EFFICIENT FRONTIER ??

"Wide diversification is only required when investors do not understand what they are doing."

- Warren Buffett

Diversification

MVT

Transaction costs

brokers' commissions and spreads

TOO IDEAL

Unrealistic

How to pick a small number of stocks to build a profitable portfolio ???

Cardinality Constrained Portfolio Selection

Under supervision of **Prof. LI Duan**

ZHOU YUNXIU

ELITE STREAM GRADUATION THESIS

3 December 2016

CONTENTS

»

01 Background

Models, theories >>> literature review

- Expected return:

$$\mathrm{E}(R_p) = \sum_i w_i \, \mathrm{E}(R_i)$$

where R_p is the return on the portfolio, R_i is the return on asset *i* and w_i is weighting of component asset i (that is, the proportion of asset "i" in the portfolio).

- Portfolio return variance:

$$\sigma_p^2 = \sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij},$$

where ρ_{ij} is the correlation coefficient between the returns on assets *i* and *j*. Alternatively the expression can be written as:

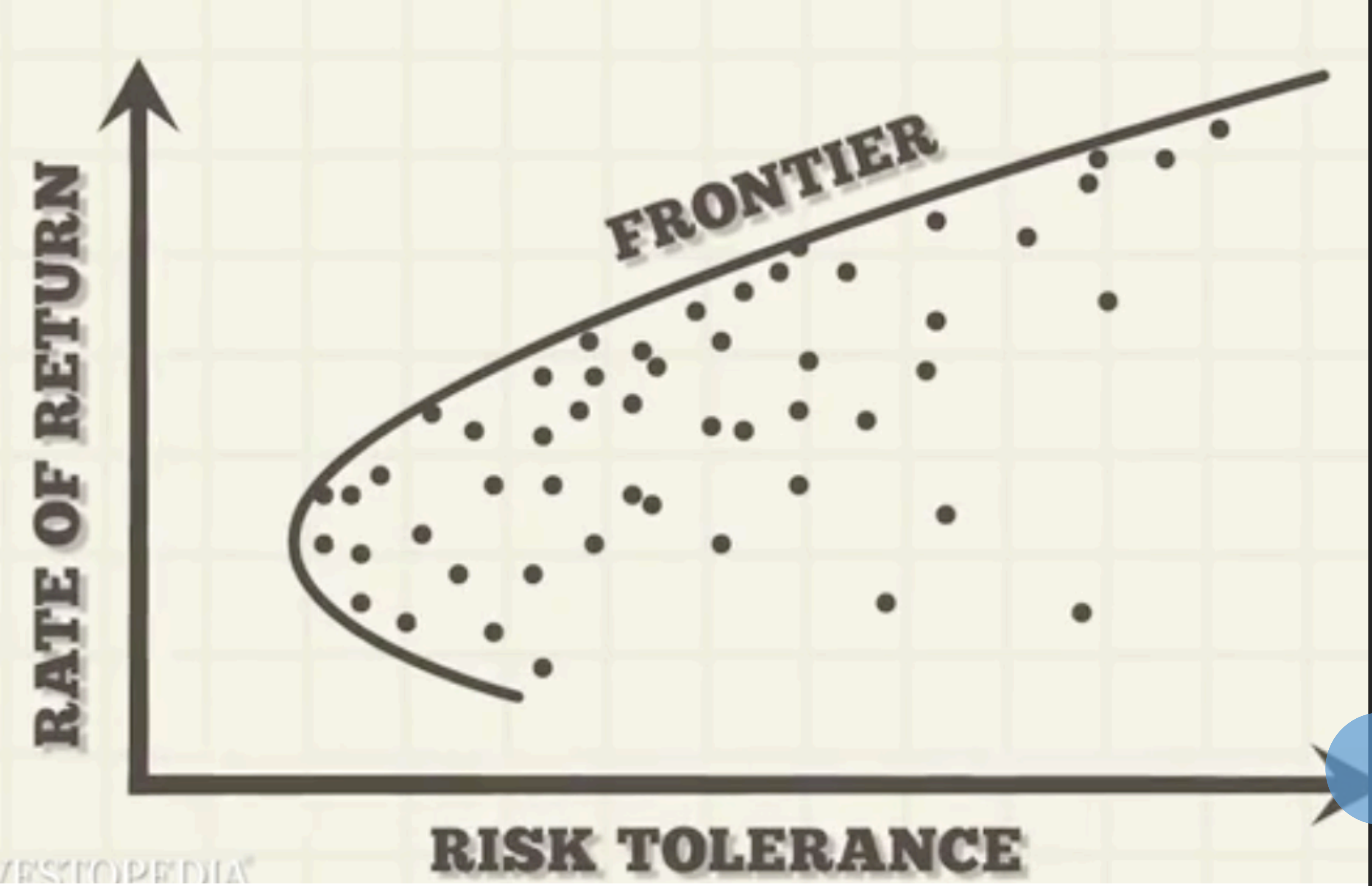
$$\sigma_p^2 = \sum_i \sum_j w_i w_j \sigma_i \sigma_j \rho_{ij},$$

where $\rho_{ij} = 1$ for *i*=*j*.

Model

Markowitz Mean-Variance Portfolio Theory

"Investors always allocate in ***all*** risky assets available in the market to fully diversify away risks"



Model

Markowitz Mean-Variance Portfolio Theory

"Investors always allocate in ***all*** risky assets available in the market to fully diversify away risks"

Problem Formulation

Generalized Markowitz's model

$$\min_{x} x'\boldsymbol{Q}x$$
$$\text{s.t. } \mathbf{r}'\text{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$

VS

Cardinality constrained mean-variance portfolio optimization

$$\min_{x} x'Qx$$
$$\text{s.t. } \text{r}'\text{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$0 \leq x_i \leq 1$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$for\ i\ from\ 1\ to\ n$$

Existing methodology

The literature in tackling CCMV in the last two decades can be roughly classified into two categories, **direct** and **heuristic** algorithms.

Kening Jiang

Factor Model Based Clustering Approach for Cardinality Constrained Portfolio Selection

Gao & Li

Adopting relaxation schemes & invoking branch-and-bound algorithms
to attain an optimality.

Factor Model Based Clustering Approach

Mind flow of **Heuristics**

01

Transformation

Characterizing risky assets by factor model

02

Grouping

Grouping risky assets using clustering algorithm

03

Selection

Identifying representative(s) from individual groups & forming the optimal portfolio

» 02 Detailed Process

Data prep & exploration >>> Heuristics >>> Optimization(direct)

Data Exploration

Hang Seng Index Components

Data source: Yahoo Finance

Periodicity: weekly

Since 2000

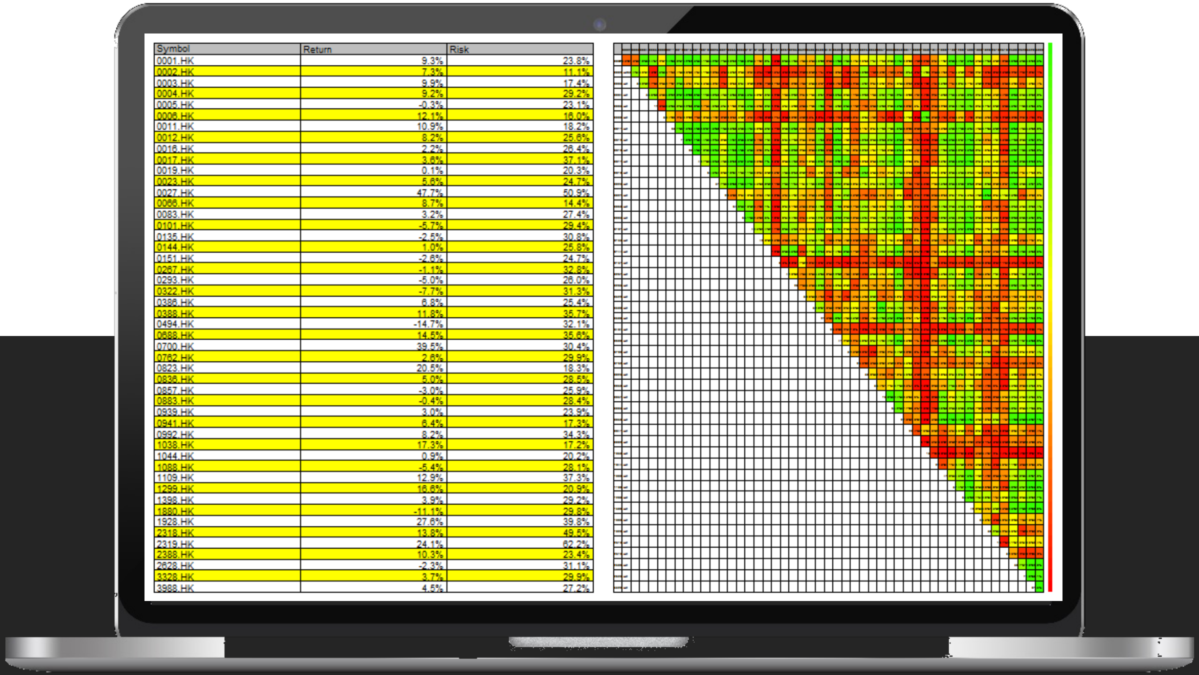
Risk-free rate

Data source: Bloomberg

Weekly HIBOR rate

Factors

- Hang Seng Composite Industrial Index
- Fama–French factors



Symbol	Return	Risk
0001.HK	9.3%	23.8%
0002.HK	7.3%	11.1%
0003.HK	9.9%	17.4%
0004.HK	9.2%	29.2%
0005.HK	-0.3%	23.1%
0006.HK	12.1%	16.0%
0011.HK	10.9%	18.2%
0012.HK	8.2%	25.6%
0016.HK	2.2%	26.4%
0017.HK	3.6%	37.1%
0019.HK	0.1%	20.3%
0023.HK	5.6%	24.7%
0027.HK	47.7%	50.9%
0066.HK	8.7%	14.4%
0083.HK	3.2%	27.4%
0101.HK	-5.7%	29.4%
0135.HK	-2.5%	30.8%
0144.HK	1.0%	25.8%
0151.HK	-2.6%	24.7%
0267.HK	-1.1%	32.8%
0293.HK	-5.0%	26.0%
0322.HK	-7.7%	31.3%
0386.HK	6.8%	25.4%
0388.HK	11.8%	35.7%
0494.HK	-14.7%	32.1%
0688.HK	14.5%	35.6%
0700.HK	39.5%	30.4%
0762.HK	2.6%	29.9%
0823.HK	20.5%	18.3%
0836.HK	5.0%	28.5%
0857.HK	-3.0%	25.9%
0883.HK	-0.4%	28.4%
0939.HK	3.0%	23.9%
0941.HK	6.4%	17.3%
0992.HK	8.2%	34.3%
1038.HK	17.3%	17.2%
1044.HK	0.9%	20.2%
1088.HK	-5.4%	28.1%
1109.HK	12.9%	37.3%
1299.HK	16.6%	20.9%
1398.HK	3.9%	29.2%
1880.HK	-11.1%	29.8%
1928.HK	27.6%	39.8%
2318.HK	13.8%	49.5%
2319.HK	24.1%	62.2%
2388.HK	10.3%	23.4%
2628.HK	-2.3%	31.1%
3328.HK	3.7%	29.9%
3988.HK	4.5%	27.2%

Symbol	Return	Risk
0001.HK	9.3%	23.8%
0002.HK	7.3%	11.1%
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0016.HK	2.2%	26.4%
0017.HK	3.6%	37.1%
0019.HK	0.1%	20.3%
0023.HK	5.6%	24.7%
0027.HK	47.7%	50.9%
0066.HK	8.7%	14.4%
0083.HK	3.2%	27.4%
0101.HK	-5.7%	29.4%
0135.HK	-2.5%	30.8%
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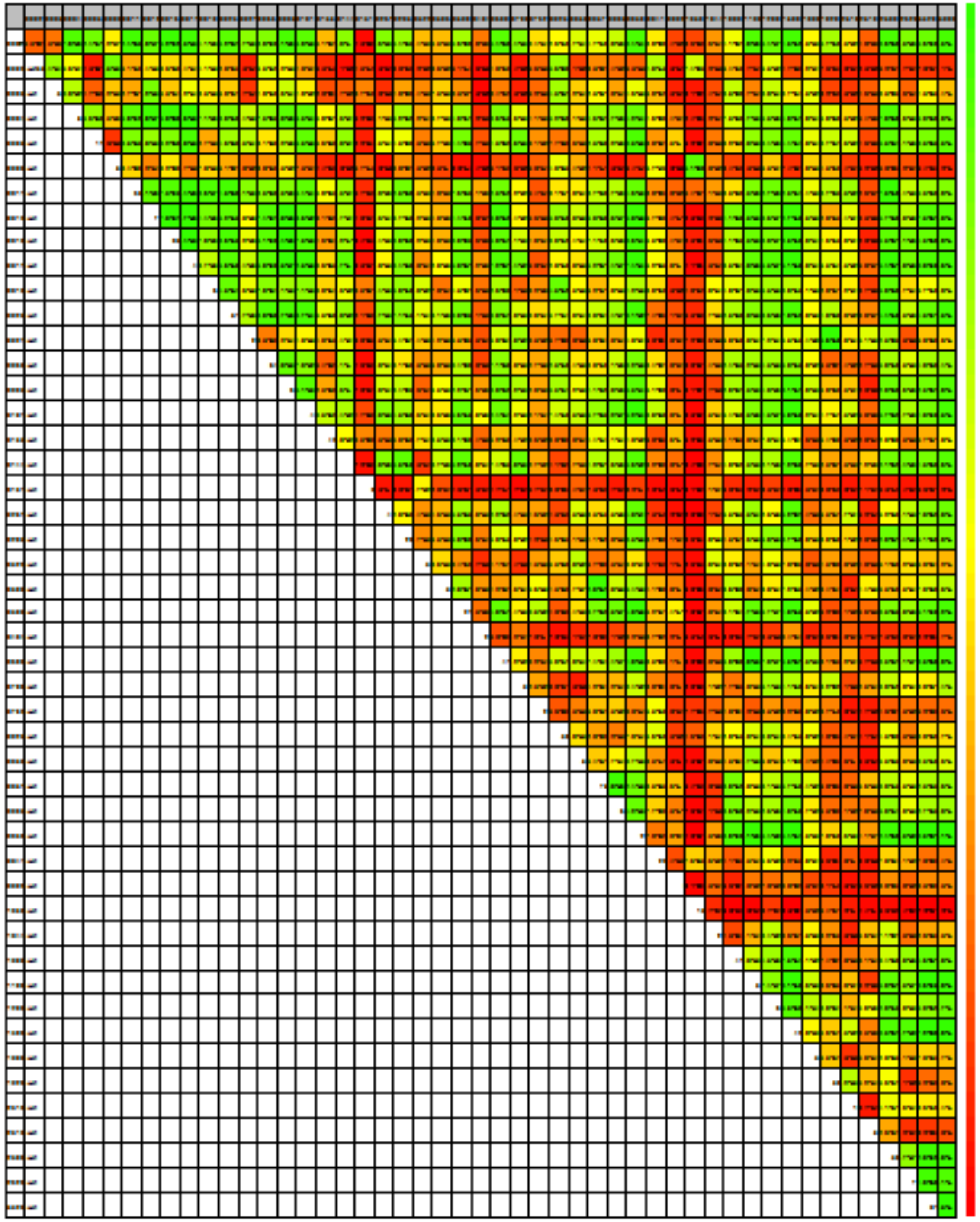


Step1: Transformation

Characterizing risky assets by factor model

$$r_i = a_i + \sum_{j=1}^{m} b_{ij} f_j + \epsilon_i, \quad i = 1, 2, \ldots, n,$$

Linear Regression

Find loading coefficients of each risky assets

multi-Dimensional vectors

each risky asset is projected into multi-Dimensional vectors.

Step1: Transformation

Characterizing risky assets by factor model

.0 Correlation

How individuals returns are related to that of other assets

.1 Industry

How individuals returns are related to industrial sectors

.2 Fama-French

How individuals returns are related to the market, company size, company Price-to-Book Ratio

FM.0: Factor model using covariance matrix

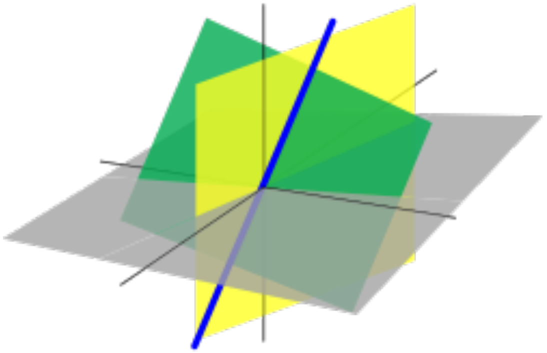
$$r_i = a_i + \sum_{j=1}^{m} b_{ij} f_j + \epsilon_i, \quad i = 1, 2, \ldots, n,$$

Factors

Individual stock returns

49 in total

	0001.HK	0002.HK	0003.HK	0004.HK	0005.HK	0006.HK	0011.HK	0012.HK	0016.HK	0017.HK	0019.HK
0001.HK	1.0000000	0.4206938	0.3155842	0.5749272	0.43654360	0.32777751	0.55435107	0.5875242	0.6259690	0.5783089	0.5369763
0002.HK	0.4206938	1.0000000	0.4602480	0.4051255	0.27674911	0.52577133	0.45970681	0.3616746	0.3995495	0.3369651	0.3893159
0003.HK	0.3155842	0.4602480	1.0000000	0.3478491	0.26999847	0.39686356	0.38860636	0.4038291	0.3559697	0.3261433	0.3526009
0004.HK	0.5749272	0.4051255	0.3478491	1.0000000	0.41618015	0.27420512	0.54671580	0.5780330	0.6081915	0.5822544	0.5167264
0005.HK	0.4365436	0.2767491	0.2699985	0.4161801	1.00000000	0.23154067	0.46581221	0.3934303	0.4356302	0.4381724	0.4080581
0006.HK	0.3277775	0.5257713	0.3968636	0.2742051	0.23154067	1.00000000	0.35495411	0.2944021	0.2940283	0.2617194	0.3194495
0011.HK	0.5543511	0.4597068	0.3886064	0.5467158	0.46581221	0.35495411	1.00000000	0.5000767	0.5553767	0.5177941	0.5266005
0012.HK	0.5875242	0.3616746	0.4038291	0.5780330	0.39343025	0.29440206	0.50007668	1.0000000	0.6475228	0.6041713	0.4822930
0016.HK	0.6259690	0.3995495	0.3559697	0.6081915	0.43563022	0.29402834	0.55537667	0.6475228	1.0000000	0.6662638	0.5312272
0017.HK	0.5783089	0.3369651	0.3261433	0.5822544	0.43817240	0.26171936	0.51779413	0.6041713	0.6662638	1.0000000	0.5050561
0019.HK	0.5369763	0.3893159	0.3526009	0.5167264	0.40805805	0.31944949	0.52660051	0.4822930	0.5312272	0.5050561	1.0000000
0023.HK	0.5431759	0.4685364	0.3871269	0.5360421	0.44694398	0.34787035	0.63906201	0.4941708	0.5302632	0.4927345	0.5287356
0027.HK	0.4586292	0.2616449	0.2396220	0.4686252	0.36572992	0.19732505	0.44958935	0.4191738	0.4235740	0.4130023	0.4091477
0066.HK	0.5018967	0.4738187	0.4050150	0.4662514	0.37169811	0.35924454	0.52689361	0.4506846	0.4709856	0.4453303	0.4907156
0083.HK	0.5943718	0.4274930	0.3661301	0.5876640	0.43213608	0.31273354	0.52749130	0.6308389	0.6987685	0.6642624	0.5093953
0101.HK	0.5603976	0.3938248	0.3833570	0.5716982	0.41602587	0.31599528	0.55188389	0.5612038	0.5963671	0.5731155	0.5050322
0135.HK	0.3904098	0.2750590	0.2411481	0.3963267	0.39219906	0.21562186	0.43045563	0.3629927	0.3988020	0.3927398	0.3869242
0144.HK	0.4456977	0.2950564	0.2793540	0.4467663	0.39481150	0.25286268	0.44906235	0.4279906	0.4634308	0.4656705	0.4066230



risky asset is projected into **49-D** vector spaces.

Step1: Transformation

Characterizing risky assets by factor model

.0 Correlation

How individuals returns are related to that of other assets

.1 Industry

How individuals returns are related to industrial sectors

.2 Fama-French

How individuals returns are related to the market, company size, company Price-to-Book Ratio

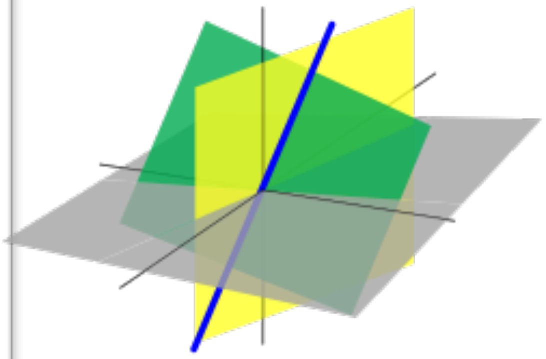
FM.1: Factor model across industry

$$r_i = a_i + \sum_{j=1}^{m} b_{ij} f_j + \epsilon_i, \quad i = 1, 2, \ldots, n,$$

Factors

Hang Seng Composite Ind
Index
11 in total

	intercept	HSCIE	HSCIM	HSCIIG	HSCICG	HSCIS	HSCIT	HSCIU	HSCIF	HSCIPC	HSCIIT	HSCIC
)001_HKW	0.00280539	-0.173410575	0.027975366	-0.038763195	-0.079299651	0.076551875	-0.039381577	-0.015679225	0.170546978	0.176970668	-0.112011009	1.033062355
)002_HKW	-0.000512195	0.003886528	-0.052383626	-0.069401313	-0.179620575	-0.000588051	0.147554758	0.579760105	0.051426572	0.071097542	-0.032802855	0.149037036
)003_HKW	-0.000913946	0.027311403	-0.121341106	-0.021809377	-0.101949764	0.020841268	0.08418749	0.69074844	0.156566272	-0.000257485	-0.038175704	0.135500015
)004_HKW	-0.001077679	0.072371848	-0.041612894	-0.235016424	0.005848378	0.155144896	0.154930805	0.428159702	-0.175021525	0.829197007	0.000850592	-0.050580701
)005_HKW	-0.002165349	-0.026865938	-0.119468566	-0.099563982	-0.132818517	0.129720038	0.040510033	0.033357557	0.835568957	-0.053864609	0.025327504	0.036045313
)006_HKW	0.000264588	-0.127308818	0.053928415	-0.189238275	0.176492695	-0.148910512	0.127777774	0.784540523	0.019313331	0.046294784	-0.147778222	0.340298187
)011_HKW	0.000418255	-0.065907216	-0.159406943	-0.04531036	-0.055489332	0.090125733	0.051561146	0.158911776	0.484333751	-0.069161018	-0.007145648	0.348109923
)012_HKW	0.002315546	0.101529071	-3.95E-05	-0.068286352	-0.23088963	0.01214863	0.096076096	0.053247279	-0.166906172	0.87730133	-0.086277455	0.303829344
)016_HKW	-0.001082159	-0.115134829	0.014524403	-0.17855566	-0.034320638	0.080699478	0.00200733	0.180919602	0.090888855	0.688377842	-0.045767171	0.151182955
)017_HKW	-0.002743878	-0.005007539	-0.026182425	-0.178385623	-0.334940835	0.135636034	0.064729831	0.111691222	0.144598366	0.890908234	0.143014442	0.063313869
)019_HKW	-0.000714024	-0.034961592	-0.018931781	-0.099335478	0.069661071	0.009276619	0.109927397	0.097474905	0.06922989	0.163285789	-0.05683562	0.45704398
)023_HKW	0.00020923	0.155509015	-0.038699893	-0.19005073	0.154279865	0.026699002	0.019522015	0.196472459	0.33783242	0.158088726	0.008658562	0.156009548
)027_HKW	0.003704172	0.247654949	-0.166191105	-0.104321515	-0.22116182	1.853930606	-0.275479005	-0.027593118	0.116488061	-0.130076692	0.029610521	-0.209100451
)066_HKW	0.000993306	-0.12096619	0.0836649	0.005632612	0.232749429	-0.053384215	0.113094476	0.061230127	0.140265091	-0.0460304	-0.023773164	0.32937143
)083_HKW	-0.001041785	0.067646172	-0.03261529	-0.234791922	0.047745466	-0.155704697	-0.010160783	0.181421304	-0.116182979	0.98145213	0.06494496	0.223907989
)101_HKW	-0.002324932	0.115442328	-0.148155514	-0.180644834	0.227606294	0.005299311	0.123948686	0.369111928	0.005994226	0.552065507	-0.076957921	0.124567786
)135_HKW	-0.003074062	0.721408903	-0.183387656	0.242265168	-0.252479016	-0.009461757	-0.093691107	0.436556339	0.053140155	0.148002063	0.023957654	0.000910765
)144_HKW	-0.000539012	0.017505666	-0.019060913	0.002335322	0.500358023	-0.08478226	0.193958515	0.162615762	0.493874332	-0.219994477	0.142229359	0.074432826
)151_HKW	-0.001919551	-0.337903476	0.018704223	-0.64663018	2.061619898	-0.169958186	0.047963846	0.382459565	0.336851667	-0.215702412	-0.292564641	0.012759639
)267_HKW	0.001977176	0.075923176	0.360423745	0.0707516	-0.059130446	-0.129196882	0.036486436	-0.056341799	0.115953529	-0.022709251	-0.138649063	0.707437872
)293_HKW	-0.003257417	-0.394121973	-0.024827331	0.014633377	0.138821983	0.041367212	-0.03737648	0.090654413	0.811054635	-0.059470704	0.243853235	0.265250772
)322_HKW	-0.001635953	0.136026078	0.054715127	-0.481131087	1.232393759	0.032899079	0.113639678	0.2123268	0.418475369	-0.518207883	-0.065062436	-0.055333427
)386_HKW	0.001661895	0.822971454	0.063147185	-0.150307742	-0.183450354	-0.034026587	-0.050232949	0.140565544	0.264249403	0.029560957	-0.017784287	0.224713296
)388_HKW	0.004265966	-0.095110358	0.580107092	0.096934096	0.031481669	-0.036380773	0.049813359	0.043837855	0.825171746	-0.240660402	-0.060896563	0.019420978
)494 HKW	-0.002009891	0.301656481	-0.034843877	-0.360042156	1.497758126	-0.181406303	-0.118909379	-0.407047207	-0.470220701	0.402793433	0.075799193	-0.012270121



risky asset is projected into **12-D** vector spaces.

Step1: Transformation

Characterizing risky assets by factor model

.0

Correlation

How individuals returns are related to that of other assets

.1

Industry

How individuals returns are related to industrial sectors

.2

Fama-French

How individuals returns are related to the market, company size, company Price-to-Book Ratio, market momentum

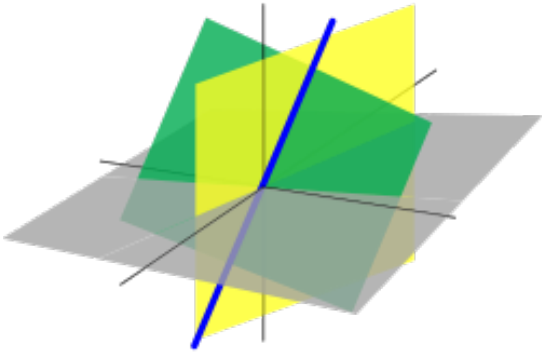
FM.2 Fama–French three-factor model including momentum

$$r_i = a_i + \sum_{j=1}^{m} b_{ij} f_j + \epsilon_i, \quad i = 1, 2, \ldots, n,$$

	alpha	Mkt.RF	SMB	HML	RF	WML
0001.HK	-0.00756	1.205127	-0.31902	0.871204233	0.041904	0.678549
0002.HK	0.0026	0.132299	-0.06166	0.123003559	0.136637	0.044677
0003.HK	0.001653	0.437313	-0.03272	0.456028277	0.049889	0.203604
0004.HK	-0.0026	1.285279	-0.49307	1.104412822	-0.26856	0.634605
0005.HK	-0.00554	0.774743	0.10272	0.363527833	-0.2419	0.44955
0006.HK	0.004098	0.147135	-0.28245	-0.03864989	0.153335	0.070674
0011.HK	-0.00174	0.736789	-0.1599	0.512768	-0.08815	0.484398
0012.HK	-0.0093	1.251505	-0.31561	1.436122797	-0.14629	0.651374
0016.HK	-0.01068	1.28951	-0.52289	1.305734744	-0.04134	0.698076
0017.HK	-0.01185	1.802074	-0.09975	1.97627423	-0.44935	0.689231
0019.HK	-0.0017	0.895887	-0.20153	0.775346795	-0.27174	0.594689
0023.HK	-0.00391	1.140767	-0.00026	0.555289095	-0.07553	0.576377
0027.HK	0.020407	1.702097	0.554019	0.53270429	0.057159	0.286859
0066.HK	-0.00024	0.785553	-0.27003	0.568420659	-0.07068	0.527629
0083.HK	-0.00028	1.496222	-0.35717	1.303607924	-0.504	0.634673
0101.HK	-0.00353	1.092324	-0.58576	0.969312796	-0.04577	0.479788
0135.HK	0.009193	1.049426	0.594554	0.128427486	0.030552	0.281064
0144.HK	-0.00043	1.103851	0.078888	0.636227369	-0.07924	0.482266
0151.HK	0.006704	0.380132	-0.41709	-0.24682322	0.063381	0.111668
0267.HK	-0.00461	1.482569	0.541803	0.419842175	-0.38747	0.54264
0293.HK	-0.00527	0.919047	-0.05761	0.753528754	-0.29987	0.455923
0322.HK	0.009467	0.566624	0.038794	1.120322329	-0.03132	0.149352
0386.HK	0.003788	0.922779	0.066959	0.096940594	0.242193	0.29553
0388.HK	0.010742	1.387892	0.312557	0.68694357	-0.2226	0.449939
0494.HK	0.007375	0.757857	-0.07292	0.103239732	-0.44447	0.241201
0688.HK	0.004454	1.317748	-0.02586	0.912761737	0.283291	0.371431
0700.HK	0.033682	1.134236	-0.00944	0.099316123	0.064001	0.3441
0762.HK	-0.00261	0.883034	-0.24682	0.138594922	-0.27761	0.25787
0823.HK	0.011203	0.458018	-0.52526	0.120286081	0.407254	0.267456
0836.HK	0.002574	0.844133	-0.37191	-0.01934385	0.563245	0.26373
0857.HK	0.006537	0.97752	0.091177	-0.13055679	-0.04187	0.330975
0883.HK	0.003416	1.184808	-0.03983	-0.26999045	0.108219	0.518346
0939.HK	0.002591	0.982069	-0.11784	0.239646347	0.267658	0.45879
0941.HK	0.001514	0.769705	-0.15433	-0.17732624	0.166166	0.262296
0992.HK	-0.0003	1.146634	0.831257	0.180580318	-0.32999	0.34784
1038.HK	0.003466	0.260223	-0.11771	0.394956974	0.199823	0.086662
1044.HK	0.012927	0.671311	0.192481	0.356005824	0.125677	0.225889
1088.HK	0.002066	1.177754	0.004169	0.110017043	0.038955	0.503772
1109.HK	0.007422	1.403384	-0.27664	1.014148098	0.166031	0.313031
1299.HK	0.010131	0.90941	0.03344	0.090836996	0.04901	0.569379
1398.HK	0.002079	1.082645	-0.31657	0.138522573	0.071281	0.479212
1880.HK	0.008544	1.021166	0.566655	0.246354626	0.047121	0.27502
1928.HK	0.029925	1.155495	-0.59515	-0.77875718	-0.65509	0.404168
2318.HK	0.013825	1.330427	-0.71224	-0.36451132	-0.13884	0.339355
2319.HK	0.014596	1.149514	-0.21213	0.407845782	-0.23284	0.196905
2388.HK	-0.00137	1.064657	0.020469	0.583729148	0.001764	0.588225
2628.HK	0.000214	1.057428	-0.23685	0.229815226	0.292212	0.342634
3328.HK	0.001197	1.233896	-0.24107	0.392376047	0.272915	0.45148
3988.HK	-0.00112	0.979807	-0.0806	0.294393158	0.137534	0.472078

Factors

- SMB
- HML
- Excess market return
- WML
- 4 in total



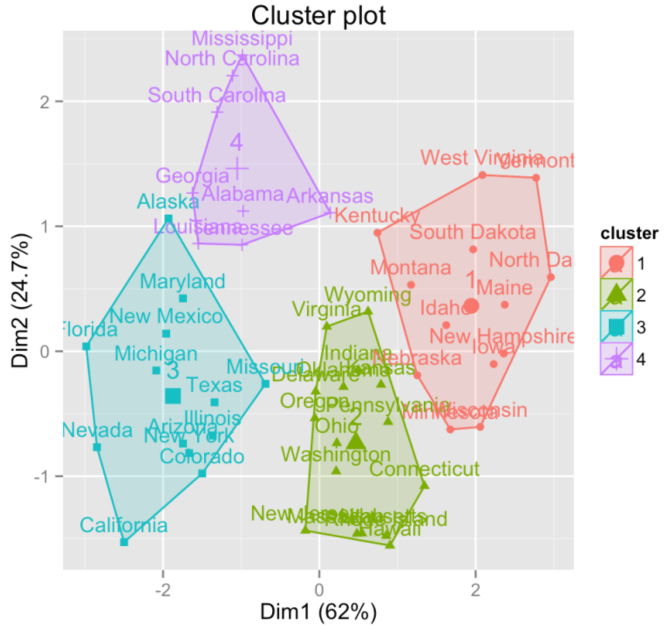
risky asset is projected into **5-D** vector spaces.

Step 2:Grouping risky assets using clustering algorithm

Goal: partition all risky assets into *k* groups risky assets using clustering algorithm

Partitioned clustering

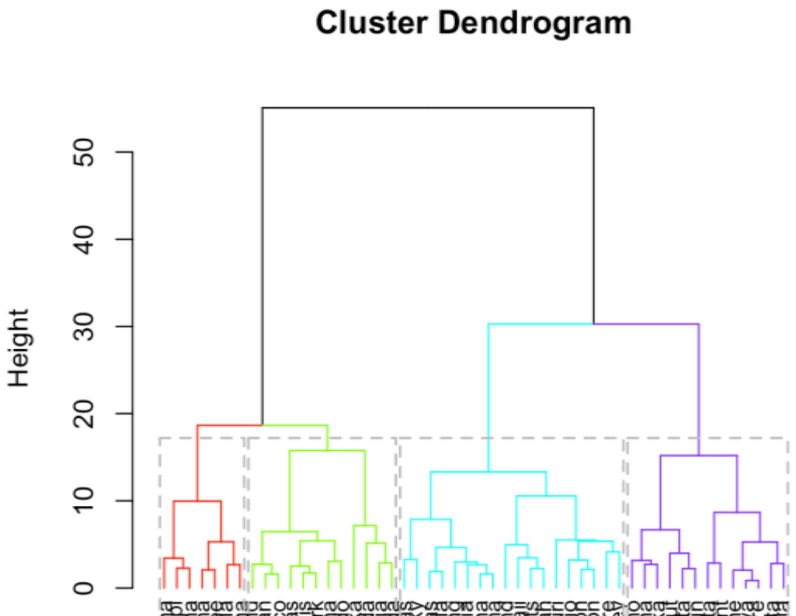
Organize elements into disjoint groups



Hierarchical clustering

Organize elements into trees.

Nested!

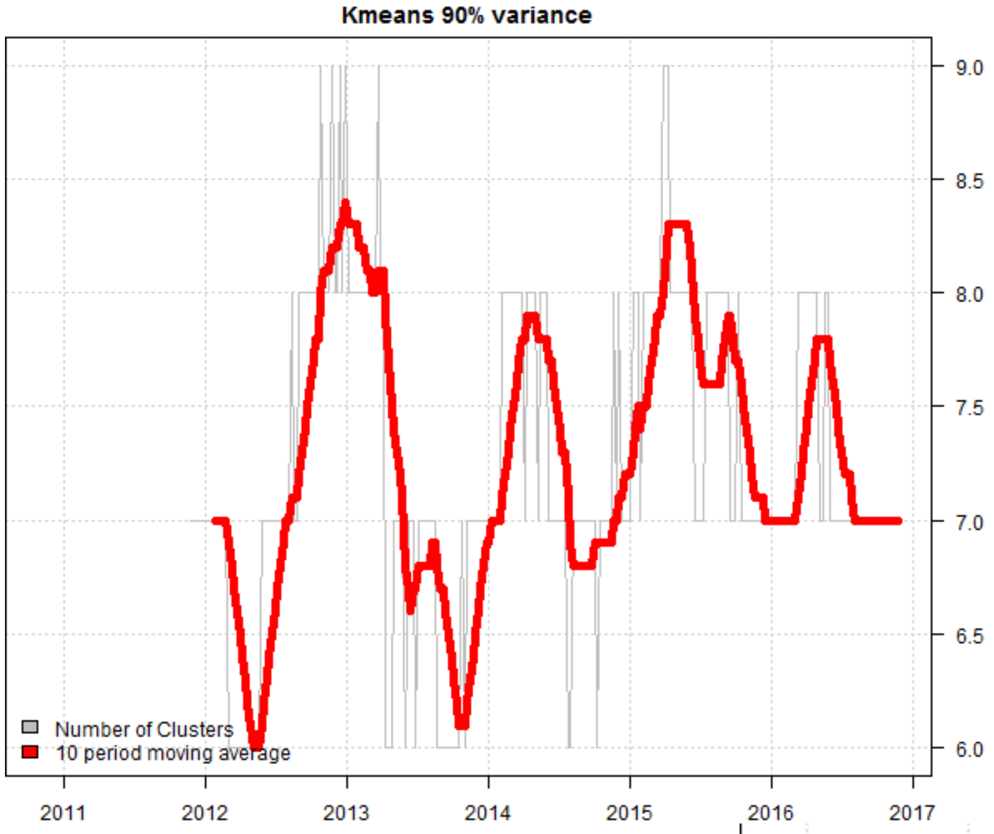


K-means realization

Preparation

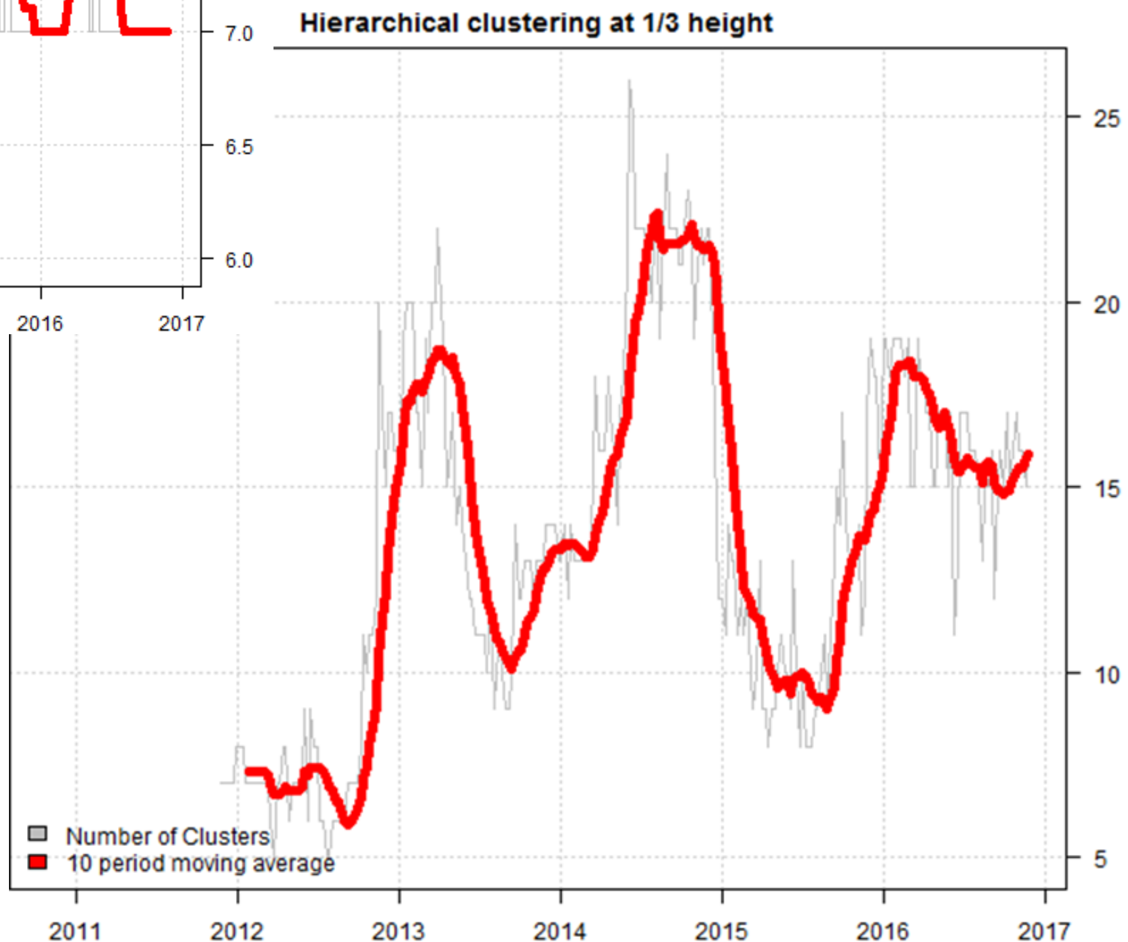
Determine the appropriate number of groups

»



7

Comparison of number of clusters made by partitioned and hierarchical clustering method

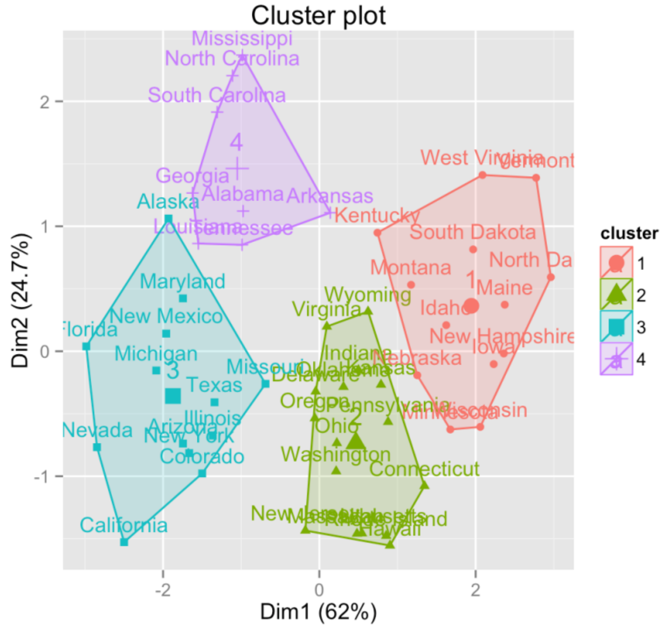


Step 2:Grouping risky assets using clustering algorithm

Goal: partition all risky assets into *k* groups risky assets using clustering algorithm

Partitioned clustering

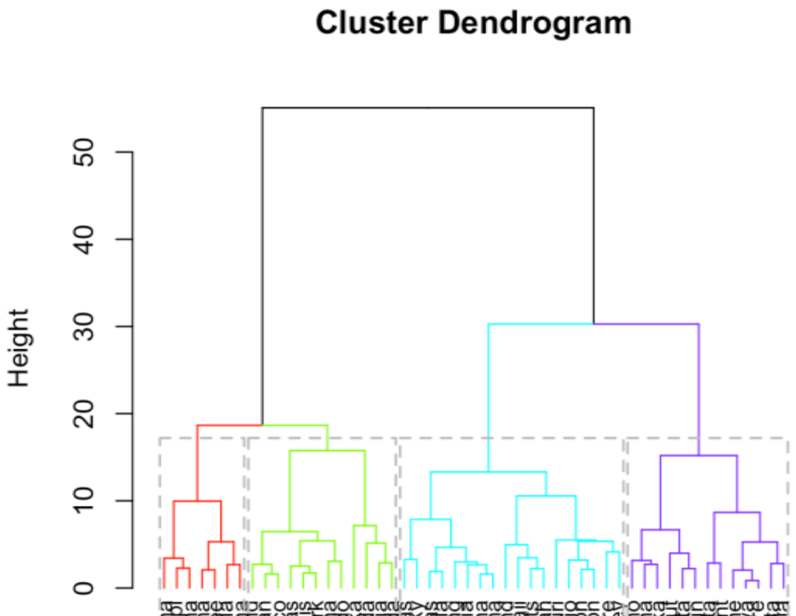
Organize elements into disjoint groups



Hierarchical clustering

Organize elements into trees.

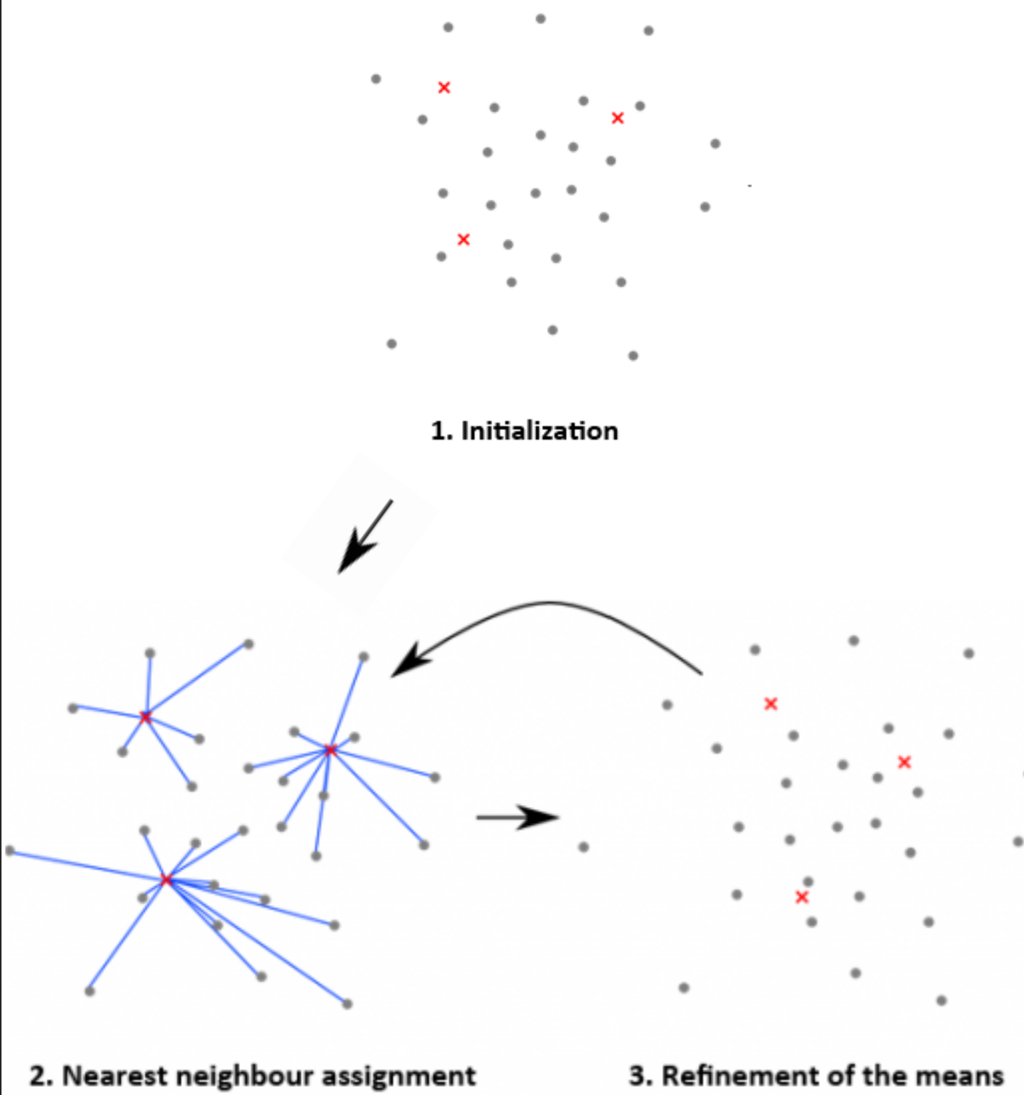
Nested!



K-means Clustering

Algorithm

1. Selects K observations randomly and set them to be the initial centroids
2. Assigns each data point to its closest centroid
3. Recalculates the centroids as the average of all data points in a cluster
4. Assigns data points to their closest centroids
5. Continues steps 3 and 4 until observations are not reassigned or the maximum number of iterations is reached.



Fast Threshold Clustering Algorithm (FTCA)

How FTCA creates clusters?

- **Pseudo code**

While there are assets that have not been assigned to a cluster

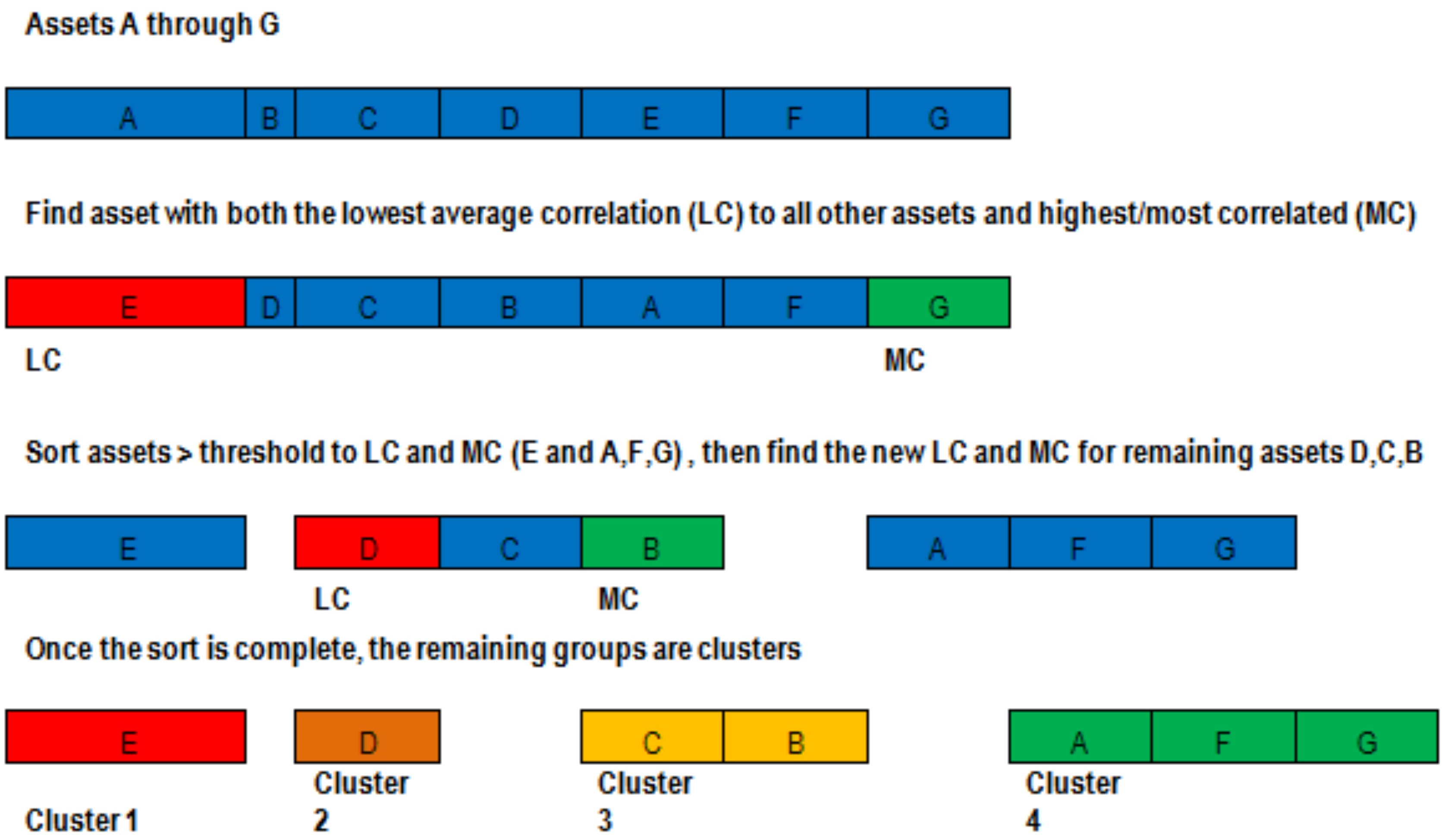
- If only one asset remaining then
  - Add a new cluster
  - Only member is the remaining asset
- Else
  - Find the asset with the Highest Average Correlation (HC) to all assets not yet been assigned to a Cluster
  - Find the asset with the Lowest Average Correlation (LC) to all assets not yet assigned to a Cluster
  - If Correlation between HC and LC > Threshold
    - Add a new Cluster made of HC and LC
    - Add to Cluster all other assets that have yet been assigned to a Cluster and have an Average Correlation to HC and LC > Threshold
  - Else
    - Add a Cluster made of HC
      - Add to Cluster all other assets that have yet been assigned to a Cluster and have a Correlation to HC > Threshold
    - Add a Cluster made of LC
      - Add to Cluster all other assets that have yet been assigned to a Cluster and have Correlation to LC > Threshold
  - End if
- End if

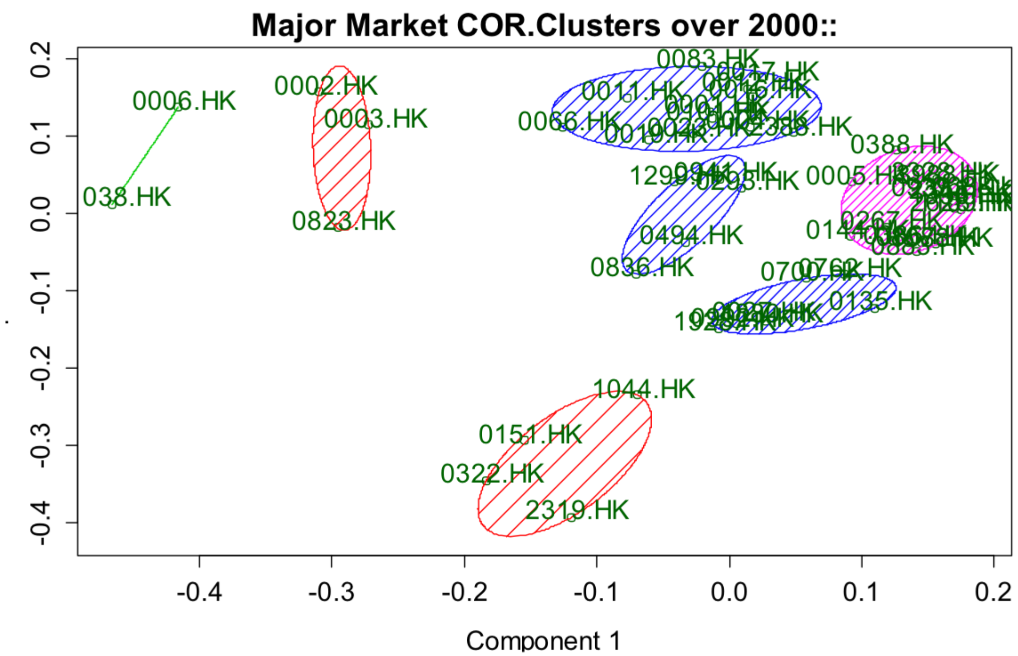
End While

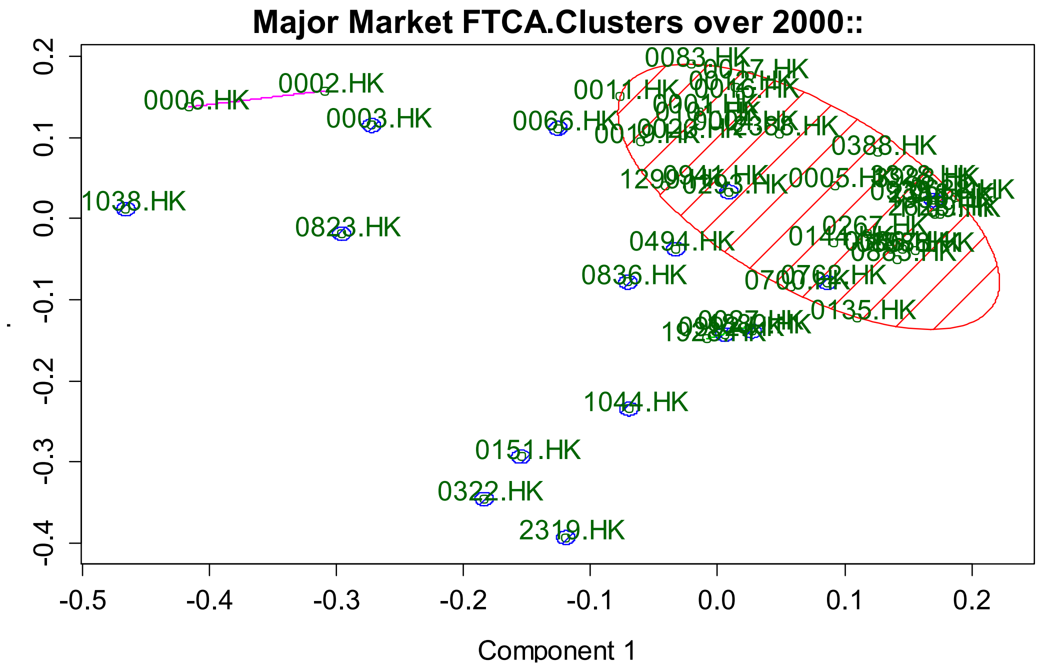
Fast Threshold Clustering Algorithm (FTCA)

How FTCA creates clusters?

- **Graphic presentation**



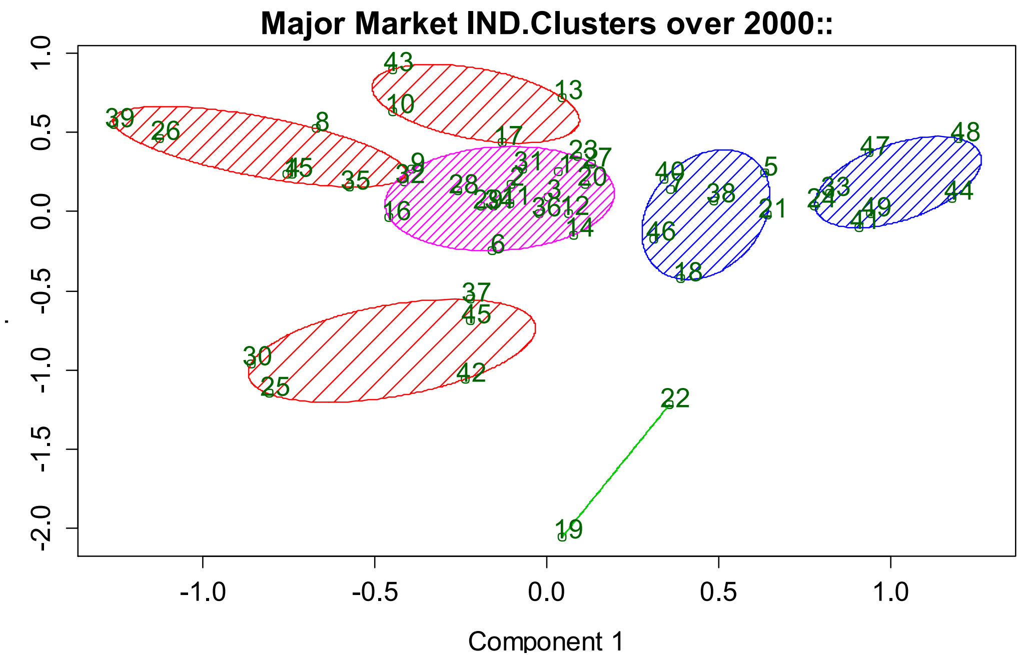


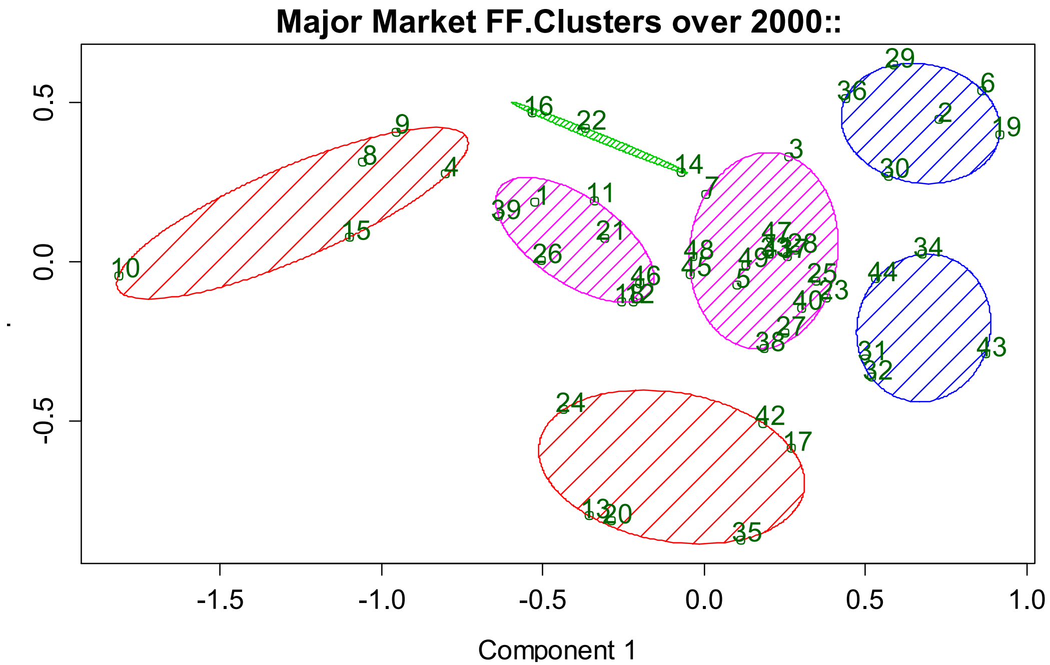


←k = 7

COR

k =18 →





←**IND**

k = 7

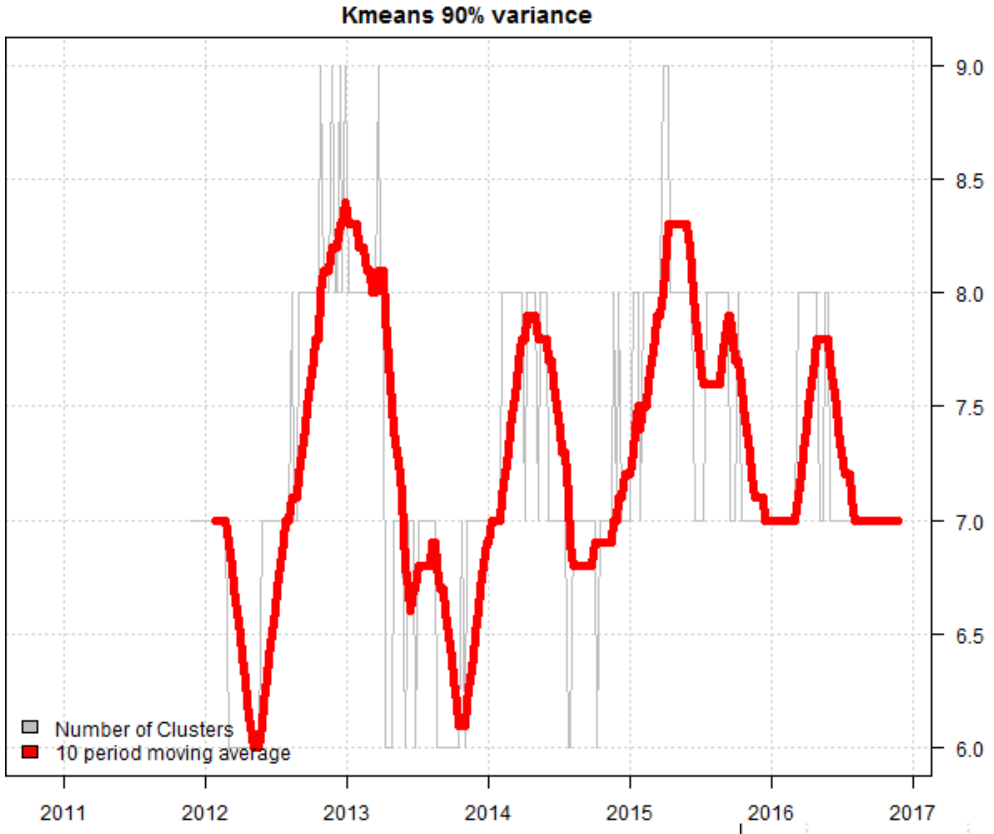
FF →

K-means realization

Preparation

Determine the appropriate number of groups

»



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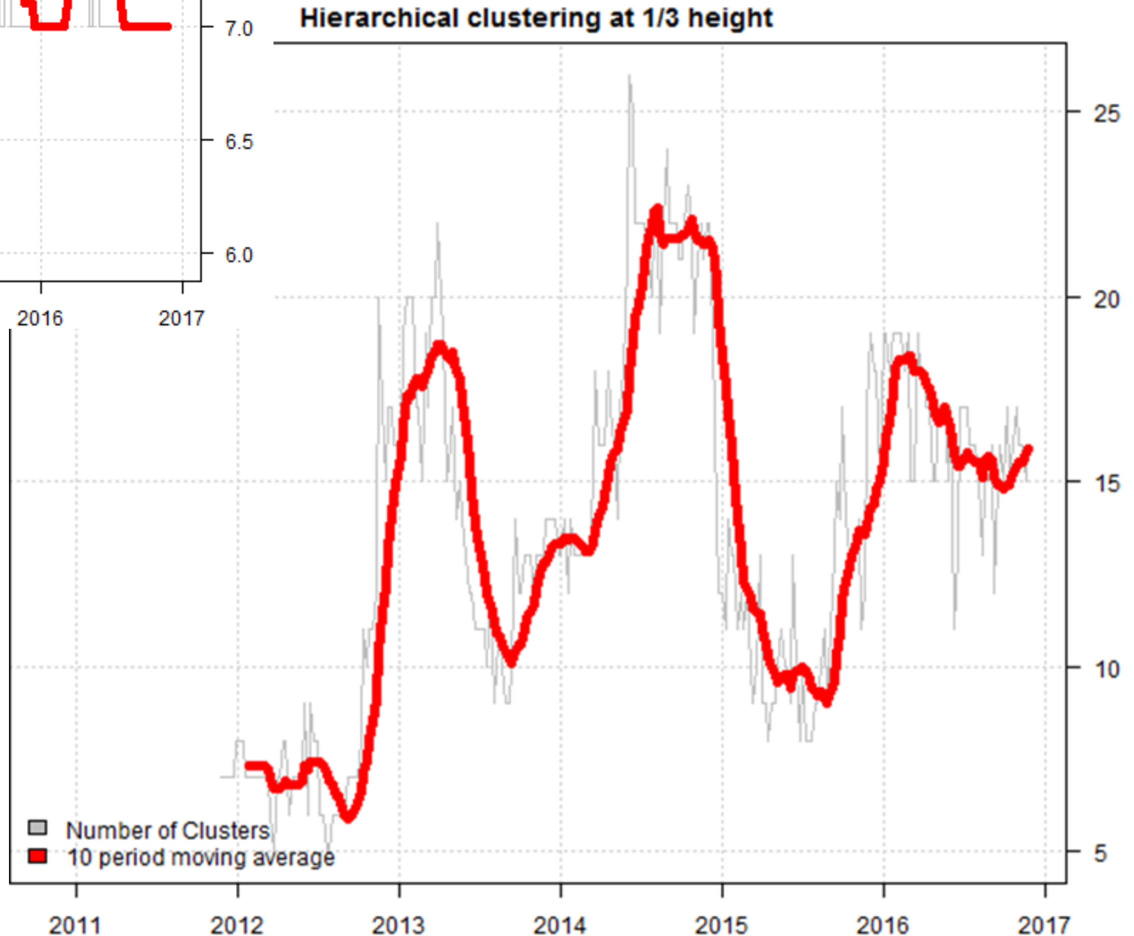


Comparison of number of clusters made by partitioned and hierarchical clustering method

Step3: Finalize portfolio selection.

Goal: Identifying representative(s) from groups and forming the portfolio

Selection by criteria

Concern: best candidate from each group may not necessarily build the best portfolio

Optimization

Revised and computational feasible problem by adding the clustering result as pre-grouping constraints

Recall :Problem Formulation

Generalized Markowitz's model

$$\min_x x'\boldsymbol{Q}x$$
$$\text{s.t. } \mathbf{r}'\mathrm{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$

$$\binom{n}{k} = \mathbf{18{,}424}$$

VS

Revised CCMV with pre-grouping

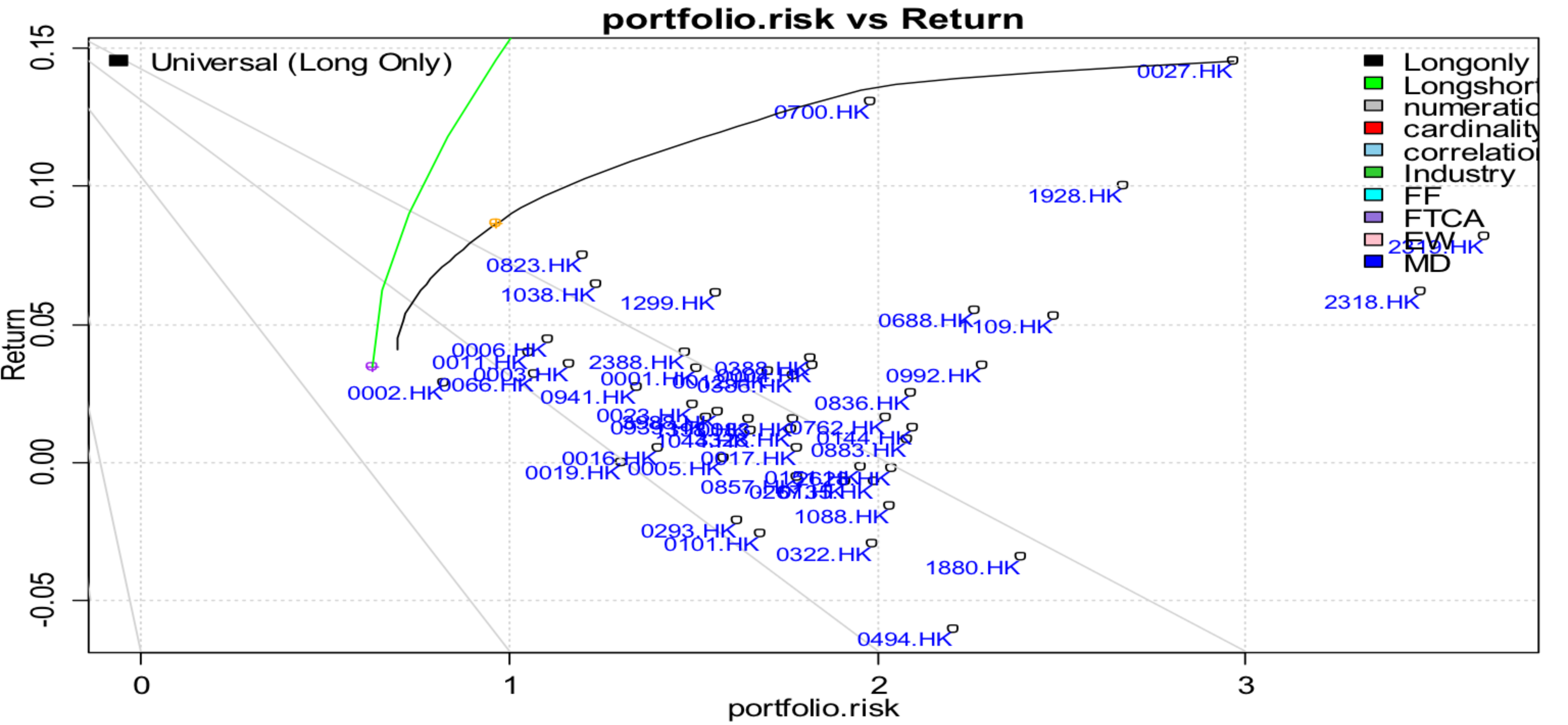
$$\min_x x'Qx$$
$$\text{s.t. } \mathrm{r}'\mathrm{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$i = 1,2, \dots, n.$$
$$j = 1,2, \dots, k.$$

$$\prod_{j=1}^{k} (\beta_j - \alpha_j + 1)$$

» 03

Outcome

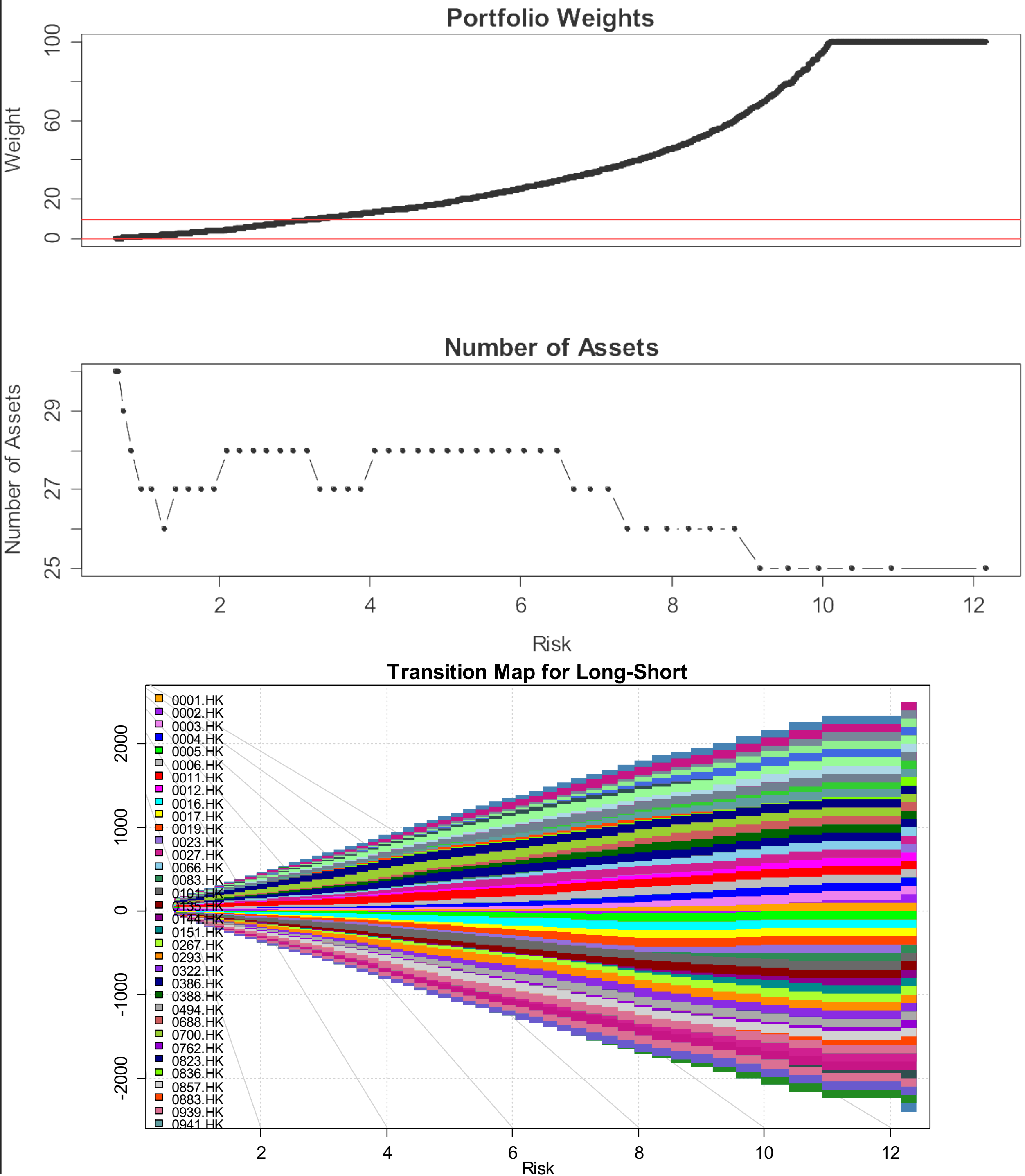
Results and interpretation: Static *EF* >>> *back test*



portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
numeratio
cardinality
correlatio
Industry
FF
FTCA
EW
MD
0027.HK
0700.HK
1928.HK
2319.HK
2318.HK
0823.HK
1038.HK
1299.HK
0688.HK
1109.HK
0006.HK
0011.HK
0003.HK
0002.HK
0066.HK
2388.HK
0001.HK
0388.HK
0386.HK
0992.HK
0941.HK
0836.HK
0023.HK
0762.HK
0144.HK
0883.HK
0016.HK
0017.HK
0019.HK
0005.HK
0857.HK
1088.HK
0293.HK
0101.HK
0322.HK
1880.HK
0494.HK
Return
portfolio.risk
0.15
0.10
0.05
0.00
-0.05
0
1
2
3

Long & short portfolio

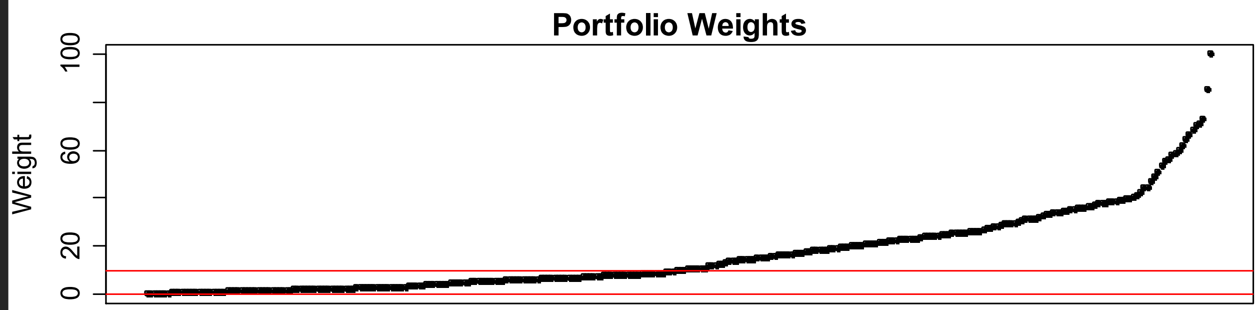
$$\min_{x} x'Qx$$
$$\text{s.t. } \mathbf{r}'\mathrm{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$

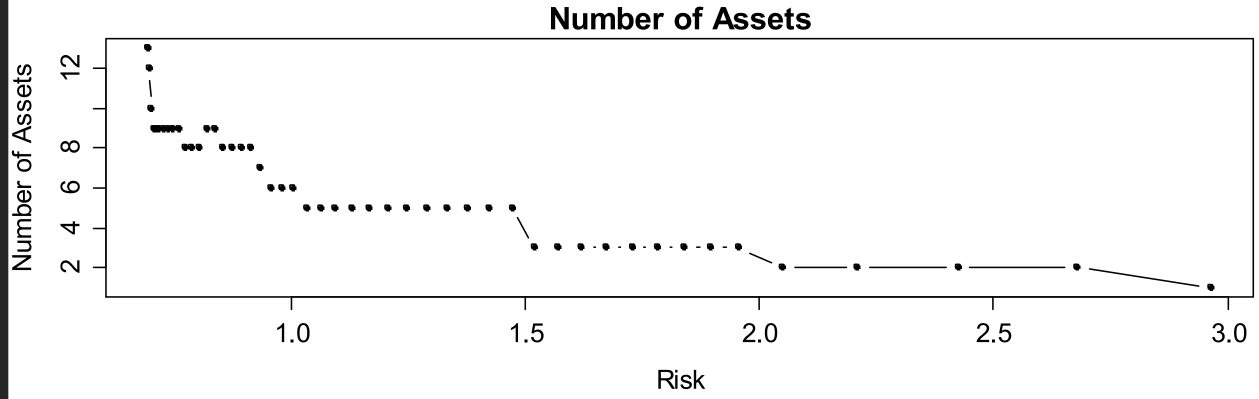


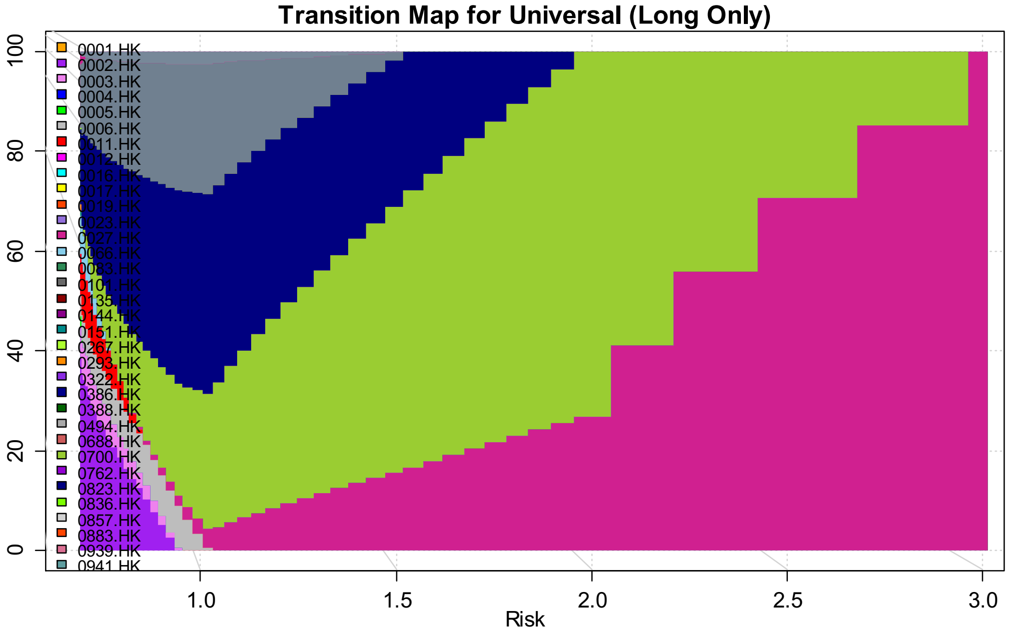
Long only portfolio

$$\min_{x} x'Qx$$
$$\text{s.t. } \mathbf{r}'\mathrm{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$0 \leq x_i \leq 1$$
$$1 \leq i \leq n$$

»

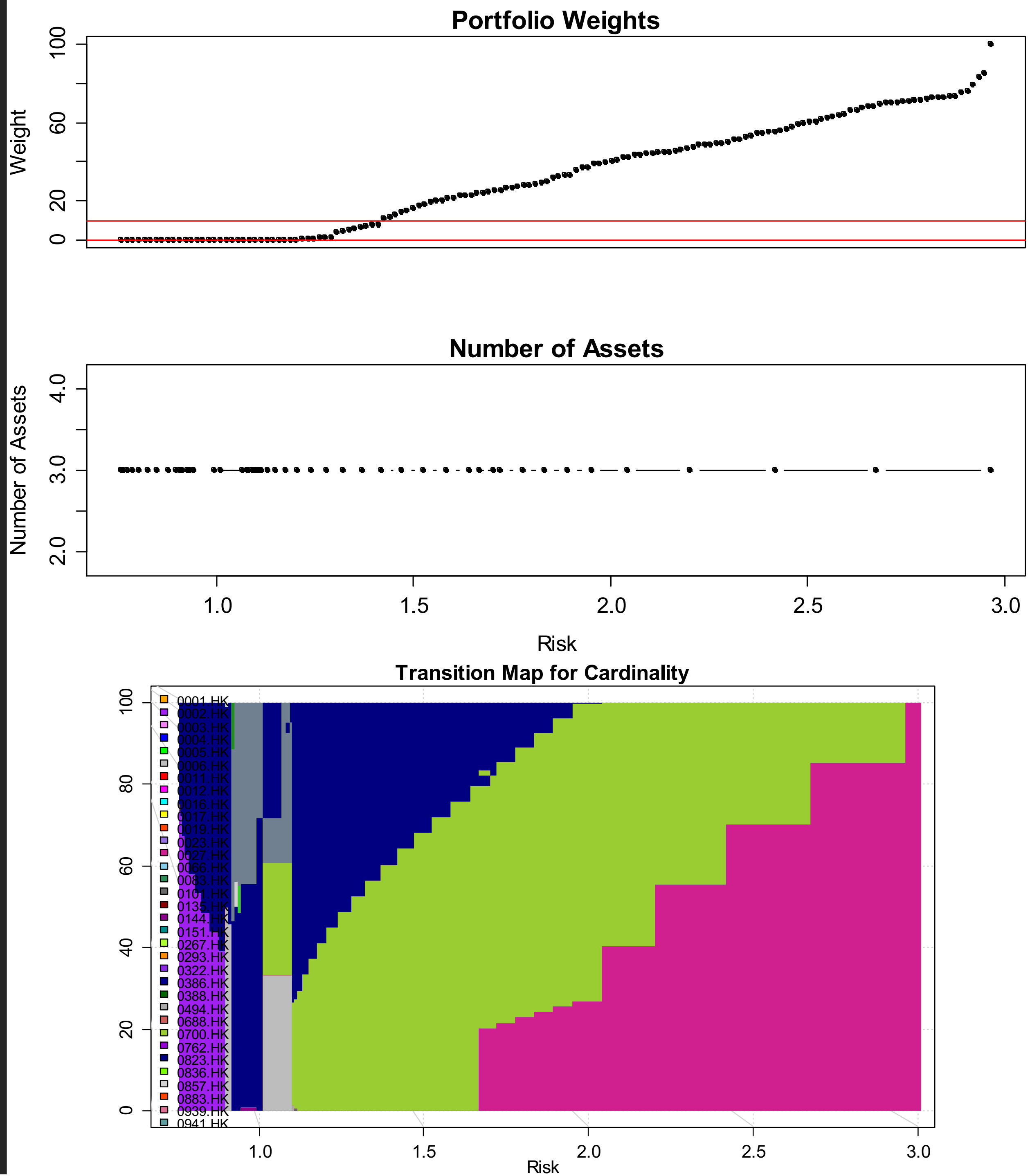




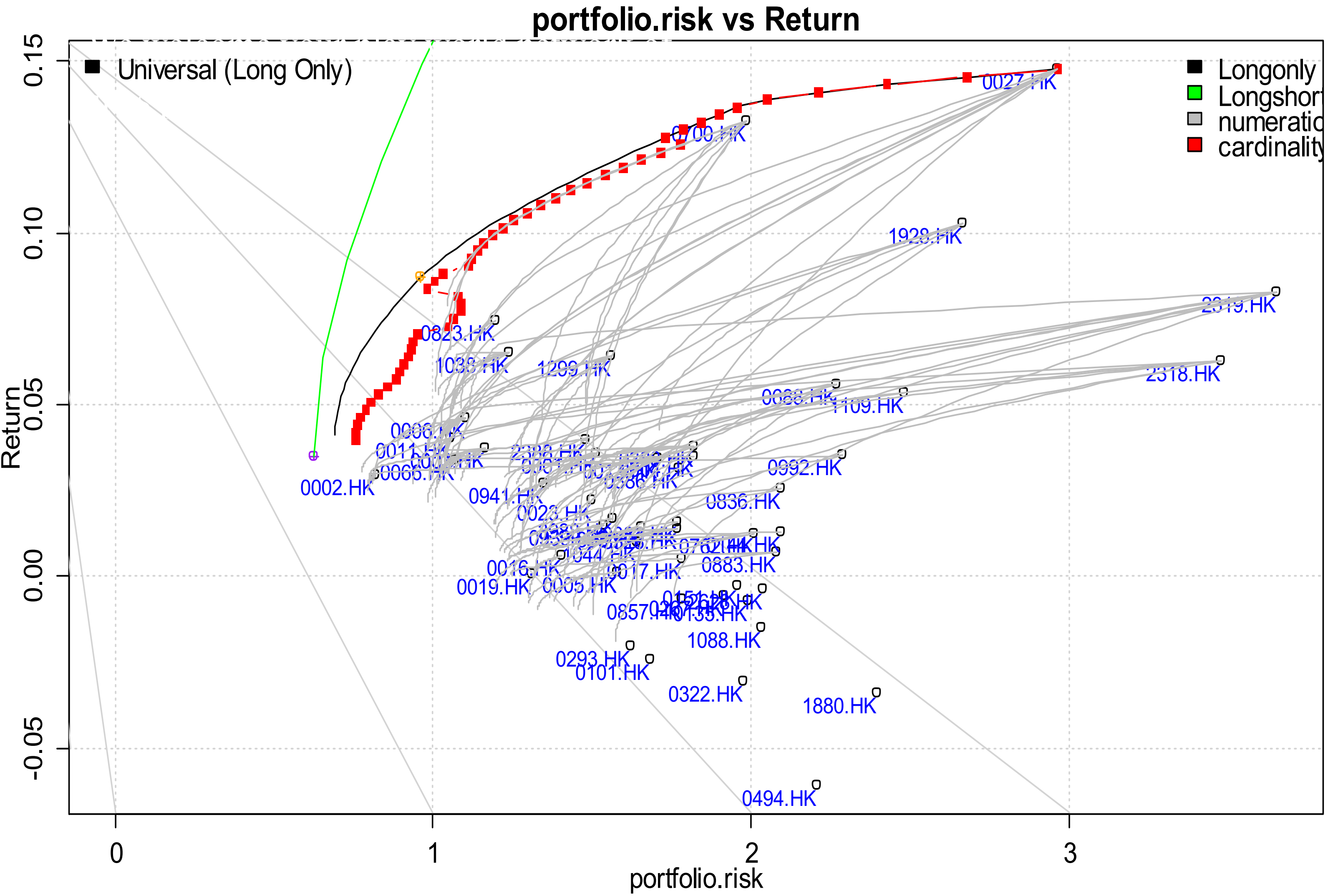


CCMV portfolio

$$\min_{x} x'Qx$$
$$\text{s.t. } r'x \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$0 \leq x_i \leq 1$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$for\ i\ from\ 1\ to\ n$$



k = 3



Efficient Frontier

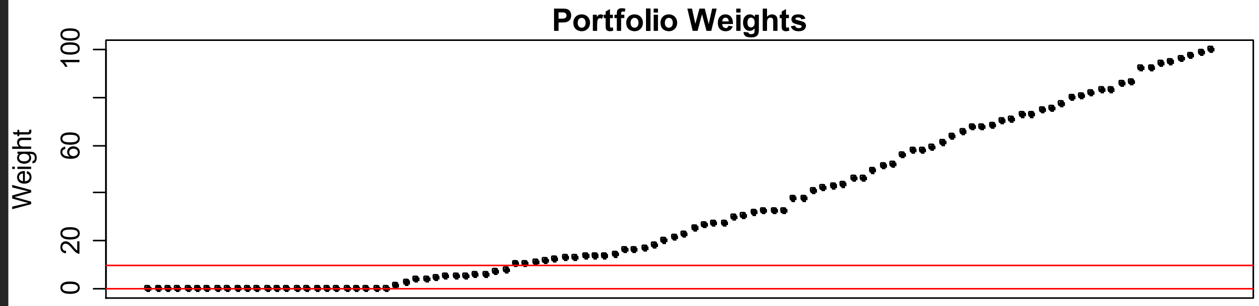
Compare & Interpretation

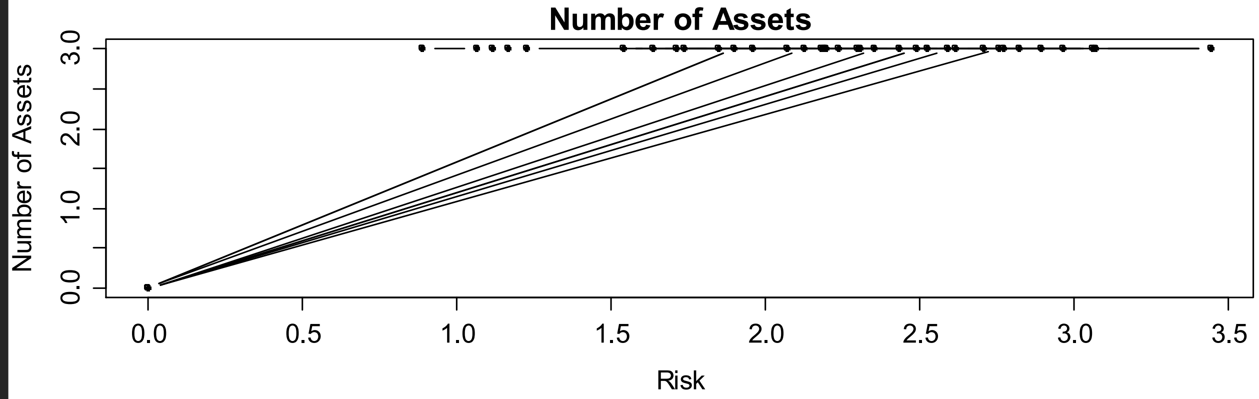
Universal
V.S
Cardinality

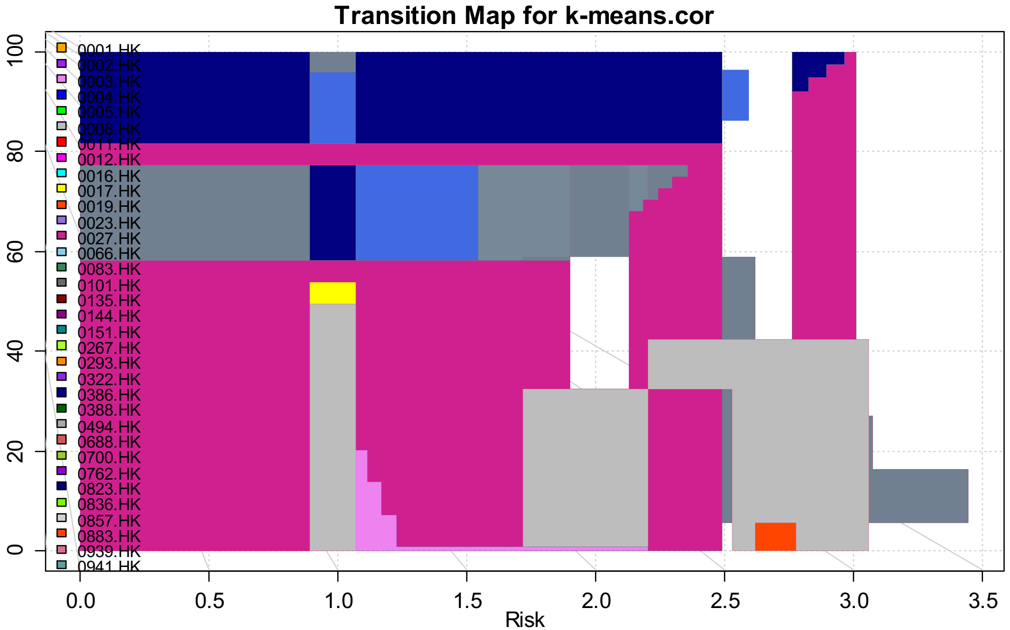
Shorting
V.S
No shorting

K-means.cor portfolio

$$\min_x x'Qx$$
$$\text{s.t. } r'x \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$i = 1,2, \ldots, n.$$
$$j = 1,2, \ldots, k.$$



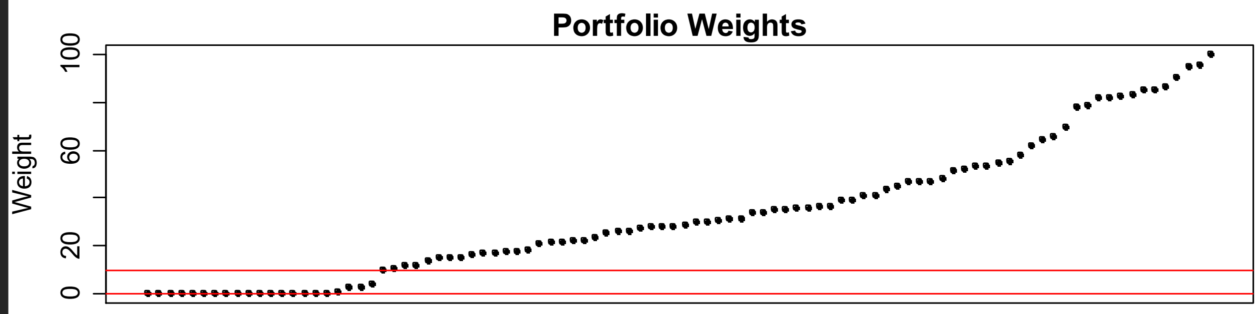


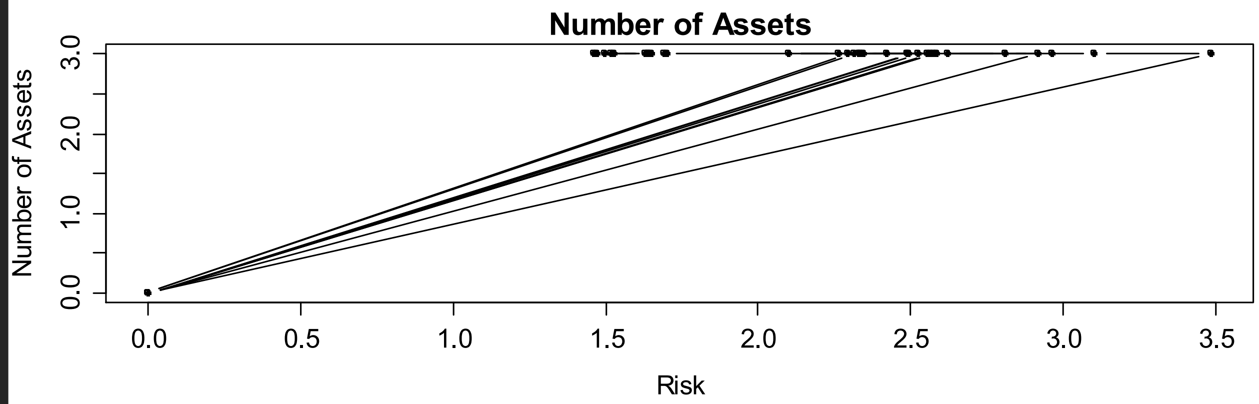


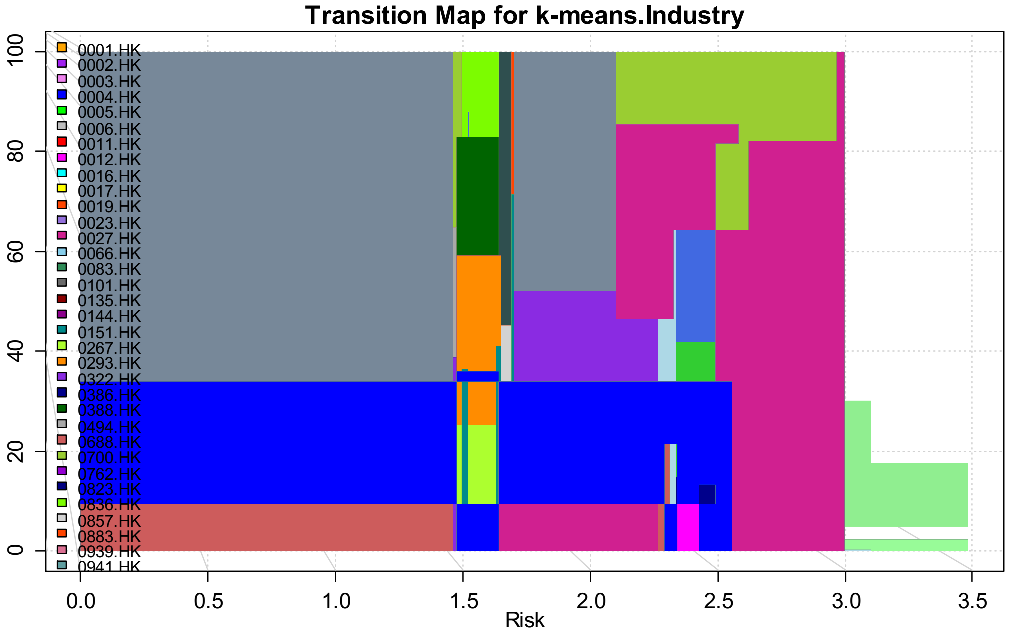
$$k = 3$$
$$j = 7$$
$$\boldsymbol{\alpha_j} = 0$$
$$\boldsymbol{\beta_j} = 1$$

K-means.IND portfolio

$$\min_{x} x'Qx$$
$$\text{s.t. } r'x \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$i = 1,2, \dots, n.$$
$$j = 1,2, \dots, k.$$







k = 3
j = 7
$\boldsymbol{\alpha_j} = 0$
$\boldsymbol{\beta_j} = 1$

K-means.FF portfolio

$$\min_{x} x'Qx$$

$$\text{s.t. } \mathrm{r'x} \geq \bar{r}$$

$$\mathbf{1}'x = 1$$

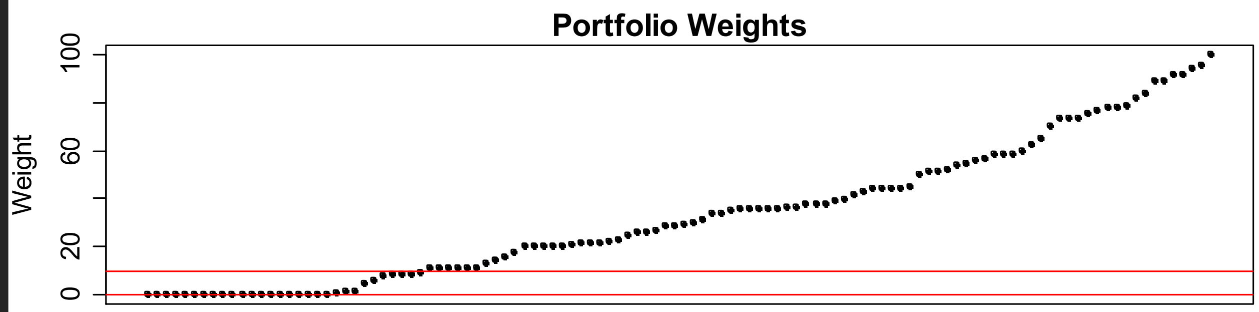
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$

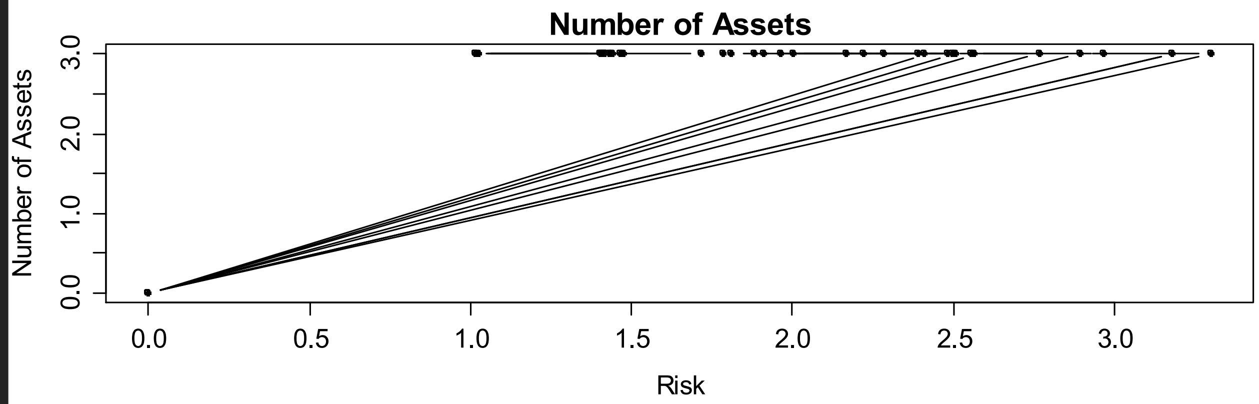
$$\sum_{i=1}^{n} b_i = k$$

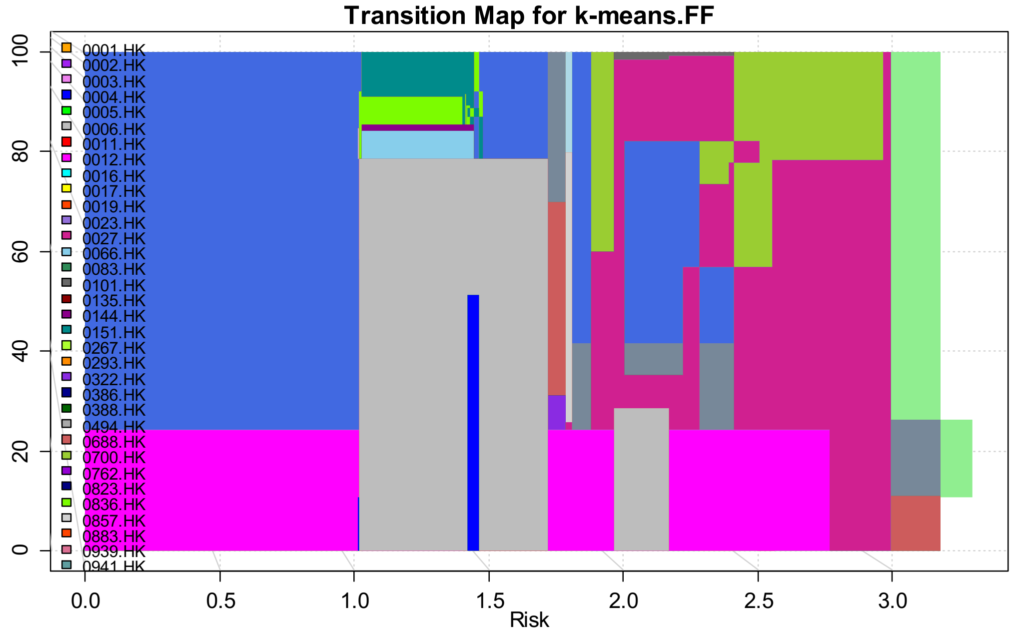
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$

$$i = 1,2, \ldots, n.$$

$$j = 1,2, \ldots, k.$$







$\mathrm{k} = 3$

$\mathrm{j} = 7$

$\boldsymbol{\alpha_j} = 0$

$\boldsymbol{\beta_j} = 1$

K-means.FTCA portfolio

$$\min_{x} x'Qx$$

$$\text{s.t. } r'x \geq \bar{r}$$

$$\mathbf{1}'x = 1$$

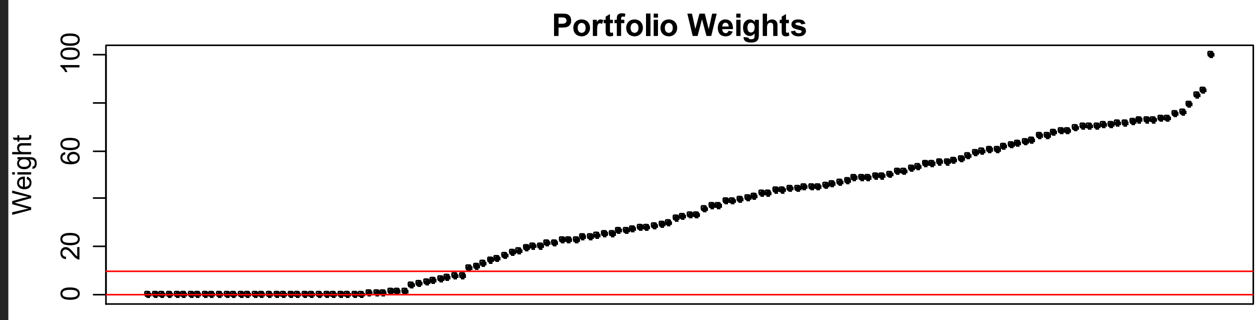
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$

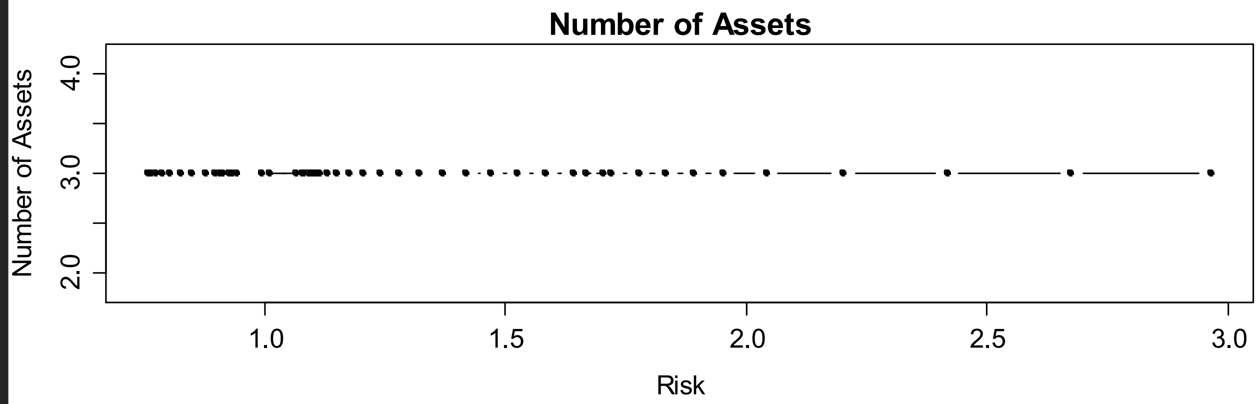
$$\sum_{i=1}^{n} b_i = k$$

$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$

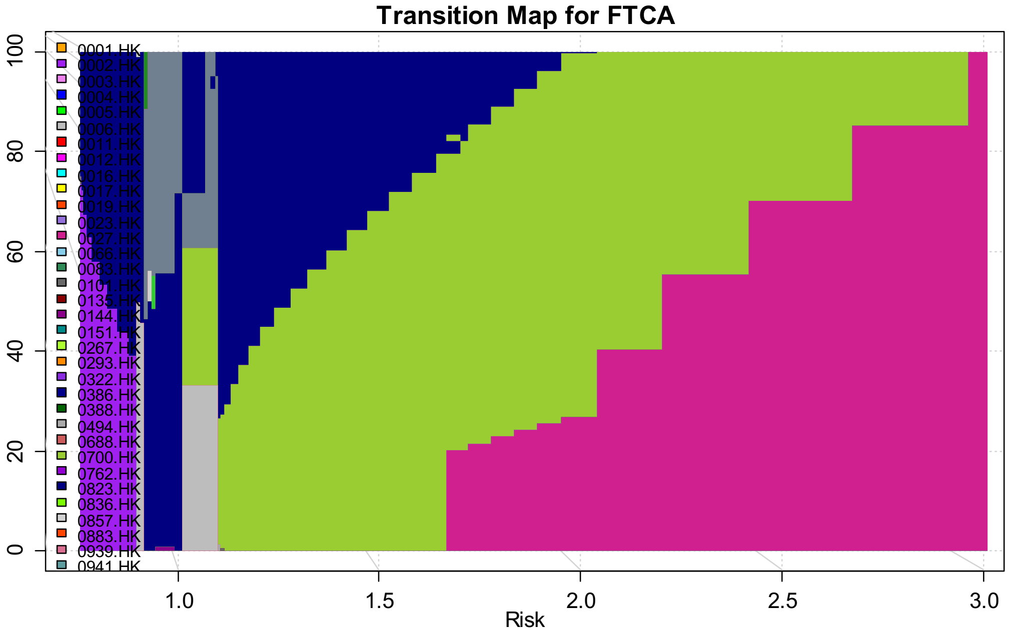
$$i = 1,2, \ldots, n.$$

$$j = 1,2, \ldots, k.$$



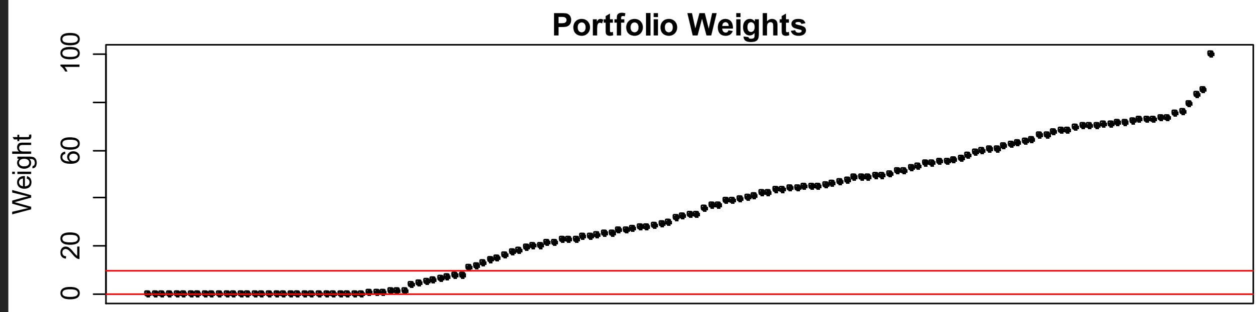


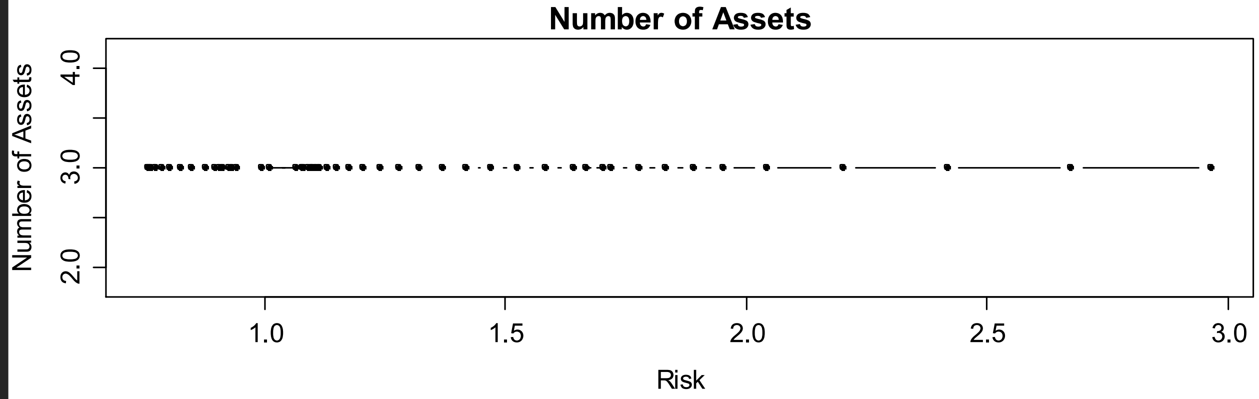
$$k = 3$$
$$j = 18$$
$$\boldsymbol{\alpha_j} = 0$$
$$\boldsymbol{\beta_j} = 1$$

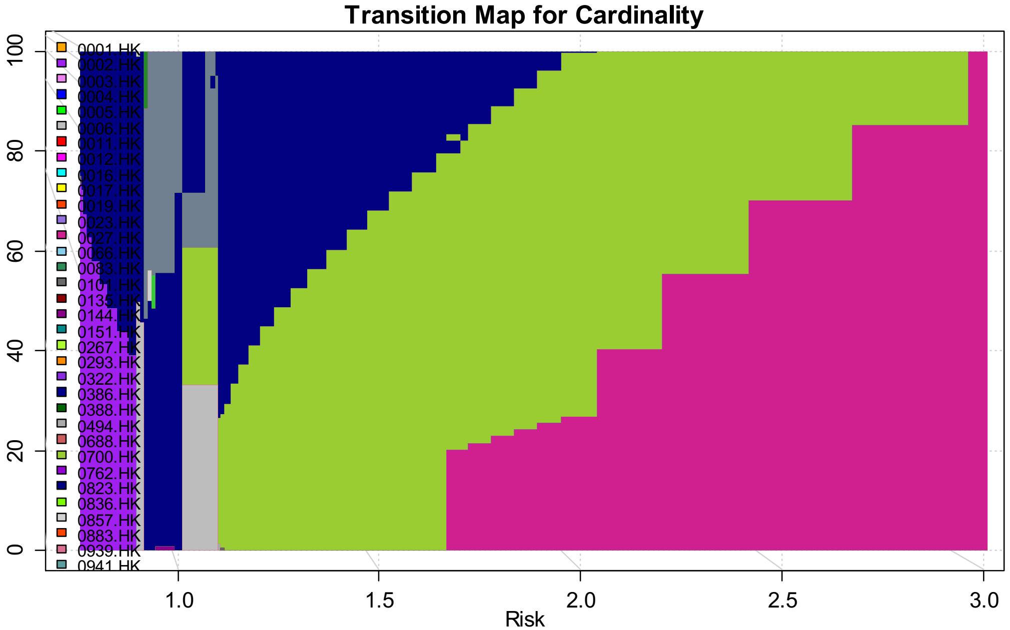


CCMV portfolio

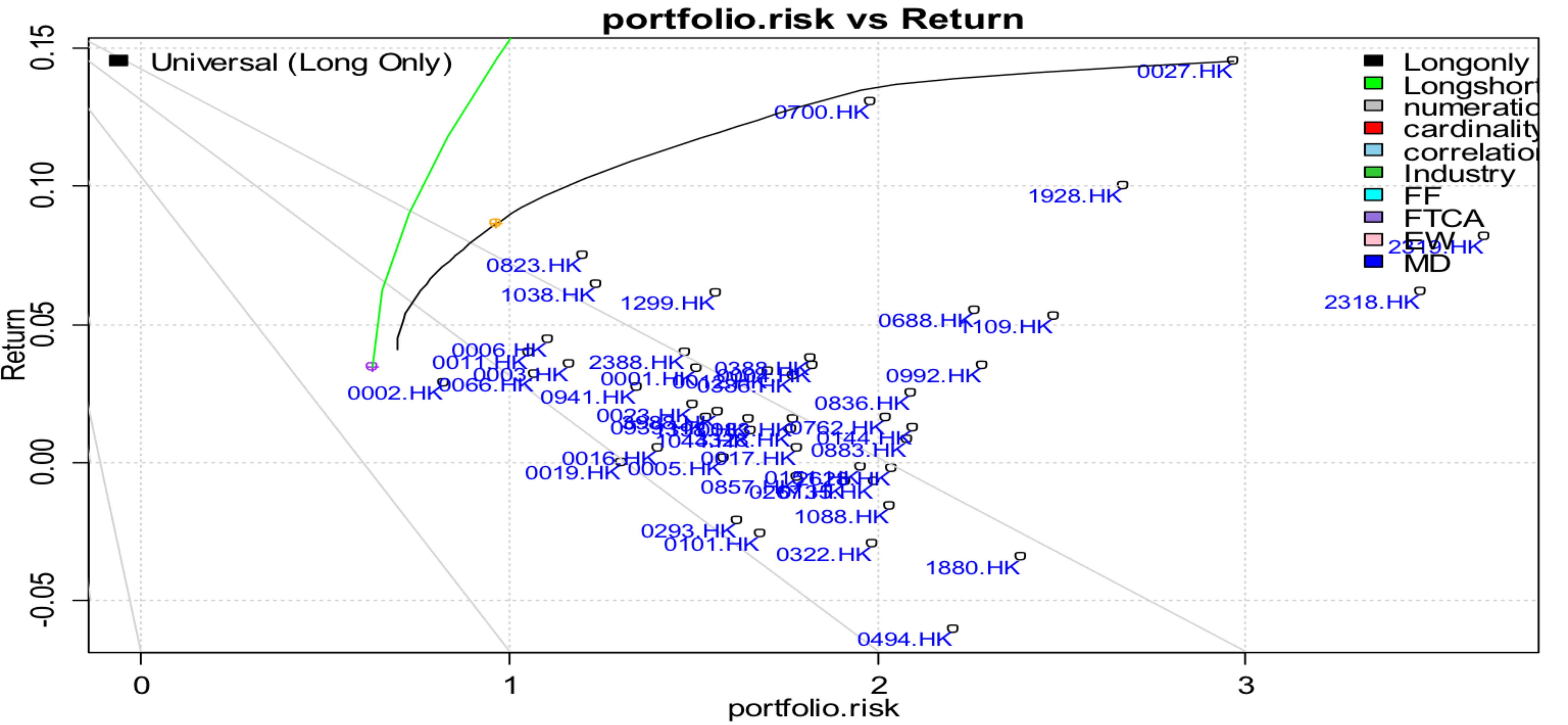
$$\min_{x} x'Qx$$
$$\text{s.t. } r'x \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$0 \leq x_i \leq 1$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$for\ i\ from\ 1\ to\ n$$



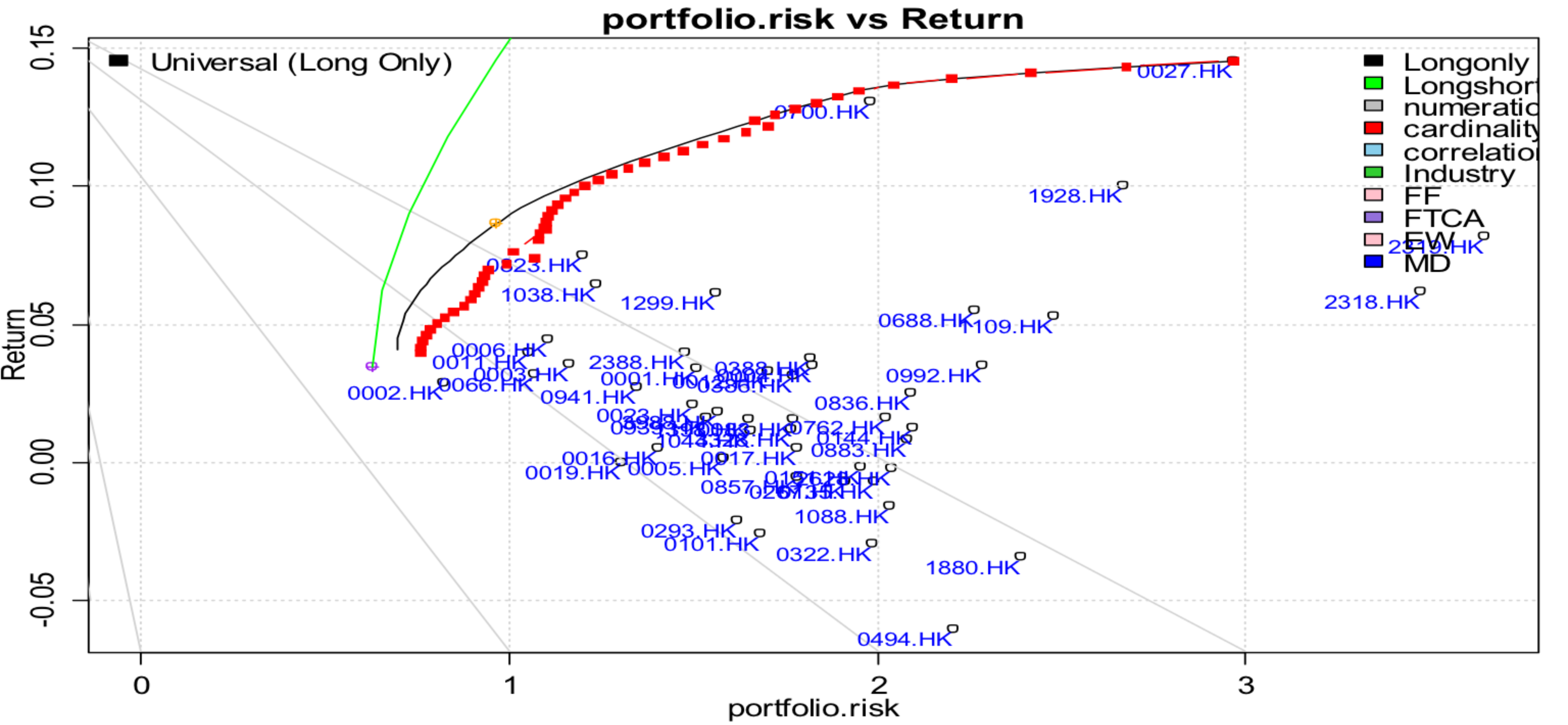




k = 3



portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
numeratio
cardinality
correlatio
Industry
FF
FTCA
EW
MD
Return
portfolio.risk
0.15
0.10
0.05
0.00
-0.05
0
1
2
3
0027.HK
0700.HK
1928.HK
2319.HK
2318.HK
0823.HK
1038.HK
1299.HK
0688.HK
1109.HK
0006.HK
0011.HK
0003.HK
2388.HK
0001.HK
0388.HK
0992.HK
0002.HK
0066.HK
0941.HK
0836.HK
0023.HK
0762.HK
0144.HK
0883.HK
0016.HK
0017.HK
0019.HK
0005.HK
1088.HK
0293.HK
0101.HK
0322.HK
1880.HK
0494.HK


portfolio.risk vs Return
Universal (Long Only)
Longonly
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Industry
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Return
portfolio.risk
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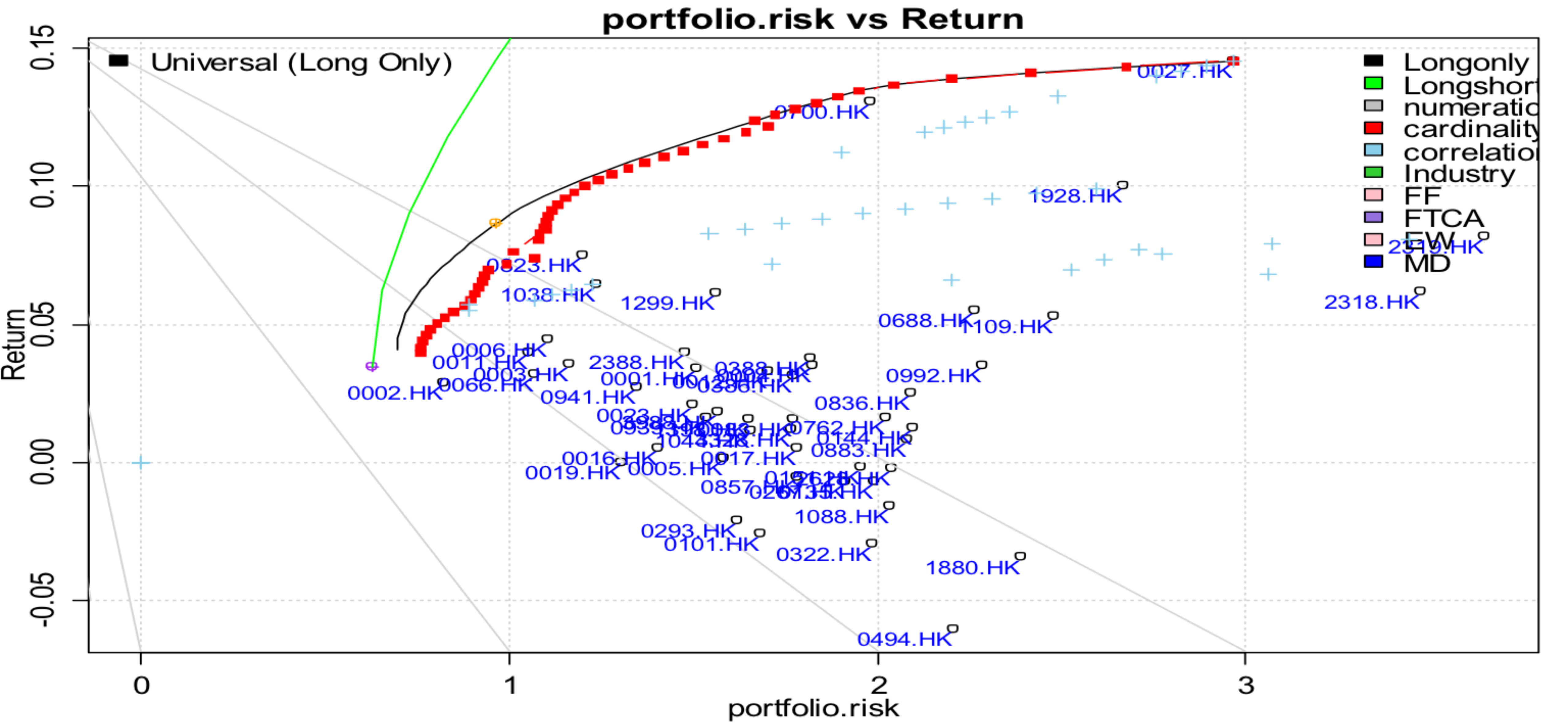

portfolio.risk vs Return
Universal (Long Only)
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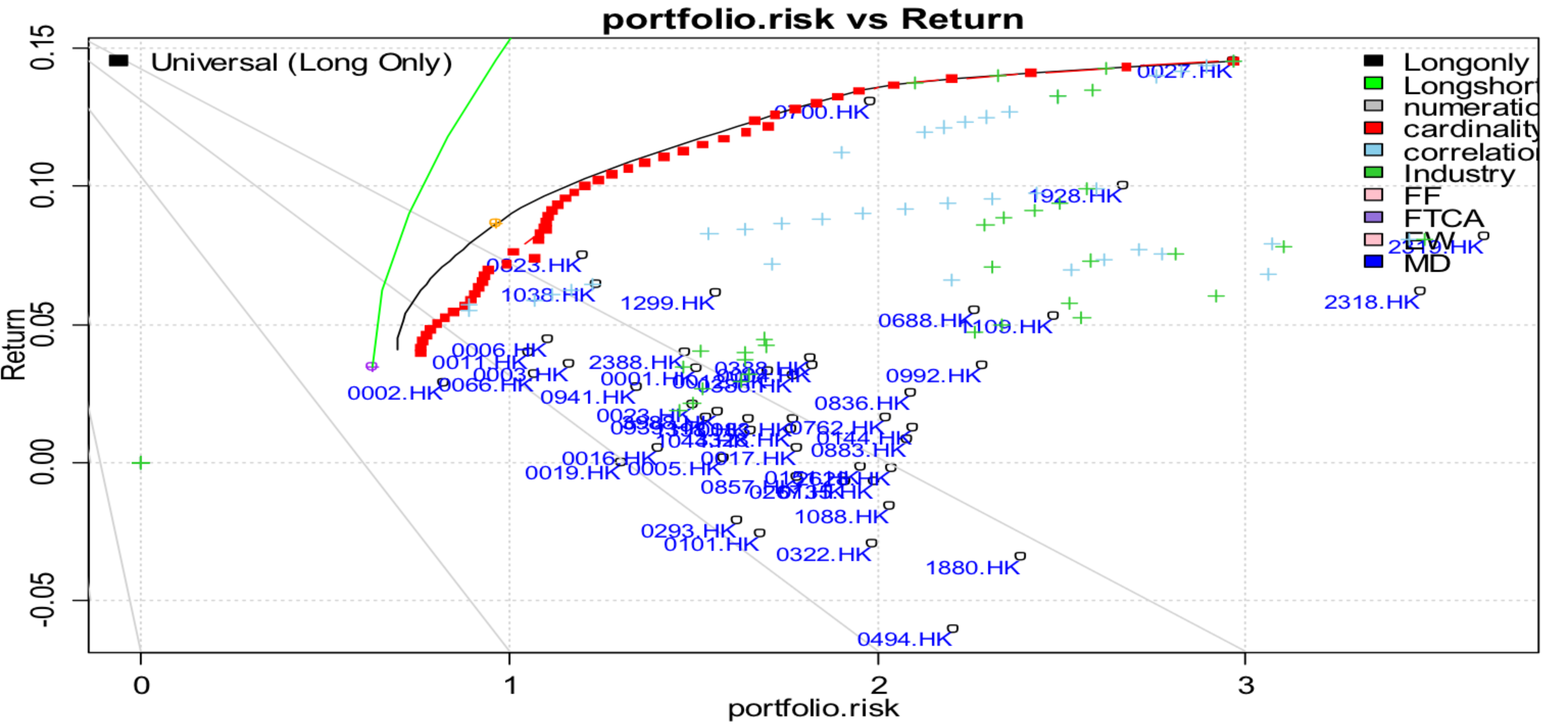

portfolio.risk vs Return
Universal (Long Only)
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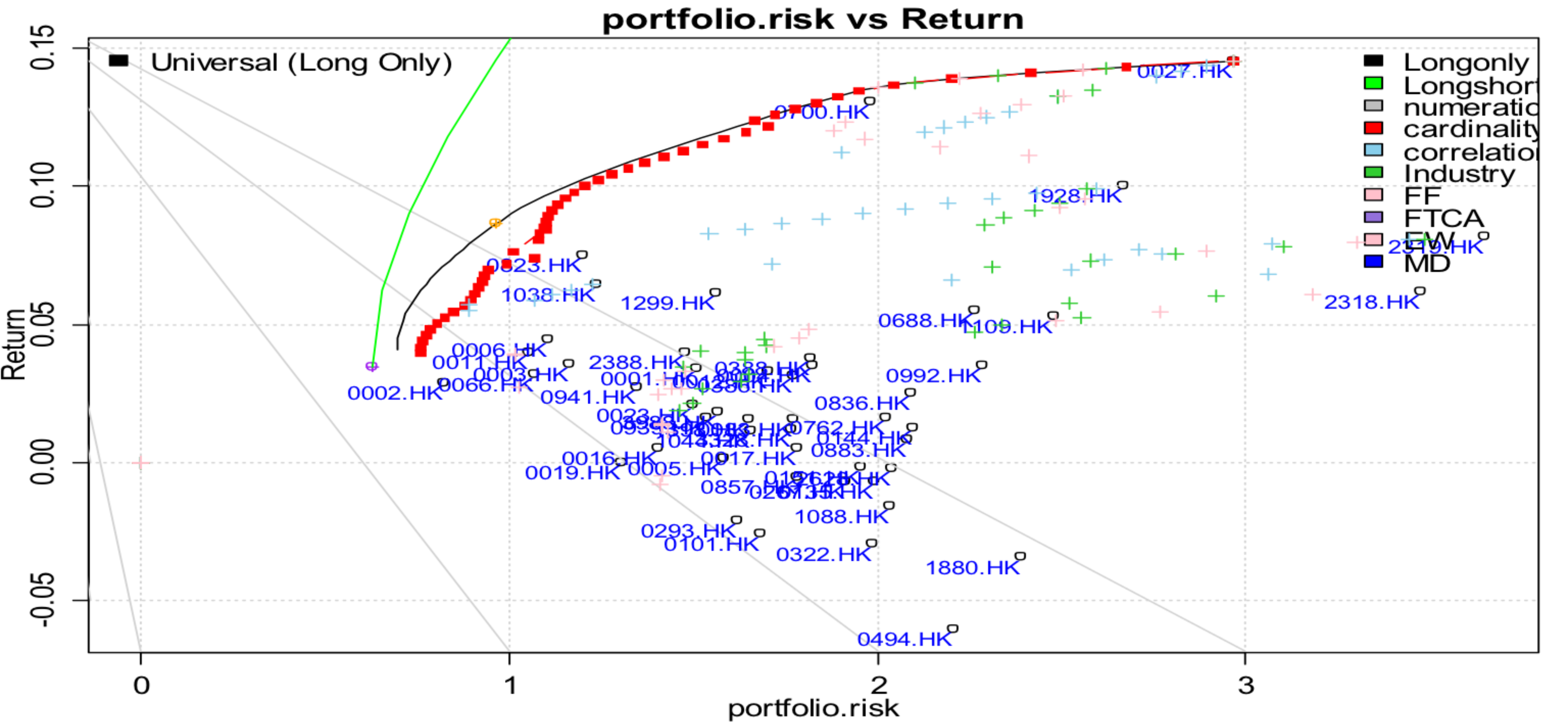

portfolio.risk vs Return
Universal (Long Only)
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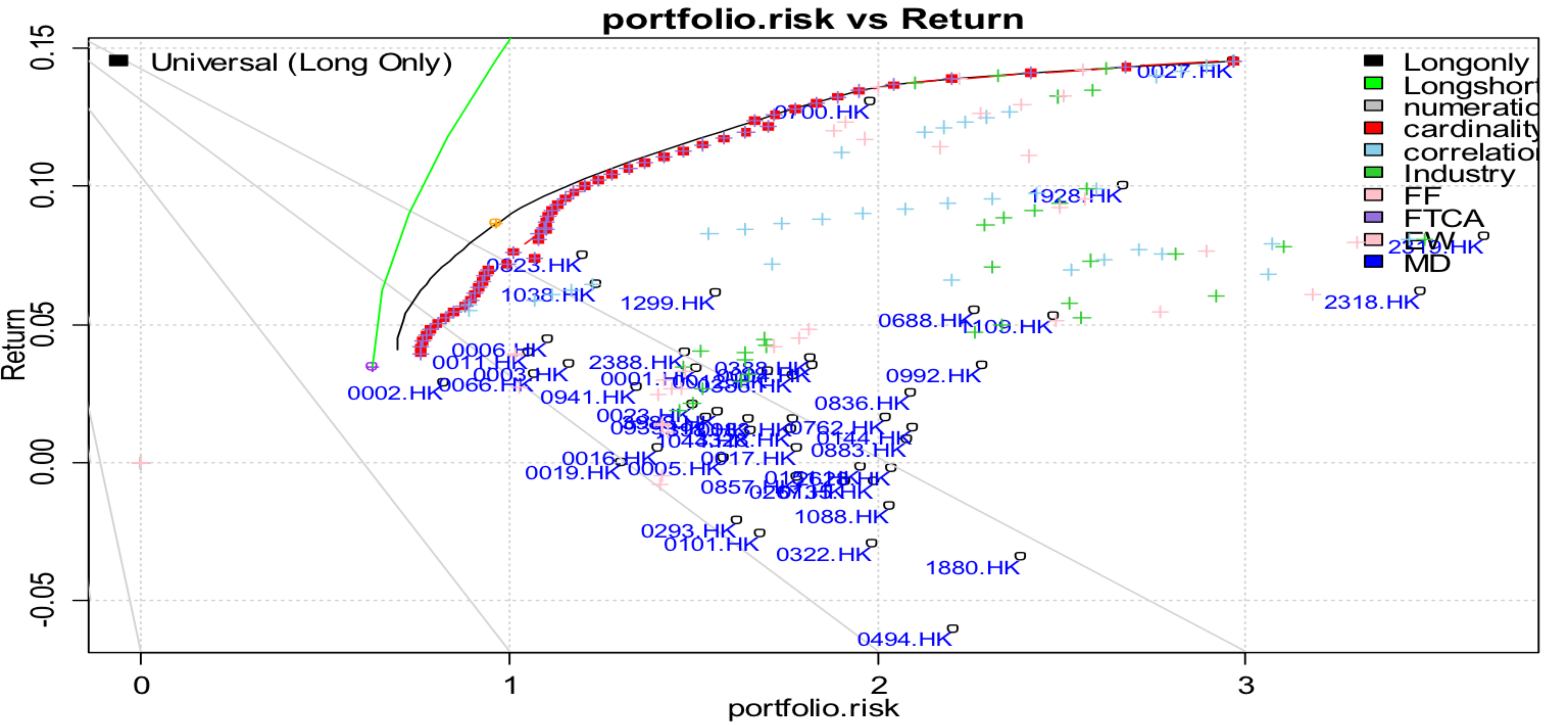

portfolio.risk vs Return
Universal (Long Only)
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correlatio
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portfolio.risk
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0941.HK
0992.HK
0836.HK
0762.HK
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0017.HK
0019.HK
0005.HK
0857.HK
1088.HK
0293.HK
0101.HK
0322.HK
1880.HK
0494.HK

K-means.cor portfolio

$$\min_{x} x'Qx$$

$$\text{s.t. } r'x \geq \bar{r}$$

$$\mathbf{1}'x = 1$$

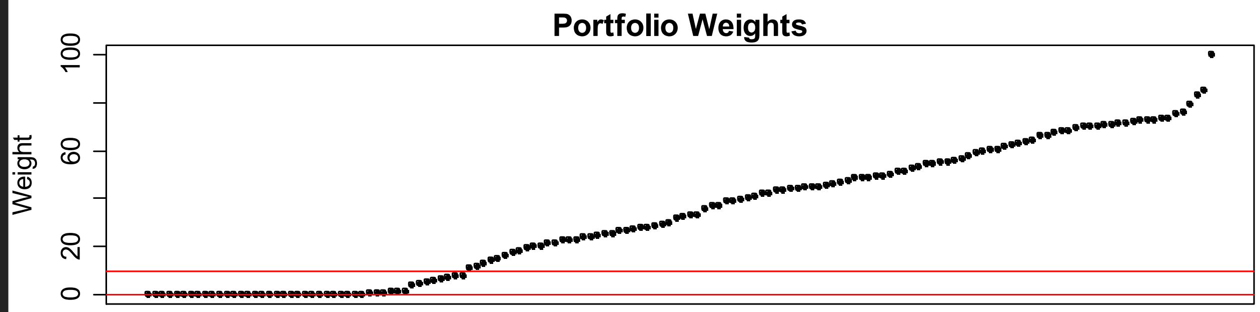
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$

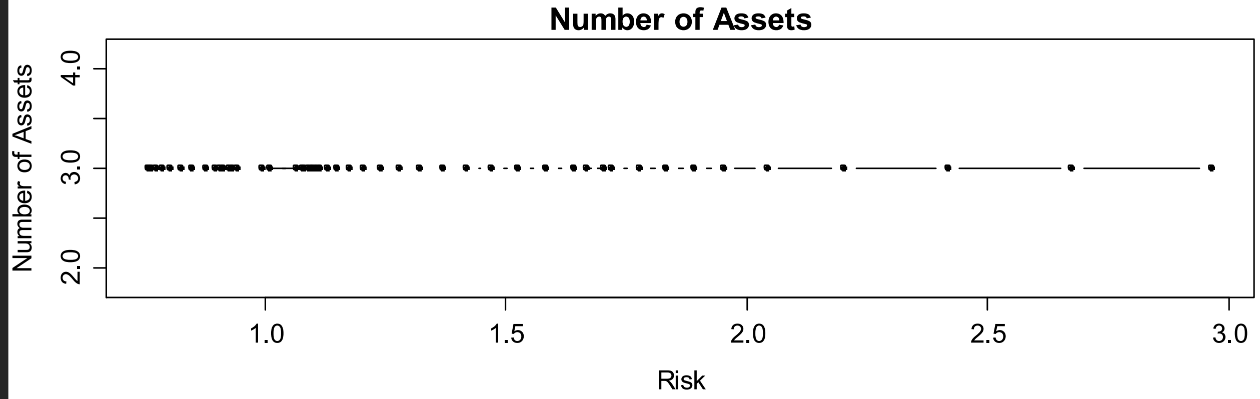
$$\sum_{i=1}^{n} b_i = k$$

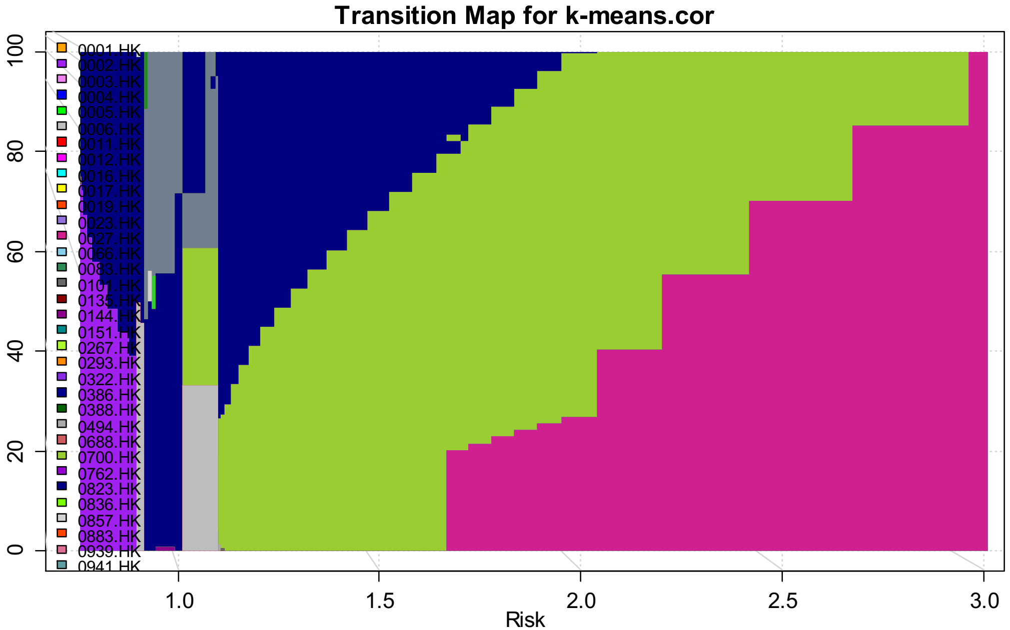
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$

$$i = 1,2,\ldots,n.$$

$$j = 1,2,\ldots,k.$$



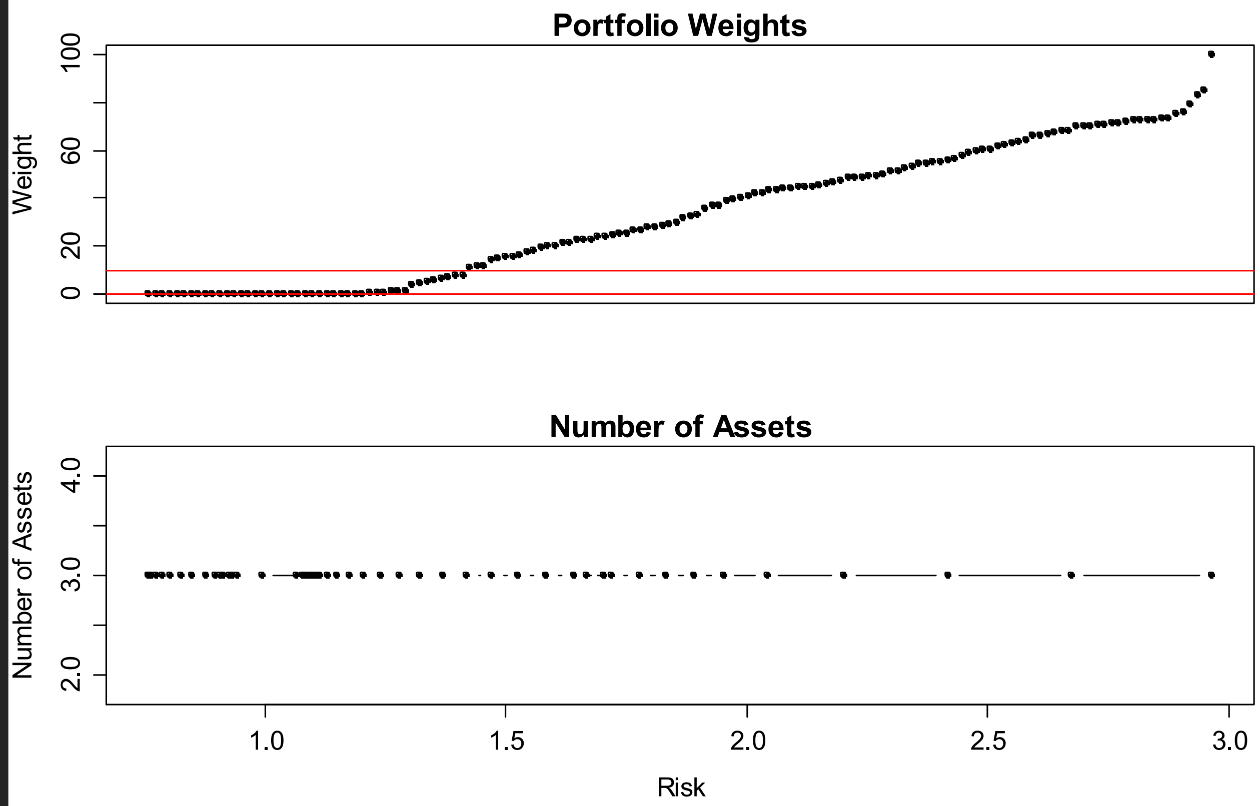




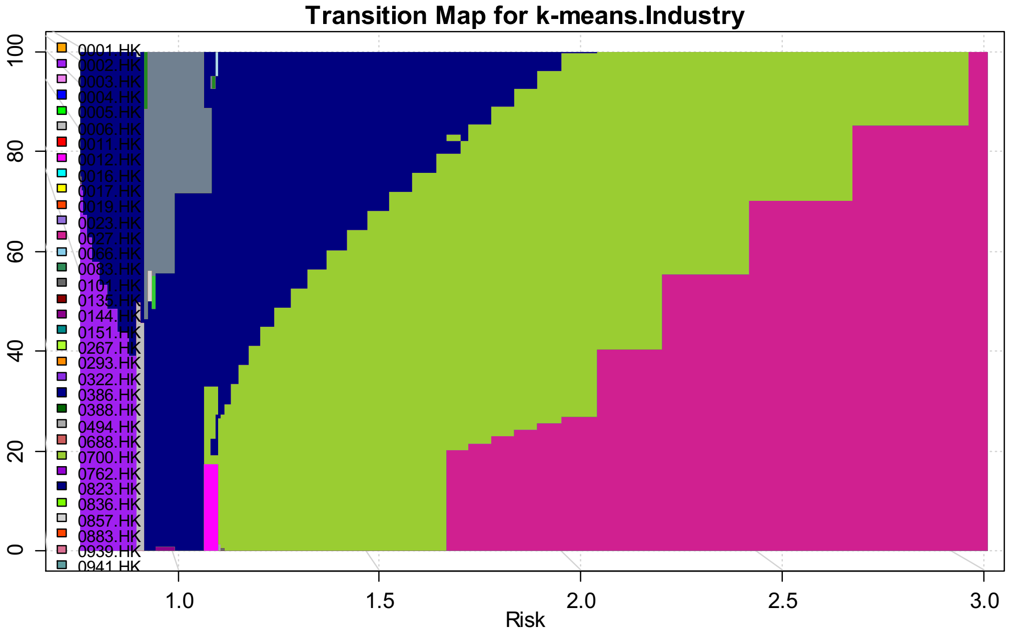
$k = 3$
$j = 7$
$\boldsymbol{\alpha_j} = 0$
$\boldsymbol{\beta_j} = 3$

K-means.IND portfolio

$$\min_{x} x'Qx$$
$$\text{s.t. } r'x \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$\boldsymbol{\alpha_j} \leq \sum_{i \in I_j}^{n} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$i = 1,2,\dots,n.$$
$$j = 1,2,\dots,k.$$

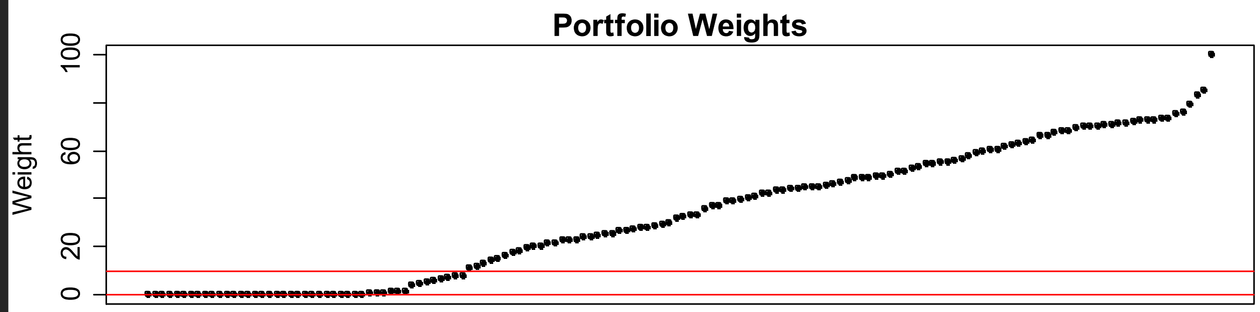


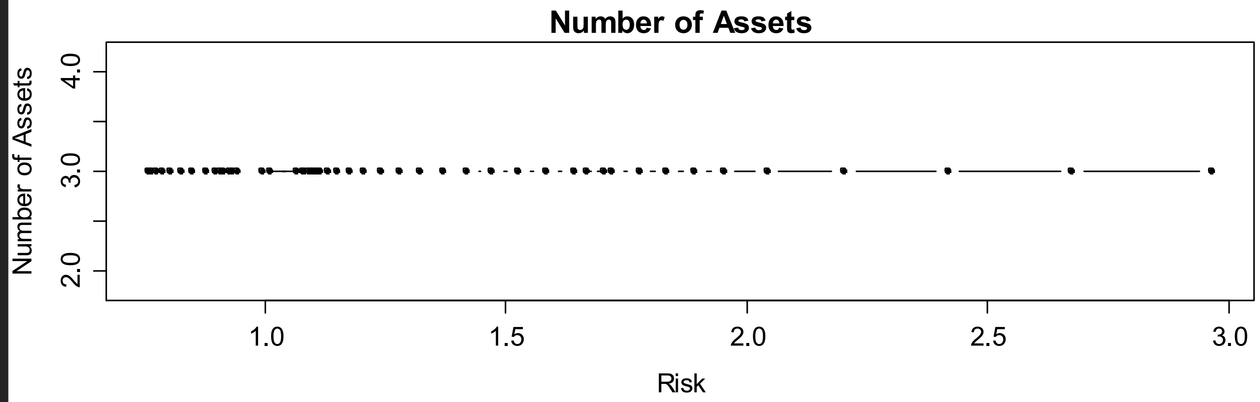
k = 3
j = 7
$\boldsymbol{\alpha_j} = 0$
$\boldsymbol{\beta_j} = 3$

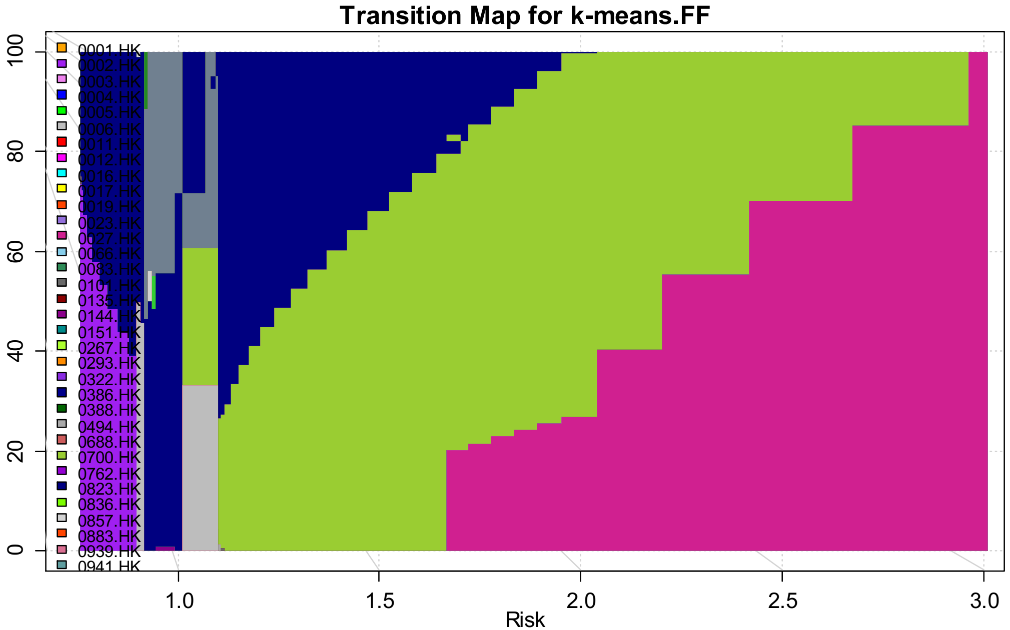


K-means.FF portfolio

$$\min_x x'Qx$$
$$\text{s.t. } r'x \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$\boldsymbol{\alpha_j} \leq \sum_{\boldsymbol{i \in I_j}}^{\boldsymbol{n}} \boldsymbol{b_i} \leq \boldsymbol{\beta_j}$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$i = 1,2,\ldots,n.$$
$$j = 1,2,\ldots,k.$$







$$k = 3$$
$$j = 7$$
$$\boldsymbol{\alpha_j} = 0$$
$$\boldsymbol{\beta_j} = 3$$

K-means.FTCA portfolio

$$\min_x x'Qx$$

$$\text{s.t. } r'x \geq \bar{r}$$

$$\mathbf{1}'x = 1$$

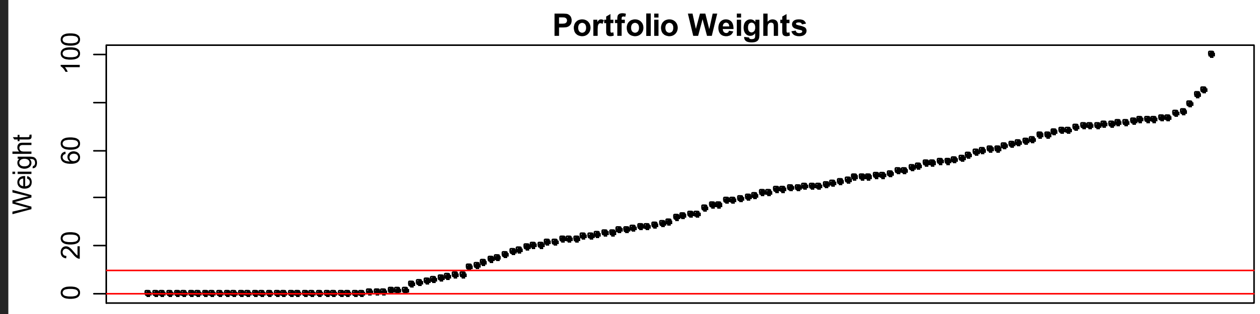
$$\boldsymbol{\alpha_j \leq \sum_{i \in I_j}^{n} b_i \leq \beta_j}$$

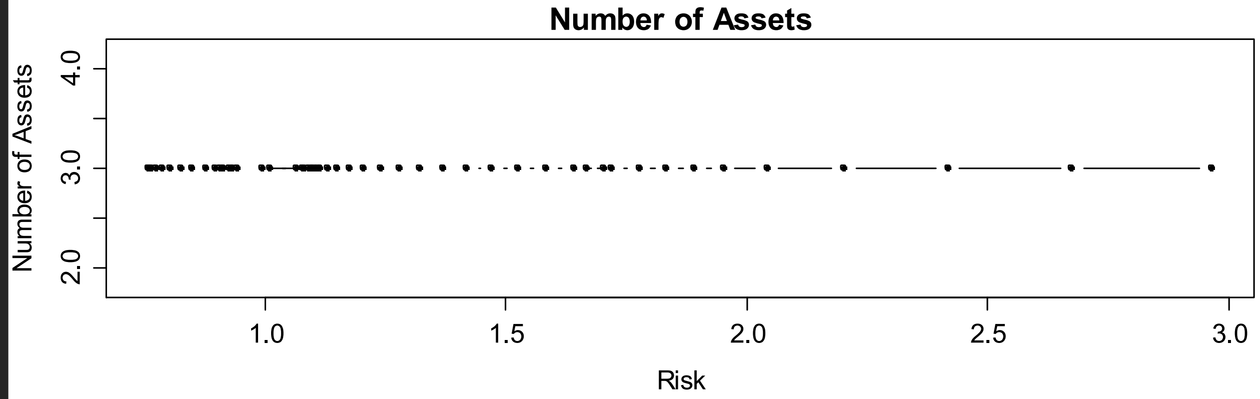
$$\sum_{i=1}^{n} b_i = k$$

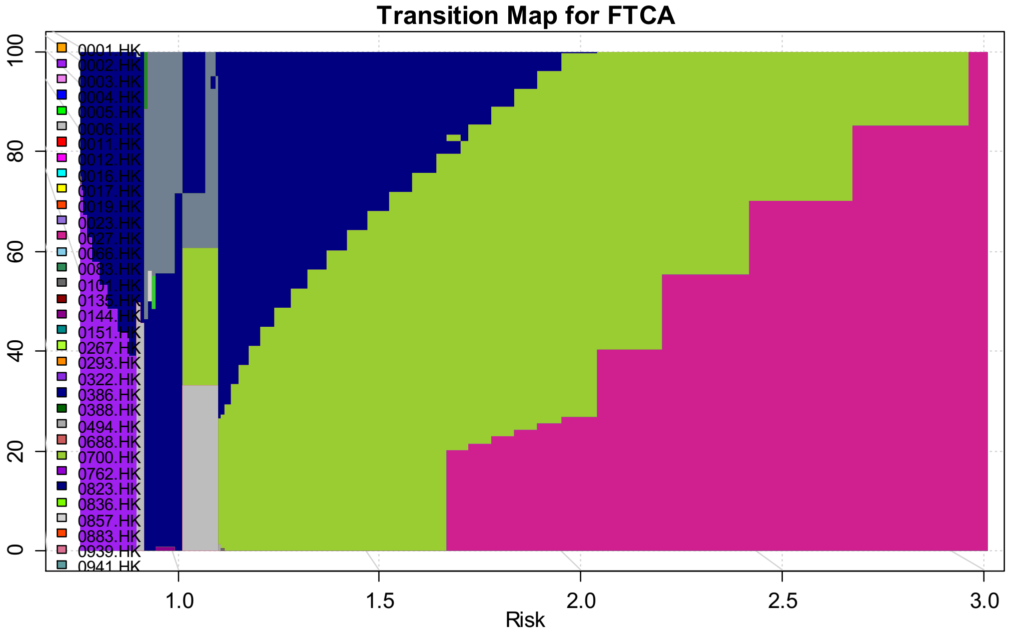
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$

$$i = 1,2, \ldots, n.$$

$$j = 1,2, \ldots, k.$$





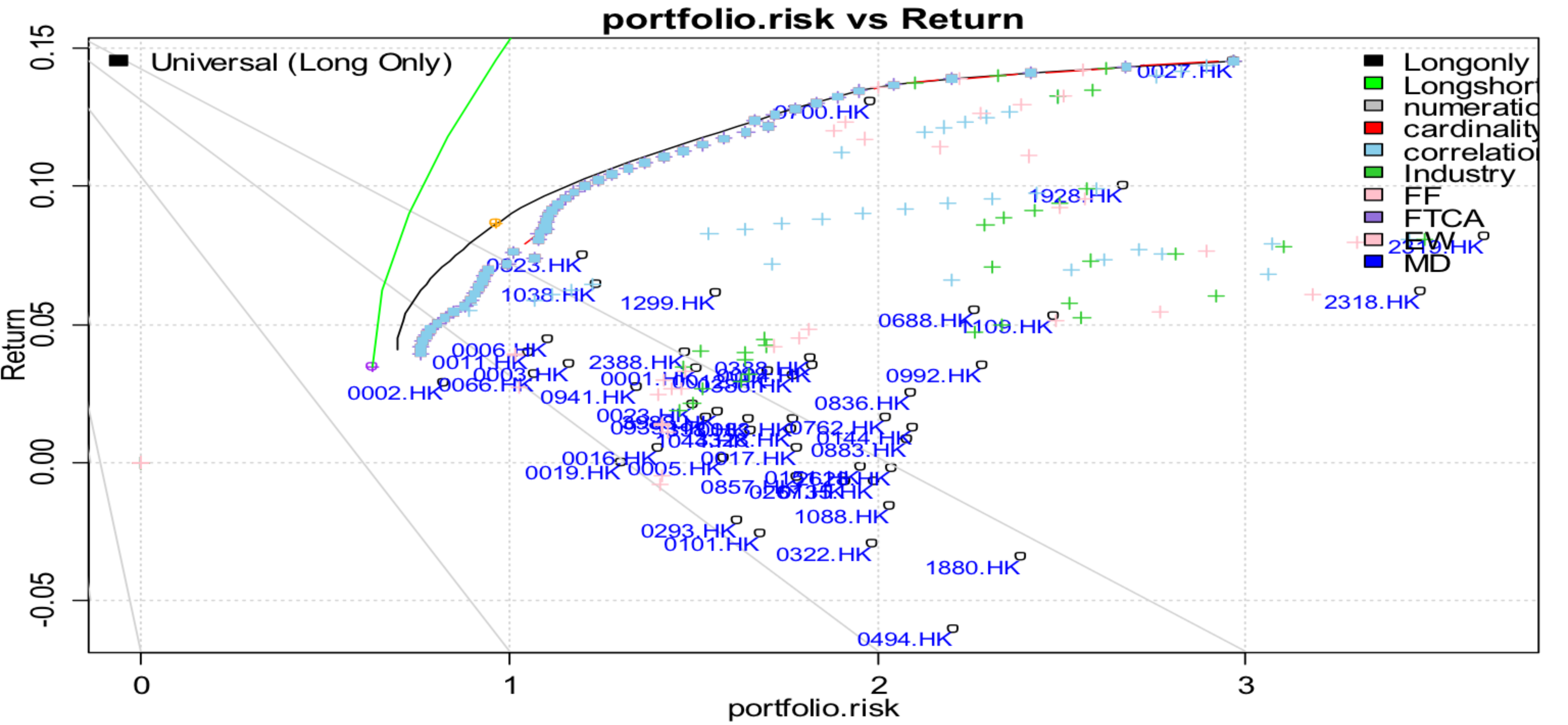


$k = 3$

$j = 18$

$\boldsymbol{\alpha_j} = 0$

$\boldsymbol{\beta_j} = 3$



portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
numeratio
cardinality
correlation
Industry
FF
FTCA
EW
MD
Return
portfolio.risk
0.15
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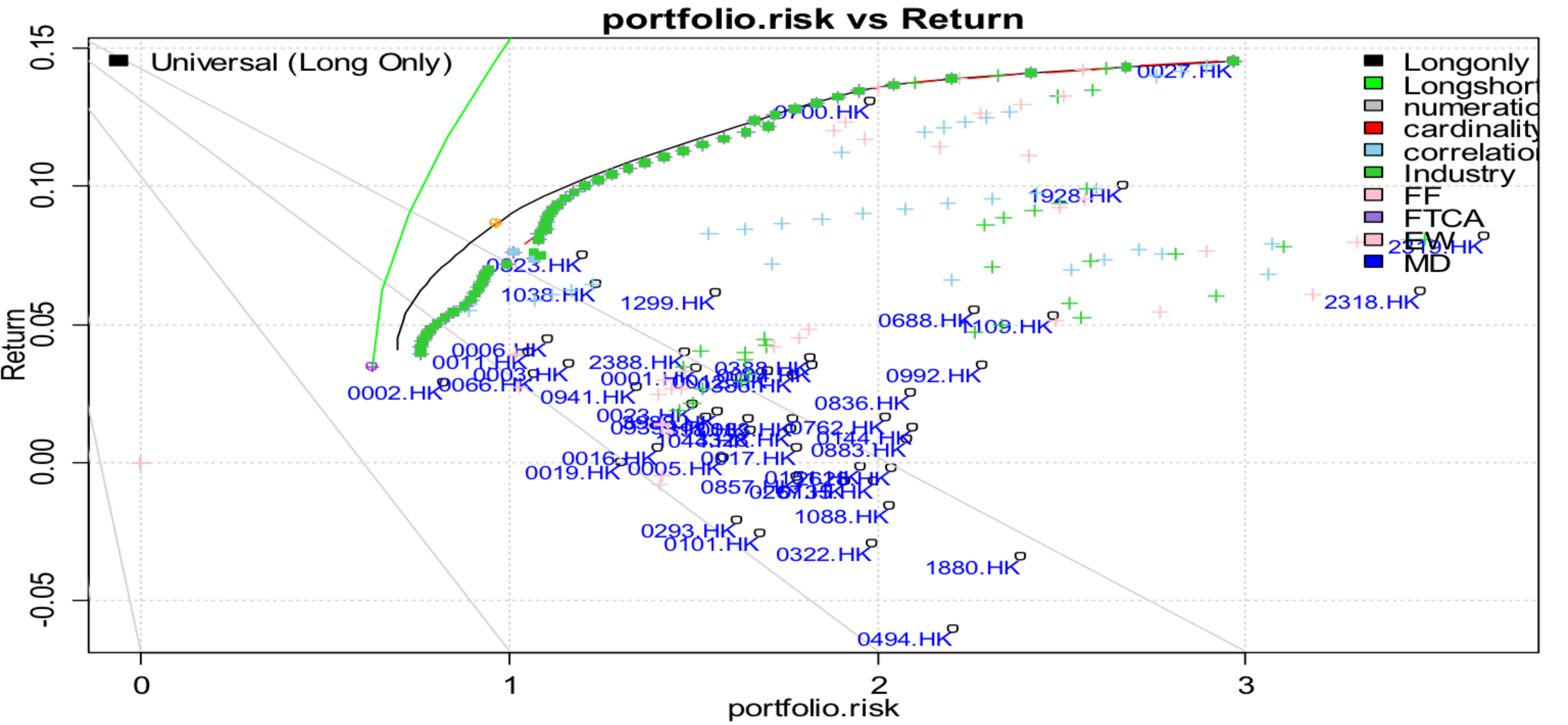
0005.HK
1088.HK
0293.HK
0101.HK
0322.HK
1880.HK
0494.HK


portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
numeratio
cardinality
correlatio
Industry
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portfolio.risk
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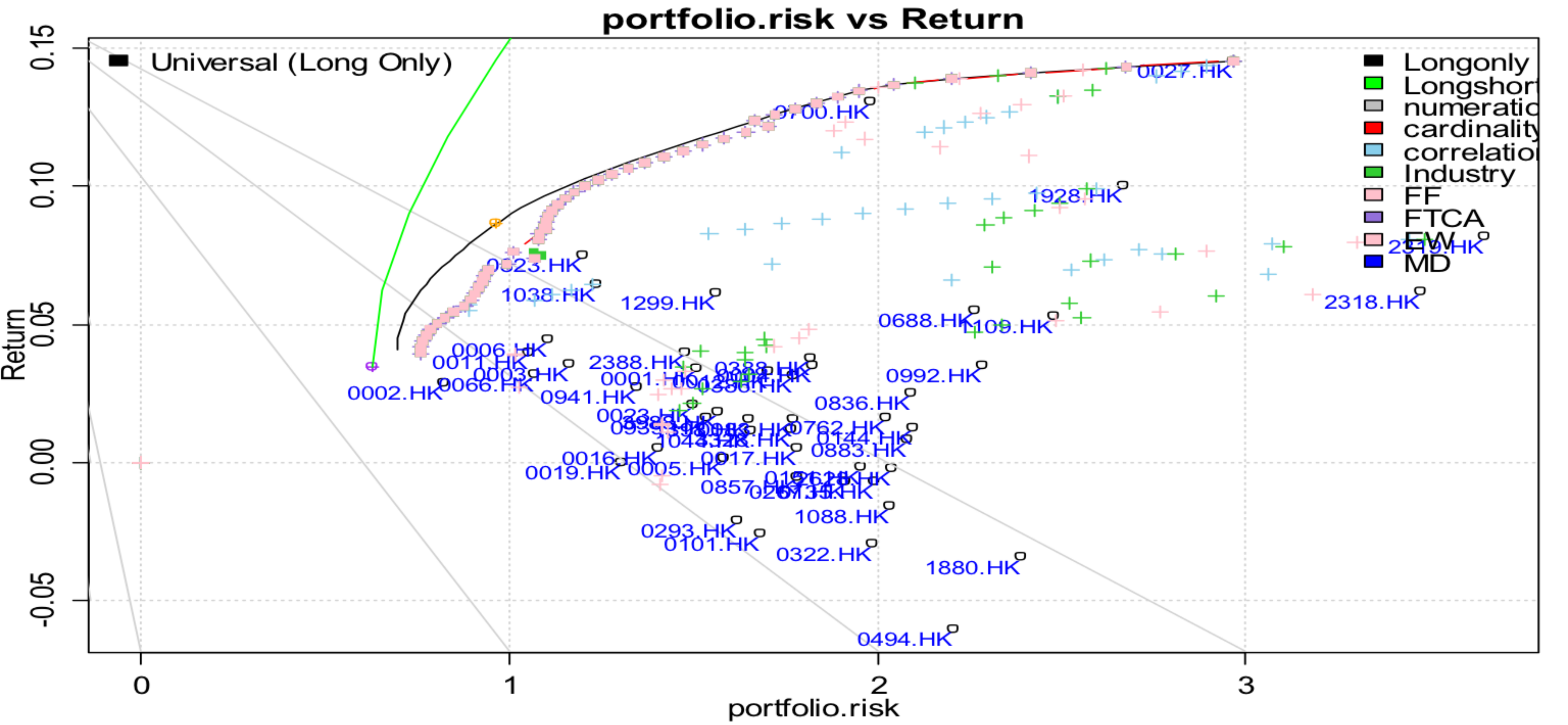

portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
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Industry
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portfolio.risk
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1880.HK
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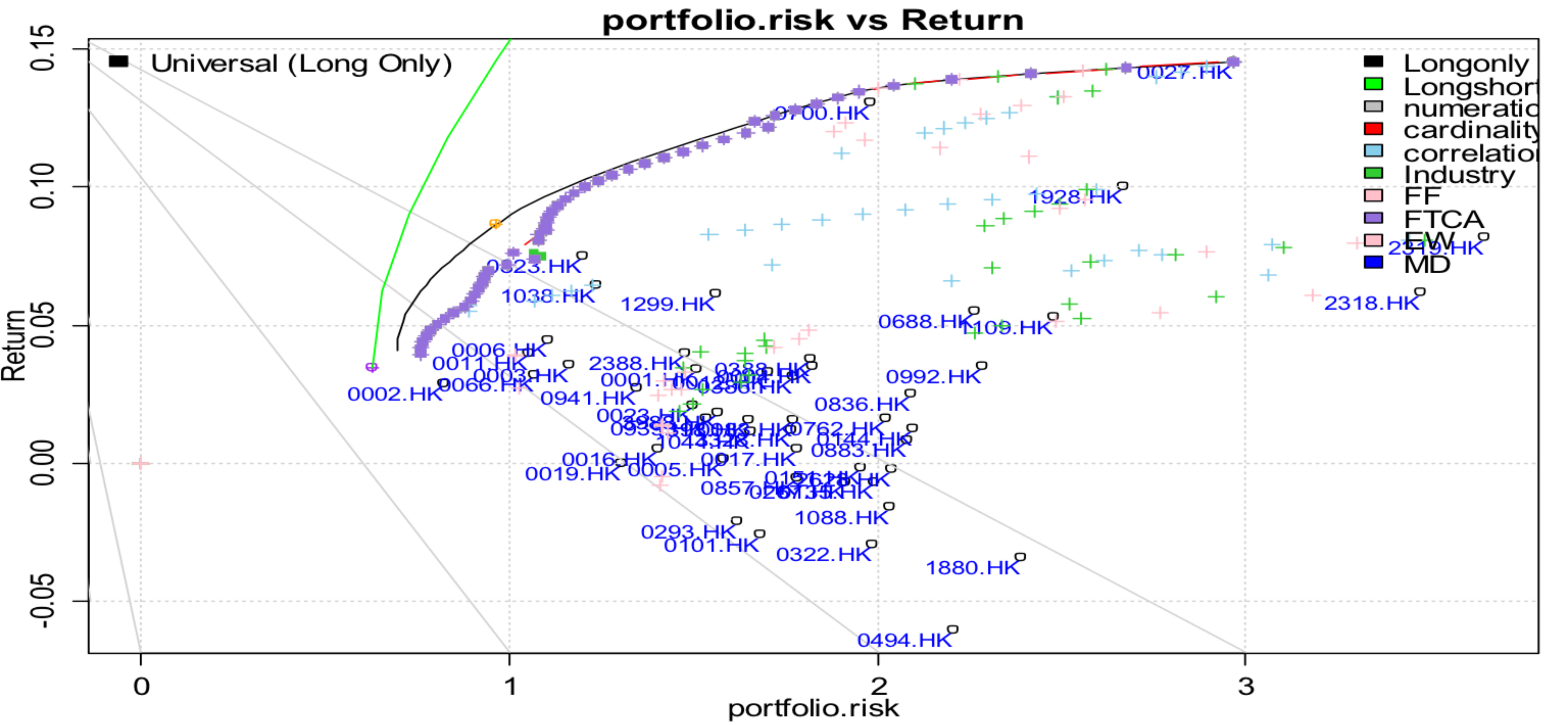
portfolio.risk vs Return
Universal (Long Only)
Longonly
cardinality
Industry
FF
FTCA
MD
Return
portfolio.risk
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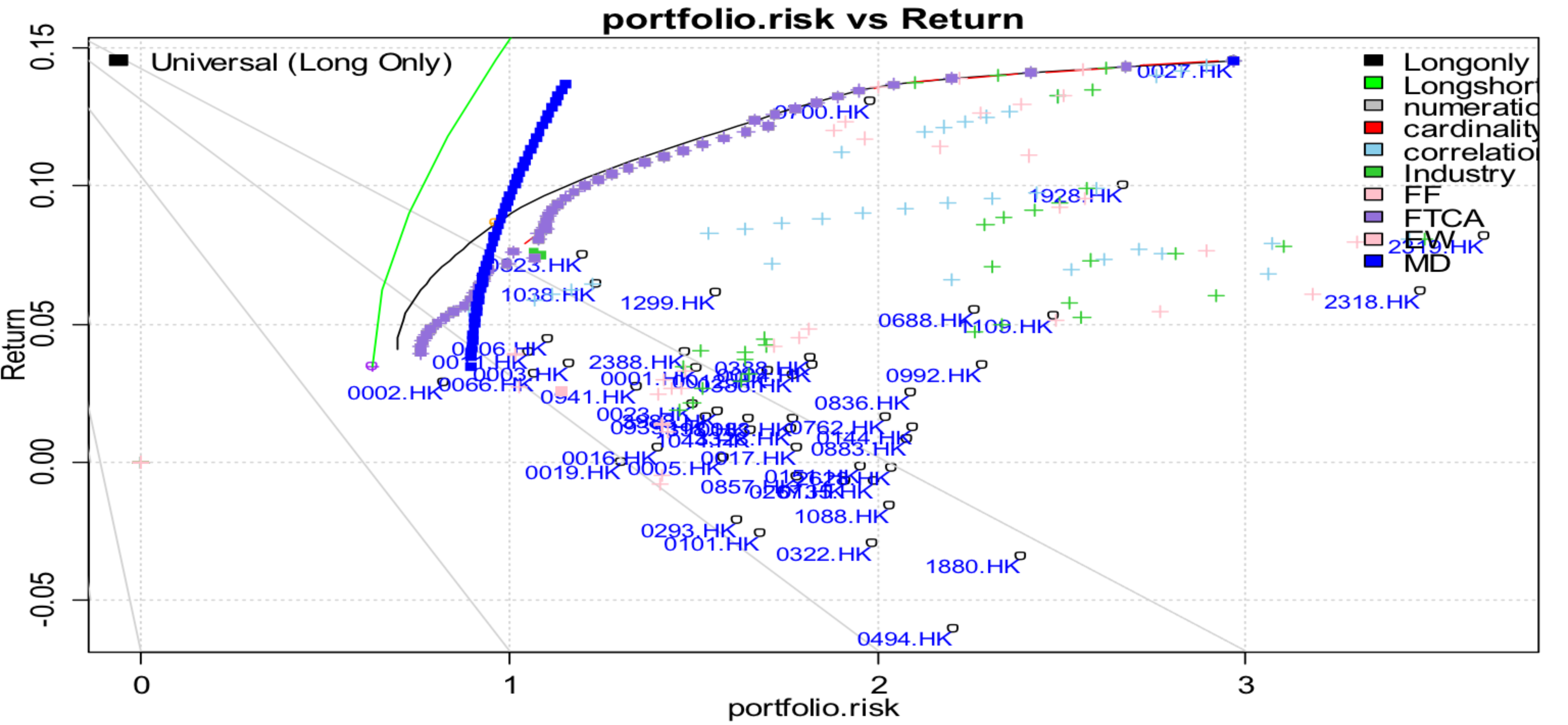
portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
numeratio
cardinality
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Industry
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portfolio.risk
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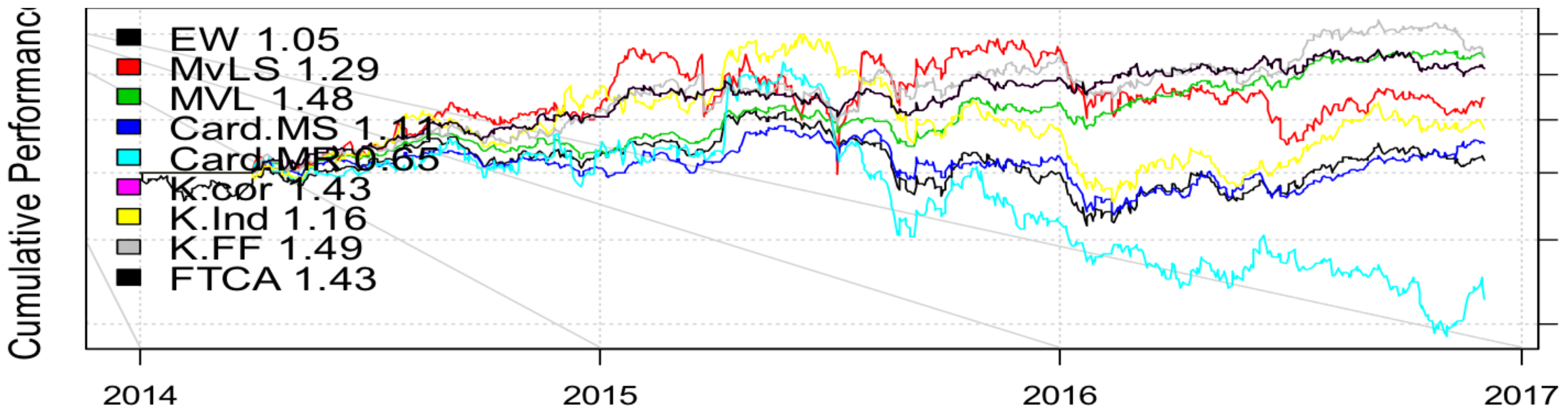
0101.HK
0322.HK
1880.HK
0494.HK

Static?

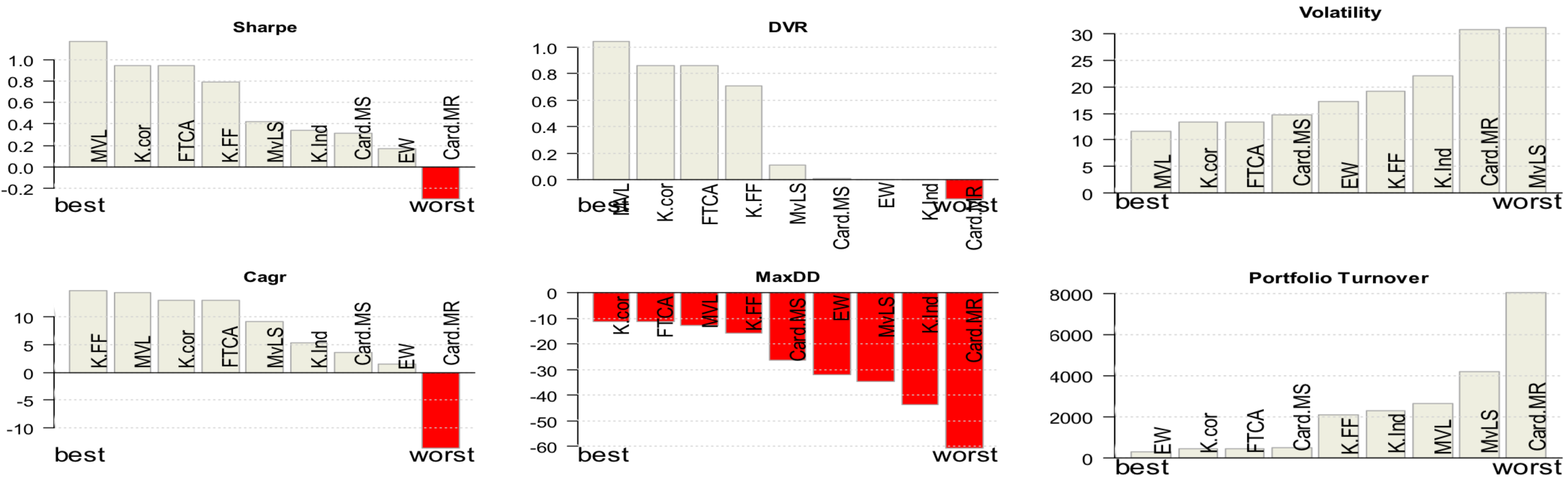
Let history have a say!

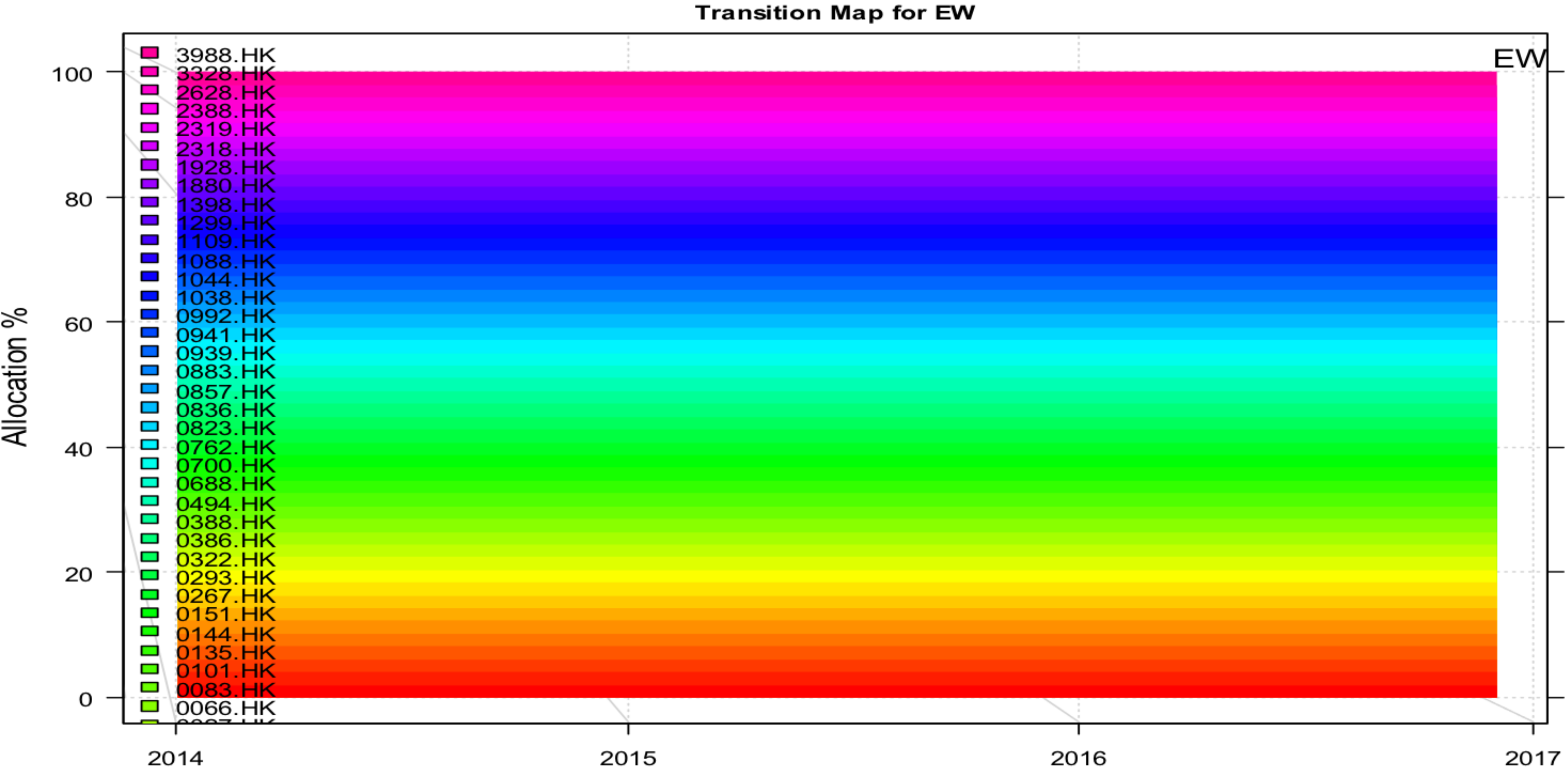
Back testing

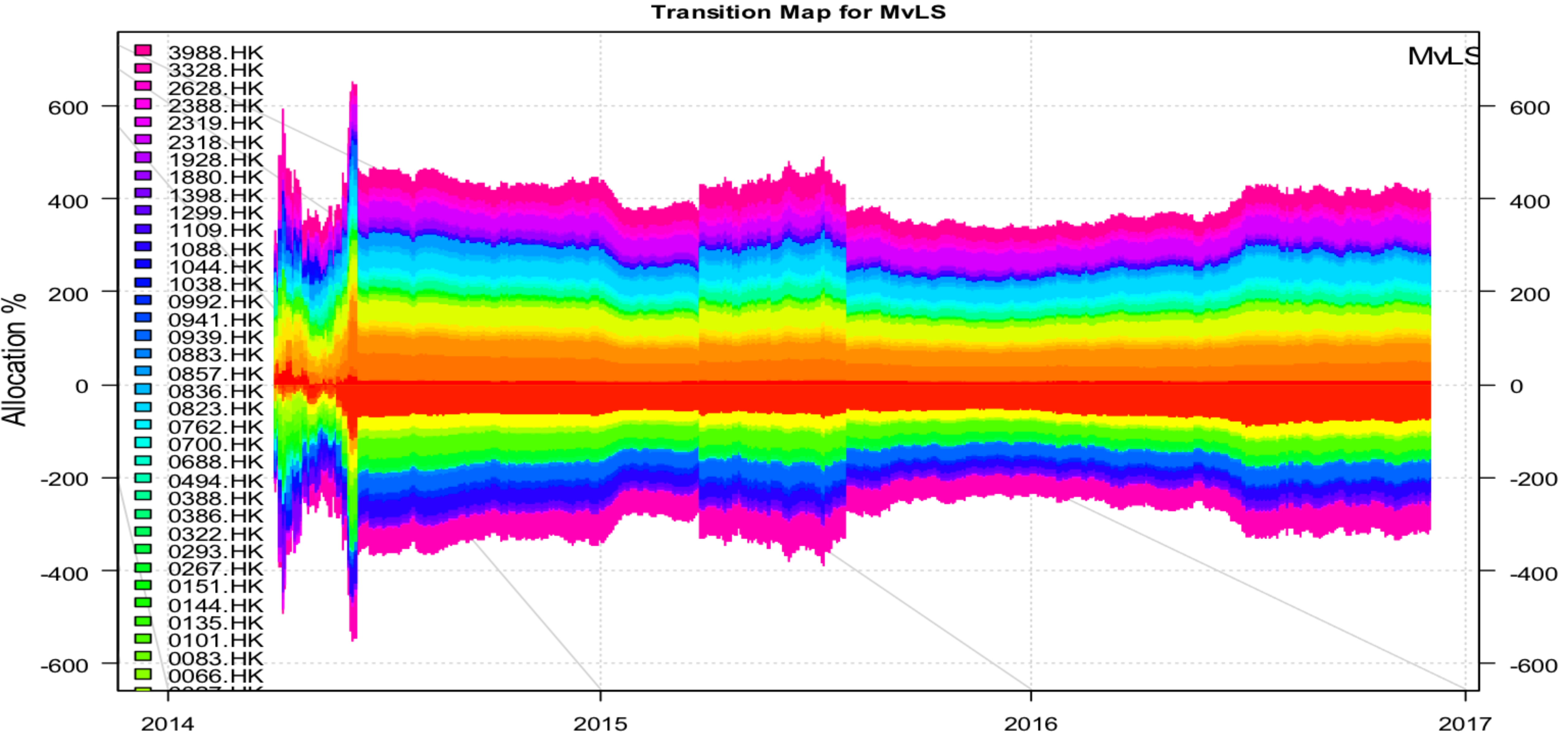
Portfolio performance across time



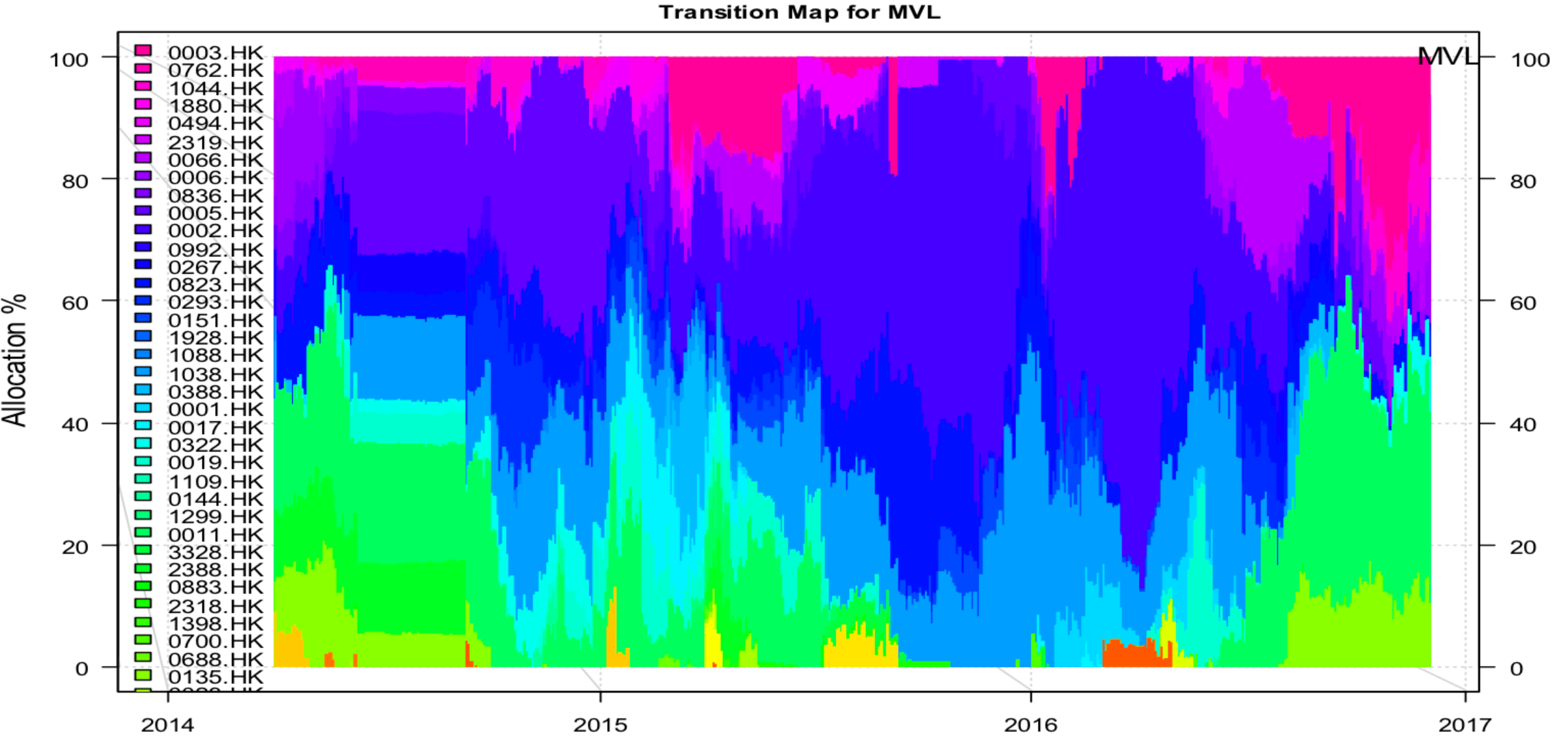
System	EW	MvLS	MVL	Card.MS	Card.MR	K.cor	K.Ind	K.FF	FTCA
Period	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016	Jan2014 - Dec2016
Cagr	1.56	9.09	14.44	3.62	-13.58	13.01	5.29	14.67	13.01
Sharpe	0.17	0.42	1.17	0.31	-0.3	0.95	0.34	0.79	0.95
DVR	0	0.11	1.04	0.01	-0.14	0.86	0	0.71	0.86
Volatility	17.26	31.06	11.7	14.69	30.82	13.4	22.04	19.14	13.4
MaxDD	-32.2	-34.59	-12.92	-26.33	-60.57	-11.36	-43.64	-15.79	-11.36
AvgDD	-4.89	-6.17	-2.14	-4.86	-10.18	-2.44	-5.49	-3.13	-2.44
VaR	-1.83	-2.33	-1.12	-1.55	-2.9	-1.35	-2.22	-1.57	-1.35
CVaR	-2.54	-3.96	-1.69	-2.26	-4.25	-1.93	-3.02	-2.65	-1.93
Exposure	99.87	91.61	91.61	91.61	91.61	91.61	91.61	91.61	91.61


Sharpe
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
MVL
K.cor
FTCA
K.FF
MvLS
K.Ind
Card.MS
EW
Card.MR
best
worst
DVR
1.0
0.8
0.6
0.4
0.2
0.0
MVL
K.cor
FTCA
K.FF
MvLS
Card.MS
EW
K.Ind
Card.MR
best
worst
Volatility
30
25
20
15
10
5
0
MVL
K.cor
FTCA
Card.MS
EW
K.FF
K.Ind
Card.MR
MvLS
best
worst
Cagr
10
5
0
-5
-10
K.FF
MVL
K.cor
FTCA
MvLS
K.Ind
Card.MS
EW
Card.MR
best
worst
MaxDD
0
-10
-20
-30
-40
-50
-60
K.cor
FTCA
MVL
K.FF
Card.MS
EW
MvLS
K.Ind
Card.MR
best
worst
Portfolio Turnover
8000
6000
4000
2000
0
EW
K.cor
FTCA
Card.MS
K.FF
K.Ind
MVL
MvLS
Card.MR
best
worst

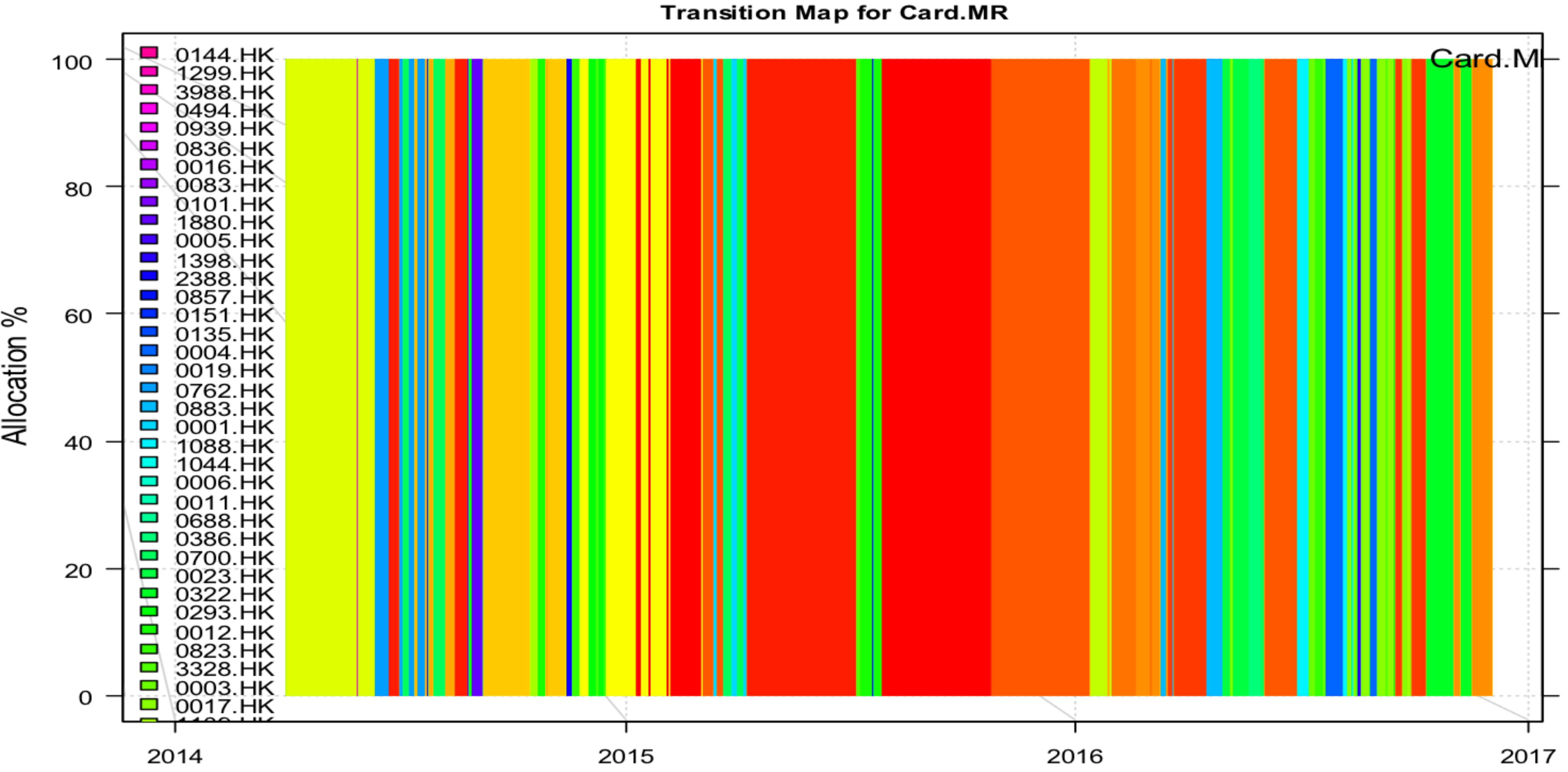

Transition Map for EW
Allocation %
EW
3988.HK
3328.HK
2628.HK
2388.HK
2319.HK
2318.HK
1928.HK
1880.HK
1398.HK
1299.HK
1109.HK
1088.HK
1044.HK
1038.HK
0992.HK
0941.HK
0939.HK
0883.HK
0857.HK
0836.HK
0823.HK
0762.HK
0700.HK
0688.HK
0494.HK
0388.HK
0386.HK
0322.HK
0293.HK
0267.HK
0151.HK
0144.HK
0135.HK
0101.HK
0083.HK
0066.HK
0
20
40
60
80
100
2014
2015
2016
2017



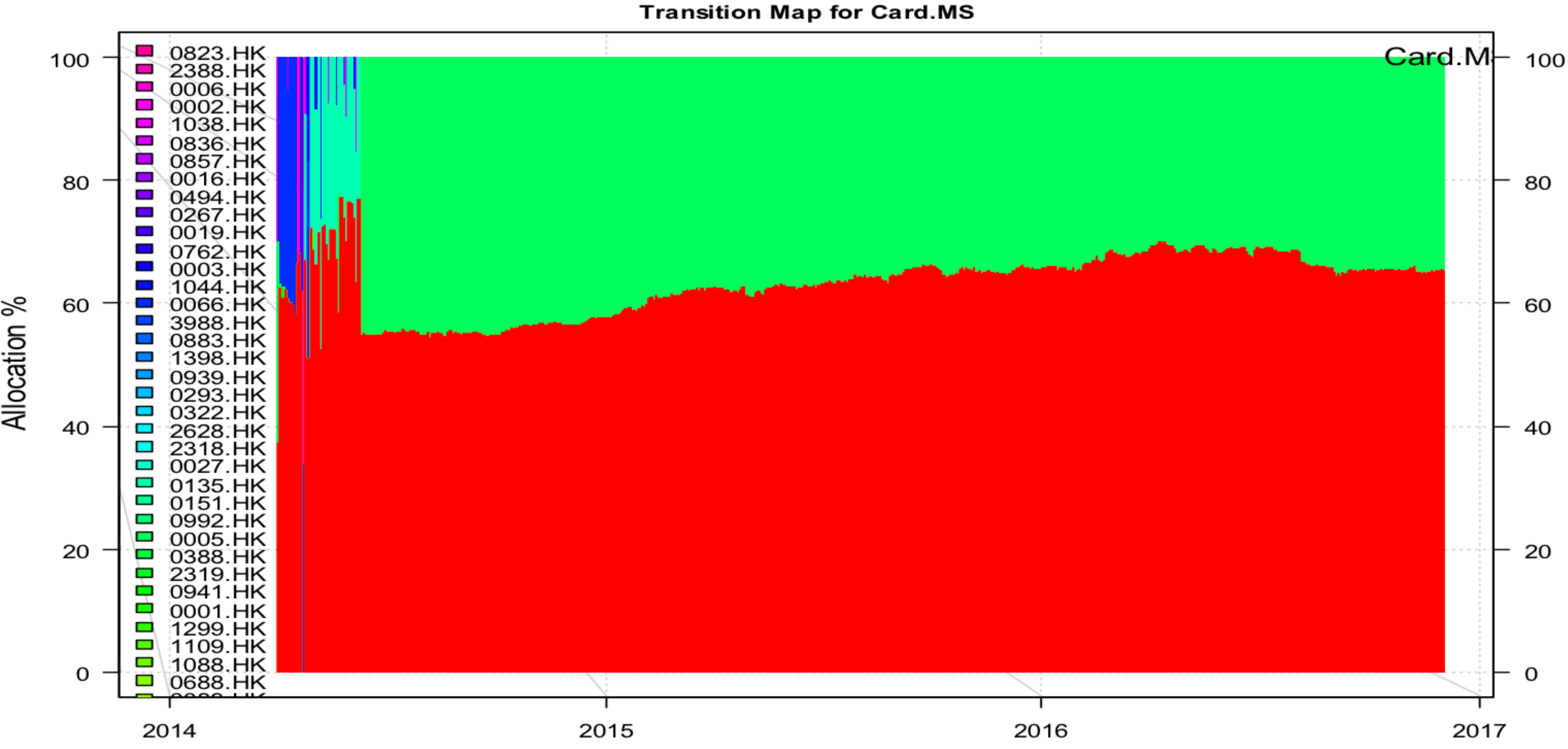
Transition Map for MvLS
MvLS
Allocation %
600
400
200
0
-200
-400
-600
2014
2015
2016
2017
3988.HK
3328.HK
2628.HK
2388.HK
2319.HK
2318.HK
1928.HK
1880.HK
1398.HK
1299.HK
1109.HK
1088.HK
1044.HK
1038.HK
0992.HK
0941.HK
0939.HK
0883.HK
0857.HK
0836.HK
0823.HK
0762.HK
0700.HK
0688.HK
0494.HK
0388.HK
0386.HK
0322.HK
0293.HK
0267.HK
0151.HK
0144.HK
0135.HK
0101.HK
0083.HK
0066.HK



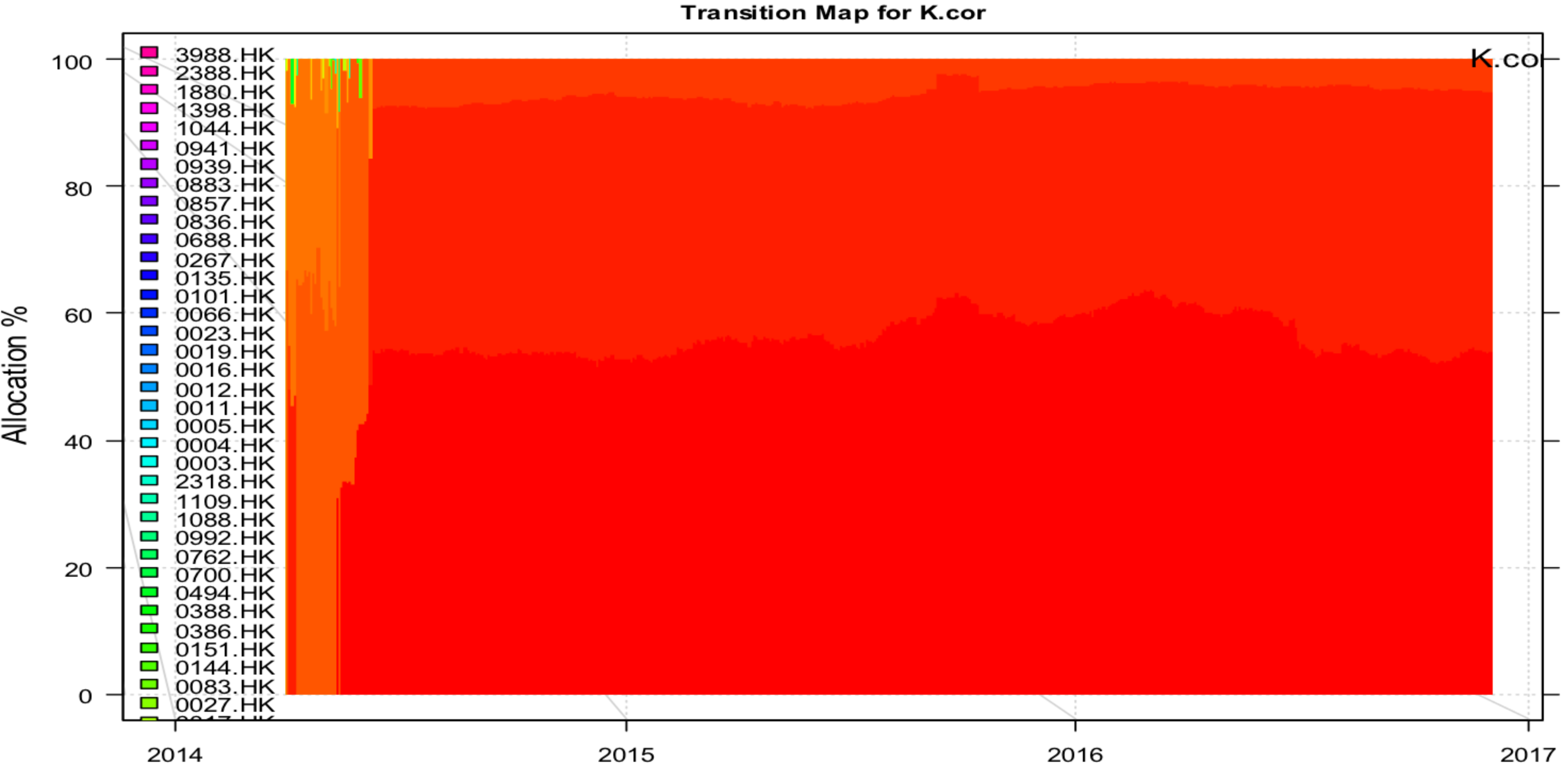
Transition Map for MVL
MVL
Allocation %
100
80
60
40
20
0
2014
2015
2016
2017
0003.HK
0762.HK
1044.HK
1880.HK
0494.HK
2319.HK
0066.HK
0006.HK
0836.HK
0005.HK
0002.HK
0992.HK
0267.HK
0823.HK
0293.HK
0151.HK
1928.HK
1088.HK
1038.HK
0388.HK
0001.HK
0017.HK
0322.HK
0019.HK
1109.HK
0144.HK
1299.HK
0011.HK
3328.HK
2388.HK
0883.HK
2318.HK
1398.HK
0700.HK
0688.HK
0135.HK



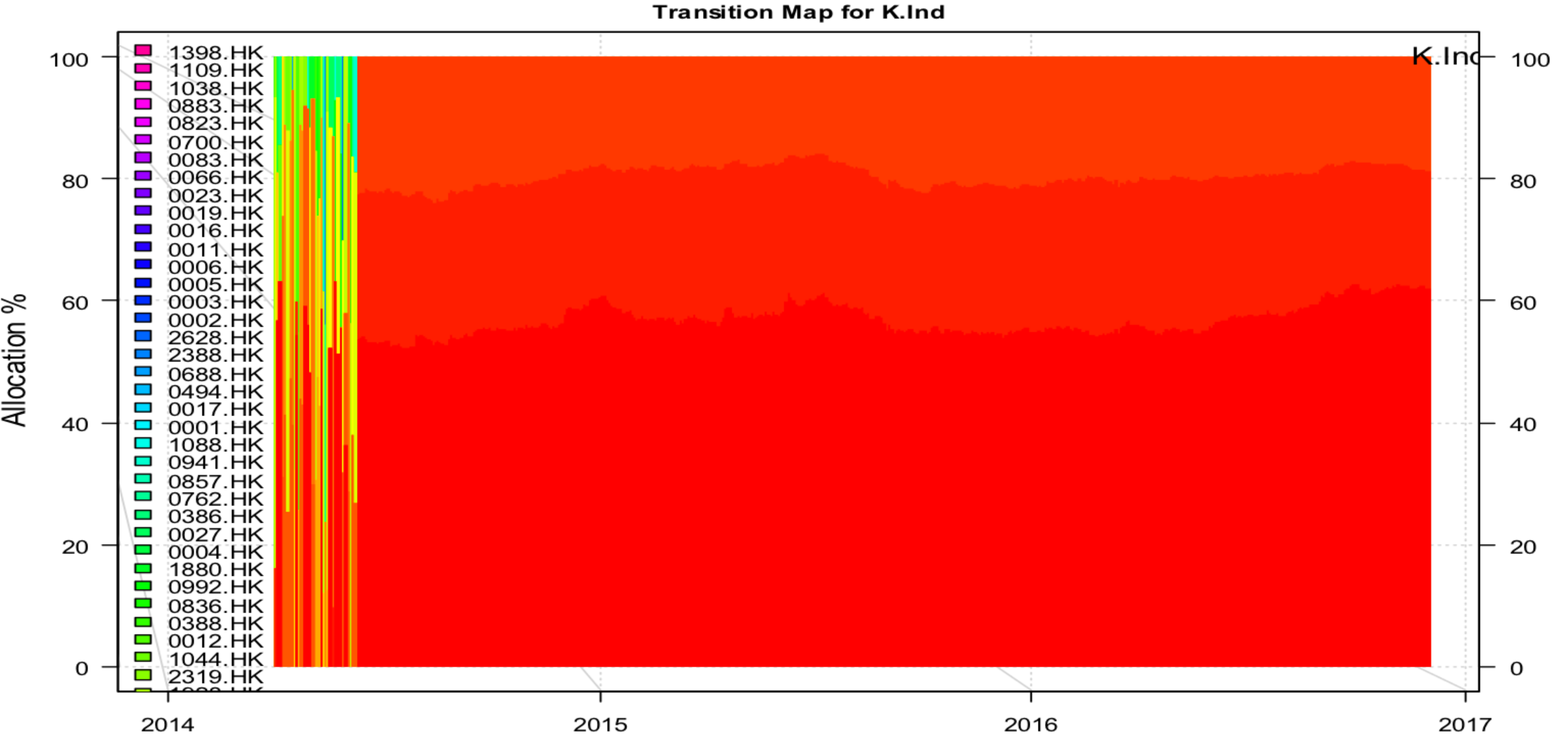
Transition Map for Card.MR
Allocation %
Card.M
0144.HK
1299.HK
3988.HK
0494.HK
0939.HK
0836.HK
0016.HK
0083.HK
0101.HK
1880.HK
0005.HK
1398.HK
2388.HK
0857.HK
0151.HK
0135.HK
0004.HK
0019.HK
0762.HK
0883.HK
0001.HK
1088.HK
1044.HK
0006.HK
0011.HK
0688.HK
0386.HK
0700.HK
0023.HK
0322.HK
0293.HK
0012.HK
0823.HK
3328.HK
0003.HK
0017.HK
0
20
40
60
80
100
2014
2015
2016
2017



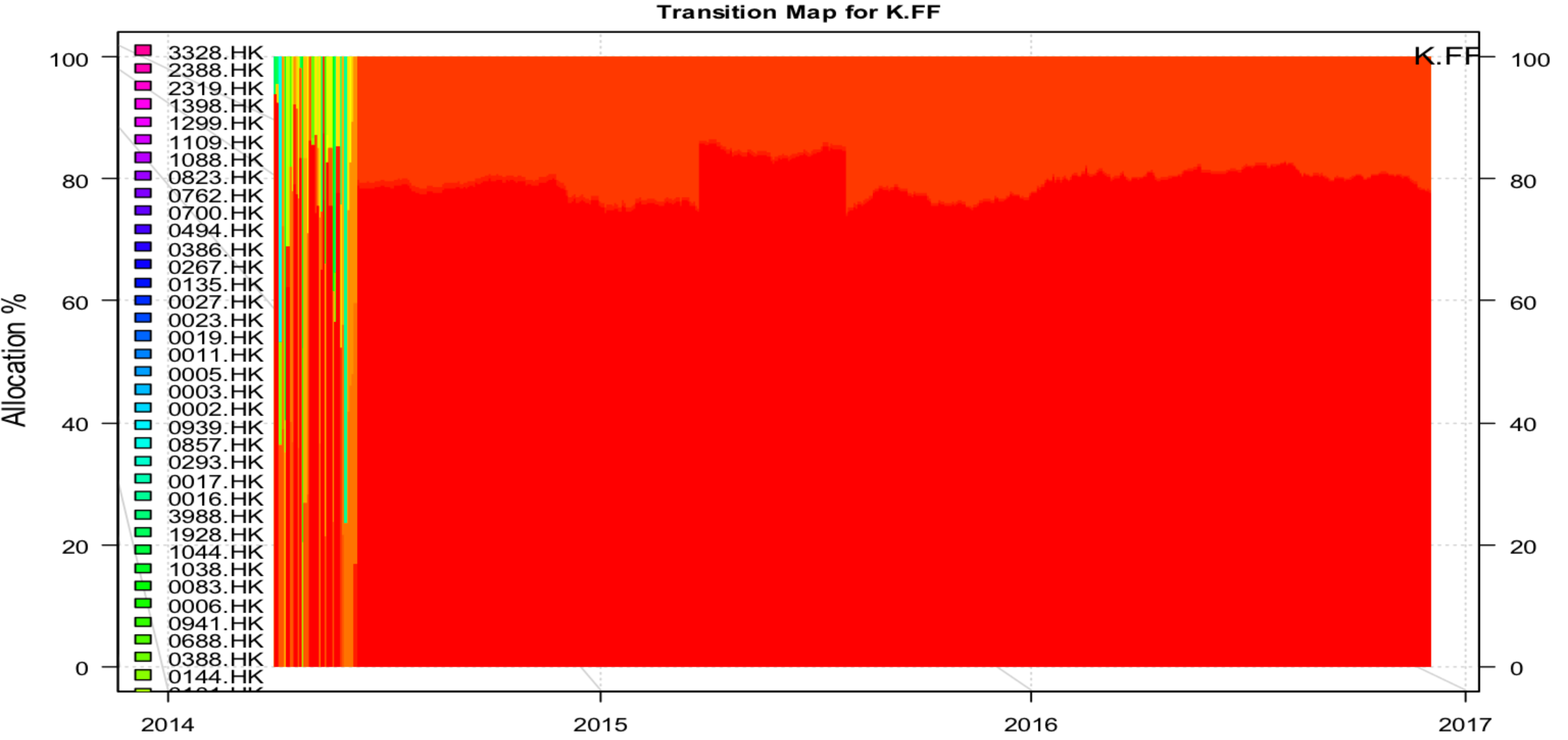
Transition Map for Card.MS
Allocation %
0823.HK
2388.HK
0006.HK
0002.HK
1038.HK
0836.HK
0857.HK
0016.HK
0494.HK
0267.HK
0019.HK
0762.HK
0003.HK
1044.HK
0066.HK
3988.HK
0883.HK
1398.HK
0939.HK
0293.HK
0322.HK
2628.HK
2318.HK
0027.HK
0135.HK
0151.HK
0992.HK
0005.HK
0388.HK
2319.HK
0941.HK
0001.HK
1299.HK
1109.HK
1088.HK
0688.HK
0
20
40
60
80
100
2014
2015
2016
2017



Transition Map for K.cor
K.cor
Allocation %
0
20
40
60
80
100
2014
2015
2016
2017
3988.HK
2388.HK
1880.HK
1398.HK
1044.HK
0941.HK
0939.HK
0883.HK
0857.HK
0836.HK
0688.HK
0267.HK
0135.HK
0101.HK
0066.HK
0023.HK
0019.HK
0016.HK
0012.HK
0011.HK
0005.HK
0004.HK
0003.HK
2318.HK
1109.HK
1088.HK
0992.HK
0762.HK
0700.HK
0494.HK
0388.HK
0386.HK
0151.HK
0144.HK
0083.HK
0027.HK

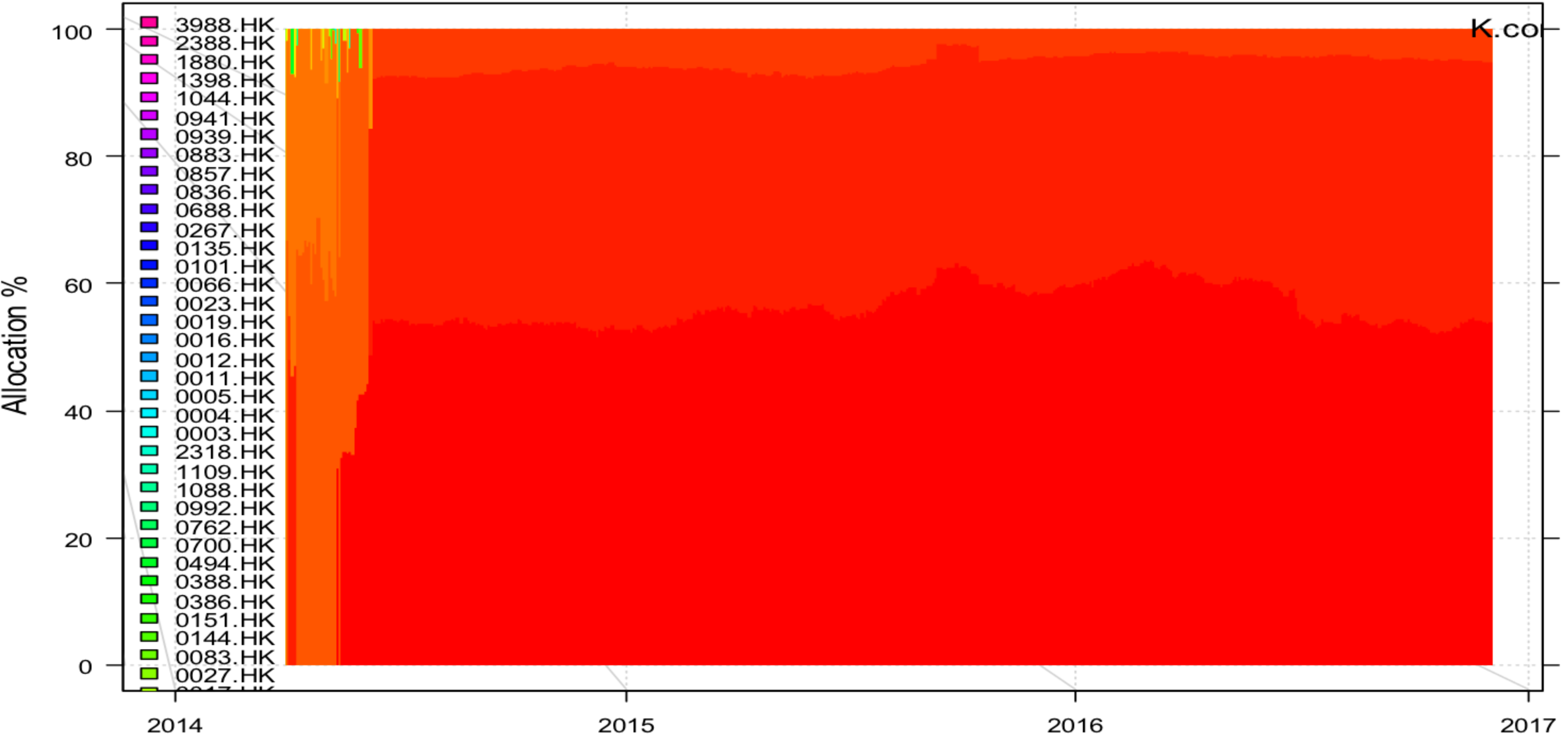


Transition Map for K.Ind
Allocation %
K.Ind
1398.HK
1109.HK
1038.HK
0883.HK
0823.HK
0700.HK
0083.HK
0066.HK
0023.HK
0019.HK
0016.HK
0011.HK
0006.HK
0005.HK
0003.HK
0002.HK
2628.HK
2388.HK
0688.HK
0494.HK
0017.HK
0001.HK
1088.HK
0941.HK
0857.HK
0762.HK
0386.HK
0027.HK
0004.HK
1880.HK
0992.HK
0836.HK
0388.HK
0012.HK
1044.HK
2319.HK
0
20
40
60
80
100
2014
2015
2016
2017

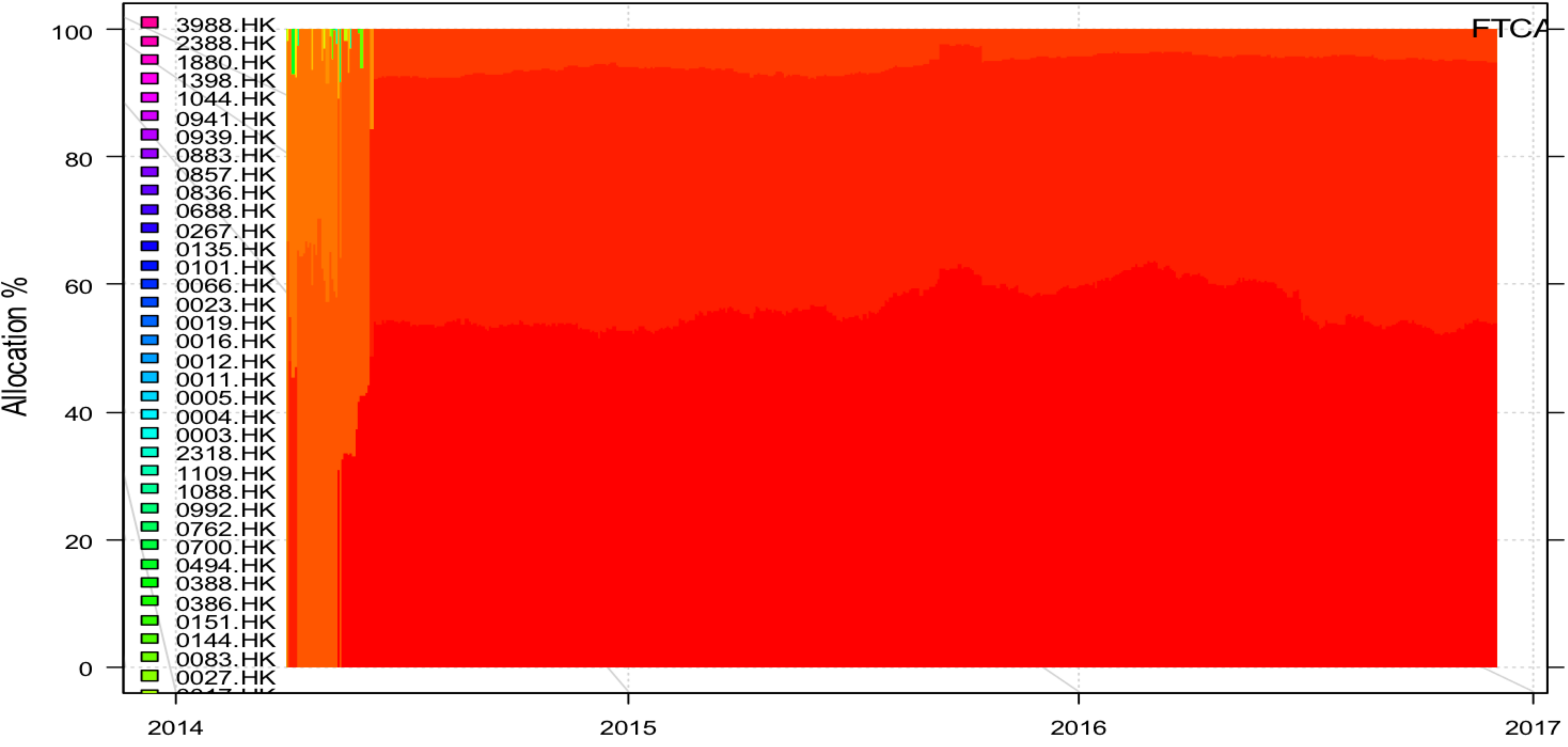


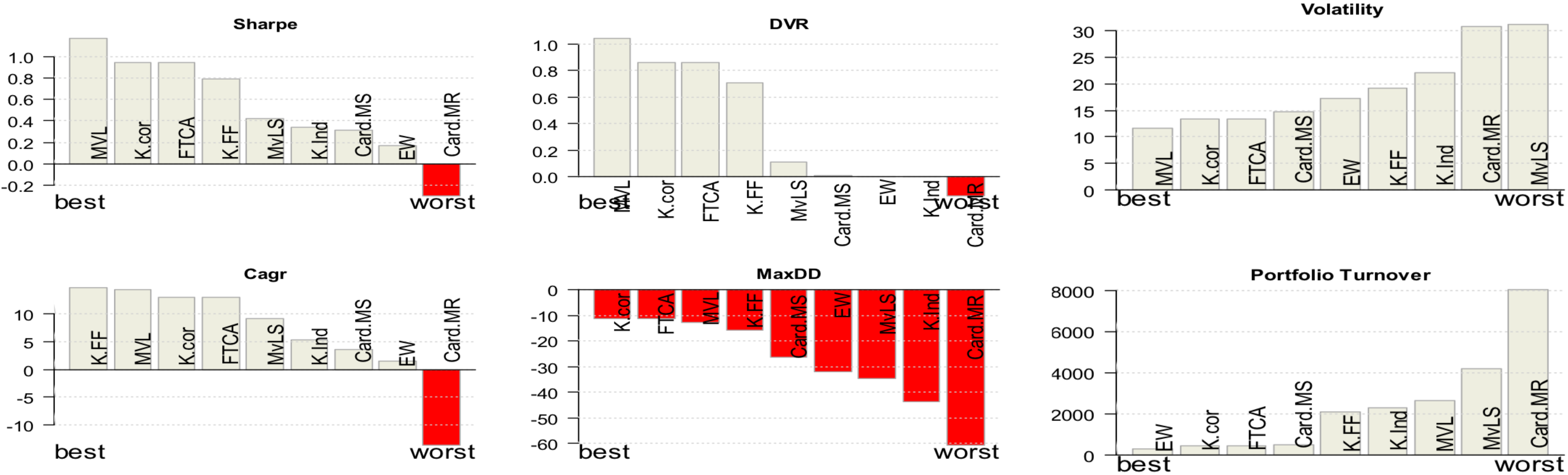
Transition Map for K.FF
Allocation %
100
80
60
40
20
0
3328.HK
2388.HK
2319.HK
1398.HK
1299.HK
1109.HK
1088.HK
0823.HK
0762.HK
0700.HK
0494.HK
0386.HK
0267.HK
0135.HK
0027.HK
0023.HK
0019.HK
0011.HK
0005.HK
0003.HK
0002.HK
0939.HK
0857.HK
0293.HK
0017.HK
0016.HK
3988.HK
1928.HK
1044.HK
1038.HK
0083.HK
0006.HK
0941.HK
0688.HK
0388.HK
0144.HK
K.FF
2014
2015
2016
2017

Transition Map for K.cor



Transition Map for FTCA





Sharpe
best
worst
MVL
K.cor
FTCA
K.FF
MvLS
K.Ind
Card.MS
EW
Card.MR
DVR
Volatility
Cagr
MaxDD
Portfolio Turnover

» 04

Review

Future work >>> Project timeline review >>> Q & A

Future Work

Possible directions

01.Problem modification

>> Changing Obj.

MAD, m.CVaR, M.Sharpe

>> Various constraints

- Shorting allowed
- Adding linear transaction cost constraints
- Minimum/maximum weight constraints

02.Factor model

Buffett’s model **7** factors

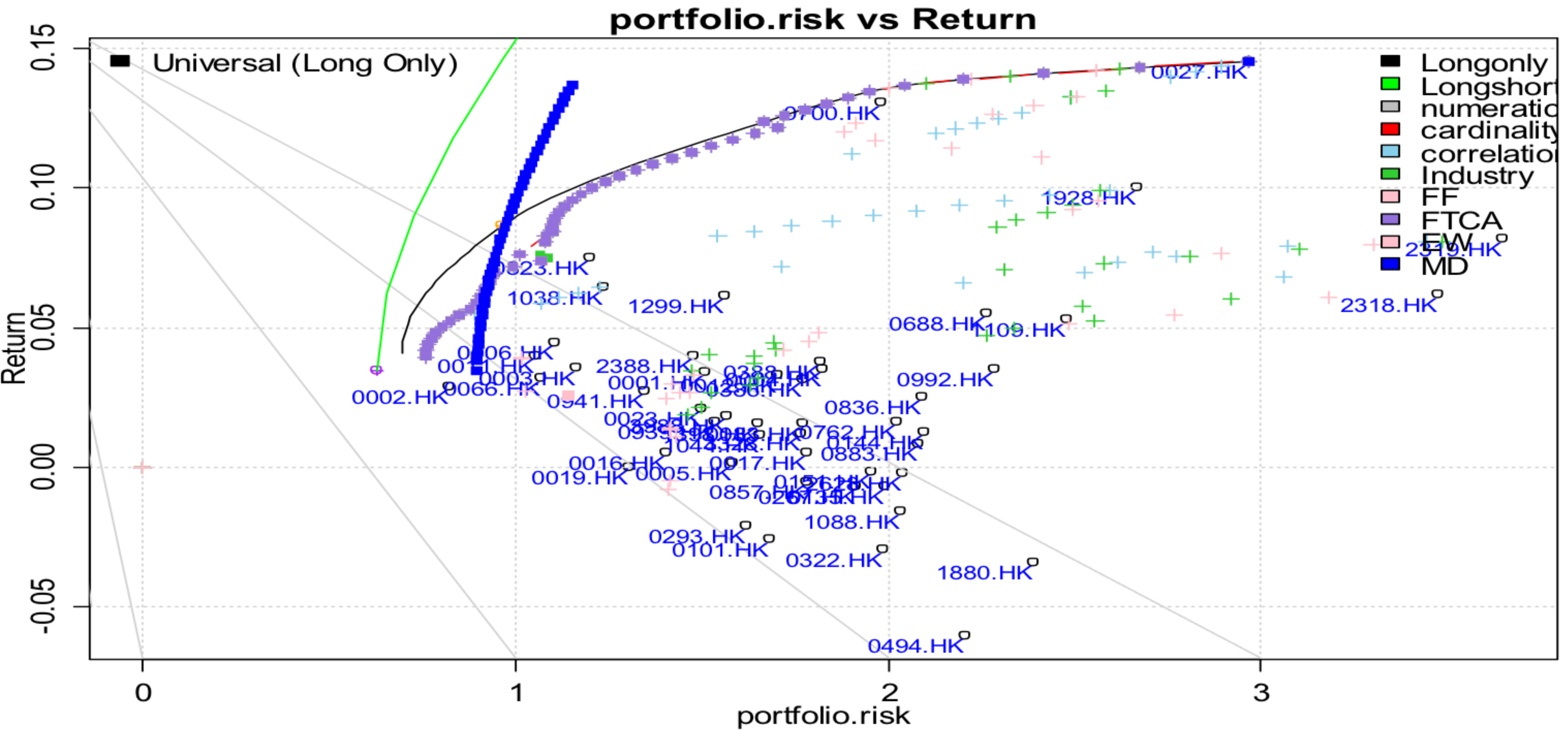
03.Clustering

Hierarchical

04.Dynamic settings

Portfolio rebalancing

Portfolio turnover


portfolio.risk vs Return
Universal (Long Only)
Longonly
Longshort
numeratio
cardinality
correlation
Industry
FF
FTCA
EW
MD
Return
portfolio.risk
0.15
0.10
0.05
0.00
-0.05
0
1
2
3
0027.HK
0700.HK
1928.HK
2319.HK
2318.HK
1038.HK
1299.HK
0688.HK
1109.HK
2388.HK
0992.HK
0836.HK
0002.HK
0066.HK
0941.HK
0762.HK
0144.HK
0883.HK
0017.HK
0016.HK
0019.HK
0005.HK
1088.HK
0293.HK
0101.HK
0322.HK
1880.HK
0494.HK

01.Problem modification

>> Changing Obj.

MAD, m.CVaR, M.Sharpe

>> Various constraints

- Shorting allowed
- Adding linear transaction cost constraints
- Minimum/maximum weight constraints

02.Factor model

Buffett's model 7 factors

03.Clustering

Hierarchical

04.Dynamic settings

Portfolio rebalancing

Portfolio turnover

01.Problem modification

>> Changing Obj.

MAD, m.CVaR, M.Sharpe

>> Various **constraints**

- **Shorting** allowed
- Adding linear transaction cost constraints
- Minimum/maximum weight constraints

02.Factor model

Buffett’s model **7** factors

03.Clustering

Hierarchical

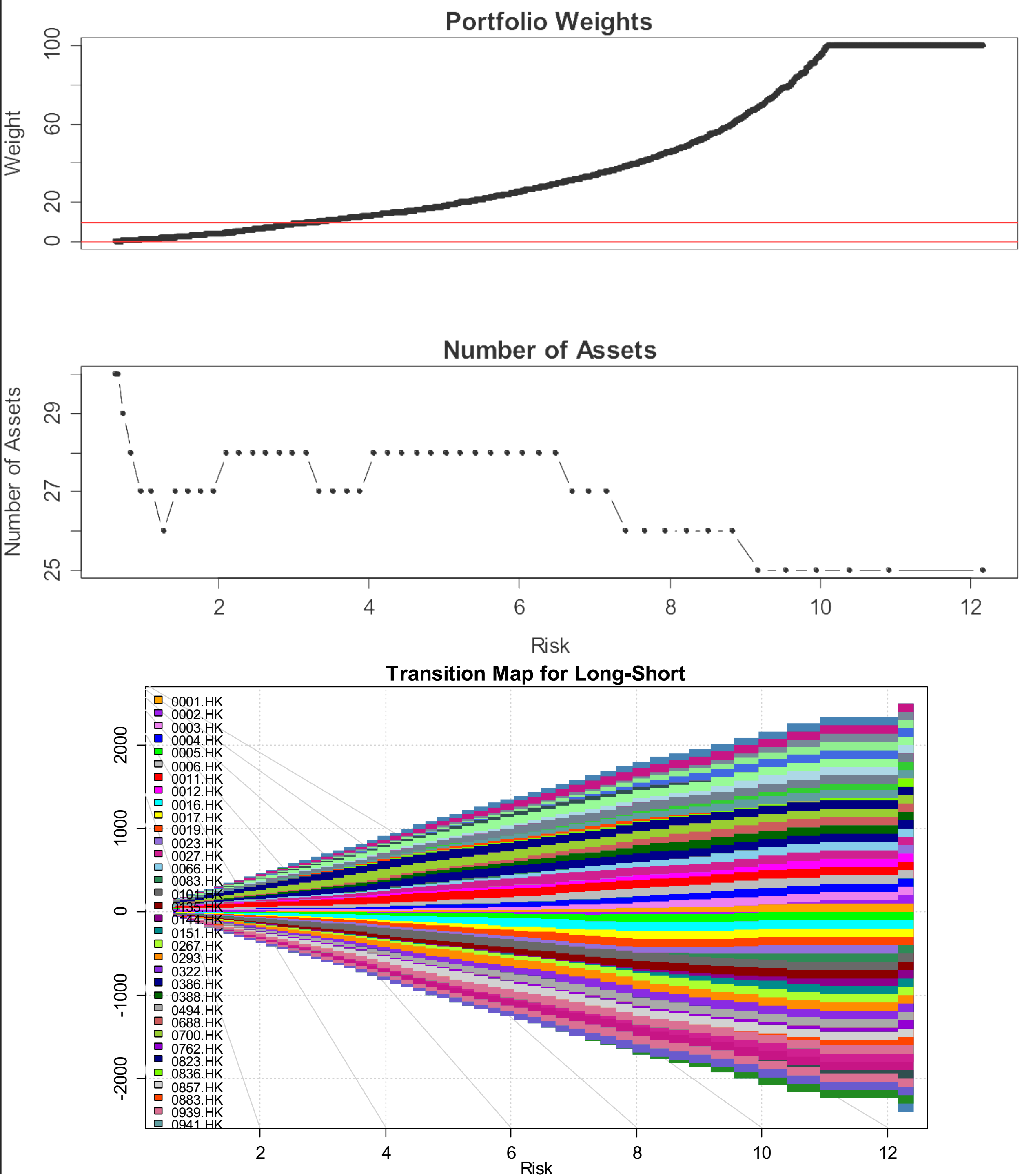
04.Dynamic settings

Portfolio rebalancing

Portfolio turnover

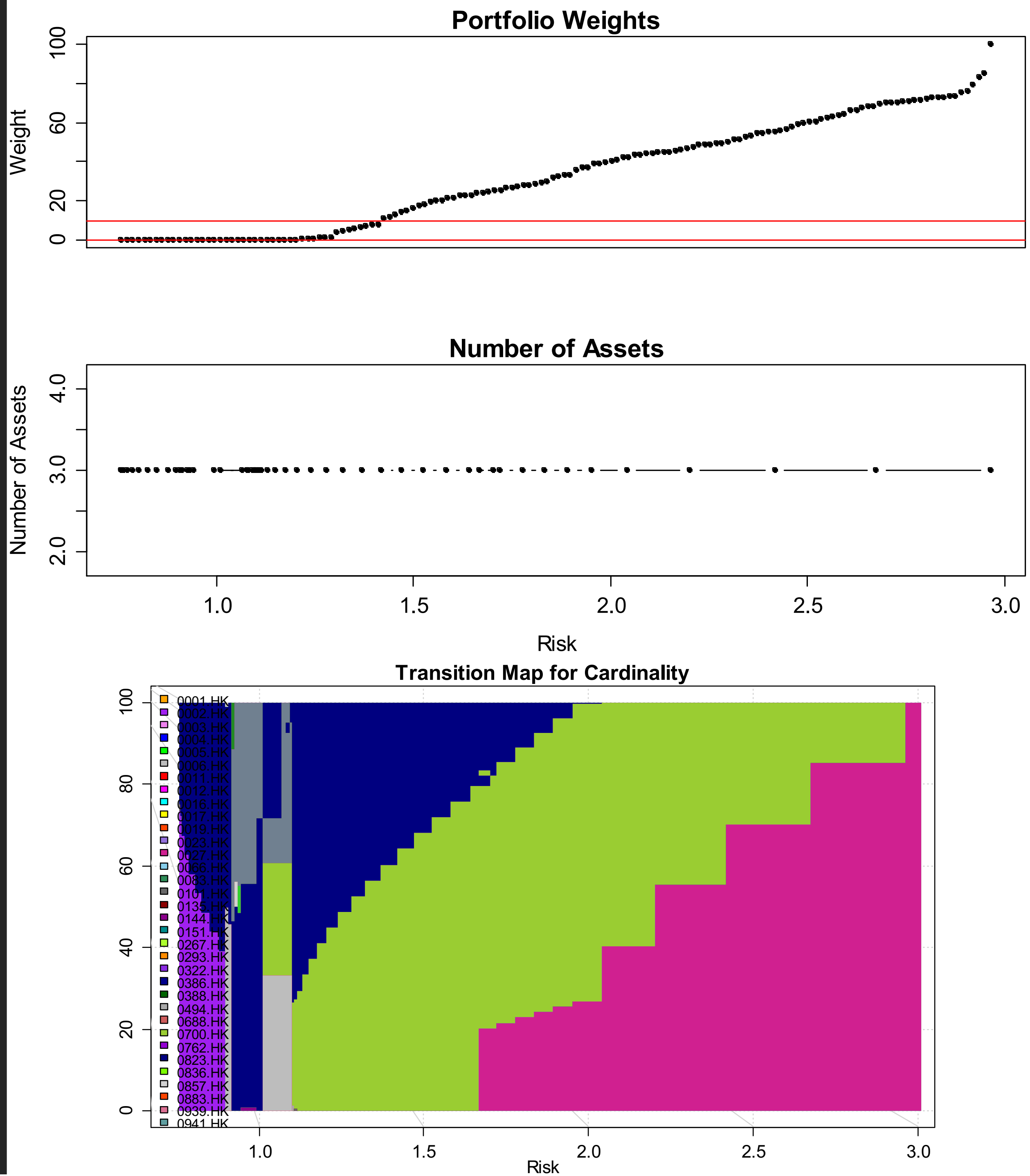
Long & short portfolio

$$\min_{x} x'Qx$$
$$\text{s.t. } \mathbf{r}'\mathrm{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$



CCMV portfolio

$$\min_{x} x'Qx$$
$$\text{s.t. } \mathrm{r}'\mathrm{x} \geq \bar{r}$$
$$\mathbf{1}'x = 1$$
$$0 \leq x_i \leq 1$$
$$\sum_{i=1}^{n} b_i = k$$
$$b_i = \begin{cases} 1, if\ x_i > 0 \\ 0, if\ x_i = 0 \end{cases}$$
$$for\ i\ from\ 1\ to\ n$$



k = 3

01.Problem modification

>> Changing Obj.

MAD, m.CVaR, M.Sharpe

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02.Factor model

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Portfolio rebalancing

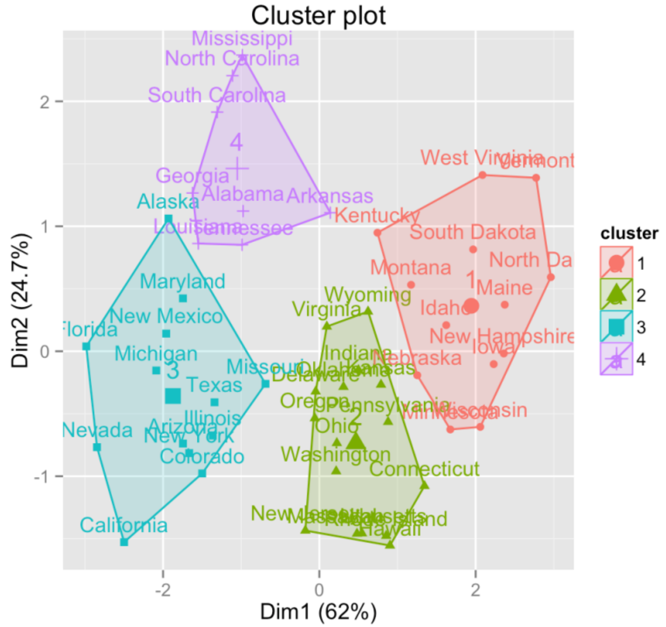
Portfolio turnover

Step 2: Grouping risky assets using clustering algorithm

Goal: partition all risky assets into *k* groups risky assets using clustering algorithm

Partitioned clustering

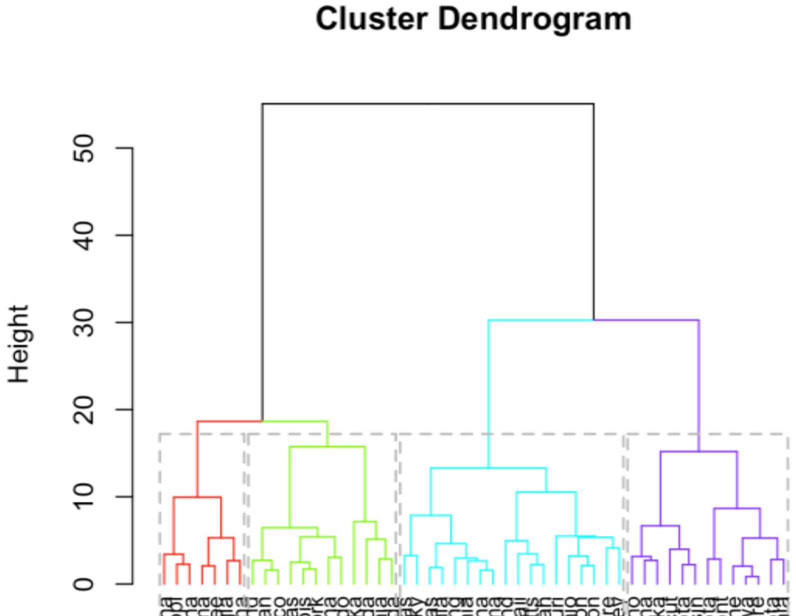
Organize elements into disjoint groups



Hierarchical clustering

Organize elements into trees.

Nested!



01.Problem modification

>> Changing Obj.

MAD, m.CVaR, M.Sharpe

>> Various constraints

- Shorting allowed
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02.Factor model

Buffett’s model **7** factors

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Project timeline look back

TIMELINE
INFOGRAPHICS

Before July — Preparation done !

1. Identification of Projects
2. Approach to Prof. LI Duan
3. Work Out a research plan
4. Signature of Supervisor
5. Approval from Major Department
6. Submission to Faculty Office
7. Approval by ELITE Stream Director and Associate Dean (Education)
8. Course Registered on CUSIS

Aug. — Coding & STAT pick up ..

Start learning **R Programming**

- though Coursera
- on the job

Register **Statistic** online courses

Literature reading...

Project schedule planning

JOHNS HOPKINS
UNIVERSITY

COURSE CERTIFICATE

09/17/2016

芸秀 周

has successfully completed

R Programming

an online non-credit course authorized by Johns Hopkins University and offered through Coursera

Jeff Leek, PhD; Roger Peng, PhD; Brian Caffo, PhD
Department of Biostatistics
Johns Hopkins Bloomberg School of Public Health

EDUCATION FOR EVERYONE · COURSE CERTIFICATE · coursera

Verify at coursera.org/verify/PZJCGQZ9XQ9Q
Coursera has confirmed the identity of this individual and their participation in the course.

Sep. Data prep.

Determine universal asset pool.
Data collection from Bloomberg
Data exploration
Start to understand the literature (gradually...)

Regular meeting with Prof. Li

Model realization in R Oct.

Successfully formulated Portfolio Optimization problem
FM.0 Factor model by correlation realized.
K-means Clustering realized.
FM.1 Industrial factor model.
... Debug ...
...... Debug ...
.... Debug ......
Constraints formulated !
Optimization problem.
Dynamic portfolio building.
Efficient Frontier explored !

Since Nov. Polishing up & documentation work

FM.2 Fama-French Model: get FF factors data prep. >>>
Model development
Learn about FTCA clustering algorithm >>> FTCA done!.

Revision and polishing
Efficient Frontier revised
Last week, graduation thesis part One
Learning about MaD portfolio selection
Last night, **back testing** and presentation slides ...

Thanks

Questions and comments are welcomed!

Special thanks to my supervisor, **Prof. LI Duan**