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Re-thinking Commercial Real Estate Market Segmentation

Franz Fuerst* and Gianluca Marcato†

School of Real Estate & Planning
Henley Business School
University of Reading
Reading
RG6 6UD
United Kingdom

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* Email: f.fuerst@henley.reading.ac.uk, Tel: +44 (0)118 378 6035, Fax: +44 (0)118 378 8172.

† [Corresponding author] Email: g.marcato@henley.reading.ac.uk, Tel: +44 (0)118 378 8178, Fax: +44 (0)118 378 8172.

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FRANZ FUERST
HENLEY BUSINESS SCHOOL
UNIVERSITY OF READING

GIANLUCA MARCATO
HENLEY BUSINESS SCHOOL
UNIVERSITY OF READING

Abstract:

Investments in direct real estate are inherently difficult to segment compared to other asset classes due to the complex and heterogeneous nature of the asset. The most common segmentation in real estate investment analysis relies on property sector and geographical region. In this paper, we compare the predictive power of existing industry classifications with a new type of segmentation using cluster analysis on a number of relevant property attributes including the equivalent yield and size of the property as well as information on lease terms, number of tenants and tenant concentration. The new segments are shown to be distinct and relatively stable over time. In a second stage of the analysis, we test whether the newly generated segments are able to better predict the resulting financial performance of the assets than the old dichotomous segments. Applying both discriminant and neural network analysis we find mixed evidence for this hypothesis. Overall, we conclude from our analysis that each of the two approaches to segmenting the market has its strengths and weaknesses so that both might be applied gainfully in real estate investment analysis and fund management.

Keywords: market segmentation, commercial real estate, financial performance measurement, cluster analysis, neural network analysis, risk diversification

JEL Classifications: C45, D4, G11, R33

Introduction

A fundamental difficulty facing investors in direct real estate is that there are no obvious *a priori* groupings or segments characterizing these markedly decentralized and heterogeneous markets. While these are readily available in other asset classes, for example groupings by industry and market capitalization in the stock market. This is particularly relevant for large institutional-type investors who seek to reap diversification benefits of their investments. A major prerequisite for achieving such diversification benefits is, of course, that the segments used in optimizing a portfolio are maximally homogenous within themselves and maximally heterogeneous across groups. A pragmatic approach used by a large number of companies providing real estate market intelligence across the world involves a division along the lines of property type (sector) and region.

While this approach provides a powerful classification grid for analyzing basic characteristics of a portfolio and categorizing new investment opportunities, its capability of predicting the performance and risk characteristics of direct investments is at the very least questionable. The practical implication of this that investment based solely on the sector-region dichotomy may result in portfolios that cannot be optimally diversified even when applying advanced optimization techniques. Therefore, this paper sets out to first test the predictive power of existing real estate market segmentations to detect whether these basic measures are sufficiently accurate. Next, we apply a two-step cluster algorithm to generate new market partitions based on additional investment characteristics and information relating to the tenant base and lease structure of a property. To this aim, we analyze the comprehensive IPD commercial real estate database for the UK over the period 1980-2006. Finally, we apply both discriminant analysis and a non-parametric neural network estimation to test the ability of the existing sector-region and the cluster-based segmentations to predict total rates of return.

Previous studies

The problem of segmenting the real estate market effectively has been studied in a number of contexts ranging from portfolio analysis to marketing and forecasting. Similar to the present paper, many of these studies start with an investigation of the relative importance of property type and/or region in explaining individual investment performance. One of the earliest studies of this topic was conducted by Eichholtz et al (1995) who found for the US market that diversification by region was more important for retail while sector turned out to be more important for office properties. For the UK market, sector was found to be more important for retail while a combined diversification across both sector and region yielded the best results for office and industrial property. Hoesli et al (1997) also conclude from their UK study that sector generally dominates region. Fisher and Liang (2000) found in their regression analysis of the US market that sector is generally more important than region in explaining quarterly returns. Lee (2001) concluded from his empirical analysis of the UK market that sector effects were more than twice as large as region effects. In a time-series analysis of these effects, Lee and Devaney (2007) generally confirm the dominance of sector over region found in the majority of previous studies but find that regional effects become almost as important as important as sectoral effects during periods of relative market calm and stability. McGreal, Adair and Webb (2009) find in a comparative study of UK and US investments that high risk portfolios are typically 100% invested in the UK and non-office investments. The authors also confirm the relevance of a risk dimension that measures to what extent the investment is income versus capital appreciation driven.

Fuerst and Marcato (2009) conclude from their time-series analysis of investment styles in the UK that multi-dimensional style analysis yields superior results compared to the commonly used two-factor analysis, and that the additional styles are able to explain both alpha performance (and the likelihood of achieving it) and systematic risk of real estate portfolios.

Beyond the analysis of the common sector-region dichotomy, relatively few studies have attempted to conceive alternative methods of classifying properties and test their predictive power. After demonstrating that neither sector nor regional classifications provide a clear demarcation of individual property performance, Devaney and Lizieri (2005) proceed to generate new segments based on cluster analysis of IPD property return data. Their results show that property size and level of capitalization rate (i.e. the equivalent yield) appear to add some explanatory power but the authors conclude that there are no obvious factors that offer superior explanations.

Blundell et al (2005) propose a different approach based on decomposition of volatility-inducing factors. These factors are categorized into four 'fundamental' causes of volatility and a larger number of 'modulators' that mitigate or exacerbate the variance emanating from the fundamentals. The authors present a tool for visualizing the multi-facetted nature of real estate risk using a radar diagram dubbed the Blundell Risk Web by UK property fund managers who frequently use this tool for their operations. Because of its comprehensiveness and clarity we adopt a similar approach for visualizing the characteristics of clusters found in this study.

Data

The empirical study of possible market segmentations is conducted on a large dataset of individual properties in the Investment Property Databank (IPD). We consider all commercial properties in the UK direct investment universe which were held over the ten-year period from 1998-2007 and have a complete set of relevant characteristics and financial data. We split the sample into two subperiods to test for stability and obtain 2,165 properties for the 1998-2002 period and 3,890 for the 2003-2007 period.

For each property, we obtained the following information:

- *Capital Value* (CV_t), representing the market value of the building at time t to capture any effect of property size on financial performance.
- *Total return*, reflecting both the capital gain (CV_t – CV_{t-1}) and the net income achieved by the investor as a percentage of the capital invested (CV_{t-1} plus capital expenditures):
- *Equivalent Yield* (EY_t), representing a cap rate considering both the current rent paid by the tenant and the market rent that will be paid at the following rent review.

Specifically, IPD computes this metric by equating the capital value as provided by an independent appraiser and the future cash flow of the property, assuming that the current market rent is the new rent the tenant will start to pay at the next rent review (i.e. zero rental growth is assumed).

- *Number of tenants* for each building. This variable is used to differentiate concentrated and diversified styles.
- *Unexpired lease term*, defined as the average number of years to lease expiry. This variable is used to classify properties with short vs. long lease terms.
- *Tenant concentration* measures the percentage of floorspace occupied by the five largest tenants in the asset.

Exhibit 1 shows summary statistics for the variables used in this analysis. The sample is not balanced over time, i.e. a number of properties entered or left the database over the ten year period. The resulting heterogeneous structure of the sample over time complicates the comparability of the summary statistics over time as it is not quality-adjusted. However, this limitation can be considered relatively minor compared to the serious survivorship bias that would be introduced by including only those properties that were held throughout the entire ten-year period.

Exhibit 1: Summary Statistics

	Sample	Valid obs. ø	Median	Std. Dev.
Total return	1998-2007	12,393	10.19	5.97
	1998-2002	12,950	9.25	1.76
	2003-2007	11,836	11.13	8.66
ECV growth	1998-2007	12,394	3.21	5.60
	1998-2002	12,950	1.66	1.63
	2003-2007	11,839	4.76	7.87
Equivalent yield	1998-2007	10,968	7.35	0.92
	1998-2002	11,460	8.08	0.13
	2003-2007	10,476	6.61	0.74
Capital value	1998-2007	16,830	2,807,500	2,270,670
	1998-2002	20,870	1,004,000	558,328
	2003-2007	12,789	4,611,000	1,776,965
Unexpired lease term	1998-2007	9,569	9.13	1.95
	1998-2002	9,293	10.80	1.10

	2003-2007	9,982	7.46	0.64
No. of tenants	1998-2007	9,634	2.30	0.48
	1998-2002	9,355	2.00	0.00
	2003-2007	10,054	2.60	0.55
Tenant concentration in %	1998-2007	9,481	91.57	1.47
	1998-2002	9,172	92.76	1.09
	2003-2007	9,943	90.38	0.34
ERV growth	1998-2007	9682.1	0.96	1.37
	1998-2002	10,226	1.83	1.52
	2003-2007	9,138	0.09	0.12

- **Analytical approach**

In order to generate new multi-dimensional clusters, we apply a scalable two-step cluster algorithm. The main advantages of this type of cluster analysis are that it can handle both continuous and categorical variables or attributes and that it is designed to handle large datasets without creating excessive computational loads. The steps are: 1) pre-cluster the cases into a large number of sub-clusters; 2) cluster the sub-clusters resulting into the desired number of clusters. The procedure is implemented by constructing a modified cluster feature (CF) tree. For the sake of comparability, the number of clusters was preset to 10 and 13 respectively to match the number of clusters used in the existing industry classifications. We also apply outlier handling by classifying any leaf entry as an outlier if the number of records in the entry is less than 25% of the size of the largest leaf entry in the CF tree. In terms of distance measure, we apply log-likelihood distance rather than the more common Euclidian distance as the former is capable of handling both continuous and categorical variables in our dataset. The basic principle behind it is the distance between two clusters is related to the decrease in log-likelihood as they are combined into a single cluster. Thus, the distance between two clusters *i* and *j* is defined as:

$$d(i, j) = \xi_i + \xi_j - \xi_{<ij>} \quad (1)$$

with

$$\xi_v = -N_v \left(\sum_{k=1}^{K^A} \frac{1}{2} \log(\hat{\sigma}_k^2 + \hat{\sigma}_{vk}^2 + \sum_{k=1}^{K^B} \hat{E}_{vk}\right) \quad (2)$$

and

$$\hat{E}_{vk} = \sum_{l=1}^{L_k} \frac{N_{vkl}}{N_v} \log \frac{N_{vkl}}{N_v} \qquad (3)$$

In the second step, we test the clusters using discriminant analysis. The main purpose of this is to build a predictive model for cluster group membership. The model is composed of a set of discriminant functions based on linear combinations of the predictor variables that yield the best 'discrimination' between the groups.

We complement this standard technique with a more recent non-parametric approach, i.e. neural network analysis. According to Haykin (1998), a neural network is a parallel distributed processor that has a natural propensity for storing experiential knowledge and putting it to use for prediction. In doing so it emulates human brain activity by going through an iterative learning process and storing the acquired knowledge as synaptic weights. Its advantages are that it is highly adaptive and more flexible than the rather rigid linear parametric methods. This is particularly true in cases where a large number of previous observations exist to 'train' the network and if the task involves recognition of groups or patterns in the data. As both of these criteria apply to our study it appears reasonable to use neural network analysis for additional tests of various real estate market segments.

Empirical Results

The two-step cluster procedure was initially applied to two subperiods with a preset number of 10 and 13 clusters respectively to ensure comparability with two segmentations commonly used in the property industry. Exhibit 2 shows the distribution of property types obtained for the set of 10 clusters in the period 2003-2007 (note: columns add up to 100%). A further inspection of cluster characteristics (Exhibit 3) reveals that the common criteria within these clusters involve both financial and spatial characteristics. The clusters show distinct profiles of properties for a number of characteristics. For example, properties in Cluster 3 are predominantly retail and concentrated in the Greater London area with very high capital values and a large number of tenants and a high degree of tenant diversification. As expected, a cross-tabulation with the more detailed L&G property classification reveals that Cluster 3 contains mainly shopping centres (Exhibit A in the appendix).

Exhibit 2: Cluster distribution

Cluster	Retail	Office	Industrial	Other
1	8.5%	7.9%	25.8%	10.6%
2	0.1%	12.1%	22.1%	6.3%
3	2.9%	0.4%	0.5%	4.7%
4	11.8%	32.2%	1.0%	19.9%
5	3.0%	2.2%	1.8%	44.2%
6	.0%	27.8%	16.6%	2.7%
7	21.8%	3.7%	8.6%	55.6%
8	27.8%	0.2%	0.0%	29.2%
9	9.8%	6.0%	11.6%	7.1%
10	14.0%	7.1%	11.9%	20.0%
N	2051	1115	1468	1.2%

A sectoral and regional dimension of the clusters is also confirmed by the maps in the appendix which show random examples of clusters. To visualize the additional dimensions captured by the new segments we complement the maps with a radar diagram which shows for each cluster the relative value for each dimension (100 is the overall sample average in each case).

Exhibit 3: Description of 10 clusters

No.	Regional Focus	Sectoral Focus	Eq. Yield	Capital Value	Lease Terms	No. of Tenants	Tenant Conc'tion
1	Diversified	Ind (58%), Ret (27%)	7.4	18,739,686	6.1	21.1	54.9
2	Reg 7,8 (70%)	Ind (69%), Off (29%)	8.1	5,347,953	6.3	4.3	95.4

3	Reg 4,5 (49%)	Ret (81%)	6.6	136,680,012	9.9	120.5	25.9
4	Reg 3 (44%)	Off (57%), Ret (38%)	6.2	13,467,075	8.0	4.9	94.5
5	Diversified	Ret, diversified (44%)	5.8	7,693,453	59.1	2.6	98.0
6	Reg 6 (99%)	Off (56%), Ind (44%)	7.3	8,886,067	7.0	3.4	97.2
7	Reg 7,9,11 (98%)	Ret (68%), Ind(19%)	6.3	8,543,710	10.9	3.2	97.9
8	Reg 6,8 (79%)	Ret (96%)	5.9	9,298,069	10.8	3.0	98.2
9	Reg 5 (97%)	Ret (45%), Ind (38%)	6.4	10,603,821	9.1	3.5	96.9
10	Reg 10,12 (100%)	Ret (52%), Ind (31%)	6.7	8,907,715	9.7	3.1	97.8

A crucial test to pass for any new set of market segments is whether they are sufficiently stable over time so that group membership remains the same for the majority of properties in a portfolio throughout the holding period. If each period yielded a completely new set of segments, this would render the classification useless for forward-looking investment and management strategies. As Exhibit B in the appendix demonstrates, the clusters obtained for the period 1998-2002 and for 2003-2007are fairly stable with 8 out of 10 clusters retaining 70% or more of the properties assigned to them in the earlier period. No cluster contains less than 50% of its members from the previous period. This stability is quite astonishing, particularly when considering that sample size has nearly doubled in the second subperiod.

In the next step, we test the predictive performance of each cluster with a discriminant analysis. If the principal goal of segmentation is to derive groups that differ significantly in their financial performance (total return, capital & ERV growth) it should be possible to predict the groupings –PAS segments or new clusters- by using these financial variables although they were not used in the formation of either of these segmentations. The results of the discriminant analysis for the 10 cluster set are reported in Exhibit 4. Overall, only about 25% of properties were classified in the 'correct' cluster based on their financial performance. For individual clusters the correct prediction rates range from 5% to 53%. Although the group means of total returns are distinct (see Exhibit D in appendix), the prediction rate is relatively low. A discriminant analysis of PAS segment prediction using the same financial predictors shows a slightly better predictor rate of 34%. Based on these results, it appears that the new clusters do not perform better than PAS segments in forming groups with homogeneous financial performance.

Finally, we use neural network analysis to see whether an alternative non-parametric method confirms or contradicts the results obtained from the discriminant analysis. In this model specification, both PAS and cluster segmentations are used to predict the average total return of an asset in the period 1998-2007. Exhibit E in the appendix demonstrates that the error sum of squares is lower for the cluster set than for the PAS segments. This indicates that the long-term predictive power of newly created clusters which take advantage of a broader set of asset characteristics is superior over the two-dimensional PAS segments. Even when broken down to individual years, the multi-dimensional clusters clearly outperform the sector-region PAS classification in terms of their predictive power. While the findings of the neural network analysis are surprising in light of the results of the discriminant analysis, there are a number of methodological reasons that could account for this difference. Apart from the obvious differences in the setup of the models (the neural network only used total returns, discriminant used total return, ERV growth and capital growth) one possible explanation is that the neural network method is more flexible than discriminant analysis and is therefore better able to predict financial performance based on the nuances of the multi-dimensional clusters.

A sequential analysis of individual factors shows that ERV growth, yield, property size, tenant diversification, lease terms and volatility measures all add predictive power to the new segments. While each new cluster exhibits a particular emphasis on a specific region and/or property sector, the clusters also incorporate properties in seemingly unrelated regions and sectors whose financial characteristics were similar in the observed period. These common characteristics provide vital clues to fund managers and investors regarding potential diversification benefits.

Exhibit 4: Discriminant analysis.

Clusters	1	2	3	4	5	6	7	8	9	10
1	**7.8**	11.0	10.6	7.8	4.9	17.2	7.7	10.5	11.7	10.6
2	3.7	**29.5**	3.7	8.8	3.5	30.9	4.6	2.1	5.8	6.9
3	5.0	.0	**35.0**	10.0	8.3	3.3	5.0	11.7	6.7	15.0
4	1.3	5.2	6.8	**45.8**	9.6	9.9	1.1	7.5	7.3	5.0
5	.8	4.6	14.5	17.6	**21.4**	4.6	3.1	12.2	15.3	4.6

6	2.1	19.2	3.1	5.7	2.7	**53.3**	1.1	1.3	4.2	6.9
7	2.4	9.3	11.4	5.7	3.9	11.1	**5.1**	28.1	7.1	15.8
8	2.2	3.1	10.4	6.2	6.7	5.4	5.0	**37.4**	10.0	13.5
9	5.3	8.6	10.0	9.1	7.7	15.8	3.3	22.2	**12.4**	5.0
10	2.8	13.2	12.5	4.5	4.0	16.2	6.0	17.2	4.7	**18.9**
Total	**7.8**	11.0	10.6	7.8	4.9	17.2	7.7	10.5	11.7	10.6
Valid N = 5049										

This table represents the correspondence between original and predicted clusters. Original clusters are in columns, and clusters predicted by discriminant analysis in rows.

Conclusions

This study set out to test whether a dichotomous classification of properties by sector and region is sufficient for a top-down approach to portfolio management and selection of investment properties. To this aim, we compare the predictive power of two existing industry classifications to the segments derived from a cluster analysis. The variables used to generate the new clusters included the equivalent yield, total capital value as well as information on lease terms, number of tenants and tenant concentration. The clustering algorithm generates groups of assets that are distinct with regard to their spatial and sectoral distribution, tenant and lease attributes and as well as average size of the assets. A test performed on the preceding five-year period shows that the obtained clusters are fairly robust and persist over time even as a large number of assets entered or left the database throughout the study period.

While the results of a discriminant analysis do not show that the new clusters are superior to PAS segments in predicting financial performance, the application of a neural network technique suggests that using the cluster groups drastically reduces the sum of errors in a prediction of total returns.

A clear disadvantage of the cluster groupings is that their profiles are more difficult to grasp than the segments based on the simple two-dimensional approach. Since both types of approaches have their own fundamental strengths and weaknesses, parallel usage of both classification methods appears to be the most promising approach. The new segments based on cluster analysis may be more suitable for identifying investment opportunities and identifying potential risks using a number of relevant attributes whereas the existing dichotomous classifications are superior when it comes to describing the fundamental characteristics of a portfolio in terms of its regional and sectoral split.

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Exhibit A: Description of 10 clusters against L&G segmentation

	Cluster Number										Total
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
Distribution Warehouse	3	24	0	2	3	26	33	0	23	35	**149**
Leisure-Other	4	2	0	2	1	0	22	12	7	6	**56**
Office Park	17	32	0	9	0	66	4	0	7	24	**160**
Other	3	5	2	17	26	3	21	11	1	10	**99**
Retail Park	62	0	2	15	0	0	85	115	31	49	**359**
Shopping Centre	53	0	57	1	1	0	2	3	3	3	**123**
Solus Unit	1	0	0	7	0	0	39	68	33	44	**192**
Std Industrial Rest UK	187	200	2	11	7	0	92	0	0	140	**639**
Std Industrial SE	189	101	5	1	17	218	1	0	148	0	**680**
Std Office Central London	5	1	5	143	9	0	0	0	0	0	**164**
Std Office Rest SE	27	54	0	4	8	244	0	1	60	0	**399**
Std Office Rest UK	36	45	0	35	1	0	37	1	0	55	**211**
Std Office West End	3	3	0	168	6	0	0	0	0	0	**181**
Std Retail	58	3	1	220	61	0	321	385	135	192	**1377**
Total	**648**	**470**	**74**	**635**	**140**	**557**	**657**	**596**	**448**	**558**	**4789**

Exhibit B: Correspondence table of cluster memberships 2003-2007 (columns) by 1998-2002 (rows)

Clusters	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0%	0%	7%	0%	94%	0%	3%	1%	2%	1%
2	1%	1%	0%	**70%**	4%	0%	0%	0%	2%	0%
3	**77%**	9%	0%	8%	0%	6%	1%	1%	4%	5%
4	0%	0%	0%	0%	0%	0%	23%	29%	0%	0%
5	2%	**83%**	0%	0%	0%	0%	18%	0%	1%	6%
6	0%	2%	0%	0%	0%	0%	**55%**	17%	0%	0%
7	1%	4%	0%	21%	2%	0%	1%	0%	0%	**88%**
8	1%	0%	0%	0%	0%	**94%**	0%	**53%**	3%	0%
9	1%	0%	0%	0%	0%	0%	0%	0%	**88%**	0%
10	17%	1%	**93%**	0%	0%	0%	0%	0%	0%	0%
Total	0%	0%	7%	0%	**94%**	0%	3%	1%	2%	1%

Pearson Chi-Square 3383.645 (Asympt. Sig. 0.000), Likelihood Ratio 2145.08 (Asympt. Sig. 0.000), Valid N = 1059

Exhibit C: Examples of spatial distributions of clusters

Exhibit D: Results of discriminant analysis

Panel A: Test Results BOX's M

		New clusters	PAS segments
Box's M		11061	3715
F	Approx.	18.238	39.933
	df1	594	910
	df2	646413	1433568
	Sig.	.000	.000
Null hypothesis: equal population covariance matrix			

Panel B Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
tr2003	.875	55.658	10	3879	.000
tr2004	.948	21.210	10	3879	.000
tr2005	.961	15.848	10	3879	.000
tr2006	.940	24.907	10	3879	.000
tr2007	.906	40.076	10	3879	.000
ervg2003	.947	21.658	10	3879	.000
ervg2004	.967	13.199	10	3879	.000
ervg2005	.978	8.632	10	3879	.000
ervg2006	.941	24.179	10	3879	.000
ervg2007	.934	27.250	10	3879	.000
ecvg2003	.849	69.037	10	3879	.000
ecvg2004	.924	31.813	10	3879	.000
ecvg2006	.937	26.129	10	3879	.000
ecvg2007	.894	46.193	10	3879	.000

Panel C: Canonical Discriminant Functions

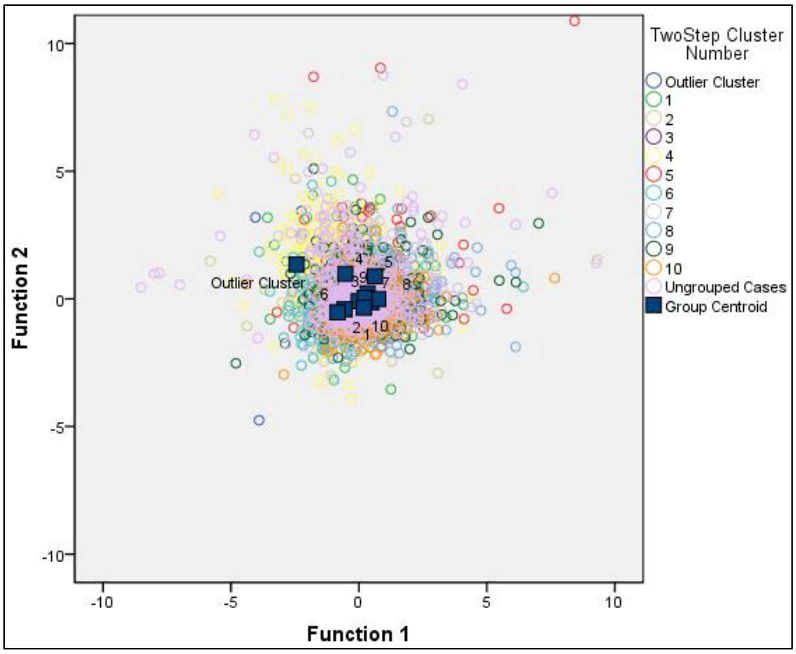
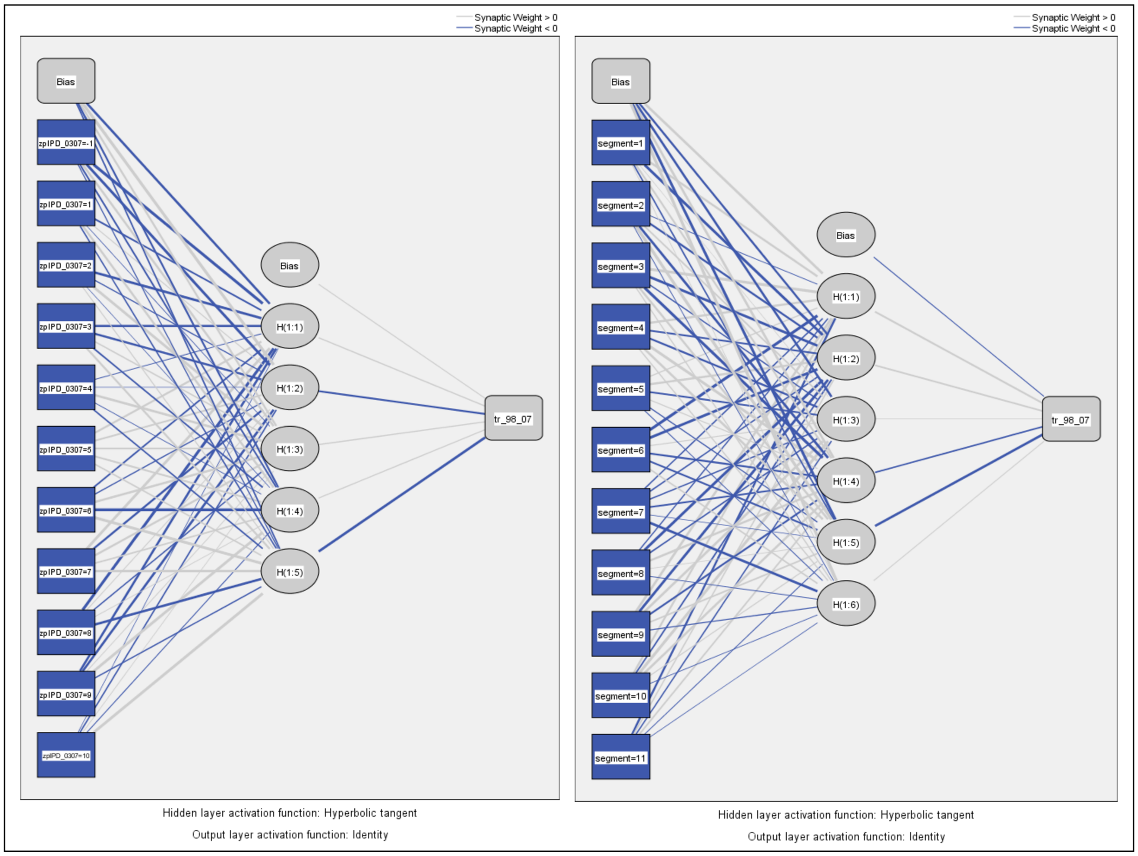


Exhibit E: Neural Network Analysis

Panel A: Network Diagrams of cluster prediction (left) and PAS segment prediction (right)



Panel B: Model Summary

		New clusters	PAS segments
Training	Sum of Squares Error	1405.222	7483.361
	Relative Error	.995	.999
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]	1 consecutive step(s) with no decrease in error[a]
	Training Time	00:00:01.263	00:00:01.575
Testing	Sum of Squares Error	280.443	2379.423
	Relative Error	.965	1.004

Dependent Variable: tr_98_07

a. Error computations are based on the testing sample.