EXCHANGE-TRADED FUNDS: A MULTIDIMENSIONAL ANALYSIS

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ABSTRACT

Exchange-Traded Funds (ETF's) have become widely held financial instruments among investors. Their popularity has produced an explosion in the number of different ETF's currently available in most financial markets. This revolution started in the early 90's with a single product which consisted of a basket of single securities that where part of (and therefore closely follow) the S&P 500 index (SPDR). The idea was to have a financial instrument that was less volatile than a single stock and yet could be traded as one thus avoiding the shortcomings of traditional mutual funds such as management fees, liquidity and tax disadvantages. The idea worked and currently there are nearly 1000 of such instruments. Our research empirically analyzes the idea that there is no need for so many of these products and therefore an investor could be better off by picking among a handful of them with each of them belonging to a statistically different cluster of such funds. To investigate this idea we randomly sampled 574 Exchange-Traded Funds (ETFs) and analyzed them using three multivariate methods: Cluster Analysis, Factor Analysis and Chernoff-Faces. For each fund, we recorded performance measures that included: Intraday, YTD, 3-Month, 1-Year and 3-Year returns. Utilizing a k-means clustering algorithm we obtained 5 clusters of the ETF's which produced (statistically) similarly behaving funds within each cluster and dissimilar ones between clusters. Factor Analysis and Chernoff-Faces were used to graphically depict the similarities of the ETF's belonging to each cluster. The analyses also showed surprising similarities for many ETF's that are supposed to follow different stock indexes, thus questioning the value of diversification for investors trusting this strategy. On the other hand, the results of this study could provide investors opportunity to further diversify their holdings by choosing funds belonging to different clusters.

JEL Codes: C1, C19, C4, C49, G1, G24, O16, R42

Keywords: Financial Markets, Exchange-Traded Funds, ETF's, Diversification, Multivariate Analysis, Cluster Analysis, Factor Analysis, Factor Loadings

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I. INTRODUCTION

Classical Exchange-Traded Funds (ETF's) are tradeable securities which derive their value from a fixed basket of stocks that track a particular index. Because of this, ETF's derive their price (and volatility) from the market movements of the underlying stocks in the basket. Not to be confused with Index Mutual Funds which are managed by institutional managers and (at least at the onset of the purchase) are not as liquid as ETF's that can be traded as regular stocks. ETF's also provide investors with diversification and the added advantages of tax efficiencies and lower expenses as compared to traditional mutual funds. At their inception in the early 1990's with SPDR (hence their nickname "Spiders"), ETF's mostly target institutional investors but very quickly got the eye of everyday investors. As of late 2006, SPDR (which follows the S&P 500 index movements) had assets of $58 billion and accounted for 16% of the ETF market share (WSJ, Nov. 10, 2006). Since the inception of SPDR the number of ETF's (iShares and the likes) has exploded to nearly 1000 different instruments currently available for trading (Morningstar, Apr. 2011). Comparisons between the advantages and disadvantages of ETF's vs Mutual funds have received wide attention in the finance literature (Gastineau, 2001, 2004; Brom and Gastineau, 2007, Blitz et.al. 2011; Aber et. al. 2009). In a nutshell, ETF's have less volatility than individual stocks, are more liquid, and in the short run, can produce higher returns than traditional mutual funds. Many investment houses (notably Fidelity and Vanguard) offer brokerage-free ETF's that are mostly tied to their large mutual funds (and some to the various indexes). This paper is not about the advantages or disadvantages but rather about diversification of an ETF portfolio. Given the large quantity of instruments being offered we proposed a multivariate approach to select instruments that follow different behavior thus an investor confronted with a decision of buying several ETF's will not need to purchase a basket that moves similarly therefore protecting them from potentially adverse market movements.

II. LITERATURE REVIEW

While abundant literature exists about the performance of index mutual funds, ETF's have received less attention than it counterpart. Early studies on ETF's were focused on the characteristics of this innovative investment instrument (Gastineau, 2002, Mussavian and Hirsch, 2002). More recent studies (Rompotis, 2006) examine their return performance and trading characteristics. Seasonal returns and volatility have been also studied by Rompotis (2007) who found a significant November effect in the sample of ETF's under study. A handful of other studies have compared traditional mutual funds and ETF's (that track the same indexes) in terms of trading costs, return performance and risk. Dellva (2001) found that the ETF's had a significant cost advantage compared to the mutual funds in their study. At least two studies (Elton et. al., 2002 and Gastineau, 2004) found that mutual funds outperform the sample of ETF's in their study. This comparison was based on a ten year period 1992-2002 and the underperformance (pre-tax) of the ETF in Gastineau's study (SPY) was 119.52% vs 120.61% and 121.68% for the Vanguard 500 and S&P 500 benchmark indexes. In a more recent study, Rompotis (2005) analyzed the performance of 16 pairs of ETF's and mutual funds against their tracking indexes and found they substantially produced similar returns and tracking errors. Agapoga (2006) found that ETF's had a lower index tracking errors and lower expenses than their mutual fund counterparts. He also suggests that their substitutability is due to a "clientele effect". A more recent study by Aber et. al. (2009) analyzed the price volatility and tracking errors of ETF's vs similar tracking mutual funds. They found that ETF's had a smaller tracking error and outperformed the index mutual fund counterparts in intraday trading. Overall the empirical studies comparing ETF's and index mutual funds offer a different picture. In the long run ETF's underperform mutual funds while on intraday trading they are better off. Additionally, ETF's track their benchmark indexes closer and have lower management fees than their related index tracking mutual funds.

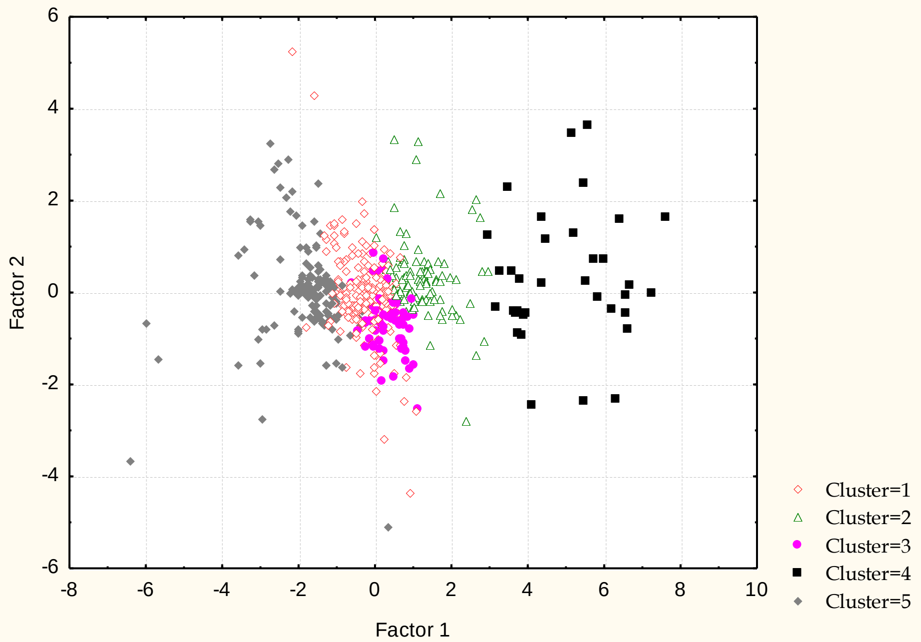
III. OBJECTIVE OF THE STUDY

This study differs from the others in the sense that we concentrate on the performance of ETF's among themselves (we don't compare them to index mutual funds or to any benchmark index). Our idea is that performance-wise most ETF's concentrate in a handful of clusters. Identifying these clusters could provide investors with a) an extra layer for diversification, or b) a way to improve performance by concentrating in ETF's that are part of a single cluster.

IV. METHODOLOGY

A random sample of 574 ETF's was collected in early 2011 from Yahoo! Finance, (finance. yahoo.com). The ETF's in our sample are listed in Appendix A. Intraday, YTD, 3-Month, 1-Year and 3-Year returns were recorded. This 5-variable sample was clustered using a K-means clustering algorithm (Hartigan and Wong, 1979) which produced 5 clusters (Appendix B). Figure 1 shows the clusters in a 2 dimensional space where the axes correspond to the principal components of the 4 variables.

Figure 1: 5-Means Clusters (2 Factor loadings)



Note that the multi-dimensional scaling is based on the Factor loadings (80% of the variance of the 4 variables is explained by these two factors) and it was used only to be able to plot the clusters in a two dimensional space. In reality the 5 clusters do not overlap as shown in Figure 2 where the clusters are shown in a 3 dimensional space by adding a third factor to the plot above (the 3 factors now account for almost 90% of the variance of the 6 variables).

The k-means clustering algorithm adds membership to the clusters by minimizing the within clusters sums of squares (see Hartigan for more detail) and thus producing k-clusters of points that are as closed as possible to every point within their clusters. The center of the cluster therefore could be an observed point (in this case an ETF) or could be a point calculated by the algorithm. In Figure 3 we show the means of each cluster based on their variables (the performance measures). Notice how different the clusters are in terms of their variable means. Also note that the intraday return mean differences (although significantly different) are meaningless given an almost negligible intraday percent returns for the day the sample was taken. In particular Cluster 5 (the highest overall returns) and Cluster 4 (the lowest overall returns) are of interest. The cluster means returns show highly significant differences as shown in the ANOVA (Table 1).

Figure 2: 5-means Clusters (3 Factors)

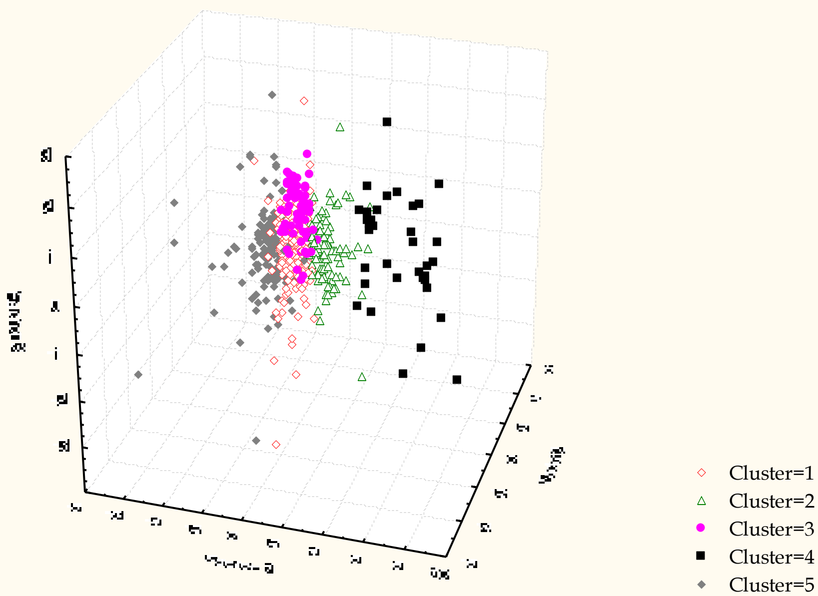


Figure 3: Variable Means for Each Cluster

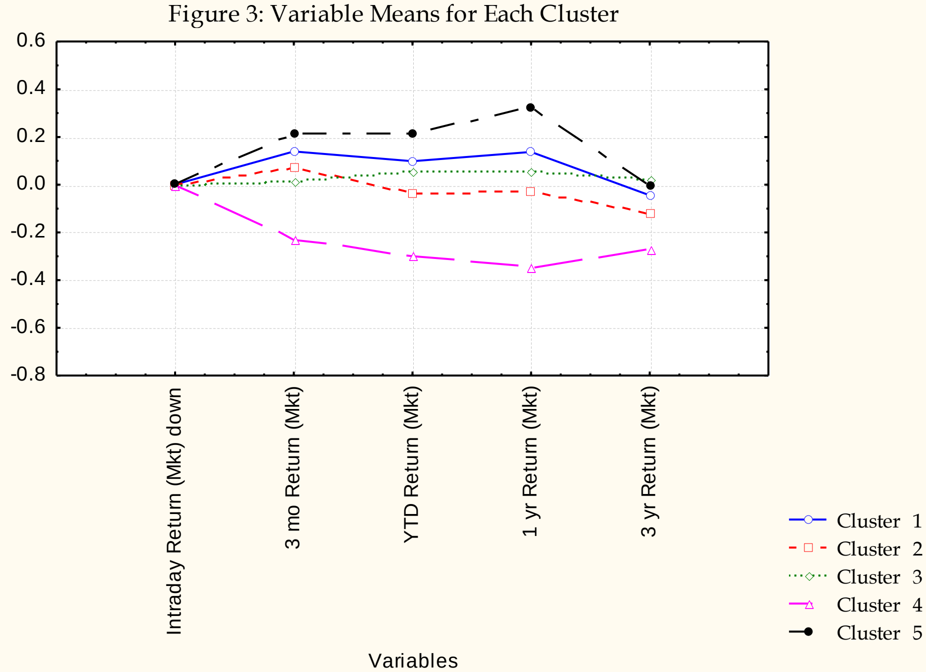


Table 1: Analysis of Variance for Cluster Means

	Between	df	Within	df	F	signif.
Intraday Return	0.00094	4	0.009986	569	13.3546	0.000000
3 mo Return	6.60256	4	3.263041	569	287.8339	0.000000
YTD Return	9.00206	4	2.775109	569	461.4388	0.000000
1 yr Return	16.08748	4	3.982818	569	574.5790	0.000000
3 yr Return	2.85034	4	2.889402	569	140.3270	0.000000

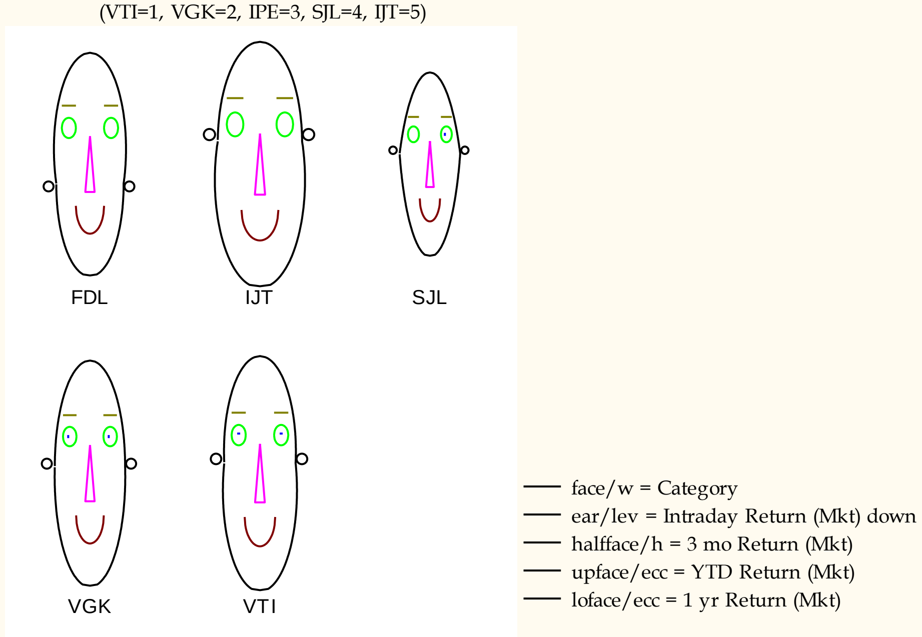
Table 2 shows the descriptive statistics for each of the clusters by variable (same data depicted in Figure 3). Highlighted clusters are the ones with the highest and lowest (overall) means (clusters 5 and 4 respectively).

Table 2: Cluster Means and Standard Deviations

	Cluster 1 (n=224)		Cluster 2 (n=97)		Cluster 3 (n=76)		Cluster 4 (n=35)		Cluster 5 (n=142)	
Performance variable	Mean	S	Mean	S	Mean	S	Mean	S	Mean	S
Intraday Return	0.001	0.004	0.000	0.004	0.000	0.003	-0.003	0.006	0.003	0.004
3 mo Return	0.140	0.053	0.072	0.062	0.015	0.048	-0.231	0.099	0.213	0.111
YTD Return	0.098	0.037	-0.038	0.056	0.056	0.042	-0.300	0.094	0.213	0.111
1 yr Return	0.138	0.048	-0.030	0.064	0.059	0.045	-0.343	0.109	0.327	0.134
3 yr Return	-0.044	0.052	-0.122	0.068	0.023	0.045	-0.268	0.144	0.006	0.083

Since the clusters are quite large, we proceeded to select the ETF's that where the closest to their cluster centroid and depict those funds by means of a Chernoff Face (Chernoff, 1973) just to see how different they looked (judging by their significantly different performance means). Figure 4 shows those ETF's (VTI, VGK, IPE, SJL, and IJT which were the funds closer to their centroids for clusters 1 through 5 respectively. Even though certain features of the faces are the same for all ETF's (eyes, eyebrows, mouth curvature and nose are the same) still we can discern differences in at least two of the faces, those corresponding to SJL and IJT (which belong to the most different clusters (4 and 5). In fact, we can almost be certain that the other 3 ETF's behave about the same in terms of these 6 performance measures. Again, this shouldn't be surprising since Figure 3 (in terms of the variable means) depicts the same as Figure 4. Again, Figures 3 and 4 complement each other, and not necessarily tell us the exact same story.

Figure 4: Chernoff Faces for each Cluster Centroid ETF
(VTI=1, VGK=2, IPE=3, SJL=4, IJT=5)



V. DISCUSSION

This analysis takes advantage of well know multivariate statistical methods to a sample of 574 ETF's based on 6 performance measures (intraday, YTD, 3 month, 1-year, and 3-year returns. The basic idea was to break down the various ETF's into similar clusters based on these 6 performance measures. Principal Components analysis was then used to plot the clusters in 2 and 3 dimensional spaces based on the Factor coordinates. The ETF's closest to the cluster centroids where plotted using Chernoff faces to show the similarity/disparity of those ETF's which can be thought as representatives of the rest of their cluster constituents. The analysis of variance for the between cluster means of the 5 performance measures shows highly statistical significant results ($p<.005$). Well known ETF's like SPY, DIA, QQQQ were found to be part of cluster I which in our analysis was the second overall performing cluster 5 was the best performer, Figure 3 and Table 1). The best performing cluster (5) included ETF's that supposed to follow a variety of indexes (BHH=technology, EEZ=Large Value Stocks, JJN=commodities, metals, PEZ=consumer discretionary, etc.). Also of interest is that the best (average-wise) two clusters (II and IV) were the largest (142, and 224) and the worst cluster (4) was had the smallest membership (35). From this we can argue that, from the strategic point of view, the two largest clusters offer the best investment opportunities. Similarly, diversification would be best achieved by investing in ETF's belonging to different clusters even though some of the clusters are not as good performers as others (in particular cluster (IV). Given that our data is a snapshot of time trading, the results shown here are mostly exploratory and applicable to this period, however they would be easy to replicate to a different sample and/or time period.

VI. CONCLUSION

Exchange traded funds are yet another financial markets instrument that have become increasingly widespread among investors. Research have found that they have desirable (and some undesirable) characteristics in comparison to other instruments in general and to index mutual funds in particular. Among the desirable factors are: less volatility than common stocks, higher intraday performance, liquidity, lower index tracking errors and (management) cost than mutual funds. On the negative side, ETF's have been shown to underperform index funds in the long run, thus not being a good choice for investors that that don't trade them often. In our study we found that performance-wise most ETF's seem to concentrate in a handful of similarly behaving clusters. Based on 5 performance variables, we identified 5 of such clusters where the 574 ETF's in our sample were assigned. If indeed the ETF's were tracking different indexes, we would had expected that most of the ETF's in each of the clusters where tracking such indexes. The surprising finding was that all of the clusters contained ETF's that track a wide variety of indexes. We also found that overall performance was attained by the 2 largest clusters (see Appendix B). This suggests that most ETF managers seem to follow similar strategies at picking the stock components for their funds. Finally the clusters offer an extra layer for diversification in the sense that investors could pick ETF's from the various clusters and by doing so further decrease the volatility of their portfolio.

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APPENDIX A

ETF Sample (n=574)

ADRA	DEF	EEN	EZY	GBB	IJK	JJC	PAF	PTJ	RPG	TDH	VIS
ADRD	DEM	EES	FAB	GBF	IJR	JJE	PBD	PUI	RPV	TDN	VNQ
ADRE	DES	EEV	FAD	GDX	IJS	JJG	PBE	PUW	RSX	TDV	VO
ADRU	DEW	EEZ	FBT	GEX	IJT	JJM	PBJ	PVI	RTH	TDX	VOE
AGG	DFE	EFA	FCG	GII	ILF	JJN	PBS	PWB	RTL	TFI	VOT
AIA	DFJ	EFG	FDD	GLD	INP	JKD	PBW	PWP	RTM	TIP	VOX
BBH	DGG	EFU	FDL	GMF	INY	JKE	PCY	PWT	RWM	TLH	VPL
BDH	DGL	EFV	FDM	GML	IOO	JKF	PDN	PWV	RWR	TLO	VPU
BHH	DGS	EFZ	FDN	GMM	IPE	JKG	PEY	PWY	RWX	TLT	VTI
BIK	DGT	EKH	FDV	GSC	ISI	JKH	PEZ	PWZ	RXD	TMW	VTV
BIL	DHS	ELG	FEU	GSG	ITA	JKI	PFA	PXE	RXI	TTH	VUG
BIV	DIA	ELR	FEX	GSP	ITB	JNK	PFF	PXF	RXL	TWM	VV
BKF	DIG	ELV	FEZ	GUR	ITE	JPP	PFI	PXH	RYE	UCC	VWO
BLV	DIM	EMG	FFR	GVI	ITF	JSC	PFM	PXI	RYF	UDN	VXF
BND	DJP	EMM	FGD	GWL	IWB	JXI	PGF	PXJ	RYH	UGE	VYM
BSV	DKA	EMV	FIO	GWX	IWC	JYN	PGJ	PXN	RYJ	UKF	WMCR
BWV	DLN	ENY	FIW	GXC	IWD	KBE	PHB	PXQ	RYT	UKK	WMH
BWX	DLS	EPP	FNI	IAH	IWF	KCE	PHO	PYH	RYU	UKW	WMW
CFT	DND	EPS	FNX	IAI	IWM	KIE	PIC	PYZ	RZG	UNG	WPS
CGW	DNH	ERO	FPX	IAK	IWN	KLD	PID	PZA	RZV	UPW	XBI
CIU	DNL	EUM	FTY	IAT	IWO	KRE	PIO	PZD	SAA	URE	XES
CMF	DOD	EVX	FVD	IAU	IWP	KXI	PIQ	PZI	SBB	USD	XGC
COW	DOG	EWA	FVI	IBB	IWR	LAG	PIV	PZJ	SCC	USO	XHB
CRO	DOL	EWH	FVL	ICF	IWS	LQD	PJB	PZT	SDD	UTH	XLB
CSD	DON	EWI	FXA	IDU	IWV	LVL	PJF	QCLN	SDK	UUP	XLE
CSJ	DOO	EWJ	FXB	IDV	IWW	MBB	PJG	QID	SDP	UVG	XLF
CUT	DPC	EWK	FXC	IEF	IWZ	MDY	PJM	QLD	SDS	UVT	XLG
CVY	DPN	EWL	FXD	IEI	IXC	MKH	PJO	QQEW	SDY	UVU	XLI
CWI	DRF	EWM	FXE	IEO	IXG	MOO	PJP	QQQQ	SFK	UWM	XLK
CXA	DRW	EWN	FXF	IEV	IXJ	MTK	PKB	QQXT	SH	UXI	XLP
CZA	DSC	EWO	FXG	IEZ	IXN	MUB	PKW	QTEC	SHM	UYG	XLU
DBA	DSG	EWP	FXH	IFAS	IXP	MVV	PLW	RCD	SHV	UYM	XLV
DBB	DSI	EWQ	FXI	IFEU	IYC	MXI	PMR	REM	SHY	VAW	XLY
DBC	DSV	EWS	FXL	IFGL	IYE	MYY	PPA	REW	SIJ	VB	XME
DBE	DTD	EWT	FXM	IFNA	IYF	MZZ	PPH	REZ	SJF	VBK	XOP
DBN	DTH	EWU	FXN	IFSM	IYG	NFO	PRF	RFG	SJH	VBR	XPH
DBO	DTN	EWV	FXO	IGE	IYH	NLR	PRFZ	RFV	SJL	VCR	XRO
DBP	DUG	EWW	FXP	IGM	IYJ	NY	PRN	RGI	SKF	VDC	XRT
DBR	DVY	EWY	FXR	IGN	IYK	NYC	PSI	RHS	SKK	VDE	XSD

DBS	DWM	EWZ	FXS	IGV	IYM	NYF	PSJ	RJA	SLV	VEA
DBT	DXD	EXB	FXU	IHE	IYR	OEF	PSL	RJI	SLX	VEU
DBU	DXJ	EXI	FXY	IHF	IYT	OIH	PSP	RJN	SMH	VFH
DBV	ECH	EXT	FXZ	IHI	IYW	OIL	PSQ	RJZ	SMN	VGK
DDI	EEB	EZA	FYX	IIH	IYY	ONEQ	PTE	RKH	SOXX	VGT
DDM	EEH	EZM	GAF	IJH	IYZ	OTP	PTF	ROB	SPY	VHT
DEB	EEM	EZU	GAZ	IJJ	JJA	OTR	PTH	ROM	TDD	VIG

APPENDIX B
Cluster I
n=224

VTI	IWZ	PWV	ENY	CVY	PJG	RGI	RSU
TMW	VUG	RSX	IWD	DJP	FGD	WMCR	SSO
IWV	EWC	FVD	IGM	GML	IJJ	IHI	OIH
IYY	FXO	DNL	PJO	FFR	RYH	EWA	UVG
PWP	RPV	PKW	EZY	FDL	IFGL	EFG	ROM
ISI	CUT	VAW	XHB	PUW	JPP	RYF	DGL
ELR	PXH	EPS	INP	ILF	JJC	SWH	DIG
PRF	ELG	FPX	DLS	REM	CSD	QQQQ	
IWB	JJG	GXC	VOE	IVE	EWY	FXH	
PTH	MXI	DLN	EEH	VTV	JJM	JKF	
VV	FDV	ADRA	IGE	PSL	FXG	PYH	
XLB	FTA	OTP	VOX	GUR	MTK	DON	
AIA	EXI	DIA	QQXT	RWX	RHS	GAF	
PJF	VIG	RSP	IXN	WPS	FCG	VIS	
VWO	GMF	SDY	TDV	IYE	NY	PIQ	
EEM	IHF	VYM	DHS	IYZ	RJZ	XLI	
PAF	MOO	PDN	DTN	FVI	BDH	PBS	
OTR	PFM	ONEQ	IFAS	ROB	TDN	QQEW	
GWX	VPL	FIW	ELV	RJA	XGC	RYT	
IVW	DBA	JKE	RJI	RTH	DFE	FIO	
IWF	SLX	IYK	HGI	RYU	PTF	IAK	
EPP	XLK	IBB	KIE	XLE	IWS	EWS	
GMM	JKI	PTJ	NYC	PID	IEO	PZI	
EXT	DVY	PPA	EWJ	DEF	PKB	NLR	
PGJ	PWC	DSI	DOD	DBN	BKF	PSJ	
SPY	IFSM	VGT	PHO	FNI	PWY	DDM	
EVX	PWB	JKD	IAH	VDE	FAB	DEM	
KLD	IWW	FEX	ITF	PFI	PTE	PSP	
DTD	XBI	IYW	EMV	OEF	PEY	XPH	
ITA	DND	TTH	IYJ	RTM	PIV	UPW	
IVV	EWT	CGW	PIC	BIK	DRW	PGF	

Cluster II
n=97

VGK	RJN	EZU	PBD
DWM	DKA	PIO	EWI
ADRD	DBO	DIM	SDP
EFV	DTH	USO	UYG
IEV	LVL	IDV	
DOL	FXB	DBB	
IFEU	GBB	DBC	
EWN	EWU	PFA	
DOO	EWO	VEU	
EKH	IXJ	CWI	
DXJ	DBV	EEN	
PEF	GSP	EWG	
DGT	IAI	DBU	
ITB	IYG	UDN	
ADRU	XLV	KRE	
PXF	PPH	IXC	
MKH	FXI	KBE	
PJB	WMH	OIL	
IOO	FEU	COW	
GII	IYF	FXE	
DEW	GWL	ERO	
EFA	FDD	QCLN	
RKH	XLF	PXN	
VEA	PZD	FEZ	
CRO	EWQ	PBW	
DBE	KCE	EFZ	
GSG	IYH	EXB	
EWK	XLG	DOG	
JXI	IAT	JJE	
GSC	VFH	SH	
IXG	RXL	RXD	

Cluster III n=76		
IPE	PHB	EEB
TIP	KXI	VHT
BSV	LQD	EWZ
GVI	NYF	BBH
ITE	CXA	TLH
TDD	XLP	UTH
MBB	EWL	JNK
TDX	PVI	WMW
AGG	BWV	ADRE
BND	SHV	TLO
LAG	BIL	BWX
CSJ	HYG	TLT
GBF	PUI	PFF
CIU	JSC	DGG
IEI	VDC	
SHY	BIV	
PZT	VPU	
FXM	PLW	
PWZ	FXY	
FXC	FXU	
UUP	FXS	
INY	IHE	
PZA	JYN	
SHM	IDU	
CFT	IEF	
MUB	XLU	
CMF	FXA	
TDH	IXP	
DFJ	PCY	
TFI	BLV	
FXF	DNH	

Cluster IV n=35
SJL
QID
REW
SFK
SZK
SCC
DUG
SJF
MZZ
SDS
SDK
RWM
RSW
DXD
SBB
SIJ
SJH
SDD
EWV
SKF
EWP
MYY
EFU
SSG
TWM
EUM
PSQ
EEV
UNG
SKK
GAZ
SMN
GEX
FXP
SRS

Cluster V n=142				
IJT	EZM	DGS	RFG	DRF
VOT	PXE	IYM	FBT	BHH
VBK	MDY	IWN	PEJ	
JKK	EES	PWO	EWM	
JKH	DES	FTY	UVU	
FXL	EWW	DSV	XRT	
IWO	RYJ	IJS	UKF	
DSG	IYT	RFV	GDX	
PWT	XOP	PJP	PXQ	
IJK	NFO	CZA	QLD	
PRN	JKG	IGN	UVT	
VCR	PWJ	JJA	UXI	
VB	PBJ	XES	DBP	
FYX	XME	XRO	IAU	
RZG	PMR	HHH	GLD	
FAD	PBE	EZA	MVV	
DSC	VO	EWD	UCC	
VXF	FXR	FXN	UYM	
JKJ	PZJ	RYE	SAA	
PYZ	FDM	FRI	ECH	
EMG	QTEC	VNQ	UWM	
XLY	JKL	SMH	UKW	
PRFZ	FVL	RWR	DBR	
IJR	IYC	IFNA	DBT	
UGE	EMM	IYR	DPN	
RCD	RZV	JJN	DPC	
PDP	PJM	PSI	UKK	
RPG	EWH	ICF	URE	
FNX	PXI	RTL	USD	
IWM	IGV	IEZ	DEB	
FXD	VBR	PXJ	IIH	
IWC	IWR	XSD	EEZ	
IWP	FXZ	FDN	DDI	
PEZ	FTC	SOXX	DBS	
IJH	RXI	REZ	SLV	