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Application of the Absorption Ratio to Illustrate Financial Connectedness and Interlinkages

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Abstract

This paper provides further evidence of the need to consider interlinkages and coupling within the financial system, particularly their impact upon portfolio management and in assessing risk exposures. This is done through application of the Absorption Ratio (AR) to ten European banks and insurance companies. In this case, the AR does not appear to act as an early warning indicator of market turmoil, which is inconsistent with the findings of Kritzman et al (2010 and 2014). However, one principal component is identified as explaining 70 to 80% of the variability in the assets' returns for some of the period under review, in particular during the time of most severe financial crisis. A high AR suggests the stocks are more tightly coupled and provides evidence of interlinkages across two subsectors and a number of countries within Europe – thereby illustrating the extent of financial linkages and the high degree of correlation across markets and subsequent ramifications for portfolio managers.

1. Introduction

Given the severity and spread of the global crisis in 2008, it provides suitable examples to illustrate the interlinkages in the financial system. Essentially, a catalyst for it was the extent of the losses sustained through the defaults in the sub-prime domestic mortgage markets in the United States. Such losses ultimately created a domino effect and amplification across global financial markets. Preceding this, global stock markets had experienced several years of healthy prosperity, for instance, the FTSE-All-Share index reached an all-time high of 3490.17[1] as at 13th August 2007. For the subsequent crisis to have been so prolific and far reaching, it suggests that a rise in US mortgage delinquency rates was merely a warning signal of things to come – indeed, the importance of considering the impact of risk contagion and interlinkages when measuring exposures to systemic risk is critical. If a financial institution falls into a state of distress, Delta-CoVaR can identify the subsequent impact on the whole financial system. Brunnermeier et al (2011) suggest that the distress of a single institution does appear to affect the wider financial system and is an example of risk contagion and spreading. The latter occurs due to interlinkages or interconnectedness within the system. Thereby, I seek to provide evidence of the connections that exist between financial institutions leading to the propagation or spreading in a crisis. This is done through application of the Absorption Ratio (AR), as proposed by Kritzman et al (2010). They suggest that this ratio captures the existence and extent of any financial linkages and highlights the greater severity of the "spreading" effect when the links are strong. Furthermore, a low AR suggests markets are less tightly coupled whereas a high ratio suggests the opposite – in the latter case a greater proportion of the assets' returns are explained by a certain number of key components or factors. The analysis is performed using ten UK and European stocks from the banking and insurance sub-sectors and all being constituents of the MSCI financials' sector index. The data is applied to assess how

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[1] Bloomberg

closely the AR follows the path of the relevant market index and whether there is a discernable pattern or relationship between the two. Rather than investigating the linkages between all industries within a given market index, I am exploring the fragility just of the financials' sector and thereby focus only on the asset returns of financial firms.

The paper is structured as follows. Section 2 presents relevant literature in relation to factor analysis and, in particular, Principal Components Analysis (PCA), a strand of research incorporating the AR. In addition, I discuss instances of the application of the AR. Within section 3, the data and its characteristics are discussed. The concepts of Eigenvalues and Eigenvectors are presented in section 4, along with their application in deriving the AR. I present the results and inferences in section 5 and end with concluding remarks in section 6.

2 Relevant Literature

2.1 Factor and Principal Components Analysis

When explaining variations in asset returns or, indeed, economic data sets, factor or Principal Component models can be utilised. In either case, ascertaining an appropriate number of factors or components is presented in the literature. For example, Connor and Korajczyk (1993), present evidence of one to six factors through interpretation of non-zero eigenvalues relating to a sample covariance matrix. Most recently, Ivanov et al (2017) identify two factors as capturing 95.4% of the variability in a specified set of US stock returns, with 80 to 90% generated from a single factor. Likewise, Bai and Ng (2007) suggest the presence of two factors when investigating the variation in monthly returns of 8,436 stocks traded on the NYSE, AMEX and NASDAQ. Interestingly, Hallin and Liska (2007) split their US economic data set into two sub-samples – 1960 to 1982 and 1983 to 2003. In the former case, three factors are identified and one factor in the later sub-sample – both indicating a low number of factors driving the US economy. Consistently, low numbers of factors are identified as the key drivers (see Ahn and Horenstein (2013)), perhaps due to the tight coupling that exists between markets as a whole and within sectors and perceived increased correlations.

In relation to PCA, it can be described as a method used to identify sets of correlated variables (asset returns in this context) that can subsequently be combined linearly into a set of components or factors. A key objective of the technique is to identify as small a set of components as possible, where the latter also account for as much of the variation in the correlated variables as possible. Of all of the components, the first one accounts for the most variation in the original variables, the second accounts for the next largest amount of variation but which is also uncorrelated with the first component. Subsequent components account for less and less variation in a descending manner and none of them correlate with any of the preceding components. It is a non-parametric type of analysis where each component is assigned an eigenvalue. The largest eigenvalues are attached to those components that explain the greatest proportion of the variation in the original variables and they are presented in descending order (the largest eigenvalue being associated with principal component number 1).

2.2 Applications of PCA

The use of PCA techniques can be found in several areas outside of finance. For instance, within genetics they are applied to determine the existence of genetically distinct sub-groups within a population set (see Patterson, Price and Reich 2006). Applications in scientific spheres are very common, particularly within physics specialisms and medical research. For example, understanding the surface properties of asteroids and variations in the degrees of weathering amongst asteroids of different size (see Koga et al 2018) or within medical research in understanding variations in success rates in lung cancer patients undergoing radiotherapy treatments (see Ellsworth et al 2017). Clearly, PCA is applied in a very diverse range of contexts, where a recognised advantage is in its ability to analyse large data sets.

With regards finance, a common application relates to the financial markets. Some research relates to specific asset classes and instruments, for example, applications to yield curves and resulting forward curves and variations in their movement through ascertaining components. According to Laurini and Ohashi (2015), the application of PCA in this context yields mixed results and is deemed to perform more effectively when the correlation matrices are based upon longer term data sets. Contrary to this, Barber and Copper (2010) indicate with greater success that PCA isolates more than 90% of the total variation in the yield curve for US Treasury Securities. They also indicate the ease of application of the technique - the components are "observable" given that they are constructed from linear combinations of data, which in itself is observable and clearly defined. From a risk management perspective, it is clearly useful to understand the dynamics in the shifts and variations of a yield curve.

When discussing financial crises, the application of PCA is widespread. In several instances, it is used to investigate spreading across markets. Upon identifying a prominent component in relation to a given region's returns, it can be applied in a Dynamic Conditional Correlation (DCC) model to estimate the impact of the dominant component on the returns of a different region. For example, Yiu et al (2010) present a finding of spreading from the US to the Asian markets following a shift in the DCC just prior to the start of the 2008 crisis. Similarly, Martinez and Ramirez (2010), apply PCA to assess the extent of market reactions across certain Latin American countries. Having identified the first principal component, it is then applied in ARCH-GARCH volatility models to analyse volatility across markets in the region – in this instance there is only a mild increase in market sensitivities to shocks as opposed to an extreme reaction. In terms of markets as a whole, Pukthuanthong and Roll (2009) isolate principal components and apply them in regressions on various individual country index returns to assess the degree of integration across international markets. The indicator used for inference on this occasion is the R-squared from the regression.

It appears that the PCA is applied in many cases to first isolate the principal components underlying the correlations in returns. Subsequently, the latter are applied in further modelling processes to understand the extent and / or existence of risk contagion. However, PCA can also be used in simply assessing how well the components explain variation in asset returns during times of financial crisis. Billio et al (2012) illustrate that a single component explains a greater proportion of the total variation in returns during such crises because firms are tightly coupled during such periods. This is consistent with Kritzman et al (2010) in relation to the Absorption Ratio and the next section presents relevant literature in the area of PCA and the AR.

2.3 Literature in Relation to the Absorption Ratio

The AR is a relatively recent advancement in approach relating to investigation of interlinkages. However, certain studies do apply or extend upon Kritzman et al (2010). An extension is provided by Reyngold et al (2015). The latter only include financial firms in their data set and their subsequent Credit Absorption Ratio (CAR) incorporates an additional component to reflect the risk of failure of the said firms within their data. Their results are broadly consistent in so far as the individual financial firm returns tend to be closely linked during times of distress and reflected in the higher values of the CAR at such times. Preparation of this ratio is rather data intensive and reliant upon accurate measures or proxies for monthly book values of both debt and equity. Furthermore, it assumes that debt levels are relatively stable over medium term horizons, when, in fact, a characteristic of certain financial institutions prior to the financial crisis was the use of short-term debt requiring regular refinancing.

Dumitrescu (2015) applies the ratio in a predictive capacity in relation to an early warning indicator of forthcoming turbulence in the markets of the European Union. Indeed, it is suggested that its predictive capacities are actually applied within industry in relation to rebalancing portfolios - if the ratio suggests tight coupling amongst assets and increased susceptibility to bad news in the broader markets, then rebalance to more defensive asset classes (see Goyal 2014). The latter findings are also promoted by the Portfolio Management industry professional body, the CFA, in their recent publications (see Kritzman 2014). However, given that individual asset management strategies are not a matter of public record, it is difficult to assess the actual extent of its use. In applying it to the data in this paper, at the very least, further evidence is provided in relation to its validity in signaling linkages.

3. The Data

As mentioned in section 1, in exploring the fragility of the financials' sector, the focus is on financial stocks across the banking and insurance sub-sectors within Europe. Therefore, the data set differs from that of Kritzman et al (2010). The latter apply a market wide index incorporating 632 stocks across a variety of large and mid-cap US stocks and 51 sub-industries. I incorporate 10 stocks from within the MSCI Europe Financials' Sector index where the stocks chosen account for over 40% of the weightings of all stocks in the index. There are 900 daily return observations for each stock - HSBC Holdings, Banco Santander, Paribas, Allianz, UBS, BBVA, Lloyds, Barclays, Prudential, and ING. The market index is the MSCI Europe Financials' Sector Index and all of the daily observations are collected for the period 30th December 2005 to 12th June 2009. This allows for incorporating sufficient time periods pre-financial crisis and also the timeframe following the crisis when the underlying market index starts to recover – from March 2009. In relation to the daily observations for return, it is derived as follows:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{3.1}$$

Where: p_t refers to the closing price of the stock or index at time t.
p_{t-1} refers to the closing price of the stock or index at time t-1.

r_t refers to the daily return of the stock or index at time t.

All data is sourced from Bloomberg and the summary statistics for the stocks and index are presented in table 3.1. The mean daily return in each case is close to zero and the impact of the 2008 crisis is reflected in the minimum return values for each variable. Augmented Dickey-Fuller tests are produced, for 1 to 10 lags in table 3.2 and all of the time series indicate stationarity.

Table 3.1: Summary Statistics for Stock Variables and Nominated Market Index.

	HSBC	Santander	Paribas	Allianz	UBS
Mean	-0.01085	-0.00308	-0.00434	-0.00650	-0.0541
Median	0.0000	0.0000	0.0000	0.0000	0.0000
Max	15.5148	23.2161	20.8968	19.4921	31.6614
Min	-18.7788	-11.9418	-17.2430	-12.9928	-17.2139

Table 3.1 cont'd: Summary Statistics for Stock Variables and Nominated Market Index.

	BBVA	Lloyds	Barclays	Prudential	ING	Market
Mean	-0.01773	-0.0561	0.00397	0.0633	-0.01614	-0.04067
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	22.0259	30.3454	25.2347	23.4568	29.2433	16.0399
Min	-12.7795	-33.9480	-24.8464	-20.0000	-27.4839	-9.8446

Table 3.2: ADF tests for Stock Variables and Nominated Market Index at 1 to 10 lags

	HSBC	Santander	Paribas	Allianz	UBS
1 lag	-29.6375*	-28.7452*	-27.0368*	-29.7439*	-29.4869*
2 lags	-25.0955*	-24.4628*	-24.8896*	-23.9711*	-25.6528*
3 lags	-20.8081*	-20.5336*	-20.6317*	-18.9890*	-22.1427*
4 lags	-18.4708*	-19.0587*	-19.0020*	-18.9318*	-19.8048*
5 lags	-18.3841*	-17.0540*	-17.8355*	-17.1769*	-18.9323*
6 lags	-16.3363*	-15.8188*	-17.3884*	-15.9228*	-18.1326*
7 lags	-14.8635*	-15.1684*	-15.8632*	-14.3038*	-16.3678*
8 lags	-14.0897*	-14.5235*	-15.2712*	-13.8153*	-14.2962*
9 lags	-13.5885*	-13.9113*	-14.2249*	-13.4396*	-13.1934*
10 lags	-13.5424*	-13.2921*	-13.7288*	-12.7183*	-13.2103*

Note: Critical values of -3.43, -2.86, -2.57. * denotes test statistic < critical values at all levels.

Table 3.2 cont'd: ADF tests for Stock Variables and Nominated Market Index at 1 to 10 lags

	BBVA	Lloyds	Barclays	Prudential	ING	Market
1 lag	-28.2832*	-26.5454*	-26.3700*	-31.1088*	-28.2755*	-28.4825*
2 lags	-23.4308*	-22.4408*	-22.6686*	-27.1607*	-24.8617*	-24.3880*
3 lags	-20.0129*	-18.9723*	-19.3143*	-21.0917*	-20.8565*	-19.8685*
4 lags	-18.5631*	-18.7637*	-18.2028*	-20.9042*	-18.9262*	-18.8846*
5 lags	-17.0573*	-18.4707*	-18.0698*	-20.2356*	-17.4280*	-17.7456*
6 lags	-15.9146*	-17.9940*	-17.3072*	-16.8913*	-15.3486*	-16.2391*
7 lags	-15.3991*	-17.5633*	-16.7939*	-15.3235*	-13.9018*	-15.0126*
8 lags	-14.7386*	-16.1846*	-14.4821*	-14.0162*	-13.2297*	-14.0283*
9 lags	-13.9369*	-14.3095*	-13.6645*	-13.2138*	-12.9712*	-13.3302*
10 lags	-12.7559*	-13.2877*	-13.1145*	-13.0608*	-12.4902*	-12.9091*

Note: Critical values of -3.43, -2.86, -2.57. * denotes test statistic < critical values at all levels.

4. Methodology

4.1 The Absorption Ratio

The AR is defined as the proportion of the total variation in the returns of a set of assets explained by a finite set of non-zero eigenvectors. According to Kritzman et al (2010), it is represented by the following expression:

$$AR_t = \frac{\sum_{i=1}^{n} \sigma_{Ei}^2}{\sum_{j=1}^{N} \sigma_{Aj}^2} \tag{4.1}$$

Where: AR_t refers to the absorption ratio at time t;
N = number of assets;
n = number of "non-zero" eigenvectors;
σ_{Ei}^2= variance of the i^{th} non-zero eigenvector;
σ_{Aj}^2= variance of the j^{th}asset.

The eigenvectors are derived specifically in relation to a covariance or correlation matrix of returns of a set of assets. The first eigenvector represents a particular linear combination of weights of each asset's return. Subsequent eigenvectors depict linear combinations of the weights orthogonal to the preceding eigenvector and the proportions of the variation in the asset returns that they represent or explain reduce in value for each subsequent eigenvector. Furthermore, each subsequent eigenvector seeks to explain the variation in the asset returns not explained by the preceding eigenvectors. For this data set daily absorption ratios are estimated for the entire data set where the associated correlation matrices and eigenvectors are derived on an EWMA[2] basis from a rolling window of returns of 365 days.

4.2 Eigenvectors and Eigenvalues

According to Tsay (2010), in applying PCA to identify the sources of variations in the returns of ten assets, we have a k-dimensional vector of asset returns denoted by R_A:

[2] EWMA – Exponentially Weighted Moving Average – giving more weight to the more recent return observations in each 365-day window versus that given to the older return observations.

$$R_A = (r_1, r_2, r_{3,} \dots \dots \dots .. r_k)' \quad where\ k = 10, \tag{4.2}$$

which, for this data set, is equivalent to:

$$R_A = (r_{HSBC}, r_{Sant}, r_{Paribas,} r_{Allianz}, r_{UBS}, r_{BBVA}, r_{Lloyds}, r_{Barc}, r_{Pru}, r_{ING})' \tag{4.3}$$

A given portfolio of assets incorporates linear combinations of the asset weights and we can depict the weights as the following vector for assets 1 to k, where:

$$W_i = (w_{i1,} w_{i2}, w_{i3}, \dots \dots .. w_{ik})' \tag{4.4}$$

$and\ w_{i1}$refers to the weight attached to asset 1

Furthermore, the return of a multi-stock portfolio, “i”, containing k stocks and where each stock is assigned a weight w_i, can be depicted as:

$$y_i = W_i R_A \equiv \sum_{j=1}^{k} w_{ij} r_j \tag{4.5}$$

where: w_{i1} refers to the weight attached to the 1st stock in portfolio “i”, r_1 is the return associated with stock 1 in portfolio “i”, w_{ik} is the weight attached to stock k in portfolio “i” and $r_k$is the return associated with stock k in portfolio “i”.

According to section 2.1, an objective of PCA in this context is to provide a means to explain correlations between stock returns through some linear combinations of the said returns, where the latter capture the variability in the original data set. Therefore, if we refer to principal component 1 (PCA1) of R_A as being associated with a particular linear combination of the stock returns, then:

$$y_1 = W_1 R_A \equiv \sum_{j=1}^{k} w_{1j} r_j \tag{4.6}$$

Furthermore, PCA1 is intended to identify the particular linear combination of the stock returns that represents the maximum variability in such returns i.e. Var (y_1) is maximised.

The second principle component (PCA2) of R_A, is denoted by the following linear combination:

$$y_2 = W_2 R_A \equiv \sum_{j=1}^{k} w_{2j} r_j \tag{4.7}$$

where: $Var(y_1) > Var(y_2)$ and $\text{Cor}(y_2, y_1) = 0$

The vector of the linear combination of weights associated with a principal component is otherwise referred to as an eigenvector, E. Therefore, for the i^{th} component:

$$W_i \equiv E_i = (e_{i1,}e_{i2}, e_{i3}, \dots \dots . . e_{ik})' \quad (4.8)$$

$$y_i = E_i R_A \equiv \sum_{j=1}^{k} e_{ij} r_j \quad (4.9)$$

For PCA1:

$$W_1 \equiv E_1 = (e_{1,1,}e_{1,2}, e_{1,3}, \dots \dots . . e_{1,k})' \quad (4.10)$$

and,

$$y_1 = E_1 R_A \equiv \sum_{j=1}^{k} e_{1j} r_j \quad (4.11)$$

An eigenvalue is associated with each principle component and eigenvector and denoted by λ_i (i^{th} component), λ_1 (1^{st} component), λ_2 (2^{nd} component). The eigenvalue / eigenvector pairs are as follows:

i^{th} component: (λ_i, E_i), 1^{st} component: (λ_1, E_1), 2^{nd} component: (λ_2, E_2)

and: $\lambda_1 > \lambda_2 > \lambda_3 > \lambda_4 \dots \dots \dots \dots \dots . > \lambda_i > 0$

The proportion of the total variation in the stock returns explained by each component is the ratio of the individual eigenvalue divided by the sum of all of the eigenvalues for all of the identified components. Furthermore, only non-zero eigenvalues and vectors are considered. The larger the eigenvalue for PCA1, the greater the proportion of the variability in the asset returns that is being explained by it. Larger values for λ_1 indicate that a single component is impacting asset returns collectively, more than any others. As the influence of a single component increases, the implication is that all stocks are being impacted by it and this is because the stocks are tightly coupled. If this was not the case, then one component would not have such a significant influence across the board.

4.3 Evaluating the Absorption Ratio

Periods of tighter coupling are measured by significant changes in the absorption ratio over time. Such shifts can indicate market fragility and returns across institutions moving together. If they are moving in a unified manner, any negative shocks can impact institutions in the same way. I calculate a moving average of the daily AR on a two-week basis and subtract the moving average of the AR over one year – then I divide by the standard deviation of the moving average of the AR over one year.

$$\Delta AR = \frac{(AR_{2-week} - AR_{1-year})}{\sigma AR_{1-year}} \tag{4.12}$$

The shift is then compared with the percentage price movements in the market index to identify any indications of spikes in the AR being followed by a significant downturn in the market.

5. Results and Inferences

5.1 Movement in the AR versus the Market Index

Figure 5.1.1 illustrates the movements in the underlying market index for the time-frame 30th December 2005 to 30th December 2011. There appears to be a period of sustained recovery in the index from March 2009 to February 2011. Accordingly, movement in the AR is observed from 30th December to June 2009 to identify how closely the AR tracks the index and to identify any potential early-warning indications of market downturns.

In generating the Absorption Ratios, there appear to be four key components identified as explaining the variability in the returns of the ten stocks, with, as expected, principal component 1 (PCA1) explaining the greatest proportion of that variability. Furthermore, PCA1 > PCA2 > PCA3 > PCA4. Summary statistics relating to the explanatory proportions assigned to each component are presented in table 5.1.1.

Figure 5.1.1: Graph of Price Movements in the MSCI Financials Sector Index

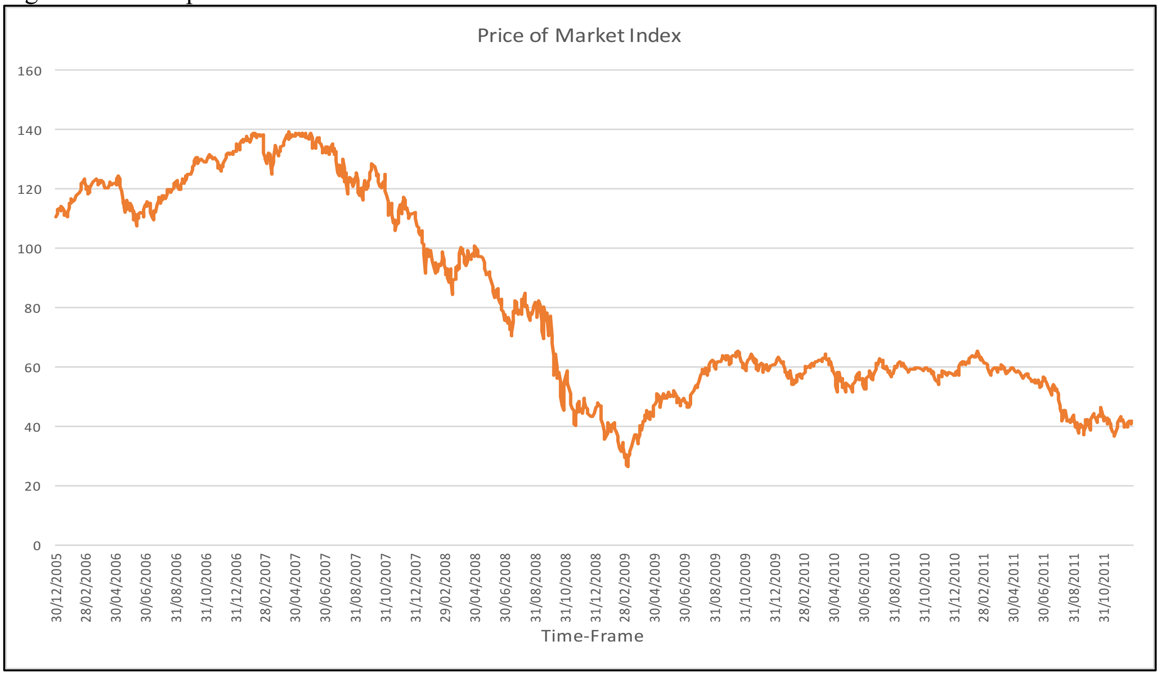


Table 5.1.1: Summary Statistics for Each Principal Component – Assigned Explanatory Proportions

	Principal Component 1	Principal Component 2	Principal Component 3	Principal Component 4	Total Proportion Across Top 4 Components
Maximum	0.7931	0.09385	0.0703	0.0742	0.9068
Minimum	0.5252	0.0451	0.0245	0.0288	0.7464
Standard Deviation	0.06472	0.008826	0.007764	0.00859	0.04191
Mean	0.67246	0.07051	0.05013	0.04336	0.83646

The maximum variation explained by four key components is almost 91%, with 80% being attributed to PCA1 i.e. 80% of the variation in all of the stock returns is explained by PCA1. The minimum variation explained by four components is 75% with 52.5% relating to the first component. Given the explanatory provided in section 2, this result in itself is not surprising –

markets in general now appear tightly coupled, and, subsequently, a very small number of risk factors can be found to drive variations in asset returns. Furthermore, one factor alone can conceivably explain 70 to 80 percent of that variation in a single sector.

In terms of further analysis, PCA1 is used when considering the movement of the AR in relation to the underlying market index. A comparison of the movement through time in the proportions attributed to PCA1 and to all four components is depicted in figure 5.1.2. It reflects a steady increase in the AR to a peak in the period July 2007 to September 2008 – coincidental with the building financial crisis.

Figure 5.1.2: Proportion of the Variability in the Stock Returns Explained by PCA1 and All Four Components

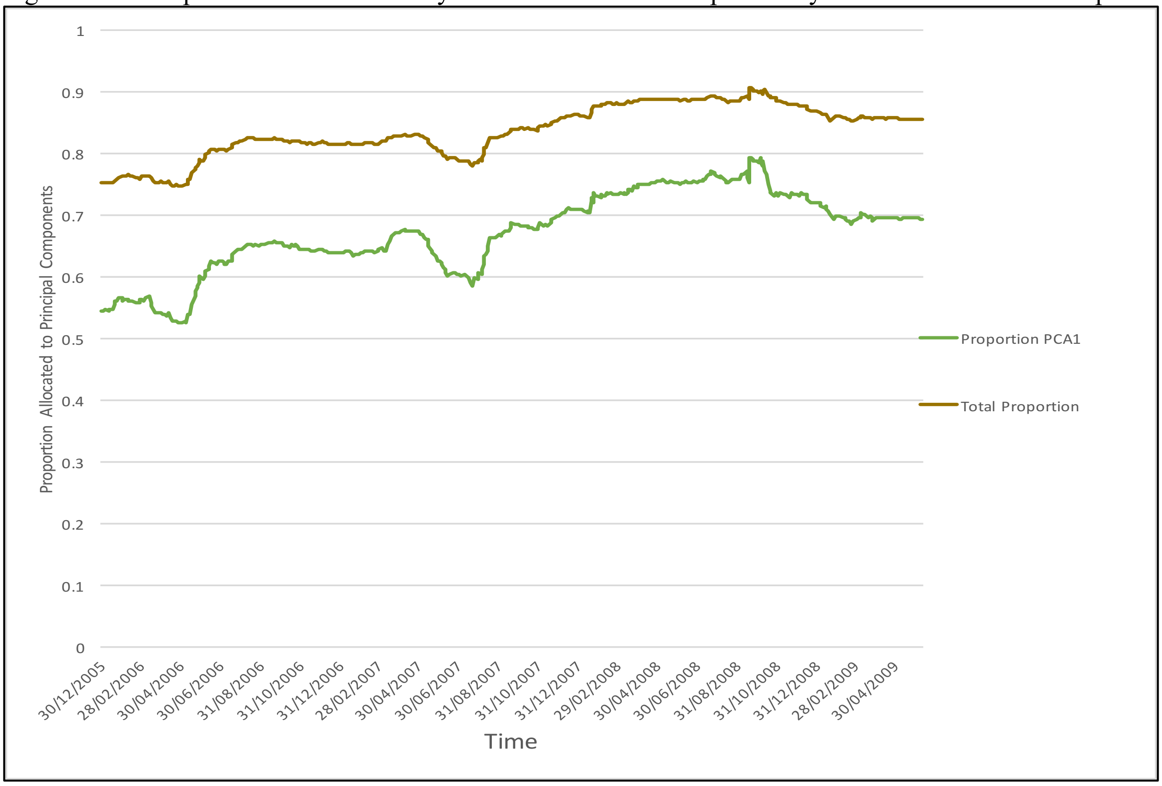
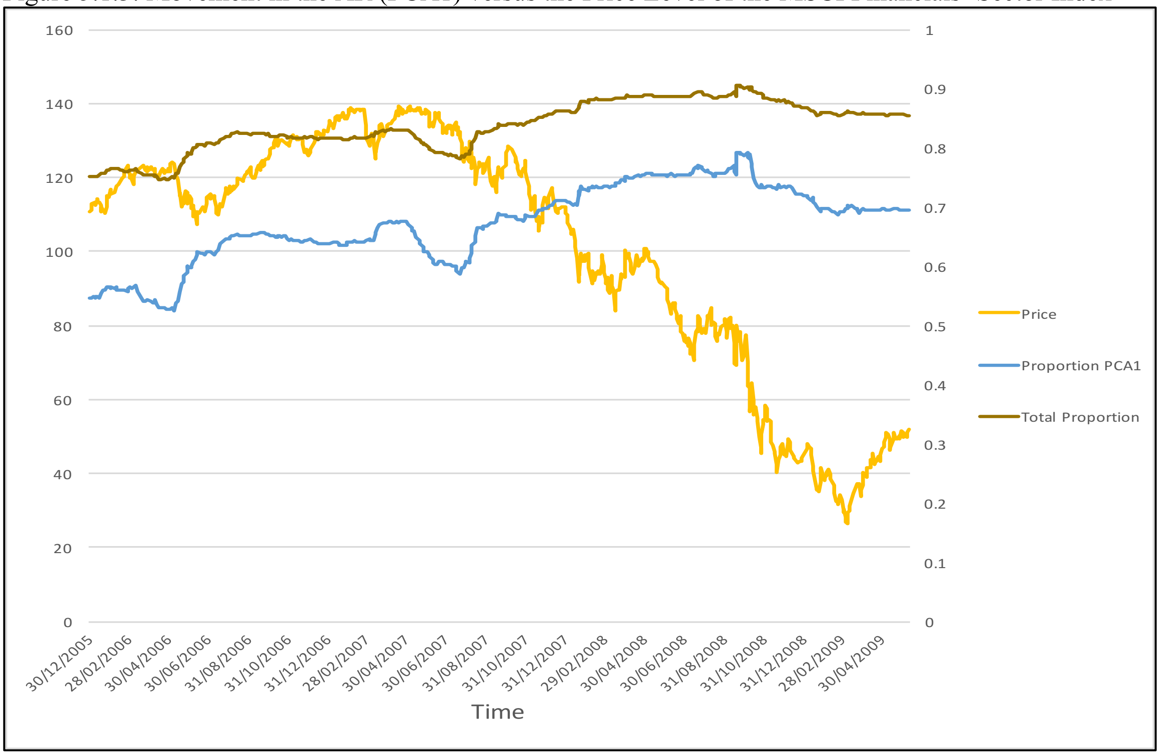


Figure 5.1.3 depicts the movement in the AR versus that of the underlying market index. In the earlier years, there does appear to be an inverse relationship between the level of the AR and the level of the underlying market index. It also presents that the AR increases quite significantly to its highest level during the financial crisis and fairly consistent with the fall in the price of the market index. However, it does not appear to be a pre-emptive or early-warning

relationship and in some instances seems to be lagging the index – for example the incline in the AR in 2007 is not exactly coincidental with the drop in the index, which begins in May 2007. A further contraindication occurs from October 2008, when the AR actually starts to reduce but the market index continues to fall quite significantly. This anomaly could be indicative of the sample size and applying just ten stocks in the analysis – future work could incorporate all stocks within a given market index, consistent with Kritzman (2010). Furthermore, as the market begins to recover in March 2009, the AR levels off and does not reduce significantly from its highest point. As indicated by Kritzman at al (2010), this could imply remaining fragility within the sector – in remaining quite high the AR reflects that the same component is explaining a large proportion of the movement in all ten stocks. Therefore, it can be argued that the stocks are still tightly coupled in their behaviour.

Figure 5.1.3: Movement in the AR (PCA1) versus the Price Level of the MSCI Financials' Sector Index



5.2 Inferences from Shifts in the AR

The graphs are not indicative of the AR being useful as an early warning indicator of pending turmoil in the markets. However, certain inferences can be made through a comparison of shifts in the AR with the largest daily movements in the market index. For the worst percentage downturns in the market index, Table 5.2 presents the proportion of those occasions when there is a corresponding 1-sigma increase in the AR.

Table 5.2: Number of times a % Drop in the Index is Accompanied by a 1-sigma increase in the AR

	>1% drop in the index	>1.5% drop in the index	>2.0% drop in the index	>2.5% drop in the index	>3.0% drop in the index	>3.5% drop in the index
% of cases with at least a 1-sigma increase in the AR	54%	55%	51%	47%	40%	39%

The figures in table 5.2 are further evidence of the AR not being an early warning indicator of pending turmoil. In addition, it appears that the more severe the drop in the index, the lower the likelihood of an accompanying significant shift in the AR. However, at the very least, the shifts are consistent with figure 5.1.3. Some of the largest downturns in the market occur from October 2008, when, intuitively, you would expect a corresponding increase in the AR – what actually occurs is a reduction and levelling off in the AR, thereby explaining the low number of occurrences of at least a 1-sigma shift.

6. Concluding Remarks

For the given data set, this empirical analysis is inconsistent with Kritzman et al (2010) in so far as the graphs themselves do not provide clear evidence of the AR acting as any kind of early warning indicator of market turmoil. Indeed, there appears a satisfactory inverse relationship with the market index but, at times, it appears to be lagging in nature. Furthermore, during the most significant period of the financial crisis, the AR eventually decreases and levels off. What Kritzman et al (2010) do provide is evidence that the majority of the worst market downturns are preceded by at least a 1-simga upward shift in the AR. They argue that the latter can then be used in day to day portfolio management to signal the need to switch between asset classes or reduce weightings in sectors that are deemed to be tightly coupled. For the data analysed in this chapter, the shifts in the AR do not infer similar findings – only half of the worst market downturns are preceded by at least a 1-sigma shift in the AR. However, the objective of this paper was to provide evidence of the connections that exist between financial institutions leading to the propagation or spreading in a crisis. In applying the Absorption Ratio, its consistently high level indicates the existence and extent of financial linkages and highlights the greater severity of the "spreading" effect when the links are strong. Furthermore, a high AR suggests the stocks are more tightly coupled whereby a large proportion of the assets' returns are explained by a single key component, PCA1. In this case, the proportion of the variation in the assets' returns explained by one principal component remained between 0.70 and 0.80 for much of the time. Such findings are important because the underlying data set encompasses financial institutions across two subsectors and a number of countries within Europe – thereby illustrating the extent of financial linkages. This indication would be an important consideration when selecting stocks – when the AR is high, one might consider rebalancing a portfolio.

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