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Rodeo or Ascot: which hat to wear at the crypto race?

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Abstract

This paper sheds light on the dynamics of the cryptocurrency (CC) sector. By modeling its dynamics via a stochastic volatility with correlated jumps (SVCJ) model in combination with several rolling windows, it is possible to capture the extreme ups and downs of the CC market and to understand its dynamics. Through this approach, we obtain time series for each parameter of the model. Even though parameter estimates change over time and depend on the window size, several recurring patterns are observable which are robust to changes of the window size and supported by clustering of parameter estimates: during bullish periods, volatility stabilizes at low levels and the size and volatility of jumps in mean decreases. In bearish periods though, volatility increases and takes longer to return to its long-run trend. Furthermore, jumps in mean and jumps in volatility are independent. With the rise of the CC market in 2017, a level shift of the volatility of volatility occurred. All codes are available on Quantlet.com

Keywords:
Cryptocurrency, SVCJ, Market Dynamics, Stochastic Volatility
JEL C51, C58, G15

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1. Introduction

The rise of the cryptocurrency (CC) sector opens up just as many opportunities as it raises questions. In particular, the functioning of its dynamics is not yet understood: first attempts to characterize this sector by standard time series methods were not successful (cf. Chen et al. (2016)). Especially the the non-stationary nature, frequent jumps, heavy tails and high volatility pose challenges for researchers. This paper attempts to characterize the dynamics of the CC market by modeling them via a stochastic volatility with correlated jumps (SVCJ) model in combination with several rolling windows. Thereby we obtain time series for each parameter. These time series reveal several recurring patterns, which can be interpreted as stylized facts.

There exists a large literature that analyzes sub-areas of the CC sector. Several indices track its dynamics (e.g. Trimborn and Härdle (2018), Elendner (2018), Rivin and Scevola (2018)) and several characteristics have been identified: Zhang et al. (2018) report heavy tails of the return distributions of CCs, the cointegration relationships of the top CCs by market capitalization is highlighted by Keilbar and Zhang (2021) and the high volatility compared to classical assets is emphasized by Härdle et al. (2020), just to name a few.
However, understanding the big picture is still a challenge. A first analysis of the whole sector has been conducted by Chen et al. (2016). By using standard time series methods, they could not capture the heavy tails of the return distributions of the CC sector. Hou et al. (2020) instead show that a model with stochstic volatility and correlated jumps (SVCJ) can meet the challenges of explaining the dynamics of such a non-stationary market. This paper takes up and extends their method by a rolling window approach to broaden the view on the CC sector and to shed light on its dynamics. The SVCJ model, introduced by Duffie et al. (2000), assumes a stochastic movement of the index returns as well as a stochastic movement of their volatility. Also, co-jumps of prices and volatility are considered. We shift several rolling windows of differing sizes

through the data, and at each time step, we estimate the parameters of the SVCJ model in a frequentist manner. Thereby we obtain time series for each parameter, which allow to characterize the dynamics of the CC sector.
In general, parameter estimates are time-varying and sensitive to the window size. However, several recurring patterns are observable that are robust to changes in window size and are supported by k-means clustering of the parameter estimates: First, volatility remains at a low level during bullish CC market movements and rises in times of bearish markets. Besides, when volatility is already on a high level, it needs longer to return to its long-run trend. Second, in times of bullish markets, the size of jumps in mean return decreases, and its volatility stabilizes as well at low levels. Third, a level shift of the volatility of volatility parameter occurred simultaneously to the rise of the CC market at the turn of the year 2017/18.

The remainder of this paper is structured as follows: Section 2 introduces the CRIX, a CC index that is used as a representative of the CC sector in the following analysis. Section 3.1 explains the methodology and estimation approach and Section 3.2 presents the estimation results and their robustness checks. Section 3.4 reveals the dependencies among parameter estimates by k-means clustering and thereby identifies several stylized facts on the CC market dynamics. All codes are available on Quantlet.com

2. Data

2.1. The CRIX - a CRyptocurrency IndeX

To analyze the dynamics of a market segment, one needs a good mapping of it. In the case of the CC market, there exist several indices that track its dynamics. Among them, the CRIX (developed at the Blockchain Research Center at Humboldt University Berlin by Trimborn and Härdle (2018)) is convincing because it optimally solves the fundamental trade-off faced by any index, an accurate representation of the market at a sparse number of constituents. By adjusting the number of constituents dynamically, the CRIX ensures high accuracy in reflecting the CC market dynamics.

$$CRIX_t = \frac{\sum_i P_{it} Q_{i0}}{\sum_i P_{i0} Q_{i0}}$$

where P_{it} refers to the price of constituent i at time t, and Q_{i0} the amount of constituent i at time point 0. At each rebalancing date (every 3 months), the optimal number of constituents is determined by an iterative algorithm: the distance between the log-return of the total market (= all available CCs) and the log-returns of several CC portfolios, consisting of $i = 1, 2, 3, ...$ CCs (sorted from top to down by market capitalization), is computed. The portfolio with the optimal number of CCs is then determined by the AIC: it minimizes the distance of the portfolio to the total market, but penalizes for an increasing number of CCs. Thereby the previously mentioned trade-off (accuracy vs. a sparse number of constituents) is solved optimally.
The period of analysis is restricted to 2015-2020. Index data is obtained from thecrix.de.

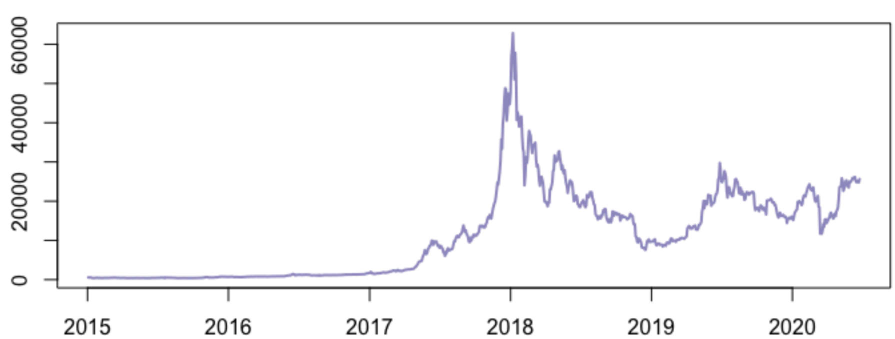


Figure 1: CRIX, a CRyptocurrency IndeX. 01-2015 to 07-2020. Data source: thecrix.de

3. Methodology

Chen et al. (2016) have shown that standard econometric time series methods like ARIMA-GARCH processes cannot capture the dynamics of the non-stationary CC market. Figure 2 displays the fitted residuals of their ARIMA(2,0,2)-GARCH(1,1) model to the CRIX. Hou et al. (2020) however caught the dynamics of the CC market very accurately by using an SVCJ model. The right plot of Figure 2 compares the fitted residuals to the standard normal distribution and confirms the appropriateness of the model.

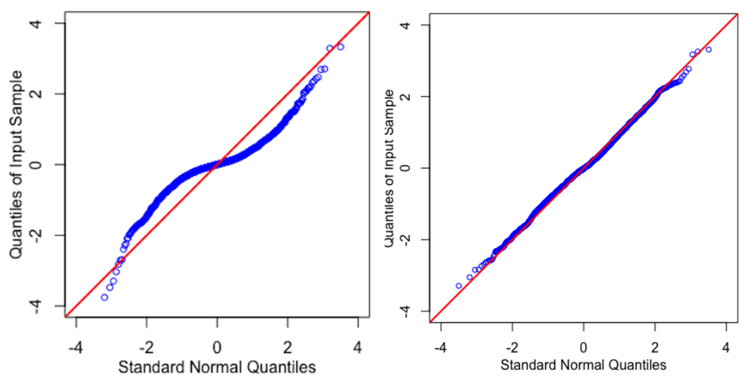


Figure 2: Left: QQ-plot of the fitted residuals of the ARIMA-GARCH process to the CRIX by Chen et al. (2016) using CRIX index data. Right: the residuals of the SVCJ model by Hou et al. (2020).

The following analysis combines the SVCJ model framework of Perez (2018) and a rolling window approach to examine the dynamics and robustness of the CC market. Thereby, time series estimates for each parameter are obtained and some dependencies among them are identified. To start with, a short description of the SVCJ model and its estimation procedure will be given, Section 3.2 presents time series for each parameter and a discussion of their behavior. Section 3.4 illustrates the interdependencies among parameters by visualizing them with k-means clustering.

3.1. SVCJ - Model and Estimation Approach

The SVCJ model, introduced by Duffie et al. (2000) adds a jump process to the stochastic volatility model of Heston (1993). In this setting, the mean index value is modeled by a geometric Wiener process, extended by a jump process:

$$d\log(S_t) = \mu dt + \sqrt{V_t}dW_t^s + Z_t^y dN_t \tag{1}$$

where S_t denotes the index value, μ the trend or drift, V_t the volatility, W_t^s a Wiener process and N_t is a pure jump process with a constant mean-jump arrival rate λ, such that $P(dN_t = 1) = \lambda dt$. The random jump size Z_t^y follows a normal distribution (cf. Equation 3a).

Additionally, the variance is modeled as a stochastic process, allowing for deviations from its long-run trend as described by Cox et al. (2005) and extended by a jump process

$$dV_t = \kappa(\theta - V_t)dt + \sigma_v\sqrt{V_t}dW_t^v + Z_t^v dN_t \tag{2}$$

where κ refers to the speed of convergence of the volatility towards its trend θ, σ_v denotes the volatility of the volatility parameter and W_t^v is a Wiener process that is correlated to W_t^s at rate ρ, $\text{Cov}(dW_t^s, dW_t^v) = \rho dt$. The SVCJ model differs from the previously mentioned Cox-Ingersoll-Ross model by allowing for correlation between the jump size of the mean trend and the jump size of the volatility:

$$Z_t^y \mid Z_t^v \sim N\left(\mu_y + \rho_j Z_t^v, \sigma_y^2\right) \tag{3a}$$

$$Z_t^v \sim \text{Exp}(\mu_v) \tag{3b}$$

where Exp denotes the exponential distribution, which ensures that jumps in volatility are positive.

Bayesian Estimation Procedure

The estimation procedure follows a Bayesian approach: we are interested in the distribution of the parameters Θ and covariates X given the CRIX index data Y.

$$p(\Theta, X \mid Y) \propto p(Y \mid \Theta, X)p(X \mid \Theta)p(\Theta)$$

where $\Theta = \{\mu, \kappa, \theta, \sigma_v, \rho\}$ and $X = \{V_t, Z_t^y, Z_t^v, N_t\}$. An implementation framework for the SVCJ model is available from Perez (2018). For the code, see Quantlet.com. In this framework, we use the Metropolis-Hastings algorithm to obtain Markov chains that converge to the posterior distribution as the number of iterations increases. For a discussion of the burn-in rate and settings of the prior distributions, please refer to Perez (2018). Several checks for autocorrelation of parameter estimates along the iterations of the Metropolis-Hastings algorithm are there discussed as well.

Implementation

The empirical calibration of equation 1 and 2 is realized by Euler discretization, rewriting it as

$$Y_t = \mu + \sqrt{V_{t-1}}\varepsilon_t^y + Z_t^y J_t \tag{4a}$$

$$V_t = \alpha + \beta V_{t-1} + \sigma_v \sqrt{V_{t-1}}\varepsilon_t^v + Z_t^v J_t \tag{4b}$$

where $Y_{t+1} = \log(S_{t+1}/S_t)$ denotes the log return. $\varepsilon_t^y, \varepsilon_t^v$ are discrete versions of the Wiener processes, distributed as $N(0,1)$ and correlated at rate ρ. The volatility is calibrated by $\alpha = \kappa\theta$ and $\beta = 1 - \kappa$. The jump processes are implemented by jump sizes Z_t^y and Z_t^v, following the distributions of Equation 3b and a Bernoulli random variable J_t, with $P(J_t = 1) = \lambda$.

3.2. Dynamics of the Cryptocurrency Market

As we are interested in the dynamics of the CC sector, we want to examine whether it is possible to precisely characterize this sector by parameter estimates of the above-described model. To do so, we apply two robustness measures: firstly, we conduct a rolling window approach, which yields time series estimates for each estimated parameter. Optimally, parameter estimates would be time-invariant, which would allow a precise description of the CC sector. Secondly, we control for the window sizes, to see whether the estimates vary with the choice of the window size. Time series estimates for each parameter are presented in Figure 3 (window size: 150 days) and Figure 4 (window sizes 150, 300 & 600 days).

The time series estimates in Figure 3a and 3b are obtained by shifting a rolling window of 150 days through the data of the period 07/2014 to 07/2020. Estimates are fluctuating a lot, which is a typical issue in Bayesian estimation as they are sensitive to changes in the input data. The fluctuating lines are parameter estimates, the solid lines in their center are moving averages of 20 days. In the next paragraphs, a discussion about i) the trend, ii) volatility and iii) jumps is conducted.

Trend. The estimates are mainly behaving as expected: μ, the trend of the return process (cf. Equation 4a), moves parallelly to the CRIX (cf. Figure 1). Especially the growth in 2017 and the drop in 2018 are well observable. However, the trend is always one step ahead of the index. This is due to the forward-looking nature of the estimation procedure: the rolling window reacts early to changes in future index values.

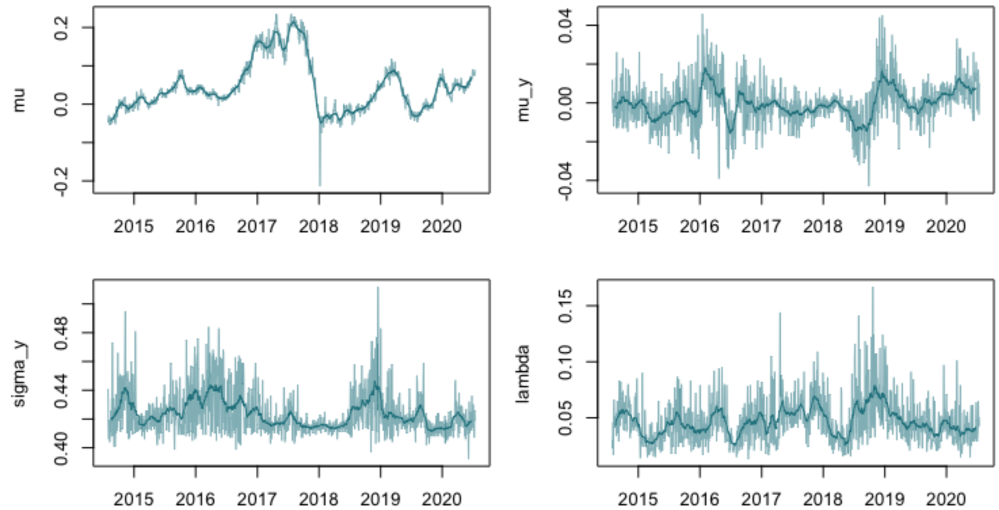
Volatility. The coefficients of volatility (α and β, see Equation 4b) reveal interesting patterns (cf. Figure 3b): α oscillates at a low level until the end of 2017, then suddenly jumps to a high level (α =0.5) at the turn of 2017/2018. A similar pattern occurs at the end of 2019: less strongly, but in the same direction, α rises again. It is interesting to note that the rise in α always correlates with downturns in the CRIX: when the CRIX falls, the volatility level rises, or in other words: when the CC market is bearish, volatility is high. An alternative interpretation is possible by the construction of $\alpha = \theta\kappa$: when the market is bearish, the volatility takes longer to return to its long-run trend (i.e. κ increases) or the long-run volatility trend θ climbs up to a higher level.

β, the coefficient of lagged volatility V_{t-1}, seems to be correlated as well to the trend of the CC market: before the rise in 2017, its values oscillate around -0.4, they stagnate at -0.2 throughout 2017, though towards the end of 2017 they drop to -0.8. The dynamics of β allow for several interpretations: volatility detaches from its lagged values in times of rising markets (β close to zero througout 2017) and quickly returns to its long-run trend (since β is reversely related to the reversion rate towards the long-run trend: $\beta = 1 - \kappa$). In bearish periods (market downturn), the values of β get closer to -1 and α increases, which indicates that volatility takes longer to return to its long-run level.

Jumps. The jump sizes (μ_v and μ_y) seem to interact with the overall CC market dynamics: in bullish periods, μ_y stabilizes at low levels and the volatility of jumps in mean σ_y stabilizes as well. Even its estimates do not fluctuate a lot. The jump arrival rate λ does not reveal any specific pattern and its values change only within a small interval (note that one would need scaled values to interpret the magnitude of the fluctuations).
In contrast to the study of Duffie et al. (2000), there is almost no correlation between the volatility of the mean trend and the volatility of the volatility, as the ρ estimates are close to zero. The estimates indicate that in certain intervals (at the end of 2015 and 2016) there are interactions between these parameters, though there is no overall effect observable.

To check whether the size of the rolling window has an impact on the parameter estimates, Figure 4 presents estimates for several rolling windows of size 150, 300, and 600 days. The three time series in each figure depict moving averages of 20 days for each window size.

The three time series are not identical and the estimates fluctuate a lot over time and are sensitive to the size of the rolling windows. The bigger the window, the more temporary fluctuations are smoothed, which is especially protruding for the parameters μ, α, ρ and σ_y. However one can observe common patterns



(a) Parameters $\mu, \mu_y, \sigma_y, \lambda$

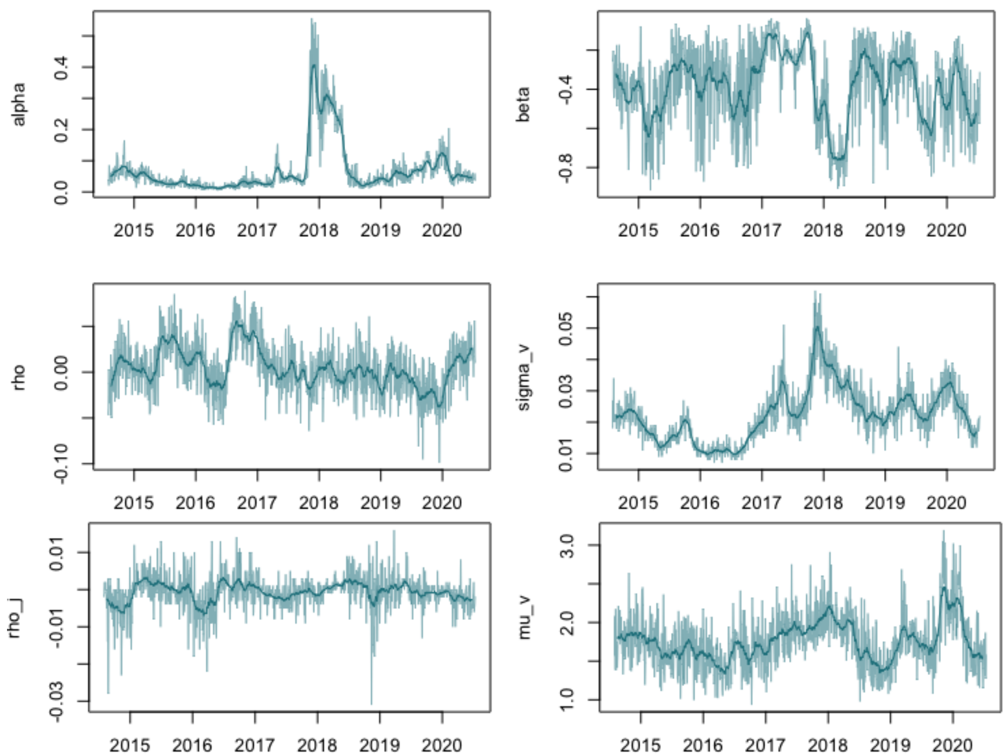
Figure 3: Parameter estimates of the SVCJ model with a rolling window of 150 days. The fluctuating lines represent actual parameter estimates, the solid lines in their center depict moving averages of 20 days. SVCJrw_graph_parameters

among the three time series:

Volatility. The time series of the parameters for volatility show matching dynamics. The dynamics of α are very robust and its three time series overlap almost over the entire period of analysis. Only around the turn of 2017/18 does α skyrocket, to varying degrees for each window size. This suggests that volatility is high when the market is falling.

Similarly, the time series of β converge at a level close to Zero throughout 2017. This confirms that volatility gets detached from its lagged values when the market is bullish. By contrast, when there is no clear market direction or when the market is falling, β deviates from Zero, i.e. volatility needs some time to return to its long-run trend and persists in its former state.

Another finding relates to the volatility of volatility σ_v: it seems that a regime change took place around the turn of the year 2017/2018. Until 2017, σ_v fluctuated at low levels and increased strongly simultaneously with the growth



(b) Parameters $\alpha, \beta, \rho, \sigma_y, \rho_j, \mu_v$

Figure 3: (cont.) Parameter estimates of the SVCJ model with a rolling window of 150 days. The fluctuating lines represent actual parameter estimates, the solid lines in their center depict moving averages of 20 days. SVCJrw_graph_parameters

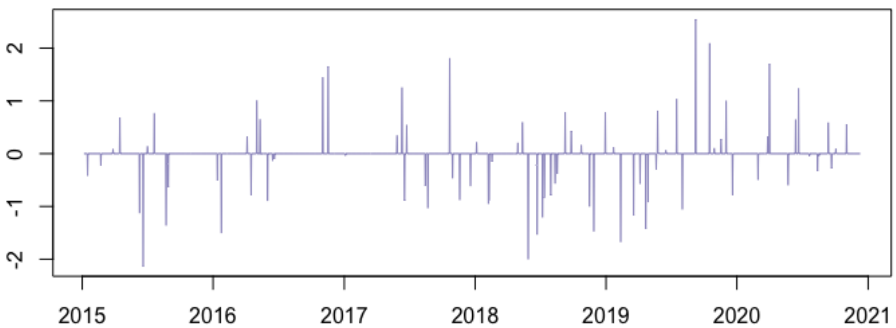
of the CC sector. After 2018, volatility remained at this elevated level. Based on the CRIX time series alone, one cannot explain this level shift, but it stands to reason that the opportunities in the CC market have attracted many investors since 2018, which may have increased applications of CCs as well as speculation, thereby increasing volatility.

Jumps. In the previous section 3.2, we observed that the size of jumps in mean μ_y declined to zero whenever the market is rising. Interestingly, this finding can be confirmed: all three time series converge simultaneously towards zero between 2017 and 2018. And not only the size of the jumps, but also their volatility decreases rapidly when the market is rising: one can wonderfully observe how the estimates of the volatility of the jumps σ_y decrease in 2017. Due to the forward-looking nature of rolling windows, estimates respond early to market changes. Weakened, but in the same direction, a convergence of the time series can be observed for the second half of 2019.

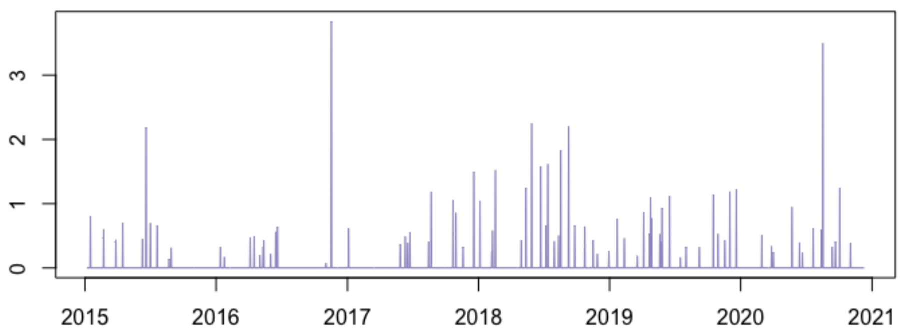
3.3. Comparison to classical assets

Do the dynamics of the CC sector differ from other asset classes or currencies? Unfortunately, up to the knowledge of the authors, there does not exist a comparable study that follows a similar methodological approach. However, in their influential article, Eraker et al. (2003) show that the SVCJ model is appropriate for modeling the dynamics of the S&P 500 index and the NASDAQ 100 index. In contrast to the present analysis, they estimate the SVCJ model once for the whole period of analysis (1980-1999) and thereby obtain one estimate for each parameter (the mean of the posterior distribution). As we have proven in the previous section, such an analysis contains many pitfalls, because parameter estimates vary over time and depend on the time horizon. A comparison of their results (regarding the S&P 500 and the NASDAQ 100, 1980-1999) and ours (regarding the CRIX, 2015-2020) is therefore not possible. However, one remark is interesting: Eraker et al. (2003) emphasize the importance of jumps in volatility to explain sudden price slumps of their indices during market distress. For the CC sector, we obtain similar results: as can be seen in Figure 5, the size and intensity of jumps in prices and volatility increases during market downturns. Since late 2017 (= the local peak of the CC sector), the frequency of jumps in price as well as in volatility increased. This finding is in line with the report of Chaim and Laurini (2018): they argue that the increase in jumps is caused by the higher attention and popularity of the CC sector.

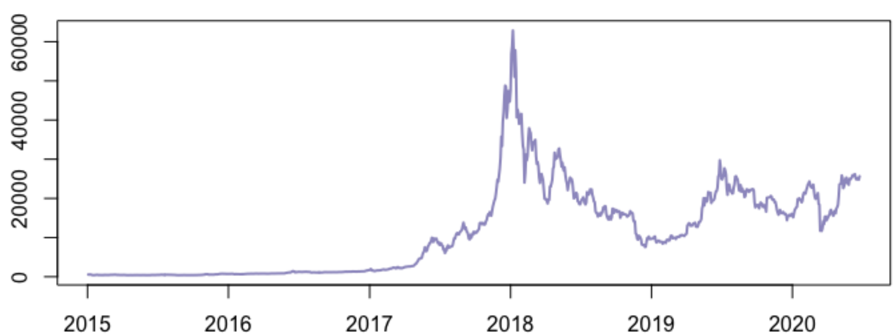
Figure 4: Paramter estimates for several window sizes (150, 300 & 600 days). SVCJrw_graph_parameters



(a) Jumps in returns



(b) Jumps in volatility



(c) the CRIX

Figure 5: The jumps in returns (a) and volatility (b) as identified by the SVCJ model and based on the entire period of analysis 2015-2020.

3.4. Cluster Analysis

Even though it is not possible to precisely characterize the CC sector by robust parameter estimates, some dependencies among the parameters were observable. Since the estimated time series are not independent, statistical inference is limited. The discussion of Section 3.2 has already introduced some relationships between trend, volatility and jumps; in this section we will extend the analysis by an examination of clusters. The clustering of parameters is not intended to show causal relationships, but merely to illustrate certain patterns. Especially when the market points in a specific direction, some parameters stabilize.

As a first example shall serve the correlation between the trend μ and the volatility parameter β. Figure 6 presents k-means clusters for this parameter pair. The elbow method yields the optimal number of $k = 3$ clusters. Below the clustered pair of parameters is the CRIX colored in the same colors as the clusters, which reveals the time dimension of the data and its link to the overall market dynamics. Note that for clustering, variables were scaled.

The clustering reveals interesting connections: there seems to be a strong relationship between the two parameters β and μ. This is impressive since the underlying CRIX data is highly non-stationary. An increase in trend is accompanied by an increase in β, i.e. β converges to zero and the current volatility breaks away from its previous values. By contrast, when the trend is decaying, β declines as well and volatility becomes more persistent. Similar patterns have been obtained by k-expectiles clustering (cf. Wang et al. (2021)).

An explanation for such an observation is difficult since the CC sector is still detached from the real economy. Some authors even argue (most prominently Yermack (2015)) that CCs should be seen as an asset class instead of a currency (since the use of CCs as a medium of exchange, storage of value, and units of account is still limited (cf. Marthinsen (2020))). This reduces CCs to speculative assets. The speculative view on CCs may deliver an explanation for the patterns between μ and β: when the *momentum* (cf. Jegadeesh and Titman (1993), Elendner (2018)), the difference between today's price of an asset and its price some days ago, is positive, investors jump on the train and the price of a CC goes straight up without fluctuating a lot. Similar behavior has been reported by Caginalp and Desantis (2011) for the price dynamics of stocks. "The trend is your friend" (Caginalp and Desantis (2011)), a famous Wall Street saying, summarizes precisely these patterns: returns are steadily positive and the market moves in one direction without fluctuating a lot. Thus, the rise of the CC sector in 2017/18 is partially driven by the growth in returns.

Another example of the interactions among parameters is presented in Figure 7. The volatility of jumps in returns σ_y and the volatility of volatility parameter σ_v seem to be reversely related: the volatility of jumps σ_y is low, when the volatility of volatility parameter σ_v increases, and vice versa. The lower graph in Figure 7 illustrates the time dimension as well as the impact of the market dynamics on this correlation: Interestingely, high volatllity of jumps in returns σ_y occurs especially when the market is not pointing in a specific direction. In such periods, volatility of volatiliy σ_v stays at low levels. This indicates that CC index dynamics in such periods are driven by jumps instead of volatility. When the market is overheated, volatility of volatility σ_v is high. Interestingely, σ_v started to increase before the CC sector reached its peakin 2017/18. Furthermore, we observe high volatility of volatility σ_v and low volatility of jumps in returns σ_y for periods of market downturns. This finding is in line with the jumps reported in Figure 5a : between 2018 and 2019, jumps in returns are mainly negative. To sum up, this indicates that price slumps are driven by both, high volatility and negative jumps in returns.

4. Conclusion

The present paper examined the crypto sector as a whole and shed light on its dynamics. By combining an SVCJ model with a rolling window approach, we obtain time series for each parameter of the model. Thereby we identify several recurring patterns: first, volatility remains at a low level during bullish CC market movements and rises in times of bearish markets. In addition, when

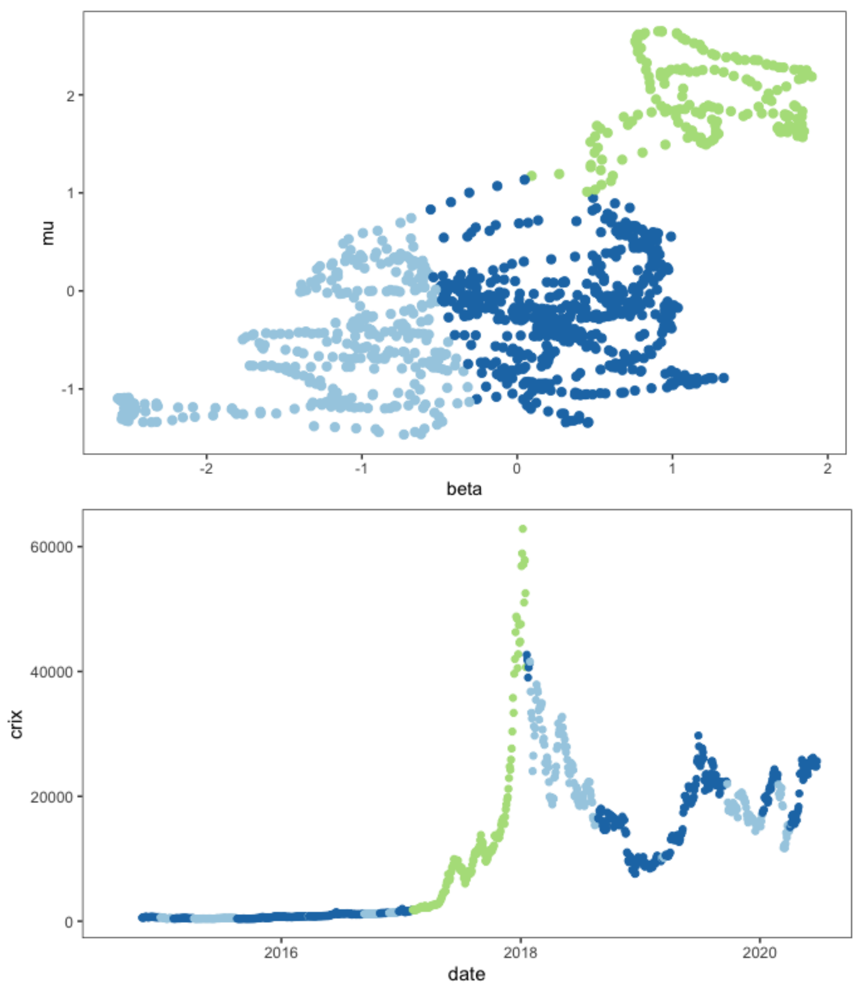


Figure 6: Top: k-means clusters of parameter estimates μ and β, $k = 3$.

Bottom: the CRIX coloured by the respective clusters.

SVCJrw_clustered_parameters

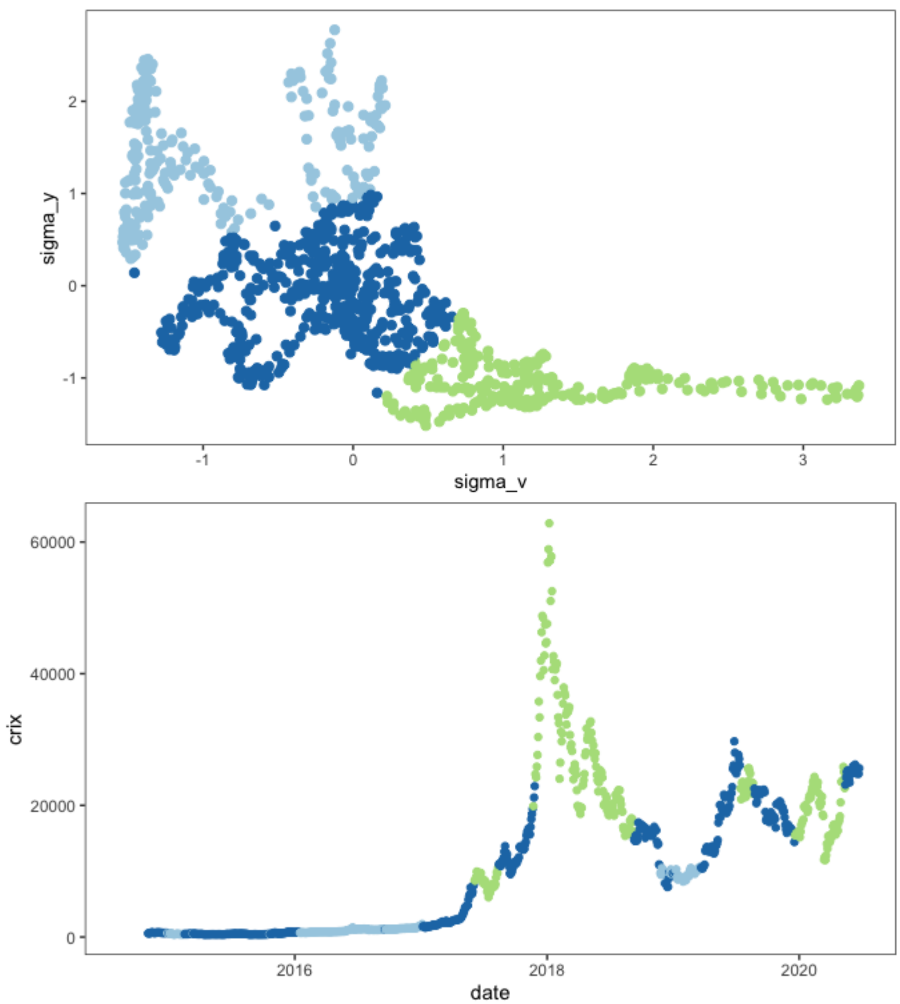


Figure 7: Top: k-means clusters of parameter estimates σ_y and σ_v, k = 3.
Bottom: the CRIX coloured by the respective clusters. SVCJrw_clustered_parameters

volatility is already on a high level, it needs longer to return to its long-run trend. Second, in times of bullish markets, the size of jumps in mean return decreases, and its volatility stabilizes as well at low levels. Third, a level shift of the volatility of volatility parameter occurred simultaneously to the rise of the CC market at the turn of the year 2017/18. Finally, the jumps in mean and in volatility seem to be independent. The findings are robust to changes in the window size and confirmed by clustering of the parameters.

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