tag{9}$$

R_t^i is the dollar return of currency i at time t, whereas $P_t^i V_t^i$ is the dollar price times basevolume of the currency traded. In the original

[1] Further details are available at https://thecrix.de/##Methodology

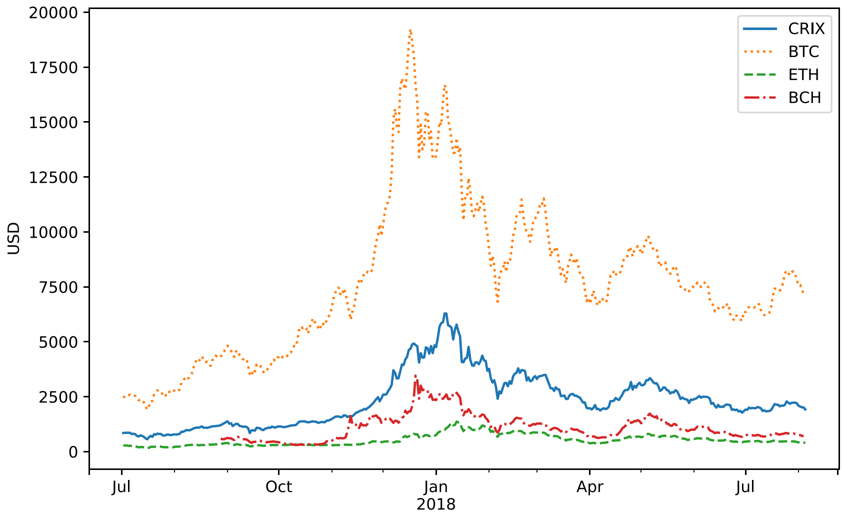


Fig. 1. The composite cryptocurrency index (CRIX). We also depict the dollar values of Bitcoin, Bitcoin Cash and Ethereum tokens for comparison. (Here the CRIX index is fixed to 100 at 2014/07/31).

paper D_T is the number of traded days in the period under analysis. Our analysis is based on daily frequency we thus set D_T to one and look at the ratio $\frac{|R_t^i|}{P_t^i V_t^i}$ at each day t in our analysis. The illiquidity factor follows the approach of Amihud (2014). The factor is the average return on the two most illiquid portfolios minus the average return on the two least illiquid portfolios whose construction we outline in the next subsection:

$$\mathrm{ILLIQ} = \frac{1}{2}(\mathrm{PF}_{12}^{\mathrm{High}} + \mathrm{PF}_{11}^{\mathrm{High}}) - \frac{1}{2}(\mathrm{PF}_{1}^{\mathrm{Low}} + \mathrm{PF}_{2}^{\mathrm{Low}}). \tag{10}$$

The real market variables thus include the variance of the CRIX, the VCRIX, an illiquidity factor and Fama's value-weighted market index. With Bitcoin being the major currency of exchange in the crypto space as well as the major transaction vehicle between exchanges, mining pools and users, we analyse how cryptocurrency portfolios interact with the underlying network features such as transaction fees or mining rewards. The technical limitations of the Bitcoin blockchain are well studied (Croman et al., 2016) and the state of the blockchain is an important indicator for the cryptocurrency market activity. We are adopting cryptomarket specific risk factors: Cost per transaction and total transaction fees to get a measure for transactional costs, as well as memorypool -size, -count and transactions per second to measure general network activity. The data and further references are available from https://www.blockchain.com/explorer. Since an increasing number of cryptocurrencies are established as ERC-20 tokens on the Ethereum blockchain, we also include Ethereum network properties in our analysis. We include cost per transaction and transaction fees as well as total daily gas used and network utilization to proxy network activity. Network utilization is the ratio of average gas used over the gas limit, giving an in indication of total utilization. The data is obtained from https://etherscan.io/. An overview is provided in appendix A1 .

Daily returns are notoriously noisy. However, we use daily frequency to mitigate the use of a relatively small sample. To put our results for the risk premia into perspective, we also construct factor mimicking portfolios (Huberman et al., 1987; Balduzzi and Robotti, 2008). In particular, given that our factors are measured with noise due to interpolations and approximations, we know that the results from factor mimicking portfolios are less biased when there is error in variables (Balduzzi and Robotti, 2008, Section 6.2). Monthly data would thus lead to less reliable results and to a very short sample size. Since we are interested in the significance of our results the use of a smaller sample is furthermore detrimental to asymptotic results.

3.2. Portfolio construction

Portfolio formation depends on the risk factor and market segment being analysed. The cross section of portfolios is usually sorted according to financial indicators such as momentum, industry or market beta. In order to adopt this to cryptocurrency markets, the portfolios are sorted according to similar market based sorts of cryptocurrencies. We focus on three main portfolio formations. The main token class we analyse is price stability, where we sort portfolios based on volatility of the tokens, the other main sort is based on the past returns of tokens and the third sort is based by the liquidity of each token. We form portfolios based on 156 tokens. We obtain the data from three major exchanges which represent a wide user base as of July 2019 and thus contains a large selection of cryptocurrencies which are accessible to a wide range of users. The 156 cryptocurrency tokens are obtained from the following exchanges: Kraken, Poloniex and Binance. The sample period consists of 1187 daily observations from 2016/04/26 until 2019/08/07, emphasizing a more recent and mature market view. An overview of all used currencies is available in appendix A8 .

We construct portfolios dynamically over time, using equally weighted cryptocurrencies, where portfolio content is adjusted

Table 1
Descriptive table of momentum, price stability and liquidity sorts (scaled by a factor of 100). Momentum forms portfolios by returns of individual tokens, price stability forms portfolios by volatility of individual tokens, and illiquidty based on Amihud's measure.

Portfolio	Momentum Sorted		Price Stability Sorted		Liquidity Sorted	
	Mean Return μ	Volatility σ	Mean Return μ	Volatility σ	Mean Return μ	Volatility σ
1	−1.5537	5.1774	−0.5455	3.3462	0.0046	4.8121
2	−1.0631	5.0460	−0.5100	4.1161	−0.1841	5.0353
3	−0.8173	5.1840	−0.5272	4.4289	−0.0533	5.5193
4	−0.6334	5.2132	−0.5854	4.7603	−0.1082	5.9952
5	−0.4604	5.4228	−0.4045	5.1066	−0.0463	6.4030
6	−0.3136	5.4235	−0.3015	5.3170	−0.0016	6.2789
7	−0.1807	5.4618	−0.2194	5.9515	−0.1379	6.5484
8	0.0348	5.7994	−0.2090	5.9905	−0.2425	6.0287
9	0.3054	5.7991	0.1265	6.5121	0.0772	6.6580
10	0.6295	6.5263	0.3844	7.1410	−0.0066	6.6003
11	1.1219	7.3746	0.4891	7.8329	−0.0784	6.7023
12	2.5953	12.4200	1.7819	11.7499	0.1790	9.0074

every 30 days. This is similar the volatility portfolio sorts of Kenneth French's Database [2] . All sorts are based on the 156 cryptocurrencies which are sorted into 12 portfolios, thus each individual portfolio $P_{i,t}$ consists of 13 equally weighted coins $c_{i,t}$, with the collection of coins $c_{i,t}^*$ in a portfolio changing every 30 days:

$$P_{i,t} = [c_{1,t}, \ldots, c_{n,t}] \quad \forall\, i = 1, \ldots, 12 \tag{11}$$

$$P_{i,t=\Delta 30}^{*} = [c_{1,t}^{*}, \ldots, c_{n,t}^{*}] \quad \forall\, i = 1, \ldots, 12 \tag{12}$$

where the inclusion of coin c_n^* depends on the average of the last $D_t = 30$ days: $\frac{1}{D_t}\sum_t^{D_t} C_t$, where C_t is the return or illiquidity of the cryptocurrency coin under consideration. And for the volatiltiy sort $\frac{1}{D_t}\sqrt{\sum_t^{D_t}(C_t - \bar{C})^2}$ based on the past returns.

Due to differences of inception and releases of the tokens, some of them are only included in their respective portfolio once they become tradable. To analyse price stability, the first set of portfolios is constructed by ranking tokens by their volatility, with portfolio 1 containing the least volatile tokens and portfolio 12 containing the most volatile ones. The second major sort is based on the return patters of tokens, similar to cross sectional momentum sorts in finance literature. For this, we form 12 portfolios were tokens are sorted by their average return every 30 days, with portfolio 1 being the lowest and portfolio 12 being the highest. The liquidity based portfolios are formed dynamically every 30 days, where portfolio 1 contains the most liquid and 12 the most illiquid currencies. All sorts are given in Table 1, with the average return μ and volatility σ of the portfolios reported. As is well known, cryptomarkets are especially volatile, which is also represented in our portfolios, with standard deviations being high.

3.3. Stationarity and transformation

If the Bitcoin series exhibits a clear trending behaviour and is not represented in rates, we consider inducing stationarity in order to avoid potentially spurious regression results. If markets are efficient prices follow a random walk which we assume applies to cryptocurrency markets. This poses no issue to further analysis since we calculated the returns and therefore ensured stationarity. Note that the autocorrelation function indicates cryptocurrencies to follow a local random walk, thus first differencing is sufficient to ascertain that the process is stationary, as is depicted in Figure 2. Only the unpredictable part of a factor can be priced as risk, a condition which is fulfilled after transforming the Bitcoin data where the autocorrelation functions exhibit little dependency over time as the first differenced autocorrelation function reveals. We further normalize the series by scaling through standard deviation to facilitate interpretation $\Delta y_t = \frac{y_t - y_{t-1}}{\sigma}$. Hence, we assume all time series such as Bitcoin transaction fees to be stationary as is depicted in Figure 2.

4. Risk premium estimation and results

4.1. Factor loadings

To estimate pricing equations (5) and (6) we commence estimating risk premia and factor loadings using the Two-Stage estimation approach, as given by Fama and MacBeth (1973). The scalars r_i, β_i and λ_i correspond to entries in R, b and λ as outlined in section 2. Our estimation setup in scalar notation is conducted as follows:

$$r_{\mathrm{it}} = a_i + \beta_{m,i} R_{m,t} + \beta_{f,i} f_t + e_{\mathrm{it}} \tag{13}$$

where each model includes two factors, the market return R_m and a factor of interest f. After the first stage time-series regression, the

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_port_form_VAR.html

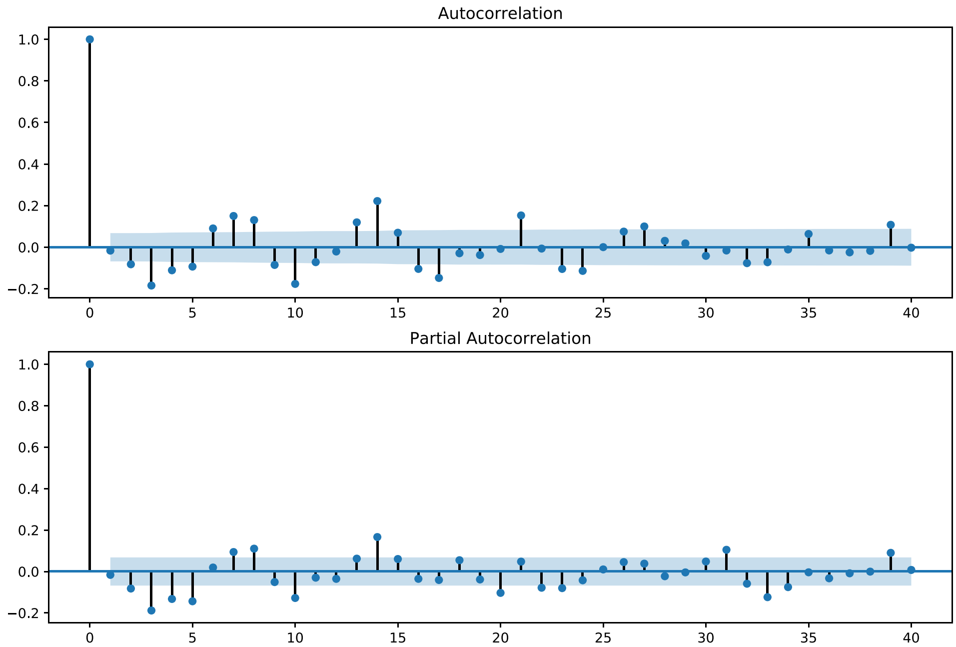


Fig. 2. Autocorrelation patterns of Bitcoin transaction fee innovations.

cross-sectional regression is estimated as:

$$\mathbb{E}_t r_{\mathrm{it}} = \lambda_m \hat{\beta}_{m,i} + \lambda_f \hat{\beta}_{f,i} + u_i \ \ i = 1, \ldots, N \tag{14}$$

For each model configuration, we repeat this approach three times for each set of portfolios we constructed. We use a set of two factors to analyse each risk factors individually while controlling for the market. In terms of cryptocurrency there is no consensus in literature on how many factors to apply in one estimation step. Different setups with more variables have led to similar results and are available from the authors.

We are interested in how our portfolios are exposed to the general cryptocurrency market risk as proxied by the CRIX index. We report factor loadings β_m and their corresponding t-values. The model (Eq. (13)) was estimated jointly with a volatility factor, results for market loadings are similar across configurations with different factors. All parameters are highly significant, thus giving solid evidence for the factor loading as can be seen in Table 2. The loadings are graphically depicted in Figure 3. We see that portfolios formed by volatility have weaker loadings in the less volatile sorts and more in the higher volatility sorts in a linear fashion. This market behaviour indicates that more volatile cryptocurrencies are less affected by the general market performance whereas low market performance usually strongly correlates with periods of increased volatility, putting our results in a reasonable economic context.

The portfolio sorts based on liquidity and returns reveal a different loading pattern. While the loading still increases with higher return portfolios, the loadings do not change as much for the average portfolio. Market loadings deviate more for the lowest and especially highest return coins. For return sorts, especially the highest portfolio loads the market risk significantly more than the other portfolios, emphasizing the relationship between the holding of high return tokens and the general market up- and downswings, which aligns with the idea of momentum strategies for trading. Thus market exposure is similar across most cryptocurrency holders, while they significantly increase for users which search for the highest return in the market. This contrasts with users interested in the stability of a coin, where the market exposure gradually increases with the amount of volatility in the group of tokens they hold.

Table 2
Portfolios loading cryptomarket risk. Portfolios sorted from lowest to highest. The top row is sorted by momentum, the middle one by volatility,whereas the lower row is sorted by liquidity. The loadings are estimated by regressing the portfolios on the market portfolio including a constant (results scaled by 100).

Portfolio	1	2	3	4	5	6	7	8	9	10	11	12
Momentum β_m	0.560	0.568	0.578	0.563	0.600	0.602	0.583	0.632	0.625	0.641	0.654	0.732
t-statistic	10.831	12.102	11.922	11.199	13.175	11.849	13.374	13.907	14.289	11.676	10.093	10.663
Volatility β_m	0.431	0.497	0.499	0.534	0.558	0.585	0.615	0.654	0.725	0.712	0.715	0.795
t-statistic	15.416	13.661	11.525	12.280	12.881	12.174	11.855	13.197	13.573	11.813	11.454	10.188
Illiquidity β_m	0.523	0.532	0.575	0.582	0.601	0.652	0.614	0.633	0.660	0.619	0.658	0.688
t-statistic	13.299	11.110	12.293	11.561	12.208	12.953	9.780	12.246	13.359	11.901	11.173	10.630

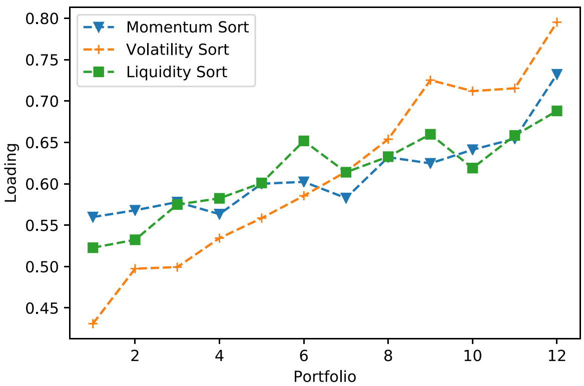


Fig. 3. Market loading of cryptocurrency portfolios sorted by return (Momentum), volatility (Price Stability) and liquidity from lowest to highest. (Loadings scaled by a factor of 100).

These findings align with rational market behaviour and thus confirm our earlier hypothesis that at least the fundamentals of an asset pricing model can be transferred and adjusted to the cryptocurrency market.

4.2. Risk premia

We now analyse the risk premium as described in Eq. (14). We obtain reasonable and interpretable parameter estimates, although direct statistical comparison with established literature such as work of e.g., Fama and French (1993) is problematic due to the very erratic nature of cryptocurrency markets. Because of the nature of the data typical R^2 value and pricing error comparisons with established literature are ambiguous. Due to the short sample size, facilitation of efficiency of estimates are of major concern. We thus impose a zero restriction on the constant in the cross sectional regression (Cochrane, 2009, p.235). We thus assume a correctly specified model, as we assumed that the constructed market factor is an accurate proxy for market returns.

Each risk factor is estimated in combination with the market factor, proxied by the CRIX. We group our results into three main groups: Ethereum network properties, Bitcoin network properties as well as market based factors. We compare the results across all three portfolio sorts. We also do split the sample into different periods. The full sample is based on data from 26/04/2016 until 07/08/2019. We split the sample into an early phase from the sample start to just before the main price explosion until 01/09/2017 and a sample afterwards until the end of the sample since we conjecture that the market structure and participants have changed over time. Table 3 presents the full sample results for risk factors related to the Ethereum network. Cost per transaction are only significant in the return sorts. And total transaction fees are not priced in by any sector of the market. The total amount of gas used per day is significant across all portfolio sorts. The risk premium is negative and indicates that investors are willing to give up returns in order to hedge against the risk of high gas utilization. The result is similar for network utilization, which is the average gas used over the gas limit. This indicates that network activity is priced in. Thus in times of decreasing returns network activity is higher, and if users are able to load that risk they are willing to give up returns for this hedge.

The Bitcoin network results presented in Table 4 are statistically weaker, since results are only significant for the return sorted case. The estimates show similarities to the Ethereum results. The cost per transaction and transaction fees are insignificant whereas metrics for the Bitcoin network activity are more significant, especially the transactions per second. The premium is positive, thus users demand returns to be compensated for the risk of high transactions per second. This possibly relates to the fact that a high amount of transactions per second delays the arrival of transaction and can be a form of settlement risk.

Table 5 presents the market factors. Results are ambiguous, with the VCRIX being significant in two sorts, carrying a slightly positive risk premium, where the real financial market factor (proxied by French's market factor) is only significant for the volatility sort. Illiquidity has a significant negative risk premium, in line with findings of financial markets such as De Jong and Driessen (2006).

Table 3
Full sample Ethereum risk factors. The first row includes the risk premium estimates, the second row in square brackets contains t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 26/04/2016 until 07/08/2019.

R_m, ETH Network	Cost Per Tx	Gas Used	Network Utilization	Transaction Fee
Momentum	−2.081, 0.009	−3.317, -7.821	−3.550, -1.678	−0.659, -3.177
t-statistic	[-1.17], [2.09]	[-2.6], [-2.23]	[-1.95], [-2.07]	[-0.27], [-0.43]
Volatility	−0.926, 0.004	−2.464, -5.92	−2.487, -1.197	0.099, 0.062
t-statistic	[-0.65], [0.98]	[-2.19], [-2.73]	[-2.17], [-2.57]	[0.06], [0.01]
Illiquidity	0.111, -0.001	−0.601, -1.31	−0.498, -0.213	−0.093, -0.101
t-statistic	[0.36], [-1.38]	[-1.42], [-2.15]	[-1.29], [-1.84]	[-0.36], [-0.27]

Table 4
Full sample Bitcoin risk factors. The first row includes the risk premium estimates, the second row in square brackets contains t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 26/04/2016 until 07/08/2019.

R_m, BTC Network	Cost Per Tx	MemPool Count	MemPool Size	Transaction Fee	Transactions/Sec
Momentum	−0.426, 0.467	2.366, 1.940	1.066, -1.423	2.208, 0.910	0.321, 4.105
t-statistic	[-0.36], [0.45]	[1.02], [1.48]	[0.72], [2.09]	[1.23], [1.17]	[0.33], [2.39]
Volatility	0.710, -0.638	0.839, 0.594	0.024, -0.108	0.625, 0.221	0.600, 4.397
t-statistic	[0.45], [-0.41]	[1.38], [1.24]	[0.03], [-0.08]	[0.51], [0.43]	[0.61], [1.21]
Illiquidity	−0.099, 0.026	0.043, 0.091	−0.051, 0.035	−0.245, -0.065	0.002, 0.538
t-statistic	[-0.38], [0.25]	[0.14], [-0.55]	[-0.21], [-0.254]	[-0.78], [-0.855]	[0.001], [1.21]

Table 5
Full sample market risk factors. The first row includes the risk premium estimates, the second row in square brackets contains t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 26/04/2016 until 07/08/2019.

R_m, Market Factors	CRIX VOL	VCRIX	ILLIQ	Real Market
Momentum	3.665, 1.468	−1.897, 0.3684	−1.368, -0.029	0.239, -2.227
t-statistic	[1.27], [1.56]	[-0.82], [-2.23]	[-1.96], [-2.36]	[0.35], [-0.78]
Volatility	−0.480, -0.231	−0.690, 0.147	−0.892, -0.021	0.561, -4.562
t-statistic	[-0.11], [-0.13]	[-0.74], [-2.13]	[-2.34], [-4.54]	[0.42], [-2.64]
Illiquidity	0.186, 0.108	0.073, -0.001	−0.163, -0.002	−0.085, 0.083
t-statistic	[0.13], [0.20]	[-0.30], [-0.025]	[-0.69], [-1.15]	[-0.36], [0.27]

As a robustness check and to put results into perspective we split the sample in two at 01/09/2017 before Bitcoin reached its maximum price in the sample. The tables are provided in the appendix. For the part of the sample from 2017 to 2019 the Ethereum network utilization proxies (Table A2) are not significant anymore, whereas possibly trading related transactional cost factors such cost per transaction and fees have become more significant. Comparing table 3 and table A2, Ethereum results at the end of the sample are in general less significant than in the full sample period. Table A3 shows that no factor related to Bitcoin is significant anymore, whereas when comparing tables 5 and A4, market related factors are still priced similarly to the previous sample. The illiquidity factor is significantly negative in all samples. The loading is low in the illiquidity sorts by construction of the factor. Similar to other findings (De Jong and Driessen, 2006), the negative risk premium for illiquidity implies that when the market return decreases, illiquidity increases, potentially leading to a decline in trading activity, thus users are willing to give up returns to hedge against this risk.

Tables A5, A6 and A7 show results for the early subsample including the years 2016 and 2017. The effects of the Ethereum and Bitcoin network factors have reversed, with only Bitcoin containing significant results. This provides evidence that in the earlier days of the market Bitcoin activity was a significant factor, which then switched to Ethereum after the increase in price and the growth of Ethereum based ERC-20 tokens. At the end of the sample, market based factors gain importance while network activity is not priced in anymore, providing evidence that market action is becoming decoupled from on-chain activity and users price this in accordingly.

Interestingly, in standard literature using portfolios sorts based e.g., on size or value, volatility risk is often found to be priced negatively because exposure to volatility can act as hedge against market downturns (Adrian and Rosenberg, 2008, Bollerslev et al., 2009). Table 5 reveals that users holding such portfolios demand a positive risk premium for volatility risk. Differing from traditional markets, the volatility risk premium is also positive for return sorted portfolios. This means that volatility and returns correlate positively, thus there is no negative premium for hedging using volatility. This difference is interesting since this implies that the very high volatility in cryptocurrency markets is not associated with general market distress (Carr and Wu, 2008) and has led to sudden and erratic increases in the value of cryptocurrencies, thus market participants evaluate this risk fundamentally different than in traditional financial markets.

5. Factor mimicking portfolios

We wish to gain further insight into the risk profile of the above discussed factors. When factors are non-tradable, pricing equation (5) holds because factor mimicking portfolios can be applied (Breeden et al., 1989; Balduzzi and Robotti, 2008; Huberman et al., 1987). To further explore the economic value of factors affecting token evaluation and market behaviour we create factor mimicking portfolios $\mathcal{M}_t$:

$$\mathcal{M}_t = \gamma_0 + \gamma_1' R_t + \varepsilon_t \tag{15}$$

which here is a $L \times 1$ vector of L mimicking factors with γ_0 and γ_1 being matrices of dimension $L \times 1$ and $L \times N$ respectively. R_t are returns from the twelve return sorted portfolios. Errors ε_t are a mean zero vector of corresponding dimension. Applied to our previous analysis, the market factor is the first entry in $\mathcal{M}_t$ and e.g., volatility the second.

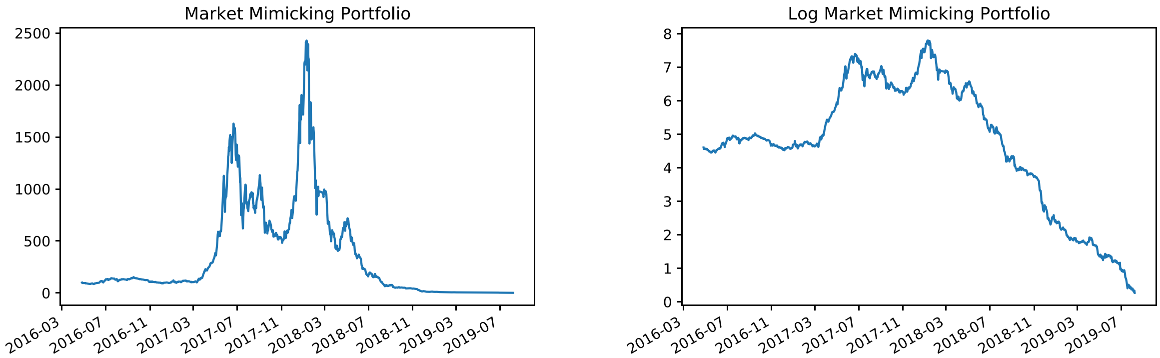


Fig. 4. Market factor mimicking portfolios for return sorts. Index fixed to 100 on the 2016/04/26.

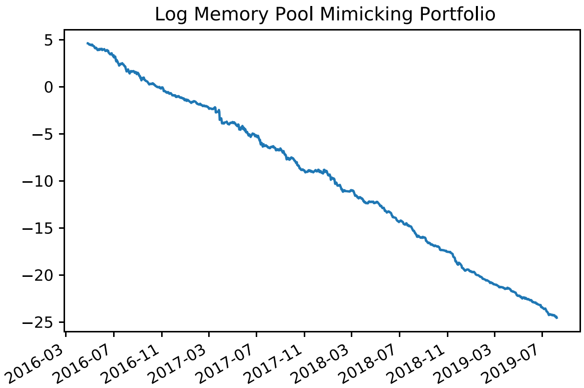


Fig. 5. Factor mimicking portfolios of Bitcoin network properties for price stability sorts. Index fixed to 100 on the 2016/04/26.

For illustration and testing the economic value of risk factors, Figure 4 shows the market factor with the index being fixed to 100 on the 2016/04/26, the start of the sample. The economic interpretation of the profile is apparent. The market factor has been at a constant level in the early stages of market development, with two notable explosive developments: first during the phase of massive price increases in summer 2017 as well as another big upswing at the beginning of 2018, with exposure to the market factor leading to decline in economic value since then. This is reasonable and aligns well with general sentiment and performance of the whole cryptocurrrency market during these periods. Figure 4 also expresses the market factor in log levels. We present the other factors in log form since we are interested in relative changes and growth rates over time.

To relate the results to the previous section we analyze factor mimicking portfolios for the Bitcoin and Ethereum blockchain as well as market based factors.

Figure 5 shows the log values of the Bitcoin memory pool mimicking portfolio, which shows that the factor would have been losing values since its construction 2016.

Figure 6 illustrates the economic value of the Ethereum network utilization. Since the beginning of the sample its value has been increasing steadily with bursts in growth until the value fluctuates around a constant value since early 2018. With respect to the previous analysis this provides additional evidence that the factor had increasing impact on the cryptocurrency market over time and then stabilised.

Figure 7shows the development of the illiquidity factor. It has been increasing value since inception and gaining, although at a lower rate after early 2018. Its growing trend throughout the end of the sample also aligns with the findings in the previous sections in which at the end of the sample market factors are of increasing importance. Together with the fact that Bitcoin network risk premia are more significant in the early sample period, and Ethereum network later, this provides additional evidence for a stage wise development of how market participants price risk. While in the early stages Bitcoin network features were priced in, once a multitude of new cryptocurrencies which are often based on Ethereum are established, the Ethereum network features gain prominence. In later stages of the sample, market based risk factors are important risk factors as the illiquidity factor's risk profile indicates. This can be interpreted as a decoupling of on-chain activity and off-chain trading related risk factors.

6. Evaluation of specific tokens

The asset pricing model allows for application to any particular coin which is traded in the market and to estimate a fair return value. We use the estimated loadings and risk premia and predict a fair value of a token given current market conditions. As an

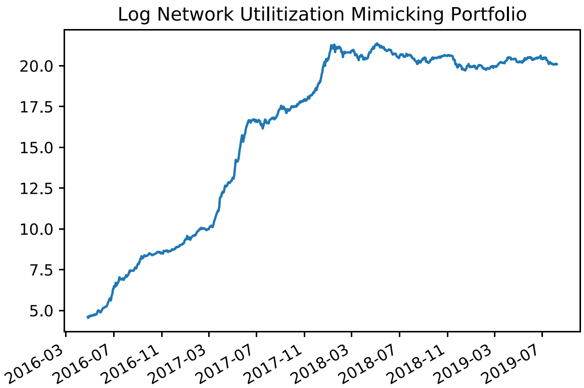


Fig. 6. Factor mimicking portfolios of Ethereum network properties. Index fixed to 100 on the 2016/04/26.

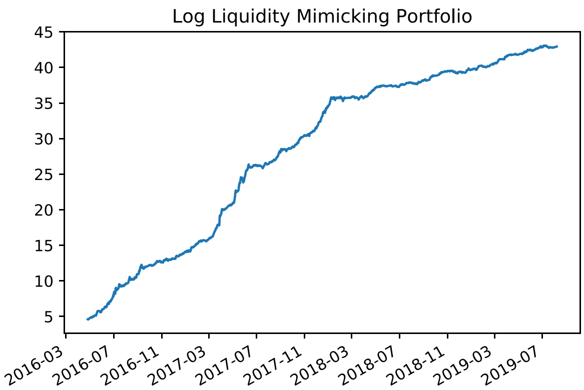
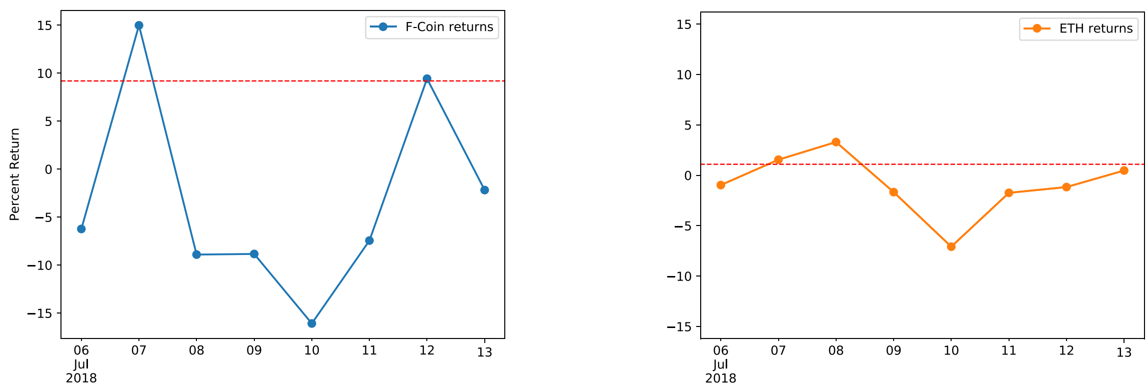


Fig. 7. Factor mimicking portfolios of illiquidty. Index fixed to 100 on the 2016/04/26.



(a) Estimated and realized F-Coin returns (b) Estimated and realized Ethereum returns

Fig. 8. Realized and estimated returns of F-coin and ETH. The red dotted lines indicate the estimated fair return in the given period as given by $E(R_{coin})$.

application, we study Ethereum as well as F-coin[3], a coin which has become infamous in the cryptocurrency space due to its transaction-fee mining. The F-coin token is linked to the F-Coin exchange and users can mine the token by trading on the platform, thus incentivising inflated trading volume on the platform. We estimate the risk premia in a subsample using a model with market and transaction-fee factor. For F-Coin we choose a short but significant timespan to estimate factor loadings, the week from 2018/07/06 until 2018/07/13. In that time period the exchange became suddenly very popular, with news about the exchange going viral and the price of the token spiking at its peak. This is is also observable through the noticeably higher factor loadings for F-coin. The factor

[3] The historic price chart is obtained from https://www.coingecko.com/en/price_charts

loadings for market and transaction fees are β_{Fcoin} = [1.004, 8.283] and β_{ETH} = [0.445, 1.300], respectively. Given pricing equation (14) the expected return in the same timespan given our estimated pricing model yields:

$$E(R_{\text{Fcoin}}) = 9.189$$

$$E(R_{\text{ETH}}) = 1.094$$

We see in Figure 8 that the F-coin token in some periods reaches the estimated return value but on average is below the expected return given our model. It is observable that Ethereum also suffered from lower performance at the point of lowest return, implying there was a general market downturn. The more pronounced movement for F-coin exemplifies the difference in exposure to market loading.

In this case the estimated return could have provided a viable trading strategy when assuming that realized returns only deviate temporarily from estimated expected returns. The estimated return of Ethereum also shows that the expected return of the model aligns with the realized returns. For the given timeframe the estimated returns provide a useful benchmark and show that basic risk-returns relations in cryptocurrency markets are valid and captured by the model with more risk exposed F-coin leading to higher expected return.

7. Conclusion

Many factors have been considered in explaining the price of assets. We analysed pricing properties of the new asset class of cryptocurrencies, investigating risk factors unique to cryptocurrencies such as blockchain transaction volume and transaction fees. Our investigation captured the very early development of the market, offering new insights into current pricing mechanisms. We find that estimation results of our modified framework are similar to established financial markets, making it applicable for further analysis once markets are more mature. Initial results show that users price volatility positively, seeing it as opportunity for higher returns. This is in contrast to traditional financial markets in which volatility is priced negatively. Furthermore our analysis provides evidence that participants in cryptomarkets are pricing in risk factors given by the Bitcoin and Ethereum network state. We find evidence that the state of the Bitcoin blockchain had a stronger effect on pricing when blockchain has been less known to the public, and was slowly replaced by Ethereum network effects when the number of cryptocurrencies based on ERC20-tokens increased. We also apply our model to Ethereum and F-coin and demonstrate its utility as benchmark. Given that the initial model produced reasonable results, a more robust analysis and interpretation can be conducted given a longer period of analysis for time periods comparable to standard asset pricing literature.

Especially in the community of computer scientists and financial practitioners this paves way for more research on the pricing of cryptocurrency tokens, and how markets for this new asset class differs from already established asset types.

Acknowledgement

This work is supported by Worley Parsons.

A.1 Description of Bitcoin and Ethereum metadata

Table A1
Description of all used Bitcoin network data. The network metadata is obtained via the API of https://www.blockchain.com/explorer and https://etherscan.io/charts

Variable Name	Description
”BTC cost-per-transaction”	Miners revenue divided by the number of transactions
”BTC mempool-count”	The number of transactions waiting to be confirmed.
”BTC mempool-size”	The aggregate size of transactions waiting to be confirmed.
”BTC transaction-fees”	The total value of all transaction fees paid to miners (not including the coinbase value of block rewards).
”BTC transactions-per-second”	The number of Bitcoin transactions added to the mempool per second.
”ETH network utilization”	Average gas used/Gas limit in percentage
”ETH transaction fees”	Total transaction fees in Ether per day.
”ETH cost-per-transaction”	Gas paid divided by the total number of transactions
”ETH gas used”	Total daily gas use in the ETH network

A.2 Risk premia of subsamples

This section contains the risk premia when splitting the main sample into early and late market subsamples. Further tables with factor loadings and robustness checks with GMM estimation of the SDF are available from the authors.

Table A2
Late Sample Ethereum Risk Factors. The first row includes the risk premium estimates, the second row in square brackets contain t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 23/08/2017 until 07/08/2019.

R_m, ETH Network	Cost Per Tx	Gas Used	Network utilization	Transaction Fee
Momentum	−5.154, 0.011	−1.393, -5.166	−0.935, 0.337	−3.340, 3.138
t-statistic	[-1.29], [1.58]	[-0.71], [-1.30]	[-1.03], [0.79]	[-1.67], [1.73]
Volatility	−3.026, 0.005	−1.170, -1.667	−1.189, -0.222	−2.483, 1.989
t-statistic	[-2.09], [2.33]	[-1.44], [-1.23]	[-1.40], [-1.09]	[-2.29], [2.45]
Illiquidity	−1.335, 0.001	−1.152, -1.713	−1.135, 0.010	−1.235, 0.128
t-statistic	[-3.29], [1.34]	[-3.06], [-0.64]	[-3.23], [0.37]	[-3.37], [0.92]

Table A3
Late Sample Bitcoin Risk Factors. The first row includes the risk premium estimates, the second row in square brackets contain t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 23/08/2017 until 07/08/2019.

R_m, BTC Network	Cost Per Tx	MemPool Count	MemPool Size	Transaction Fee	Transaction/sec
Momentum	−1.889, 0.615	0.030,0.562	−0.856, 0.459	−1.016, 0.024	0.093, 4.131
t-statistic	[-1.50], [0.76]	[0.02], [0.86]	[-0.74], [0.27]	[-0.76], [0.06]	[0.07], [1.01]
Volatility	0.143, -1.025	−1.309, -0.142	−1.205, -0.830	−0.624, 0.124	−0.924, 0.315
t-statistic	[0.08], [-0.73]	[-0.36], [-0.08]	[-1.07], [-1.19]	[-0.45], [0.29]	[-0.52], [0.06]
Illiquidity	−1.066, -0.079	−1.265,-0.063	−1.153, -0.046	−1.275, -0.032	−1.190, -0.147
t-statistic	[2.87], [-1.04]	[-3.32], [-0.68]	[-3.16], [-0.53]	[-3.16], [-0.72]	[-2.63], [-0.18]

Table A4
Late Sample Market Risk Factors. The first row includes the risk premium estimates, the second row in square brackets contain t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 23/08/2017 until 07/08/2019.

R_m, Market Factors	CRIX VOL	VCRIX	ILLIQ	Real Market
Momentum	2.396, 1.294	−2.268, 0.141	−5.23, -0.061	−0.065, -7.022
t-statistic	[1.62], [2.57]	[-1.33], [1.57]	[-3.67], [-3.69]	[-0.03], [-1.69]
Volatility	−3.812, -0.997	−1.358, 0.044	−2.61, -0.024	−0.854, 0.846
t-statistic	[-2.36], [-1.72]	[-1.83], [0.59]	[-3.23], [-2.74]	[-0.36], [-0.08]
Illiquidity	−0.385, 0.282	−1.193, 0.007	−1.095, 0.001	−1.133, -0.046
t-statistic	[-0.48], [1.07]	[-3.34], [0.65]	[-3.04], [0.21]	[-3.09], [-0.13]

Table A5
Early Growth Ethereum Risk Factors. The first row includes the risk premium estimates, the second row in square brackets contain t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 26/04/2016 until 01/09/2017.

R_m, ETH Network	Cost Per Tx	Gas Used	Network utilization	Transaction Fee
Momentum	1.417, 0.003	1.516, 2.608	1.481, 0.889	1.785, 0.889
t-statistic	[2.70], [1.51]	[1.02], [0.63]	[1.11], [0.48]	[1.02], [1.46]
Volatility	1.530, 0.001	1.537, -2.935	1.536, -0.091	1.567, 0.253
t-statistic	[3.90], [-0.05]	[3.05], [-0.07]	[3.21],[-0.06]	[3.40],[0.41]
Illiquidity	1.360, 0.001	1.318, -1.78	1.324, -0.066	1.303, -0.0065
t-statistic	[3.63], [-1.53]	[3.06], [-0.84]	[3.11], [-0.77]	[3.10], [-1.06]

Table A6
Early Growth Bitcoin Risk Factors. The first row includes the risk premium estimates, the second row in square brackets contain t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 26/04/2016 until 01/09/2017.

R_m, BTC Network	Cost Per Tx	MemPool Count	MemPool Size	Transaction Fee	Transaction/sec
Momentum	1.567, -0.040	2.199, 1.071	2.180, 0.699	2.872, 1.329	0.818, 1.789
t-statistic	[3.25], [-0.07]	[2.18], [2.01]	[2.44], [2.25]	[1.34], [1.95]	[0.89], [2.17]
Volatility	1.512, 0.127	2.089,0.736	2.005, 0.451	1.672, 0.114	1.057, 1.536
t-statistic	[1.81], [1.64]	[3.23], [2.11]	[2.86], [1.02]	[1.96], [0.21]	[1.12], [0.21]
Illiquidity	1.287, -0.018	1.419, 0.156	1.414, 0.090	1.399, 0.077	1.215, 0.326
t-statistic	[3.32], [-0.31]	[3.64], [0.82]	[3.65], [0.67]	[3.02], [0.34]	[3.08], [0.96]

Table A7
Early Growth Market Risk Factors. The first row includes the risk premium estimates, the second row in square brackets contain t-values. The first column entry is the market factor, the second entry is the factor specified in the respective column header. The sample period is from 26/04/2016 until 01/09/2017.

R_m, Market Factors	CRIX VOL	VCRIX	ILLIQ	Real Market
Momentum	2.222, 0.392	−0.889, 0.145	0.243, -0.033	1.569, -0.408
t-statistic	[1.10], [0.35]	[-0.53], [1.41]	[0.41], [-2.91]	[3.47], [-0.43]
Volatility	2.667, 0.774	−0.322, 0.105	0.655, -0.025	1.250, -1.803
t-statistic	[3.62], [2.10]	[-0.41], [2.36]	[1.67], [-4.89]	[1.48], [-2.08]
Illiquidity	1.245, -0.027	1.405, -0.006	1.209, -0.0056	1.322, 0.131
t-statistic	[2.83], [-0.17]	[3.23], [-0.35]	[3.35], [-1.47]	[3.71], [0.53]

A.3 Table of all tokens

Table A8
An Overview of all used cryptocurrencies. Summary statistics based on return time series

	mean	std	min	25%	50%	75%	max
ADA	−0.001648	0.052147	−0.175703	−0.030353	−0.002627	0.023583	0.224881
ADX	−0.002244	0.075188	−0.301408	−0.035557	−0.008420	0.029105	0.698079
AE	−0.004520	0.055394	−0.209604	−0.032497	−0.001928	0.024742	0.251352
AION	−0.004225	0.062685	−0.244375	−0.041873	−0.005283	0.031191	0.231389
AMB	−0.003821	0.066608	−0.256725	−0.043755	−0.005236	0.034351	0.293417
APPC	−0.002342	0.068653	−0.282479	−0.044857	−0.003970	0.034987	0.293163
ARDR	0.004563	0.074643	−0.292435	−0.033674	−0.001310	0.036154	0.431298
ARK	−0.002734	0.061363	−0.226053	−0.038238	−0.004881	0.027920	0.373588
ARN	−0.000942	0.078738	−0.259968	−0.045688	−0.006010	0.034109	0.619322
AST	−0.003901	0.078282	−0.249455	−0.050895	−0.004409	0.039505	0.362901
BAT	0.001108	0.061249	−0.215677	−0.037789	−0.003301	0.035259	0.302194
BCC	0.002174	0.081424	−0.274091	−0.037716	−0.003587	0.026573	0.554743
BCD	−0.005097	0.073929	−0.743753	−0.031644	−0.004169	0.019315	0.583228
BCN	0.009500	0.176177	−0.512250	−0.035630	0.000146	0.027454	5.508065
BCPT	−0.004307	0.074518	−0.251349	−0.044671	−0.007801	0.034689	0.415130
BLZ	−0.004716	0.063099	−0.246502	−0.038418	−0.007799	0.034361	0.266534
BNB	0.007440	0.072624	−0.250419	−0.025738	−0.000712	0.035936	0.511840
BNT	−0.003970	0.049117	−0.184764	−0.028883	−0.001184	0.019335	0.244834
BQX	−0.002528	0.087539	−0.265014	−0.048396	−0.006368	0.029585	0.589508
BRD	0.001660	0.057291	−0.310331	−0.024339	0.000798	0.028350	0.499392
BTC	0.002682	0.031903	−0.159290	−0.008916	0.001692	0.015504	0.189773
BTG	−0.003121	0.052567	−0.177237	−0.030957	−0.003523	0.024552	0.275681
BTS	0.004169	0.072650	−0.311002	−0.026401	−0.002205	0.028724	0.727043
CDT	−0.002836	0.068930	−0.246451	−0.042345	−0.005008	0.039084	0.355624
CHAT	−0.011364	0.087278	−0.310975	−0.063548	−0.009845	0.021115	0.399436
CLAM	0.004049	0.075546	−0.531014	−0.030228	0.000862	0.031920	0.809643
CMT	−0.000208	0.067094	−0.229194	−0.036799	−0.003852	0.034267	0.257825
CND	−0.002184	0.062251	−0.223438	−0.037373	−0.004101	0.033484	0.356848
CVC	−0.000916	0.081761	−0.276129	−0.037047	−0.004074	0.030112	0.671363
DASH	0.003642	0.050537	−0.228223	−0.021869	0.000881	0.024702	0.264681
DCR	0.005419	0.075593	−0.253152	−0.031329	−0.003607	0.029510	0.925922

(continued on next page)

Table A8 (*continued*)

	mean	std	min	25%	50%	75%	max
DGB	0.007636	0.104712	−0.323119	−0.036301	−0.002507	0.034375	1.111465
DGD	−0.004342	0.062247	−0.230667	−0.036281	−0.006849	0.023899	0.365450
DLT	0.000738	0.100198	−0.282412	−0.049570	−0.007962	0.036376	1.145766
DNT	−0.002347	0.074104	−0.235674	−0.043585	−0.006170	0.033641	0.448382
DOGE	0.003964	0.063814	−0.273642	−0.022963	−0.000937	0.020896	0.563569
EDO	−0.001059	0.052021	−0.160606	−0.030736	−0.001119	0.023812	0.341306
ELF	−0.000963	0.066815	−0.238038	−0.031603	−0.004770	0.027570	0.434905
ENG	−0.002925	0.073009	−0.216925	−0.043993	−0.004615	0.033389	0.470894
ENJ	0.003620	0.100892	−0.235275	−0.040984	−0.004987	0.033739	1.150158
EOS	0.000382	0.064732	−0.199110	−0.028750	−0.001962	0.024170	0.531960
ETC	0.003801	0.061459	−0.256535	−0.024250	0.000671	0.027706	0.524651
ETH	0.005673	0.056058	−0.260804	−0.020504	0.001520	0.029030	0.261954
EVX	0.001311	0.102564	−0.234466	−0.041132	−0.006641	0.028956	1.488829
FCT	0.004447	0.074336	−0.270287	−0.031361	0.000017	0.035349	0.465615
FUEL	−0.004279	0.065642	−0.226621	−0.044243	−0.006475	0.030208	0.286966
FUN	−0.005165	0.064733	−0.248370	−0.037496	−0.004207	0.024724	0.436598
GAME	0.007701	0.099549	−0.319272	−0.041148	−0.003586	0.038957	1.405283
GAS	−0.002113	0.072650	−0.262632	−0.041496	−0.005423	0.029292	0.503888
GNT	0.000062	0.075915	−0.275173	−0.041351	−0.003200	0.032307	0.640345
GTO	−0.003468	0.065501	−0.226550	−0.037973	−0.006661	0.025530	0.385079
GVT	−0.002580	0.063717	−0.243416	−0.039597	−0.006226	0.033993	0.266931
GXS	−0.001855	0.053434	−0.176658	−0.032085	−0.003827	0.027866	0.243292
HSR	−0.000951	0.069430	−0.213704	−0.042418	−0.002597	0.027782	0.296455
ICN	−0.005823	0.062966	−0.211349	−0.039727	−0.004948	0.026482	0.254456
ICX	−0.003941	0.059953	−0.215073	−0.034924	−0.003935	0.027857	0.287128
INS	−0.002403	0.063218	−0.221981	−0.033908	−0.000968	0.028901	0.273097
IOST	−0.002075	0.068307	−0.263449	−0.035921	−0.003271	0.028154	0.351644
IOTA	−0.003645	0.057843	−0.195336	−0.033496	−0.004426	0.024384	0.189138
KMD	−0.001110	0.055519	−0.191775	−0.034832	−0.003419	0.028752	0.186617
KNC	−0.003108	0.072425	−0.214506	−0.039589	−0.006875	0.026451	0.445417
LBC	0.003204	0.090333	−0.283783	−0.044241	−0.005638	0.039965	0.766945
LEND	−0.002315	0.062539	−0.240593	−0.039932	−0.005737	0.031214	0.229632
LINK	0.001637	0.074457	−0.272482	−0.041246	−0.004511	0.043262	0.319304
LRC	−0.002836	0.067810	−0.244544	−0.039984	−0.004414	0.033357	0.495344
LSK	0.004596	0.073656	−0.266879	−0.030115	−0.003395	0.030033	0.618652
LTC	0.003995	0.054392	−0.296532	−0.016196	−0.000285	0.019222	0.607709
LUN	−0.000840	0.067439	−0.263842	−0.038270	−0.006045	0.039897	0.440352
MAID	0.002959	0.058438	−0.244287	−0.026204	0.000891	0.032306	0.482305
MANA	0.002138	0.105747	−0.546100	−0.035396	−0.005023	0.032483	1.661047
MCO	0.002550	0.081864	−0.242380	−0.035812	−0.001730	0.034331	0.886860
MDA	0.001149	0.086183	−0.322932	−0.038508	−0.005831	0.029402	0.481041
MOD	−0.004766	0.074326	−0.323964	−0.045982	−0.007548	0.031842	0.457780
MTH	−0.002960	0.082031	−0.323654	−0.044202	−0.003138	0.032715	0.748065
MTL	−0.002923	0.070019	−0.297434	−0.038388	−0.006329	0.031147	0.473911
NANO	−0.002143	0.063450	−0.221727	−0.038827	−0.004319	0.023141	0.270993
NAV	0.008025	0.120839	−0.582005	−0.042777	−0.003529	0.039742	2.013813
NCASH	−0.006105	0.057833	−0.257449	−0.036069	−0.003355	0.029362	0.255696
NEBL	−0.002525	0.060755	−0.242782	−0.040283	−0.003879	0.031440	0.278867
NEO	0.000172	0.066925	−0.197385	−0.034069	−0.005086	0.026045	0.418624
NULS	−0.000788	0.068509	−0.247965	−0.036241	−0.004008	0.029661	0.343569
NXT	0.003252	0.069742	−0.377738	−0.027562	−0.003607	0.022006	0.551434
OAX	0.000681	0.116991	−0.283001	−0.045044	−0.005169	0.032771	1.820402
OMG	−0.002813	0.061374	−0.268229	−0.033377	−0.003413	0.025117	0.330916
OMNI	0.005501	0.108175	−0.394436	−0.046935	−0.004229	0.045005	1.124302
ONT	−0.003179	0.067223	−0.238077	−0.034473	−0.007657	0.021663	0.491510
OST	−0.002487	0.072361	−0.274237	−0.038211	−0.004969	0.036408	0.608241
PASC	0.003001	0.082851	−0.262148	−0.041482	0.000079	0.038176	0.615067
PIVX	−0.004232	0.059611	−0.203069	−0.034001	−0.004197	0.021947	0.538598
POA	−0.005573	0.063368	−0.274478	−0.043648	−0.005469	0.032308	0.211926
POE	−0.004103	0.065936	−0.221757	−0.037152	−0.003189	0.028954	0.646991
POWR	−0.002099	0.058222	−0.185570	−0.037295	−0.003132	0.026543	0.277457
PPT	−0.004407	0.062692	−0.214556	−0.039147	−0.006122	0.023769	0.324758
QSP	−0.003900	0.063694	−0.223377	−0.045817	−0.005152	0.035213	0.305094
QTUM	−0.000724	0.075785	−0.266087	−0.037379	−0.003502	0.019989	0.668494
RCN	−0.001928	0.076075	−0.252663	−0.042496	−0.006709	0.033510	0.527155
RDN	−0.003109	0.067320	−0.228125	−0.040494	−0.005351	0.029505	0.422746
REP	0.004609	0.076230	−0.294190	−0.031696	0.002030	0.032767	0.828456
REQ	−0.003684	0.067196	−0.263283	−0.040478	−0.004515	0.032053	0.448315
RLC	−0.000093	0.065519	−0.208360	−0.043268	−0.001118	0.035728	0.399813

(*continued on next page*)

Table A8 (*continued*)

	mean	std	min	25%	50%	75%	max
RPX	−0.017822	0.059062	−0.164895	−0.062775	−0.013093	0.017046	0.126205
SALT	−0.007719	0.070355	−0.219547	−0.047038	−0.007542	0.032961	0.277288
SC	0.008504	0.098437	−0.395266	−0.034885	−0.003272	0.032996	1.023997
SNGLS	−0.002142	0.084471	−0.389818	−0.046190	−0.005128	0.035977	0.504482
SNM	−0.003263	0.072408	−0.266799	−0.042540	−0.002729	0.034213	0.413984
SNT	−0.004361	0.051996	−0.208191	−0.033062	−0.005194	0.020874	0.212509
STEEM	0.004285	0.088483	−0.295059	−0.039305	−0.004724	0.031731	0.867329
STORJ	−0.001059	0.070958	−0.191195	−0.034496	−0.005058	0.031352	0.611058
STORM	−0.004981	0.054531	−0.224936	−0.033708	−0.007295	0.026739	0.208663
STR	0.005140	0.080091	−0.309688	−0.027994	−0.003440	0.026750	1.021865
STRAT	0.005125	0.082627	−0.261973	−0.037391	−0.002249	0.036403	0.388444
SUB	−0.007439	0.076286	−0.311977	−0.045075	−0.010070	0.035595	0.322255
TNB	−0.003106	0.063723	−0.234433	−0.037798	−0.004645	0.031076	0.343754
TNT	−0.001523	0.082279	−0.262191	−0.044934	−0.005168	0.032148	0.744951
TRIG	−0.005351	0.088638	−0.416057	−0.061127	−0.012066	0.038368	0.325860
TRX	0.001308	0.059325	−0.219953	−0.028407	−0.002831	0.028571	0.297914
VEN	−0.002676	0.064204	−0.142763	−0.045269	−0.008558	0.039391	0.238008
VIA	0.007811	0.101533	−0.299614	−0.043380	−0.000424	0.045300	1.140249
VIB	−0.001354	0.069709	−0.253466	−0.041589	−0.003312	0.036697	0.349477
VIBE	−0.000899	0.092749	−0.251392	−0.043445	−0.007427	0.031265	1.062434
VTC	0.007475	0.105914	−0.413960	−0.041692	−0.005762	0.032428	1.301281
WABI	0.001159	0.080409	−0.266612	−0.046317	−0.009013	0.039246	0.496216
WAVES	−0.000044	0.060957	−0.199939	−0.029511	−0.003260	0.023924	0.393643
WINGS	−0.003952	0.069205	−0.292613	−0.039445	−0.004576	0.030314	0.572496
WTC	−0.000099	0.079730	−0.253761	−0.043480	−0.002249	0.033403	0.558668
XEM	0.007476	0.080950	−0.305041	−0.032450	−0.002226	0.034285	0.742876
XLM	−0.001073	0.049173	−0.128640	−0.030949	−0.003715	0.023009	0.162256
XMR	0.004618	0.059470	−0.255466	−0.024458	0.000534	0.028661	0.584186
XPM	0.005252	0.093060	−0.343456	−0.030950	−0.003168	0.027308	1.063413
XRP	0.004484	0.068074	−0.295979	−0.020018	−0.002320	0.018238	0.885283
XVG	−0.004158	0.071213	−0.283757	−0.041728	−0.004375	0.026072	0.348706
XZC	−0.003751	0.046876	−0.207063	−0.031217	−0.003655	0.023437	0.205809
YOYO	−0.002221	0.066982	−0.219170	−0.044544	−0.003099	0.036570	0.300097
ZEC	0.002383	0.064733	−0.261009	−0.031673	−0.001697	0.028633	0.843754
ZIL	−0.003866	0.057984	−0.205322	−0.031588	−0.002630	0.023180	0.384347
ZRX	0.002812	0.072678	−0.261283	−0.037279	−0.003107	0.038297	0.363916

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