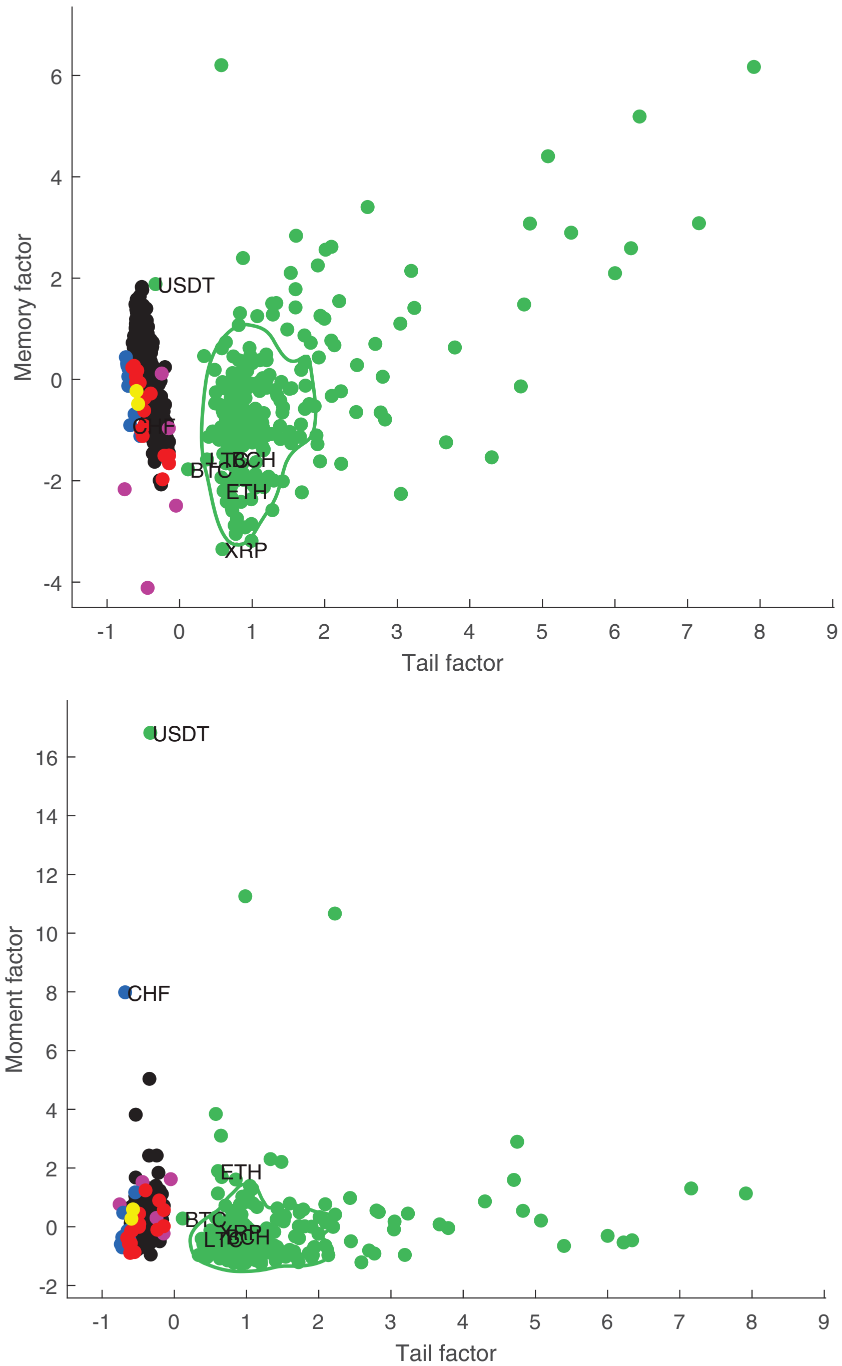

Figure 4. Assets projections on the factors space: (a) tail and memory factors; (b) tail and moment factors. SFA_Cryptos

of the 24 columns, N_S is the number of projection directions giving perfect classification when S is used, P_S is the percentage of the projection directions examined that provided perfect classification, while $\min I, \max I$ are the minimum and the maximum index I value for perfect classification, respectively. The critical value for significance of the I index for $\alpha = 5\%$ and $n = 906$ is 0.0108. The order of the 24 indicators is as the order of rows in Table 2.

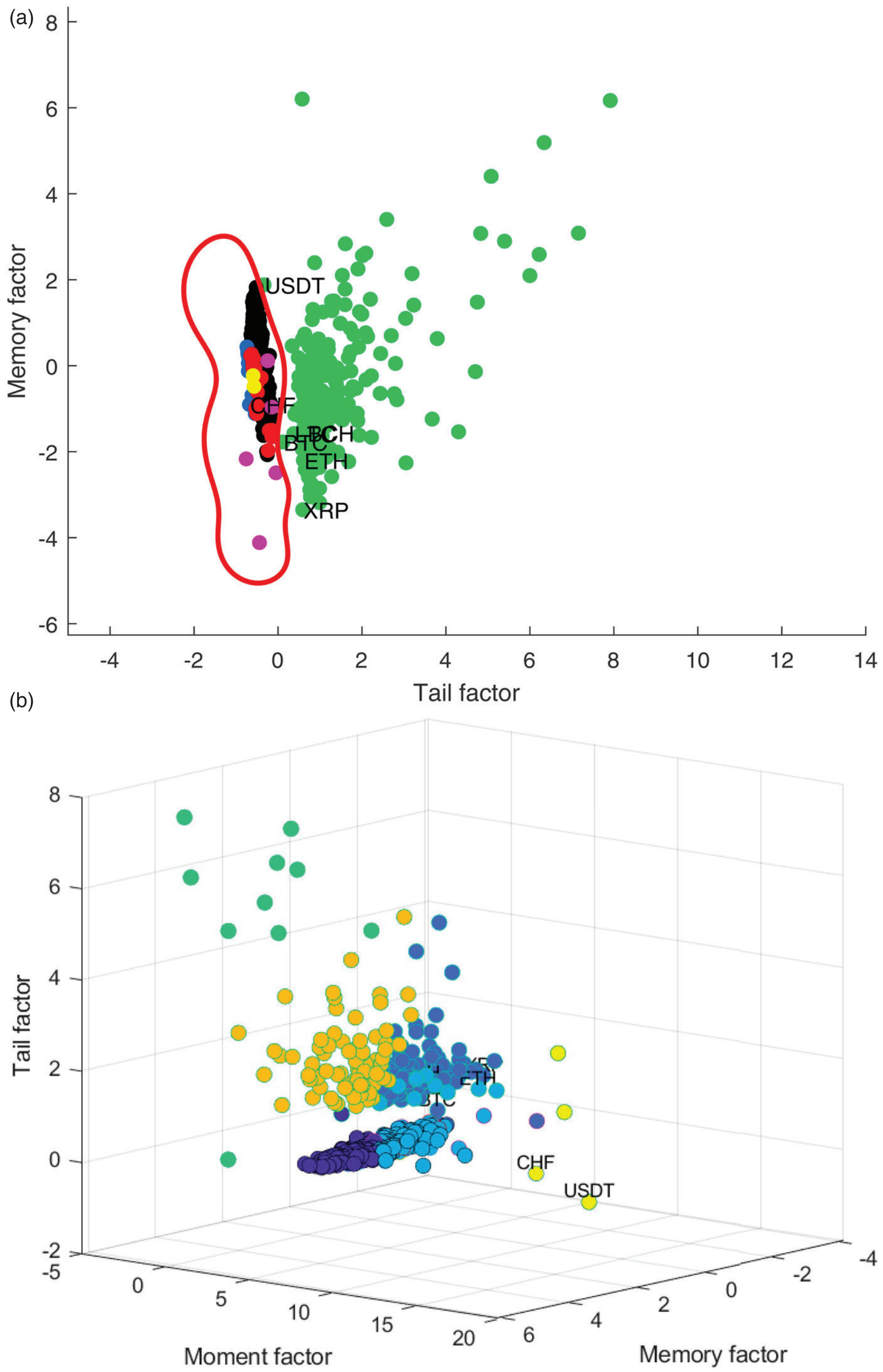

Figure 5. Assets classification: (a) Support Vector Machines; (b) K-means. SFA_Cryptos

In the following, we present the results of the MVCS method for perfect classification of cryptocurrencies from the other assets. For all five other asset structures (stocks, exchange rates, commodities, bonds and real estate indexes), none of the combinations of M and S examined below provided perfect classification.

Table 4. Results of the MVCS method.

M	S	N_S	P_S	min I	max I
3	1–12	12	0.007%	0.043	0.096
6	1–12	181618	0.050%	0.028	0.096
3	13–24	0	0	n/a	n/a
6	13–24	0	0	n/a	n/a

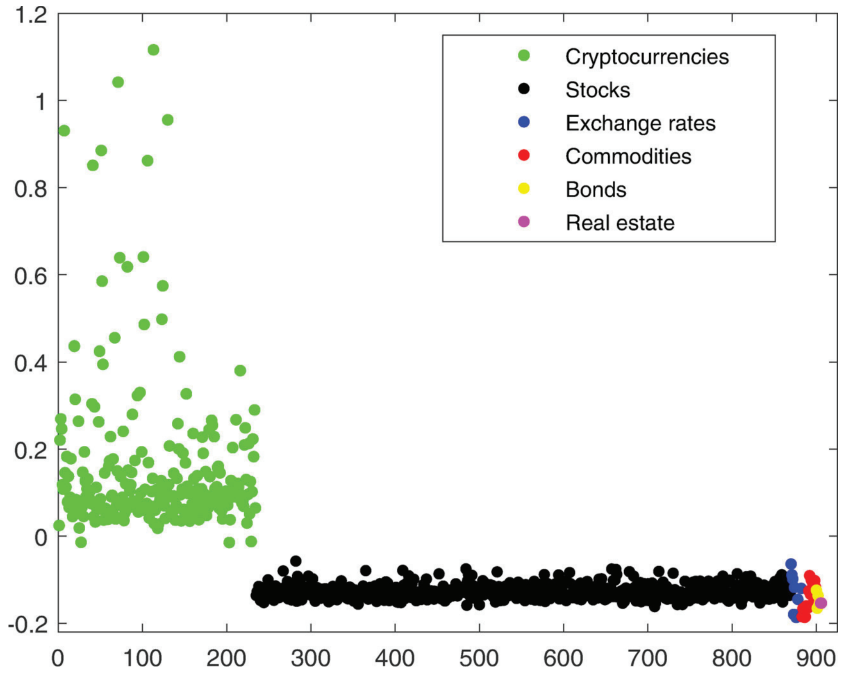

Figure 6. Projections of a subset of the data (the first 12 indicators) for $M = 6$ on the projection direction that gave the largest index value among those that gave perfect classification of the cryptocurrencies. VCS_Cryptos

Due to processing power constraints, we first split the data in two subsets: the first subset consists of columns/indicators 1–12 of matrix $\mathscr{X}_T$ and the second includes columns/indicators 1–12 of matrix $\mathscr{X}_T$. For the same reason, projection directions are used only for $M = 3, 6$ (the number of projection directions used is $M^{d-1} = M^{12-1} = M^{11}$ for each case). Results are shown in Table 4.

The projection direction that provided the largest index value for columns 1–12 (obtained for $M = 6$) is: $(-0.062, 0, 0, -0.108, 0.217, -0.433, -0.866, 0, 0, 0, 0, 0)$. The projected values in this case are shown in Figure 6. As shown in this Figure, the projected values of all cryptocurrencies are greater than the projected values of all other assets, and a vertical hyperplane in the middle of the gap will separate cryptocurrencies from the other assets in the space of the data. Therefore, separation is evident. Also, all 181618 projection directions that achieved perfect classification provided also a statistically significant index values for the normal model.

These results indicate that columns 1–12 are more important for separation of cryptocurrencies than columns 13–24, since only the former confirm separation. Following this, we next applied the MVCS method to columns 1–12, which we further split to columns 1–6 and 7–12. Here, we used $M = 3, 6, 9, 12, 15$ and 18. For columns 7–12, no $M-$value provided perfect classification for the cryptocurrencies. On the other hand, for columns 1-6 and $M = 9$, 12, 15 and 18, cryptocurrencies were completely separated from all the other assets; see Table 5. Therefore, we can conclude that the most important columns for complete separation are the first six.

Next, the first six indicators/columns are further examined. The MVCS method is applied to all six quintets (each derived by omitting in turn one of the six columns). Higher values of M are used ($M = 18$, 24 and