Comovements in the prices of securities issued by large complex financial institutions

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This working paper is an extension of the December 2003 *Financial Stability Review* article 'Large complex financial institutions: common influences on asset price behaviour?' The main changes are the inclusion of a section on principal component analysis, an extension of the econometric estimation of the factor models, and a more detailed description of the paper's results. We are grateful to Tom Doan, Mardi Dungey, Jacob Lund and two anonymous referees for many useful comments and Sheila Scott for research assistance.

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Contents

Abstract

In recent years, mergers, acquisitions and organic growth have meant that some of the largest and most complex financial groups have come to transcend national boundaries and traditionally defined business lines. As a result, they have become a potential channel for the cross-border and cross-market transmission of financial shocks. This paper analyses the degree of comovement in the prices of securities issued by a selected group of large complex financial institutions (LCFIs), and assesses the extent to which movements in the prices of these securities are driven by common factors. A relatively high degree of commonality is found for most LCFIs (compared with a control group of non-financials), although there are still noticeable divisions between subgroups of LCFIs, both according to geography and primary business line.

Key words: Financial institutions, comovements and factor analysis.

JEL Classification: C39, G15.

Summary

In recent years, mergers, acquisitions and organic growth have meant that some of the largest and most complex financial groups have come to transcend national boundaries and traditionally defined business lines. As a result, they have become a potential channel for the cross-border and cross-market transmission of financial shocks, which is especially relevant for analysis of financial stability in an international financial centre such as London.

To identify the degree to which large complex financial institutions (LCFIs) have exposures to common factors, this paper analyses the degree of comovement in the prices of securities issued by a selected group of LCFIs - more specifically, their share price returns and movements in their credit default swaps (CDSs). A number of techniques are employed to analyse information from the correlation or covariance matrices of these asset prices, including heat maps of correlations, cluster analysis, minimum spanning trees, principal component analysis and factor modelling.

Such an analysis of comovement in market prices captures both market perceptions of direct exposures between LCFIs and exposures to similar external factors. Knowledge of these common factors could help to identify potential channels for financial stability threats, such as through interlinkages between LCFIs or common vulnerabilities. The approach used does not, however, attempt to capture the degree of contagion that may occur during periods of financial stress, as the empirical estimation does not focus exclusively on such periods.

The various techniques applied to analyse comovement provide corroborating results for our peer group of LCFIs. Across the techniques employed, we find a relatively high degree of commonality in the asset price movements of LCFIs (compared with a control group of size/country-matched non-financials). This emphasises the relevance for financial stability of monitoring LCFIs as a special class of financial institutions.

However, there is also clear evidence that a divide still exists between US and European institutions within the LCFI group. Some segmentation is also evident along national lines within Europe and between pure brokerage houses and the banking-oriented institutions. Despite the liberal inclusion of unobserved factors to explain movements in the securities prices of LCFIs, around a quarter of equity returns' variance and a quarter of the variance of CDS price changes has to be allocated to unexplained or idiosyncratic factors on average. So despite recent mergers and acquisitions, LCFIs do not yet form a purely homogeneous group affected equally by common factors.

1. Introduction

Some of the largest and most complex financial groups have come to transcend national boundaries and traditionally defined business-lines. As a result, their overall health may no longer depend so much on their 'home' market. This consolidation of financial sectors and development of large complex financial institutions (LCFIs) was documented in the G10's Report on Consolidation in the Financial Sector (Ferguson Report (2001)).

Global financial consolidation is especially relevant for the Bank of England, because London's role as an international financial centre means that most LCFIs have significant operations in London's financial markets. For the United Kingdom, global financial consolidation suggests that monitoring of national banking systems should be supplemented with analysis of developments among these large globally active LCFIs. Given their wide-ranging activities, surveillance of LCFIs also provides a unique window on international financial market developments.

This article seeks to determine the extent to which LCFIs are influenced by common factors. Knowledge of these common factors is important for the assessment of risks to financial stability emanating from LCFIs. Borio (2003), for example, suggests that, when compared with institution-specific factors, systemic risks arising through 'common exposures to macroeconomic risk factors across institutions' carry the 'more significant and longer-lasting real costs' to the financial system.

An obvious way to investigate the commonality of exposures across LCFIs is to examine published accounts. However, the general opacity of corporate accounts, the ability of institutions to shift exposures off balance sheet and different accounting regimes combine to make this a daunting exercise. For example, as highlighted in the UK FSAP,[1] few UK financial institutions currently report reconciliations of their financial accounts prepared in UK standards, to international or US GAAP standards.

This article takes a complementary approach and examines the asset price behaviour of LCFIs on the assumption that sophisticated market participants are able to see through the veil of accounting (and possibly incorporate information not published in corporate accounts) when pricing assets. In particular, correlation matrices are computed for equity returns and changes in

[1] The IMF published the results of the United Kingdom's Financial System Stability Assessment in February 2003.

credit default swap (CDS) premia, applying several techniques to summarise the essential features of these two correlation matrices. Many of these techniques simply provide graphical or numerical summaries of a subset of the correlations. The approach used does not, however, attempt to capture the degree of contagion that may occur during periods of financial stress, as the empirical estimation does not focus exclusively on such periods. The correlation structure of LCFIs' equity returns and CDS changes could easily be time varying and these issues are left open to further research.

To the extent that equity prices reflect (discounted) future income streams, a high correlation between equity returns of LCFIs may indicate exposures to common return factors. Similarly, if CDS premia are taken as indicative of the risk of the institutions, similar behaviour of CDS premia may suggest exposure to common risks factors. The analysis of common factors influencing LFCIs' asset prices encompasses both perceptions of direct exposures between LCFIs and exposures to similar external factors.

2. Defining large complex financial institutions

When defining a group of LCFIs, the size of a financial institution's balance sheet may not necessarily be a good indicator of its contribution to systemic risk. A retail bank, for example, could be very large, but strictly regulated, subject to deposit insurance, and not very interconnected with the rest of the financial system.

Interconnections between financial institutions, through both similar exposures to external factors and exposures to each other, tend to be more evident where the institutions are engaged in financial market activities. As a result, significant participation in financial market activities is perhaps a better criterion for identifying a group of LCFIs. Furthermore, to be an LCFI, the financial institution would be expected to be involved in a diverse range of financial activities in a diverse range of geographical areas – that is, to be complex as well as large.

The approach taken here is to choose a small number of admittedly arbitrary criteria that are reasonably simple, but easily verifiable, and that provide a relatively intuitive list of LCFIs.[(2)]

[(2)] It should be emphasised that exclusion from this set of LCFIs does not imply that other financial institutions are systemically unimportant or unworthy of monitoring. The task is merely to identify a manageable number of institutions amenable to statistical analysis.

To join the group of LCFIs studied, a financial institution must feature in at least two of the following six league tables:(3)

- Ten largest equity bookrunners worldwide.
- Ten largest bond bookrunners worldwide.
- Ten largest syndicated loans bookrunners worldwide.
- Ten largest interest rate derivatives outstanding worldwide.
- Ten highest FX revenues.
- Ten largest holders of custody assets worldwide.

Table A summarises the final list of 15 financial institutions that form the group of LCFIs used subsequently, giving their ranking within each category and the number of criteria that they meet in the final column. The tables in Appendix A provide more detail and a list of sources.

Since the choice of league tables was to some extent dictated by availability, the inclusion of certain institutions in the final group is open to debate.(4) However, most major US and European institutions are present (although the exclusion of all Japanese banks may be thought controversial), and, for the purposes of this article, marginal changes in the list do not alter the conclusions reached.

In the following section we describe the asset price data used in the study. Section 4 applies variants of cluster analysis to the data in order to explore the network structure of the companies. Section 5 presents the results of principal components analysis which inform the specification of factor models in Section 6. The paper ends with some concluding thoughts.

(3) Based on data available in October 2001.

(4) If the criteria are taken as given, the group of LCFIs is reasonably robust over time. Taking league tables from one year later, Société Générale and Lehman Brothers fall out of the group and State Street joins.

Table A Selected large complex financial institutions: ranking

Name	Host country	Equities	Bonds	Syndicated loans	IR derivatives	FX revenues	Custody assets	*No. of categories
Citigroup	US	5	1	2	4	1	4	6
Deutsche Bank	DE	9	4	4	2	3	5	6
Credit Suisse	CH	6	6	8		4		4
JP Morgan Chase	US		5	1	1		3	4
Barclays	UK		10	5	8	6		4
Goldman Sachs	US	2	9		6			3
HSBC	UK			10		2	9	3
Société Générale	FR	8			9		10	3
Bank of America	US			3	3	8		3
Lehman Brothers	US	7	8					2
Merrill Lynch	US	1	3					2
Morgan Stanley	US	4	2					2
UBS	CH	3	7					2
ABN Amro	NE					7	6	2
BNP Paribas	FR				5		7	2

**This is the total number of categories for which an LCFI receives a ranking. Citigroup for example receives a ranking for all categories and therefore has a total of six ranking points.*

3. LCFI asset price descriptions

A. Equity prices

Equity prices denominated in US dollars for the LCFI group are taken from Datastream for the period 30 May 1994 through 25 November 2002. We have daily observations for 14 of the LCFIs. Goldman Sachs is the omitted company and is excluded since it only went public in May 1999, making the period of analysis relatively short. The start date for the sample was determined by the listing date for Lehman Brothers. We use weekly equity returns, calculated using Monday closing prices, in the subsequent analysis.

B. Credit default swap prices

In order to focus on the risks impinging on the LCFIs we also consider asset prices that are more directly related to the price of credit risk exposure to each company. Ideally, we would have liked to examine credit spreads (LCFI corporate bond yield minus the risk-free bond yield) for the same sample period we considered for equities. However, comparable and reliable bond data are not available for sufficient numbers of LCFIs over a long period of time. In particular, it is impossible to find bonds of similar maturity that are actively traded for more than a handful of LCFIs.

Instead we use data on credit default swap prices which are both empirically and theoretically closely linked to the spread of corporate bond yields over a reference rate (Blanco, Brennan and

Marsh (2003). The data are taken from CreditTrade and JP Morgan Securities, and represent mid-market prices. They benefit from having constant maturity of five years and are available for 13 LCFIs.[5] Unfortunately, since the CDS market is a relatively new one they are only available since January 2001. Weekly changes in CDS prices are calculated using Monday prices.

C. Correlation matrices

Figure 1 summarises the correlations between LCFIs based on equity returns (above the leading diagonal) and CDS price changes (below the leading diagonal). Black and dark-grey shading denote very high (>0.6) and high (0.5-0.6) correlations respectively, while light-grey and no shading denote low (0.4-0.5) and very low (<0.4) correlations. The preponderance of dark shading in the top-left quadrant implies generally high correlation between US LCFIs using both equity and CDS prices. The mixture of shading in the bottom-right quadrant implies that the European LCFIs are typically less highly correlated with each other, but that hot (and cold) spots occur. The predominantly light off-diagonal quadrants show that European LCFIs are not typically highly correlated with US institutions using either equity or CDS prices. As a comparison, we present equity returns correlations for a control group of non-financial companies matched to the LCFI group by market capitalisation and country in Figure B1 in Appendix B. It is noticeable that these correlations are on average much lower than between the LCFIs.

In this paper, we will assume that the covariance matrices are stable. In subsequent sections we apply techniques that summarise the key features of these two covariance matrices to understand better the common factors that drive LCFI asset prices and to identify the extent of the heterogeneity of LCFIs.

[5] HSBC and Credit Suisse are excluded as the data suppliers did not deem their CDS prices to be sufficiently liquid.

Figure 1. Heatmap of bivariate correlations using equity returns and CDS price changes[(6)]

	Citi	BoA	Merrill	Lehman	JPMC	MSDW	Goldman	HSBC	Barclays	Cr Suisse	UBS	Deutsche	SocGen	BNPP	ABN
Citi	-	0.67	0.74	0.68	0.73	0.74		0.45	0.37	0.47	0.39	0.46	0.39	0.36	0.44
BoA	0.78	-	0.60	0.58	0.68	0.60		0.42	0.31	0.44	0.38	0.39	0.35	0.33	0.40
Merrill	0.58	0.50	-	0.78	0.67	0.82		0.43	0.30	0.46	0.40	0.44	0.38	0.35	0.40
Lehman	0.63	0.62	0.64	-	0.65	0.80		0.44	0.32	0.47	0.44	0.44	0.41	0.40	0.37
JPMC	0.69	0.71	0.65	0.65	-	0.71		0.39	0.30	0.45	0.36	0.45	0.38	0.35	0.39
MSDW	0.68	0.66	0.78	0.75	0.74	-		0.48	0.30	0.47	0.41	0.45	0.38	0.39	0.41
Goldman	0.74	0.72	0.75	0.73	0.75	0.89	-								
HSBC								-	0.54	0.44	0.39	0.41	0.47	0.43	0.47
Barclays	0.34	0.22	0.22	0.07	0.28	0.31	0.28		-	0.45	0.39	0.34	0.44	0.40	0.43
Cr Suisse										-	0.69	0.54	0.52	0.52	0.59
UBS	0.34	0.29	0.36	0.23	0.34	0.28	0.31		0.56		-	0.52	0.51	0.49	0.55
Deutsche	0.56	0.36	0.28	0.25	0.36	0.31	0.36		0.47		0.42	-	0.55	0.51	0.54
SocGen	0.36	0.38	0.16	0.09	0.28	0.31	0.29		0.32		0.45	0.56	-	0.79	0.50
BNPP	0.32	0.31	0.25	0.13	0.27	0.35	0.31		0.32		0.41	0.63	0.77	-	0.51
ABN	0.50	0.27	0.42	0.33	0.45	0.44	0.51		0.58		0.62	0.74	0.38	0.45	-

Key: Correlations of equity returns are given above the leading diagonal, correlations of CDS price changes are given below the leading diagonal.

Correlation:

- Greater than 0.6
- Between 0.5 and 0.6
- Between 0.4 and 0.5
- Less than 0.4

[(6)] Note that equity prices for Goldman Sachs and CDS prices for HSBC and Credit Suisse are not available.

4. Network analysis

A. Cluster analysis

Cluster analysis attempts to determine the natural grouping of observations and is best viewed as an exploratory data analysis technique. It is applied here to determine groups of LCFIs whose share or CDS prices behave in similar ways. These companies can then be considered to be similar institutions whose share returns or CDS price changes are probably driven by common factors. The number and nature of these common factors are discussed in later sections.

Though many types of cluster analysis exist, this paper uses one of the most popular – agglomerative hierarchical cluster analysis. The algorithm begins with each observation (LCFI) being viewed as a separate group (giving N groups each of size 1). The closest two groups are then combined (giving N-2 groups of 1, and one group of 2). This process continues until all observations are combined into one group (of N LCFIs).

The agglomerative technique of cluster analysis involves at least two choices at the outset of the analysis – which dissimilarity measure is to be used to compare observations and what should be compared when groups contain more than one company. The first choice is relatively straightforward. Since we have time series of normalised stock returns for each observation, the Minkowski distance metric with argument 2, the default metric in most cluster analysis packages, forms the same clusters as would occur when comparing correlations.(7) Limited experimentation suggests that the results are robust to the use of other dissimilarity measures.

The decision of how to compare correlations when groups contain more than one company is less straightforward. One method is to compute the dissimilarity between two groups as the dissimilarity between the closest pair of observations between the two groups (known as single linkage or nearest neighbour clustering). At the other end of the spectrum, complete linkage or furthest neighbour clustering uses the farthest pair of observations in the two groups to determine dissimilarity. The middle route of average linkage clustering, not surprisingly, uses the average dissimilarity of observations between groups. Single linkage clustering tends to produce long, thin clusters and is not used below. The other two methods typically produce more compact groupings that are amenable to the type of analysis we wish to perform. Here we use the average

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(7) The Minkowski distance metric with argument 2 computes $\sqrt{\sum_{t=1}^{T}\left(x_{ti}-x_{tj}\right)^2}$ where x_{ti} denotes the equity return (or CDS price change) for LCFI i at time t. This is equivalent to the Euclidean distance between two vectors.

method based on arguments of robustness and consistency but again our main findings seem robust to using complete linkage clustering. [8]

The clustering results of the 14 LCFI's equity returns are shown in a dendrogram in Figure 2. We identify two major clusters since the method clearly divides the LCFIs into US and European groups. Within these regional groups, however, sub-groups can be identified.[9] The North American bloc consists of two sub-groups: (i) the three money centre banking groups (Citigroup, JP Morgan Chase and Bank of America), and (ii) the three brokerage houses (Merrill Lynch, Morgan Stanley (MSDW) and Lehman Brothers). The European bloc contains sub-groups made up largely of national clusters. Thus the Swiss banks join together, as do the two British banks, and the two French banks. The six continental banks form a single cluster before the UK banks are added. The first LCFIs to join (the two French banks) do so quite a long way from the bottom of the dendrogram, indicating relatively high levels of idiosyncrasies (reflecting the substantially less than perfect correlations in Table A).[10]

The clustering of LCFIs according to changes in CDS prices is similar (Figure 3). Again, the European LCFIs are grouped together first along regional/national boundaries and then to form a large group, while the US banks broadly group as for equity returns.[11] There are two exceptions. First, JP Morgan Chase now clusters with the brokerage houses rather than the money centre banks, perhaps reflecting the large share of total risk due to the JP Morgan half of

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[8] Further details on cluster analysis can be found in Kaufman and Rousseeuw (1990).

[9] An informal approach, which is used in hierarchical cluster analysis, to select the number of clusters, consists of examining the changes in the distance between the clusters. Large changes in distances at which clusters (cluster solution) are formed indicate the significance of the cluster. In Figure 2 for example, the change in the distance between the two-cluster solution and the three-cluster solution is greater than the change in the distance between the three-cluster solution and the four-cluster solution. This suggests that the two cluster solution is the most important. The exact measurement of large (in Euclidean distance) is less clear. A formalisation of this procedure has been suggested and details can be found in Rencher (2002) and references therein.

[10] Note that the left-right ordering of the LCFIs conveys no information.

[11] The early clustering of the European LCFIs near the bottom of the dendrogram may seem counterintuitive given that Table A shows the correlation between European LCFI CDS prices to be lower than that of US LCFIs. The quick clustering reflects the noticeably lower variance in European CDS price changes which is in turn caused by the lower level of European CDS prices (see Section V for further discussion).

the franchise.[12] Second, Lehman Brothers forms an outlier, only joining the rest of the LCFIs when the European and US groups have combined. Lehman Brothers' business is notably different from the other brokerage houses, since it is much more concentrated in fixed-income markets and is significantly smaller in revenue terms.

Cluster analysis is not an exact science and robustness testing is important. One consideration is that the correlations and clusters calculated previously may be merely picking up the fact that the LCFIs are all highly correlated with world or local market indices rather than with each other. The partitioning of LCFI clusters along national lines may then be driven by market segmentation rather than by nationally separated risk-return characteristics. To strip out the world and local market effects, and hence to concentrate on the extra correlation caused by being an LCFI we first purge the data by performing the following regression:

$$r_t = \alpha + \beta W_t + \delta L_t + r_t^* \qquad \textbf{(1)}$$

where the dependent variable is the equity return for the LCFI at time *t*, *W* represents the return on the world equity index and *L* represents the return on the relevant local stock index. Cluster analysis is then performed on the residuals of the regression, r^*, which are free from world and local market effects. The resulting dendrogram (Figure 4) shares many of the same sub-groups (ie the French banks join quickly, as do the three large US money centre banks), but importantly the figure suggests that the three US brokerage houses are different from all of the banking-oriented LCFIs once market effects are removed. The US money centre banks cluster with a large group of European banks, then the two French banks before finally clustering with the three US brokerage houses. Unfortunately, there is no recognised world or national index for CDS prices making a similar exercise for CDS price changes impossible. Because this market is primarily used to hedge counterparty exposure, it is dominated by quotations for large financial institutions. Hence an index constructed as an average of available quotes would be highly correlated with the LCFI-specific quotes by construction, making inference difficult.

As a final robustness test, we perform an equity returns-based cluster analysis for the control group of matched non-financial companies. The dendrogram is given in Figure B2 in Appendix

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[12] JP Morgan Chase clusters with the money centre banks even if equity returns are examined over the period corresponding to the CDS data, suggesting that the shift in cluster is related to the asset rather than the period examined.

B. It is only intended to be indicative since this control group is obviously split across several sectors unlike the LCFI group (which explains why the dissimilarity measure for the control group is so much higher than for the LCFIs). However, it does not show the characteristic US-European split seen for the LCFIs, indicating that this is an important feature to be explained.

Figure 2. Average clustering for 14 LCFIs using equity returns

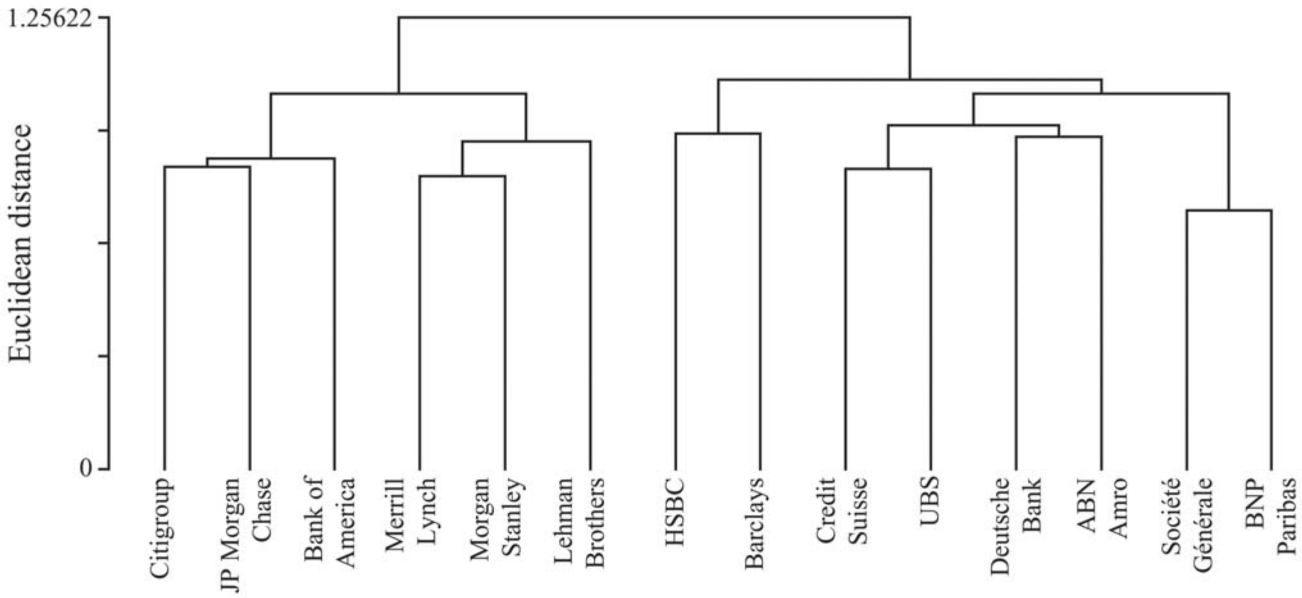


Figure 3. Average clustering for 13 LCFIs using changes in CDS prices

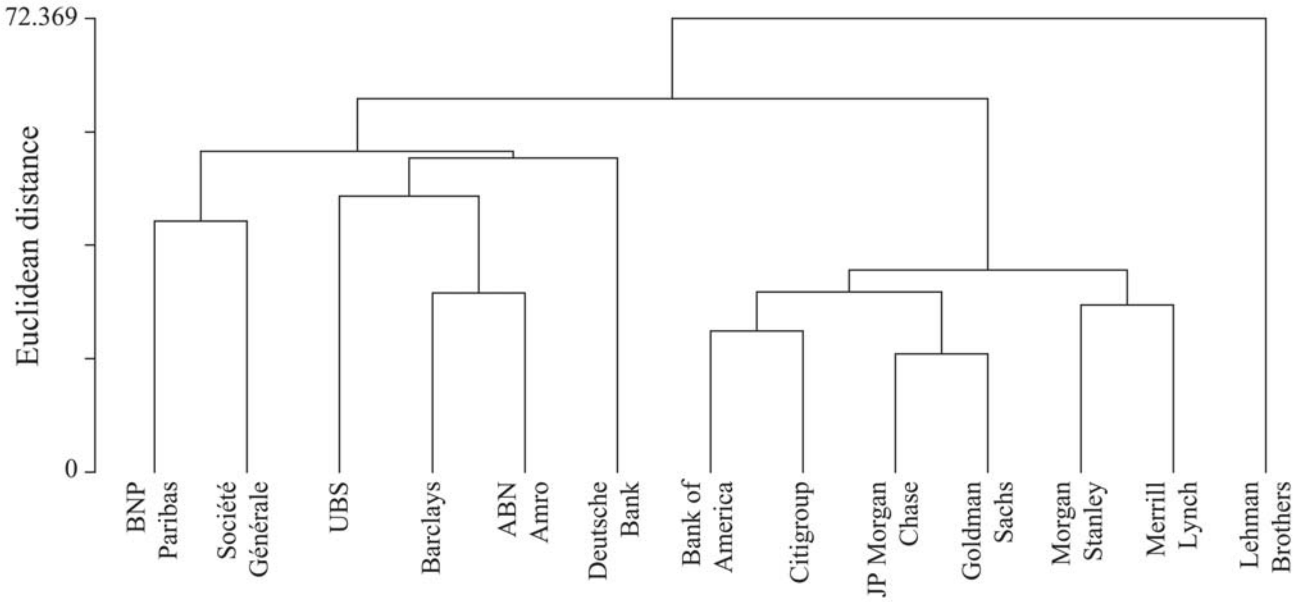
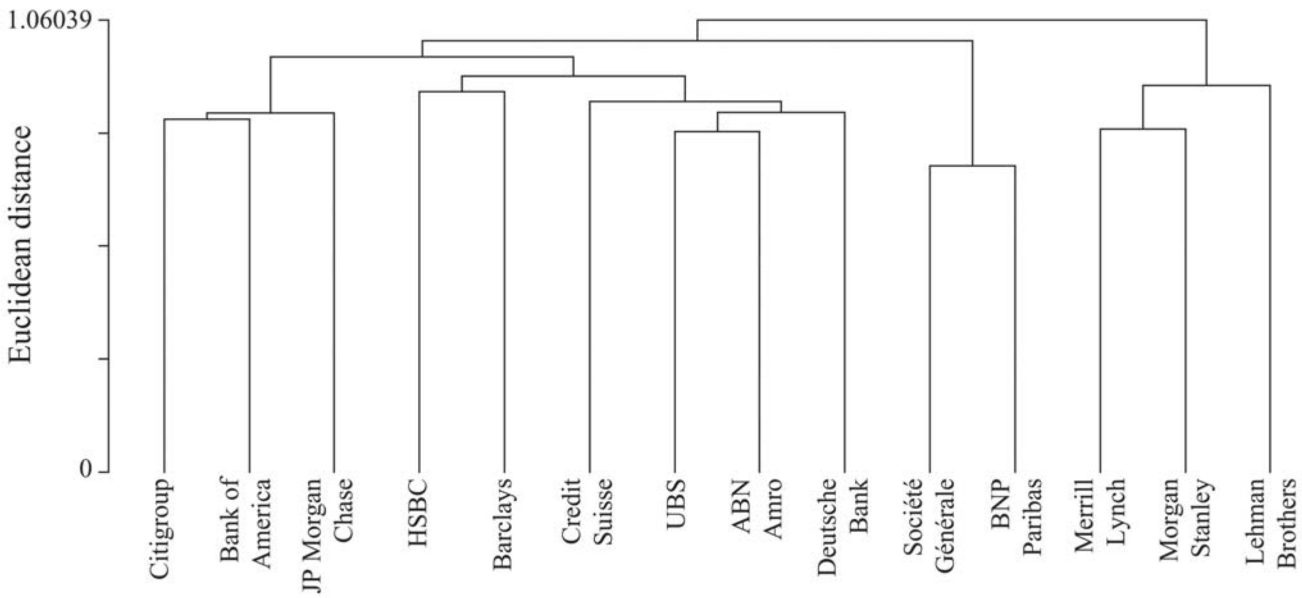


Figure 4. Average clustering for 14 LCFIs using residual equity returns



B. Minimum spanning trees

Agglomerative cluster analysis separates the LCFIs into groups of similar institutions. Companies progress from being individual and isolated (at the bottom of the dendrogram) to all being clustered in a single group (at the top). The dendrogram tells us which LCFIs are similar to other LCFIs, and which groups of LCFIs are similar to other groups of LCFIs. But not all institutions are equally important. Some are closely related to many others, possibly spread across several groups. These LCFIs are important nodes in a network. The minimum spanning tree (MST) can be used to identify these important institutions.

The MST is a graph with a set of N-1 links between the N objects (LCFIs). An explanation of the computation of the MST in the context of financial data is provided by Mantegna and Stanley (2000). Here we briefly outline the steps in the construction of the tree.

1. Compute the "distance", $d(i,j)$, between LCFIs i and j for all $N(N-1)/2$ pairs. The usual functional form is $d(i,j) = \sqrt{2(1-\rho_{ij})}$ where ρ_{ij} is the correlation coefficient between i and j. The MST is based on distances rather than correlations since the latter do not satisfy the three axioms of a metric while the former does.[13]

[13] Function x should satisfy the following three axioms to be considered a metric: (i) $x(i,j) = 0$ if and only if $i = j$, (ii) $x(i,j) = x(j,i)$ and (iii) $x(i,j) \leq x(i,k) + x(k,j)$. There are no negative correlations within our LCFI data set and in the

2. Order the distances in increasing order. Suppose the first few are *d*(A,B) = 0.5, *d*(A,C) = 0.55, *d*(B,D) = 0.6, *d*(E,F) = 0.65, *d*(C,B) = 0.7, *d*(A,E) = 0.75 …
3. The pair with the shortest distance form the first two nodes of the MST and are joined by a link. Thus the MST begins A-B.
4. Consider the two LCFIs with the next shortest distance, A and C. A is already part of the MST and so C is added to the MST via a link with A. The MST is now C-A-B.
5. Similarly, D joins next with a connection to B, and the MST becomes C-A-B-D.
6. Neither of the next pair is currently in the MST and so both need to be added. The MST becomes C-A-B-D and E-F.
7. The next pair (C and B) are already connected in the first part of the MST. This link can be ignored for the purpose of building the MST.
8. The two parts of the MST are joined in the next step where a link is made between A and E.
9. The procedure is repeated for all $N(N-1)/2$ distances, after which all N LCFIs will be represented in the tree.

The MST is attractive because it provides a unique arrangement of LCFIs which selects the most relevant connections of each of them. It reduces the $N(N-1)/2$ correlation coefficients into N-1 links. This, of course, raises the key question of whether essential information is lost in the reduction. Onnela, Chakraborti, Kaski, Kertesz and Kanto (2003) find that summary statistics of the MST (eg the mean distance) are highly correlated with summary statistics of the whole correlation matrix (eg the mean correlation coefficient). This suggests that the information lost is not hugely important. Further, Mantegna (1999) and Onnela *et al* (2003) show that an MST can provide a reasonable economic taxonomy of US equities, since branches of the tree can be clearly identified as business sectors.

The MST based on equity returns given in Figure 5 reveals a similar pattern to the dendrograms above – the links between US LCFIs are typically high, as are some national links between European institutions. MSDW – HSBC is the main link between the US and European networks, but note that this is a very weak link with a correlation of just 0.477. The *lowest* correlation

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subsequent MST plots we give the correlation between nodes rather than the distance since this is more easily interpreted subsequent MST plots we give the correlation between nodes rather than the distance since this is more easily interpreted.

between any two US LCFIs is 0.585 (Lehman Brothers – Bank of America), much larger than the strongest link between a US and European LCFI.

Figure 5. Minimum spanning tree for 14 LCFIs using equity returns

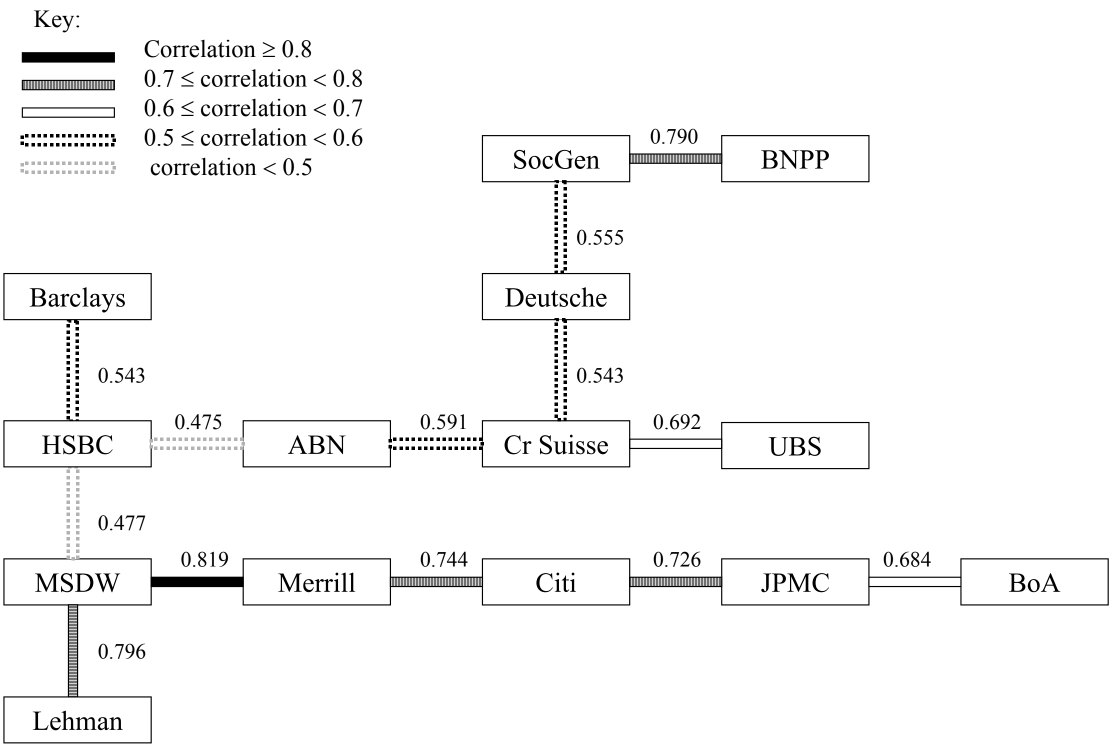


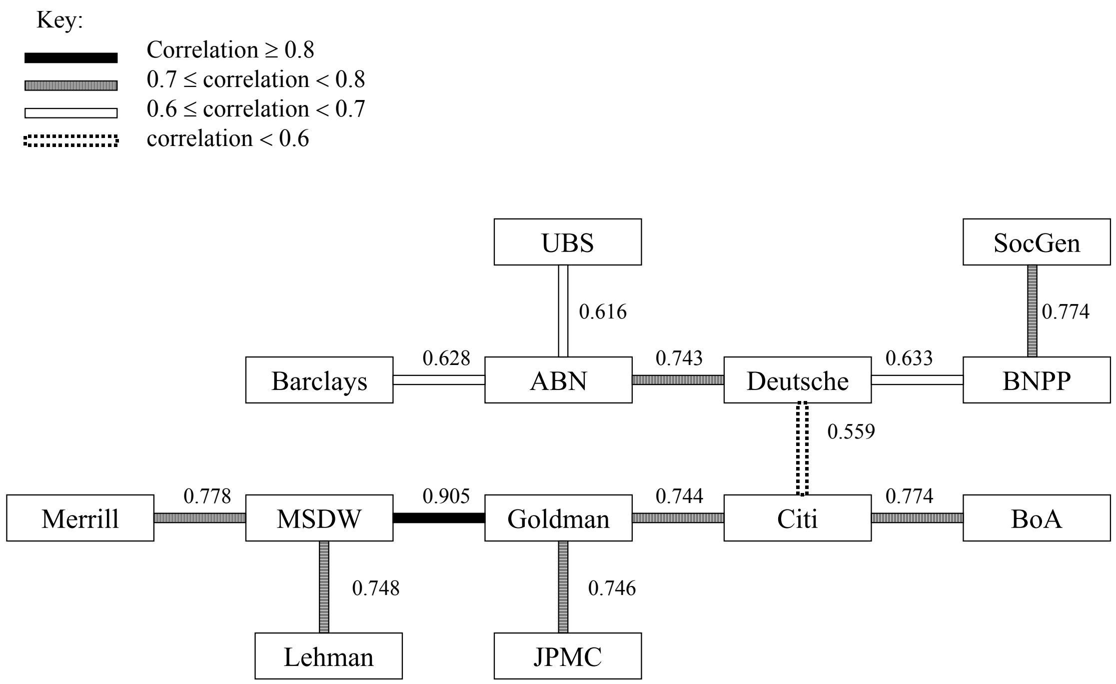
Figure 6, based on changes in CDS prices, provides a very similar picture despite the different assets, time periods and samples of LCFIs analysed. The US brokerage houses cluster strongly in both, the money centre banks are closely related in both, and although the equity-based links are not strong, the French banks cluster with Deutsche Bank in both. Above all, the LCFIs again form US and European groups with a relatively weak link between Deutsche Bank and Citigroup joining them. That these companies link the two halves of the MST makes intuitive sense as these are the only two banks to rank in the top 10 in each of the six LCFI criteria (Table A). Nevertheless, only one of the 21 CDS-based correlations between US companies is lower than the Citigroup-Deutsche Bank link that joins the US and European LCFIs.(14) These relatively low correlations between the US and European branches of the MSTs using both equity returns and changes in CDS prices suggest that shocks specific to one region may not be transmitted through normal interlinkages to LCFIs in the other region as easily as to LCFIs in the same region. Of course, this depends upon just how low we think a correlation of 0.5 really is. As a benchmark, Figure B3 in Appendix B gives the MST for the panel of 14 non-financial companies based on

(14) The Bank of America – Merrill Lynch correlation is just 0.494.

equity returns for the sample period used for LCFIs. Most significantly, any split between groups is not simply US-Europe. Further, the highest correlation in the non-financial MST is 0.468, slightly below the lowest correlation in the LCFI group.

The MST analysis then suggests that while the LCFIs as a whole are more correlated than a selection of size/country-matched non-financial companies, the links between specific sub-groups of LCFIs are much stronger. A shock to a particular LCFI is likely to spread to near neighbours, although since certain links are relatively weak, there may be points at which the transmission of shocks breaks down.

Figure 6. Minimum spanning trees for 13 LCFIs using changes in CDS prices



Each company has a number of other companies that are directly linked to it in the MST. This number is usually referred to as the vertex degree of the company. The higher the vertex degree, the more important it is likely to be in transmitting shocks from one part of the tree to another. Simply counting the number of links for each company is one measure of network importance. A refinement of this measure accounts for the fact that some links are stronger than others. The weighted vertex degree sums the correlation coefficients on each link for the LCFI. The higher this weighted vertex degree the more important the LCFI. Both of these methods of determining the importance of a company focus on local importance since they only consider the direct links.

A third criterion, the centre of mass, considers the whole of the MST. The more important the LCFI the lower its mean occupation layer, $l(v_c)$ defined as

$$l(v_c) = \frac{1}{N}\sum_{i=1}^{N} lev(v_i) \qquad \textbf{(2)}$$

where $lev(v_i)$ is the level of vertex v_i. The levels, are measured in natural numbers in relation to the central vertex v_c, whose level is taken to be zero. All nodes are assigned an equal weight and consecutive layers are assumed equidistant from one another.

Table B. Importance measures for each LCFI

	Equity returns			CDS price changes		
	Vertex degree	Weighted vertex degree	Mean occupation layer	Vertex degree	Weighted vertex degree	Mean occupation layer
Citigroup	2	1.47	4.00	**3**	*2.08*	**2.17**
Bank of America	1	0.68	5.69	1	0.77	3.08
Merrill Lynch	2	*1.56*	3.38	1	0.78	3.92
Lehman Brothers	1	0.80	3.85	1	0.75	3.92
JP Morgan Chase	2	1.41	4.77	1	0.75	3.33
Goldman Sachs	NA	NA	NA	**3**	*2.40*	*2.42*
Morgan Stanley	**3**	**2.09**	*2.92*	**3**	**2.43**	3.00
HSBC	**3**	1.50	**2.77**	NA	NA	NA
Barclays	1	0.54	3.69	1	0.63	3.75
Credit Suisse	**3**	*1.83*	3.23	NA	NA	NA
UBS	1	0.69	4.15	1	0.62	3.75
Deutsche Bank	2	1.10	3.85	**3**	1.94	*2.25*
Société Générale	2	1.35	4.62	1	0.77	3.33
BNP Paribas	1	0.79	5.54	2	1.41	3.00
ABN Amro	2	1.07	*2.92*	**3**	1.99	2.83

Table B reports these three measures of importance for both asset classes. For ease of interpretation the most important LCFI under each measure/asset class combination is made bold, and the next two most central LCFIs are italicised. The only LCFI to be in the top three for each measure based on equity returns is MSDW. This accords with its central position linking the US and European branches of the MST and the higher correlation level among US LCFIs. Both Citigroup and Goldman Sachs are in the top three for each CDS-based measure, and MSDW is top for two. While Citigroup appears the most important in a global sense (since it has the lowest mean occupation layer), MSDW appears the most important in a local sense, having the highest vertex degree and weighted vertex degree. We interpret these results as suggesting that MSDW is central to the US broker group while Goldman Sachs links this group with Citigroup and the banking community in general.

The network analysis in this section was designed to highlight the segmentation of the LCFI group. We have found a clear divide between US and European LCFIs that can only be partially explained by market segmentation effects. At a secondary level, European LCFIs also divide along national lines. Based on equity returns, there is some evidence that the pure brokerage houses (Lehman Brothers, Merrill Lynch, MSDW) are separated from the banking oriented LCFIs. We have also found that certain institutions are crucial nodes in the network. MSDW appears to play an important role in linking US and European branches, and is central to the cluster of brokerage houses. Citigroup also plays a role in linking the brokers to the bankers, particularly when using CDS prices.

Having identified important segmentations we now turn to examining the degree of commonality in asset price movements of the LCFIs. The next section uses principal components analysis to examine the number, nature and importance of the common factors behind LFCI asset prices. The following section extends this using factor analysis.

5. Principal components analysis

A. Principal components analysis of equity returns

The well-known and widely used capital asset pricing model (CAPM) suggests that the risk premium earned on equity is the product of the risk premium on the market portfolio and the beta of the stock. The CAPM is a single factor model, where the factor is the market risk premium and the loading on that factor equals the equity's beta. However, more general models of asset prices, such as the arbitrage pricing theory, suggest that multiple factor models should be more appropriate. Unfortunately, these more general models typically do not specify what those factors are and even how many factors are needed to price assets. Some approaches pre-specify macroeconomic variables (Chen, Roll and Ross (1986)) or proxies for fundamental variables (Fama and French (1993)). Others extract the unspecified factors using a statistical approach such as factor analysis (Roll and Ross (1980)), maximum explanatory component analysis (Xu (2003)) or principal components analysis (Connor and Korajczyk (1986) (1988) (1993)). In this section, and as a precursor to the factor modelling performed in the following section, we apply principal components analysis to our asset prices. Principal component analysis is a dimension reduction technique that can be applied to a correlation matrix to determine the most important uncorrelated sources of variation. The objective is to determine how many factors are needed to adequately explain LCFIs' equity and CDS prices. Further, consideration of the factor loadings may give insights into the nature of the factors.

Table C. Principal components analysis of LCFI equity returns

Component	Eigenvalue	Proportion of variance explained	
		Marginal	Cumulative
1	7.27732	0.5198	0.5198
2	1.77120	0.1265	0.6463
3	0.83853	0.0599	0.7062
4	0.74070	0.0529	0.7591
5	0.55895	0.0399	0.7990
6	0.51137	0.0365	0.8356
7	0.44788	0.0320	0.8676
8	0.42125	0.0301	0.8977
9	0.31268	0.0223	0.9200
10	0.28641	0.0205	0.9404
11	0.26444	0.0189	0.9593
12	0.20909	0.0149	0.9743
13	0.19804	0.0141	0.9884
14	0.16214	0.0116	1.0000

Eigenvectors	1	2	3	4	5	6
Citi	0.29587	-0.27659	0.04680	-0.00031	0.15845	0.04297
BoA	0.26721	-0.24211	0.04788	0.07125	0.51819	0.38522
Merrill	0.29323	-0.31342	-0.04033	-0.03563	-0.27892	-0.13240
Lehman	0.29208	-0.26812	-0.04762	-0.08381	-0.40636	-0.06756
JPMC	0.28182	-0.28877	-0.04515	-0.04211	0.31799	0.18871
MSDW	0.29966	-0.30395	-0.02289	-0.07497	-0.26068	-0.15209
HSBC	0.24536	0.12509	0.56662	-0.06974	-0.01600	-0.38530
Barclays	0.20934	0.24504	0.67236	0.09610	-0.08466	0.23719
Cr Suisse	0.27464	0.21910	-0.15584	0.40831	-0.15569	0.21552
UBS	0.25225	0.25451	-0.24544	0.44694	-0.29252	0.21685
Deutsche	0.25745	0.18072	-0.29649	0.00304	0.27408	-0.55353
SocGen	0.25589	0.34055	-0.12093	-0.49732	0.00440	0.15803
BNPP	0.24708	0.34311	-0.16712	-0.51277	-0.04199	0.19783
ABN	0.25429	0.25327	-0.03075	0.29732	0.31661	-0.31660

Most principal components studies in finance select a cut-off number in the range 0.8-1.0. If the eigenvalue for a component falls below this cut-off number, the factor is not considered significant in explaining returns.[15] Rencher (2002) suggests three additional methods for

[15] This method retains the specified number of factors or principal components that accounts for a specified percentage of the total variance; 80% in this case.

deciding how many principal components or factors to retain. First to retain the components whose eigenvalues are greater than average of the eigenvalues. Second, use a *scree graph*, which plots the eigenvalues against their indices. This produces a downward sloping graph with a break in the downward slope. The breakpoint is used to differentiate between the "important and unimportant principal components". Third, a likelihood ratio test (chi-square) is used to test whether the k smallest eigenvalues are small and equal, implying that they reflect just noise. We employ the chi-square test of the eigenvalues. A brief description of the test statistic and the results are given in the Appendix B, Table B1.(16)

The first panel of Table C suggests that either two or three components are significant for equity returns depending on the exact cut-off number selected.(17) The first two components explain almost two thirds of the variance in returns, the third component explains a further 6%, and the fourth component explains just over 5%.(18) The second panel of Table C gives the eigenvectors associated with the first six eigenvalues. The first component appears to be common to all LCFIs since the eigenvectors are of similar magnitude and all positive. The second component discriminates between US and European companies while the marginal third component discriminates between the UK and continental European LCFIs.

Analysis of the residuals, r^*, of equation **(1)** that strips our market effects, suggest as many as six principal components may be significant (Table D). The interpretation of the first two remains

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(16) There are other methods for determining the optimal number of principal components. See for example Bai and Ng (2002) and references therein. Bai and Ng (2002) suggested an information criterion (couched as a model selection problem) which can be used to determine the number of factors (or principal components) for factor models of large dimensions. We also carried out this test using a modified version of the Matlab™ routines provided by Serena Ng, available at: http://www.econ.lsa.umich.edu/~ngse/research.html . The results appear to be sensitive the maximum number of factors that were pre-assigned. We do not report these results but will be made available upon request.

(17) On the other hand, the chi-squared test tends to suggest the existence of up to eleven "important" or "significant" factors/principal components. See the Appendix for details. In general, although the first few principal components would normally summarise the data adequately, the remaining components may also contain some useful information. However, the purely statistical nature of principal component analysis makes interpreting all of the principal components or factions somewhat problematic.

(18) Since we are trying to model individual stock returns, the cumulative proportion explained is likely to be relatively low compared to studies that use portfolio returns where idiosyncratic risk is diversified away.

the same – the first component is common to all LCFIs and the second differentiates between US and European institutions. This implies that even when purged of local and world market effects, important common and regional factors remain. The third component could be capturing Swiss banks. The other components are less easily interpreted but their significance suggests that there is structure beyond the simple common and regional effects already noted.(19)

Table D. Principal components analysis of LCFI residual equity returns

Component	Eigenvalue	Proportion of variance explained	
		Marginal	Cumulative
1	3.62940	0.2592	0.2592
2	1.79585	0.1283	0.3875
3	1.25632	0.0897	0.4773
4	1.09897	0.0785	0.5558
5	0.96984	0.0693	0.6250
6	0.83045	0.0593	0.6843
7	0.77276	0.0552	0.7395
8	0.74797	0.0534	0.7930
9	0.66389	0.0474	0.8404
10	0.53091	0.0379	0.8783
11	0.51858	0.0370	0.9154
12	0.42752	0.0305	0.9459
13	0.41636	0.0297	0.9756
14	0.34118	0.0244	1.0000

Eigenvectors	1	2	3	4	5	6
Citi	0.33925	-0.17269	-0.23558	0.22408	-0.15258	0.07401
BoA	0.31141	-0.08661	-0.10869	0.36913	-0.31909	-0.19675
Merrill	0.35318	-0.28090	0.07452	-0.20528	0.18197	0.04393
Lehman	0.34497	-0.20436	0.06159	-0.35003	0.20068	0.00650
JPMC	0.32126	-0.21943	-0.14528	0.16892	-0.40621	-0.09222
MSDW	0.33047	-0.31170	0.00988	-0.29839	0.17471	-0.11283
HSBC	0.15592	0.11744	-0.38018	0.22650	0.59282	0.08963
Barclays	0.22381	0.23246	-0.12013	0.33624	0.28639	0.41665
Cr Suisse	0.23195	0.08051	0.48881	0.16173	0.01629	0.16769
UBS	0.19343	0.16381	0.57294	-0.00291	0.12499	-0.10831
Deutsche	0.18928	0.25357	0.09955	-0.18275	-0.36720	0.66232
SocGen	0.24212	0.48032	-0.22423	-0.26732	-0.09420	-0.14390
BNPP	0.20402	0.48088	-0.19978	-0.31909	-0.07862	-0.29241
ABN	0.17345	0.26327	0.27545	0.36620	0.08223	-0.40773

(19) Again, the likelihood ratio test (Table B1, Appendix B) for the number of significant principal components suggests that there may be as many as eleven important principal components or factor for the residual equity returns. However, this test assumes multivariate normality whilst the principal component analysis does not and would generally tend to suggest a higher number of significant eigenvalues.

B. Principal components analysis of changes in CDS prices

A similar process suggests three factors are also significant in explaining changes in CDS prices (Table E). Again, the first is a common component and the second differentiates between US and European LCFIs. The third component, though more clearly significant than in the equity returns-based analysis, is less interpretable. The three components together explain three quarters of the variation in CDS price changes.[20] In the next section we take the number and nature of these components to inform the specification of a factor model for the asset prices of the LCFI.

Table E. Principal components analysis of LCFI CDS price changes

Component	Eigenvalue	Proportion of variance explained	
		Marginal	Cumulative
1	6.59185	0.5071	0.5071
2	2.26211	0.1740	0.6811
3	1.06275	0.0817	0.7628
4	0.65387	0.0503	0.8131
5	0.61202	0.0471	0.8602
6	0.47833	0.0368	0.8970
7	0.31433	0.0242	0.9212
8	0.28978	0.0223	0.9435
9	0.23902	0.0184	0.9619
10	0.18428	0.0142	0.9760
11	0.14550	0.0112	0.9872
12	0.09122	0.0070	0.9942
13	0.07495	0.0058	1.0000

Eigenvectors	1	2	3	4	5	6
Citi	0.32807	-0.09835	-0.06861	-0.43519	0.12912	0.06442
BoA	0.29970	-0.17554	-0.26590	-0.25604	0.47245	0.12245
Merrill	0.29117	-0.22309	0.15189	0.40880	-0.27301	-0.06037
Lehman	0.27699	-0.32883	0.01249	-0.00775	-0.16858	0.30650
JPMC	0.31610	-0.18967	0.00959	-0.04765	0.15528	0.02227
Goldman	0.33824	-0.22050	0.00291	0.07707	-0.07068	-0.18378
MSDW	0.33130	-0.22566	-0.01643	0.24670	-0.07158	-0.33633
Barclays	0.19463	0.31528	0.47154	-0.07666	0.39046	-0.57561
UBS	0.22085	0.29931	0.34562	0.38005	0.32591	0.60310
Deutsche	0.25483	0.35009	-0.05436	-0.46544	-0.38350	0.06729
SocGen	0.20855	0.37321	-0.48916	0.20847	0.17965	0.00699
BNPP	0.21618	0.37654	-0.43541	0.27203	-0.19134	-0.14655
ABN	0.27412	0.27108	0.35690	-0.15617	-0.38510	0.12150

(20) Likelihood ratio tests (Table B1, Appendix B) suggests that there may be up to ten “important” principal components.

6. Factor modelling

In this section, results from the previous sections are used as a guide in building factor models for equity returns and changes in CDS premia. The goal is to be able to understand what proportions of the variation in LCFI equity returns and changes in CDS premia can be explained by factors common to all LCFIs, by regional and sectoral-specific factors and by idiosyncratic factors unique to each LCFI. The principal component analysis conducted in the previous section is closely related to factor analysis. Both methods extract factors from either the correlation structure of the assets or from the raw data. With large datasets, results obtained from both are almost indistinguishable. Indeed, factor models can be estimated by a principal axes method which is almost identical to principal components analysis.[21] See Anderson (2003) for further details.

A. A factor model of equity returns

Observed factor models suffer from the lack of theoretical guidance as to the nature of the factors used. A search of likely macro factors did not highlight any particularly strong relationships with the LCFI share prices that were robust across changing time periods, beside the world and local stock markets. The usual alternative of unobserved factor models is often difficult to interpret. Since our earlier findings are suggestive of the nature of the factors affecting LCFI share prices we combine observed and unobserved factors and impose some structure on the unobserved components to aid interpretation.

The structure of the factor model developed in this section draws on King, Sentana and Wadhwani (1994), Dungey (1999) and Dungey, Fry, Gonzalez-Hermosillo and Martin (2003). The equity returns of each LCFI are presumed to evolve in response to movements in a number of observed and unobserved factors. We include the local and world stock market returns as observed factors, following the form of equation **(1)**. Since previous sections have suggested structure in the residuals of this equation we also initially include an unobserved factor common to the entire set of LCFIs, unobserved factors common to the regional (US and European) groupings of the LCFIs, and unobserved factors assumed at this stage to be related only to individual LCFIs. The factors can be viewed as proxies for the variation in observable

[21] The extracted principal components can also be considered as a reduced-rank regression problem. See Rinsel and Velu (1998). In fact, one could test the rank using likelihood ratio tests along the lines of cointegration.

macroeconomic variables that explain the variation in LCFI equity returns.[22] In later sections we enlarge this set of factors to understand better the evolution of equity prices.

The equity return for LCFI i at time t is expressed as:

$$r_{it} = \overbrace{\alpha_i + \beta_i W_t + \delta_i L_{it}}^{\text{observed factors}} + \overbrace{\lambda_i C_t + \gamma_i R_{kt} + \phi_i f_{it}}^{\text{unobserved factors}} \qquad i = 1,...,n \qquad k = US, Eur \qquad \textbf{(3)}$$

where the return is expressed as the sum of the world and local equity market dollar-denominated returns, W_t and L_{it} respectively, a time-varying common unobserved factor, C_t, a time-varying unobserved regional factor, R_{kt} and a time-varying residual factor, f_{it}. The unobserved factors are each specified as stationary and independent disturbance processes.[23] The time-invariant loadings on these factors vary across LCFIs and are given by the parameters β_i, δ_i, λ_i, γ_i and ϕ_i.

The possibility that the observed variables might be correlated with the unobserved factors in the residuals is very important.[24] This may bias the parameter estimates in the first stage of the estimation process and could make the use of the resulting residuals problematic. These issues have recently come to the fore in the context of panel data and cross-sectional regression models with common shocks, in Pesaran (2002) and Andrews (2003), for example. A solution to this potential problem, suggested by Pesaran (2002), is to augment the observable factor regression models, estimated in stage one, with cross-sectional averages of the dependent (the $Y's$) and independent (the $X's$) variables.[25] In our formulation this means augmenting the observables

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[22] Although our tests for the effects of macro factors on the return generating process for LCFI's suggests that only the global stock and national stock indices have reasonable explanatory power, it is possible that movements in global and national stock indices capture the variation in a large number of economic variables.

[23] The equity returns and change in CDS price of each LCFI are stationary and so compatible with the factor specification. Dungey and Martin (2004) show how this model can be extended to deal with GARCH-type effects at the cost of a huge increase in estimation time. This extension is left for future work.

[24] A standard assumption for linear regression model is that the errors are mean zero and are uncorrelated with the regressors.

[25] Further details of the asymptotic results which guarantee this specification can be found in Pesaran (2002).

factor models with cross-sectional averages of the LCFI equity returns and the local stock market returns.[26] This is described below:

$$r_{it} = \overbrace{\alpha_i + \beta_i W_t + \delta_i L_{it}}^{\text{observed factors}} + \psi_i \overline{r}_t + \xi_i \overline{L}_t + r_{it}^* \qquad \textbf{(3a)}$$
$$r_{it}^* = \overbrace{\lambda_i C_t + \gamma_i R_{kt} + \phi_i f_{it}}^{\text{unobserved factors}} \qquad i = 1,\dots,n \qquad k = US, Eur$$

Where the cross-sectional averages of the LCFI equity returns are given by $\overline{r}_t = T^{-1}\sum_{t=1}^{T} r_{it}$ and the cross-sectional averages of the local market returns by $\overline{L}_t = T^{-1}\sum_{t=1}^{T} L_{it}$. r_{it}^* are the residual LCFI equity returns. A simple weighting scheme, where the sum of the absolute values of the weights is equal to one, is assumed in deriving these cross-sectional averages.

The model is estimated in two stages. First, the LCFI equity returns are regressed on the two observed factors and a constant. The R^2 of each regression gives the proportion of equity returns variance explained by these two observed factors. The residuals of these regressions are then used in the second stage unobserved factor model.

The residuals of the first stage estimation have the following factor structure (the second stage unobserved factor model):

$$\begin{bmatrix} r_1^* \\ r_2^* \\ \vdots \\ r_n^* \end{bmatrix} = \begin{bmatrix} \lambda_1 & I_1\gamma_{US1} & (1-I_1)\gamma_{EU1} & \phi_1 & 0 & \cdots & 0 \\ \lambda_2 & I_2\gamma_{US2} & (1-I_2)\gamma_{EU2} & 0 & \phi_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \lambda_n & I_n\gamma_{USn} & (1-I_n)\gamma_{EUn} & 0 & 0 & \cdots & \phi_n \end{bmatrix} \begin{bmatrix} C \\ R_{US} \\ R_{EU} \\ f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} \quad \text{or} \quad r_t^* = BF_t \qquad \textbf{(4)}$$

where r^* is the $N \times 1$ vector of stacked equity residual returns, F is an $(N + 3) \times 1$ vector of latent factors and B is an $N \times (N + 3)$ matrix of coefficients attached to the factors, some of which are restricted to zero. I_i denotes an indicator variable for each LCFI that takes the value unity if that LCFI is US-based and zero otherwise. It follows that:

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[26] The world stock market factor is unaffected as it is common to the all LCFIs.

$$\text{var}\left(r^*\right) = B\,\text{var}(F)B' \quad \textbf{(5)}$$

The variance-covariance matrix var(r^*) will have $N(N + 1)/2$ unique elements. Using these moment conditions we can identify at most $N(N + 1)/2$ parameters from the system of equations. There are N parameters relating to the loadings on the common factor, N factors relating to regional factors and N loading parameters on the residual factors. These moment conditions plus the assumption that var(F) = I_{N+3} produces the necessary identifying condition that $N \geq 5$; equity returns for at least five LCFIs are necessary to estimate the system. The assumption that var(F) = I_{N+3} is necessary since var(F) is unobserved. To the extent that this assumption is violated, the parameter estimates will absorb the true variance of the factors meaning that comparing the magnitudes of the factors is uninformative. However, the following decomposition of the unconditional variance is unaffected:

$$\frac{\lambda_i^2}{\text{var}(r_i^*)} = \text{contribution of the common factor to variance of equity residuals of } i$$

$$\frac{\gamma_i^2}{\text{var}(r_i^*)} = \text{contribution of the regional factor to variance of equity residuals of } i$$

$$\frac{\phi_i^2}{\text{var}(r_i^*)} = \text{contribution of the residual factor to variance of equity residuals of } i$$

These statistics give the sample average proportion of each LCFI's residual returns variance due to shocks from each factor. Estimation of the model is performed using generalised method of moments (GMM) of Hansen (1982) and further details of its application in this context are available in Dungey (1999) and Dungey, Fry, Gonzalez-Hermosillo and Martin (2003).[27] To implement the GMM we use the moment (orthogonality) conditions defined above. However, if there are more moment conditions than parameters to be estimated the model would be over-identified. These over-identifying restrictions are tested using Hansen (1982) chi-squared test.[28]

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[27] We note that estimating this model through maximum likelihood estimation methods could be deemed more efficient. However, using GMM is more robust to the failure of normality. Nevertheless, the model is re-estimated using the Kalman filter. We get very similar results for the coefficient estimates (up to sign flips). We are reasonably confident that the unobserved factor model used here is well specified. See subsection C for details.

[28] This test generally applies to the efficient GMM estimator (a two-stage or iterative procedure which uses an optimal weighting matrix). In this paper we use a consistent one-stage GMM and an identity matrix as the weighting matrix. This was preferred to the efficient estimates. See Ogaki (1993), Hamilton (1994) and Jagannathan and

Finally, to facilitate the extraction of the unobserved factors, the model in equation **(4)** is rewritten in a general state-space form and estimated using maximum likelihood (ML) and the Kalman filter.[29]

B. Estimation results

Table F (and Figure 7) gives the proportion of equity returns variance contributed by the observed and unobserved factors. These results are for the model estimated in equation **(3a)**, which uses the augmented form of the observable factor model. The unobservable factor part of this model is detailed in equation **(4)**.[30] The augmentation of the observable factor model appears to have increased the explanatory power or contribution of the combined observed factor; which now explains between 53% and 76% of the variance across the LCFIs compared to between 37% and 64% (Appendix C) when using only the observed factors to filter the returns in stage one.[31] The explanatory power of the unobserved common factor appears to be low and evenly spread except for two European LCFIs (Société Générale and BNP Paribas) where at least 10% of their variation is explained by the unobserved common factor. The role of the regional factor is mixed. The European factor seems to be a French factor in disguise with the 9% and 14% of the variation in variation in Société Générale and BNP Paribas explained by the regional factor. This latter finding reflects the separation of the French LCFIs from the other banks shown in Figure 4. The contribution of the idiosyncratic factor averages about 28%. We provide a comparable chart in Figure C3 in Appendix C for the controlled group large non-financial corporates.

Skoulakis (2002) for a review the GMM methodology. Cochrane (1996) has also suggested alternative specification tests for GMM models.

(29) The ML coefficient estimates were similar (up to sign flips) to those obtained by GMM. We are reasonably confident that the unobserved factor model used here is well specified. King, Sentana and Wadhwani (1994) and Hamilton (1994) provide details on the Kalman filter. See subsection C for details.

(30) For comparison purposes, results for factor models estimated for the residual generated using the basic filtration (only the observed variables), as described in equation **(3)**, are given in Appendix C.

(31) As expected, the explanatory power of the model in stage one increases with the inclusion of the cross-sectional averages of the LCFI returns and local market returns. This means that the exercise in stage two – the unobservable factor model of the residuals from stage one – will only attempt to explain about 25% of the overall variation. However, given that these extra variables are significant, it suggests the correction is necessary. Overall, these results will more robust in the light of the statistical properties described in Pesaran (2002).

Table F. Decomposition of variance of equity returns (using the augmented observable factor model specification in stage one)

		Contributions to variance			
	Variance	Observed	Common	Regional	Idiosyncratic
Citi	0.00279	71.2%	3.3%	2.0%	23.6%
BoA	0.00225	57.1%	2.2%	11.5%	29.3%
Merrill	0.00395	73.0%	6.5%	2.9%	17.6%
Lehman	0.00471	71.2%	3.9%	5.1%	19.8%
JPMC	0.00301	62.9%	6.2%	5.8%	25.1%
MSDW	0.00430	76.5%	3.4%	1.5%	18.6%
HSBC	0.00211	56.2%	0.6%	0.1%	43.0%
Barclays	0.00219	53.2%	3.2%	0.4%	43.1%
Cr Suisse	0.00284	65.5%	1.2%	5.7%	27.6%
UBS	0.00217	62.5%	2.0%	3.7%	31.8%
Deutsche	0.00203	61.0%	2.3%	0.0%	36.8%
SocGen	0.00294	57.5%	14.0%	14.0%	14.5%
BNPP	0.00257	56.0%	11.5%	9.1%	23.4%
ABN	0.00212	62.2%	3.3%	2.2%	32.3%

Figure 7. Decomposition of variance of equity returns (using the augmented observable factor model specification in stage one)

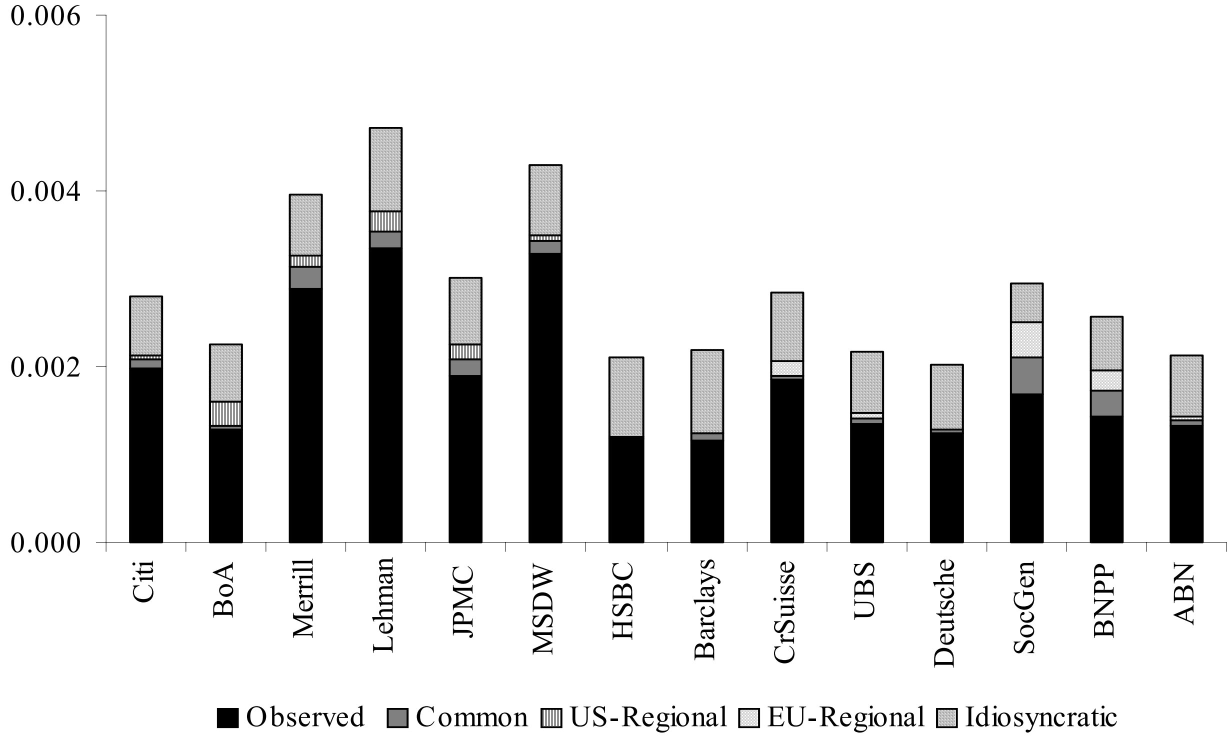
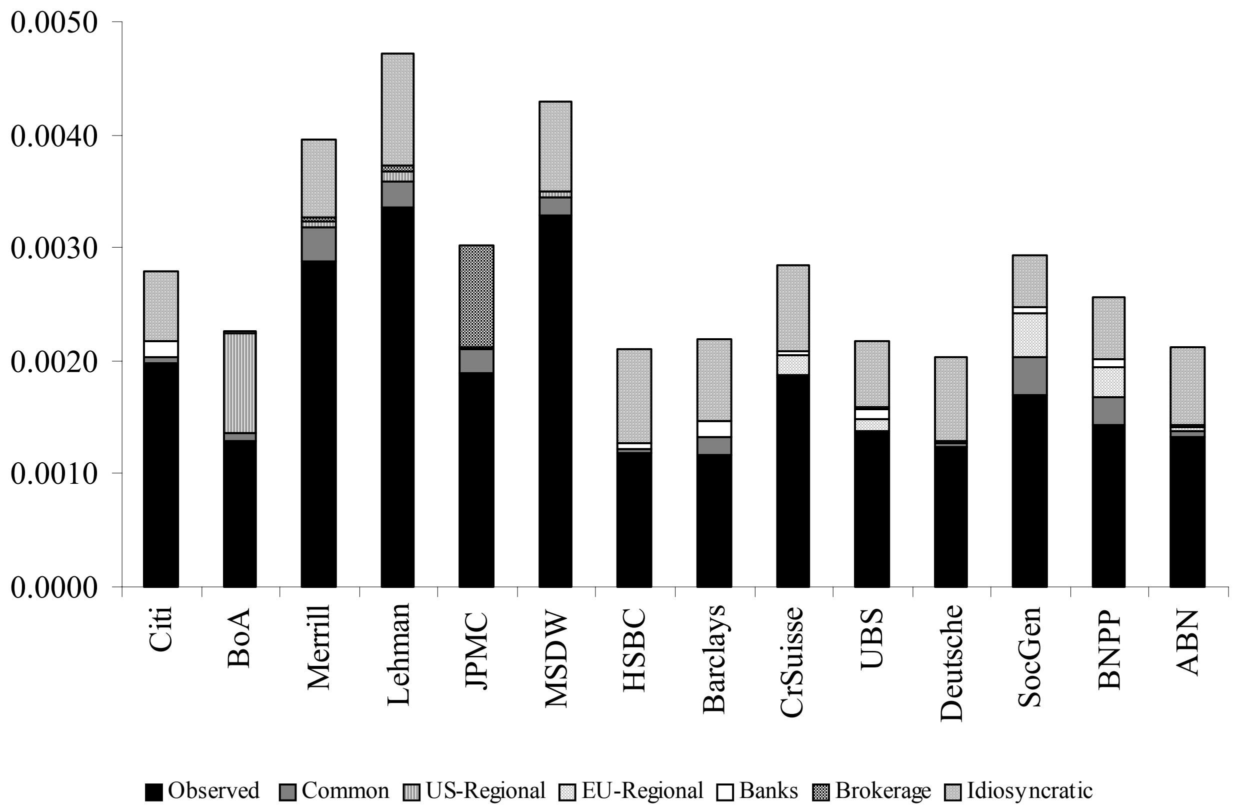


Table G. Decomposition of variance of equity returns with sectoral factors (using the augmented observable factor model specification in stage one)

	Contributions to variance					
	Observed	Common	Regional	Bank	Brokerage	Idiosyncratic
Citi	71.2%	1.4%	0.2%	4.9%	0.5%	21.8%
BoA	57.1%	3.3%	39.8%	0.3%		0.0%
Merrill	73.0%	7.5%	1.4%		1.0%	17.1%
Lehman	71.2%	4.9%	1.7%		1.5%	20.7%
JPMC	62.9%	7.0%	0.5%	0.0%	29.7%	0.0%
MSDW	76.5%	3.8%	1.1%		0.1%	18.6%
HSBC	56.2%	1.4%	0.2%	2.6%		39.6%
Barclays	53.2%	6.9%	0.6%	6.6%		32.7%
Cr Suisse	65.5%	0.8%	5.9%	1.2%	0.0%	26.7%
UBS	62.5%	1.0%	4.7%	4.6%	0.6%	26.6%
Deutsche	61.0%	1.9%	0.0%	0.7%	0.0%	36.5%
SocGen	57.5%	11.8%	13.0%	1.8%		15.8%
BNPP	56.0%	9.6%	9.9%	2.8%		21.6%
ABN	62.2%	3.0%	1.9%	0.1%		32.9%

Figure 8. Decomposition of variance of equity returns with sectoral factors (using the augmented observable factor model specification in stage one)



This factor model can easily be augmented to analyse the importance of further factors, subject to identification and degrees of freedom considerations. In particular, Figure 4 suggests that the brokerage houses and banks behave somewhat differently. Given that the LCFIs in our sample include brokerage houses, global money centre banks, LCFIs that include both types of operation and more peripheral banks we experimented with including sectoral factors. In particular, taking a narrow approach we included a brokerage factor for Merrill Lynch, Lehman Brothers and MSDW, and a money centre factor for Citibank, Bank of America, JP Morgan Chase and Deutsche Bank. While these additional factors only appear to contribute significantly in a few cases they do help to reduce the average proportion of variance across all LCFIs attributed to idiosyncratic shocks from 28% to 22.2%. A broad approach includes a 'bank' factor for Citibank, Bank of America, JP Morgan Chase and all the European LCFIs, and a 'brokerage' factor for Citibank, Merrill Lynch, Lehman Brothers, JP Morgan Chase, MSDW, Credit Suisse, UBS and Deutsche Bank. Table G (and Figure 8) gives the decomposition of the factors using both the augmented (econometric adjustment) observed factor model (stage one) and the augmented (with additional sectoral factors included) unobserved factor model. The average contribution of the remaining idiosyncratic factor to the overall variance is about 22.2% compared to 28% (Appendix C) for the residual generated without including the cross-sectional averages in stage one. The bank factor is evenly spread and marginally significant for Citigroup, Barclays and UBS. The brokerage factor is only significant for JP Morgan Chase where it explains almost 30% of the variation in its residual equity returns. The brokerage factor is virtually insignificant for the remaining brokerage houses explaining in each case, less than 1.6% of their variance.

C. Extracting the unobservable factors

The unobserved idiosyncratic factors in the augmented model (equation **(4)**) can be extracted once estimated by applying the Kalman filter to the system. To apply the Kalman filter, we write the model in equation **(4)** in the following general state-space form (in matrix notation):[32]

$$F_t = A_t F_{t-1} + w_t \qquad \text{Transition equation} \qquad \mathbf{(6)}$$

$$r_t^* = \beta' F_t + v_t \qquad \text{Measurement equation} \qquad \mathbf{(7)}$$

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[32] The Kalman filter is a recursive procedure that computes the unobserved variables using some initial information. Extensive discussions of the Kalman Filter can be found in amongst others, Harvey (1993), King, Sentana and Wadhwani (1994), Hamilton (1994), Kim and Nelson (1999) and Camba-Mendez *et al* (2001). Detailed results from our Kalman filtering estimation are available upon request.

Equation **(6)** (where F_t are the factors) defines the path of the unobserved vector of states or unobserved factors, F in equation **(4)**, and equation **(7)** (where r_t^* are the residuals from the observables models estimated in stage one) gives the return generating process of the residual LCFI returns. The correlation matrix for the extracted idiosyncratic factors is given in Table D1 and Table D2 in Appendix D. The average correlation between the idiosyncratic returns, which is arguably a measure relevant for macro-prudential purposes (Borio (2003)), is just -0.04[33] and hence we feel reasonably justified in claiming the factors to be idiosyncratic.[34] In addition, the factor decompositions obtained through the Kalman filter were identical to GMM decompositions.[35]

D. Unobserved factor model of credit default swap prices

Since there is not yet a reliable world or even country index of credit default swap prices it is not possible to extract the effect of the observed world and country factors when looking at changes in CDS prices. However, a similar exercise using simply unobserved common, regional and idiosyncratic factors to decompose the variance of CDS price changes yields the results described in Table H and Figure 9. Table I and Figure 10 add the broadly defined sectoral factors used for equity returns above.

The first point to note is the marked asymmetry in the variance of US and European LCFI CDS prices. The cost of credit default protection on European LCFIs is substantially less than for US financials.[36] Since we compute the variance in the change in the CDS price (and not the percentage change) the European LCFIs also have substantially lower variance. A second feature

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(33) The average correlation of the extracted idiosyncratic returns for the residuals generated in stage one using the standard observable model is -0.06.

(34) Lawley's asymptotic tests (see Morrison (1990)) for independence of the correlation matrix suggests that the matrix is not independent. However Fisher's z-transform of the standard t-test for the significance of individual correlation coefficients suggests that over 67% of the idiosyncratic correlations were insignificant. Details of these tests are available in Stevens (2003).

(35) Detailed results from our Kalman filtering estimation are available upon request.

(36) This may be due to the greater perceived protection afforded European banks by national governments or simply reflects the segmentation of this relatively new market. Blanco, Brennan and Marsh (2003) and the references therein discuss this market in more detail.

is that Lehman Brothers has by far the highest CDS variance (and the highest equity variance), and was the outlier LCFI in the cluster analysis in Section 3.

Once (broadly-defined) sectoral factors are included in the analysis, the contribution of the common factor to variance is around 10 squared basis points for most of the US LCFIs and both Deutsche Bank and ABN. The regional factor is important for all US LCFIs. The bank factor is very important for the French banks and UBS but is close to zero for most US LCFIs. The brokerage factor is very important for Merrill Lynch, Lehman Brothers, MSDW and Goldman Sachs, but is essentially zero for Citigroup (in contrast to the equity results) and is relatively low for JP Morgan Chase. Idiosyncratic contributions average 22% across the panel but range from 4% (Deutsche) to 52% (Barclays).

Table H. Decomposition of variance of CDS price changes

		Contributions to variance		
	Variance	Common	Regional	Idiosyncratic
Citi	41.35	91.9%	0.0%	8.1%
BoA	31.25	66.9%	1.7%	31.5%
Merrill	46.00	36.5%	30.3%	33.2%
Lehman	71.88	42.2%	20.6%	37.2%
JPMC	48.63	57.8%	10.9%	31.4%
MSDW	37.05	52.2%	38.9%	8.9%
Goldman	40.85	62.4%	24.1%	13.5%
Barclays	4.32	10.2%	25.5%	64.3%
UBS	7.14	15.9%	23.1%	61.0%
Deutsche	15.85	22.3%	49.7%	28.1%
SocGen	9.03	11.3%	34.1%	54.6%
BNPP	6.91	12.1%	44.4%	43.5%
ABN	12.17	30.5%	34.4%	35.1%

Figure 9. Decomposition of variance of CDS price changes

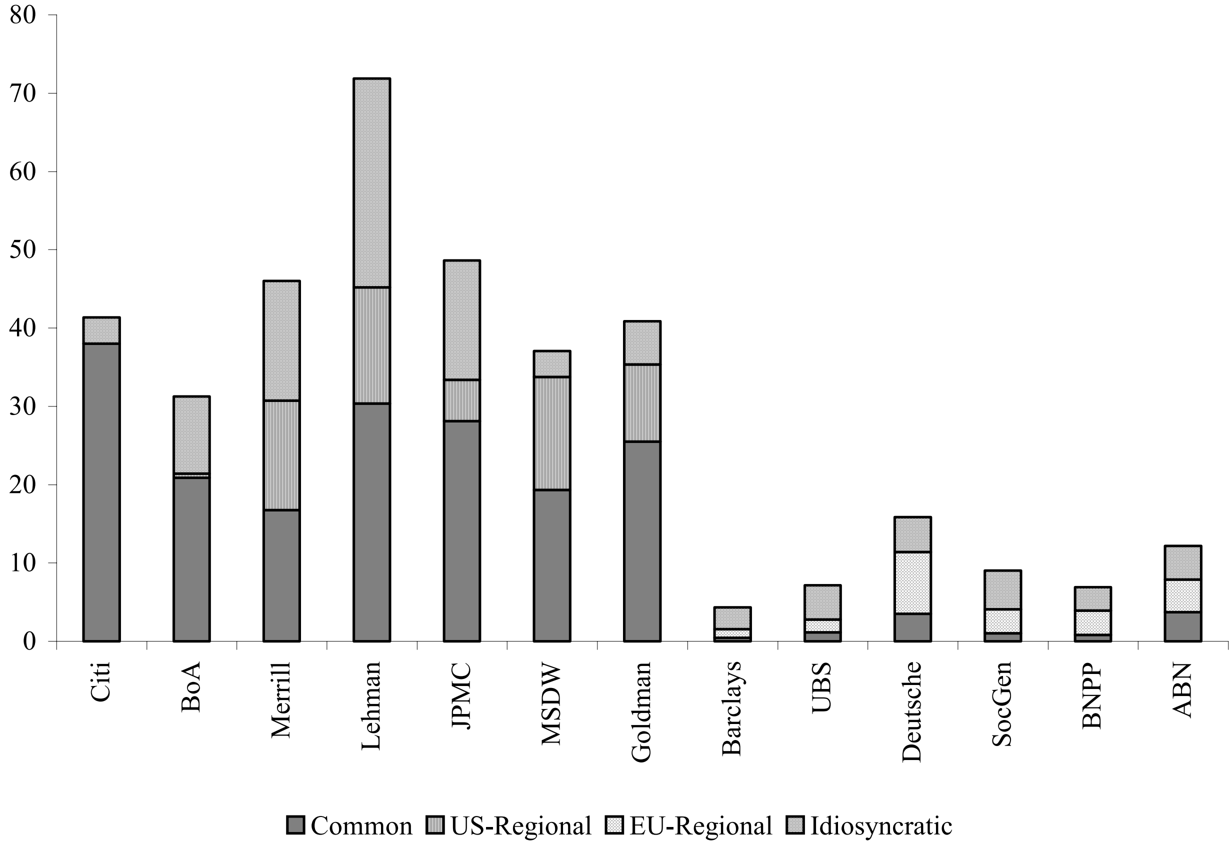
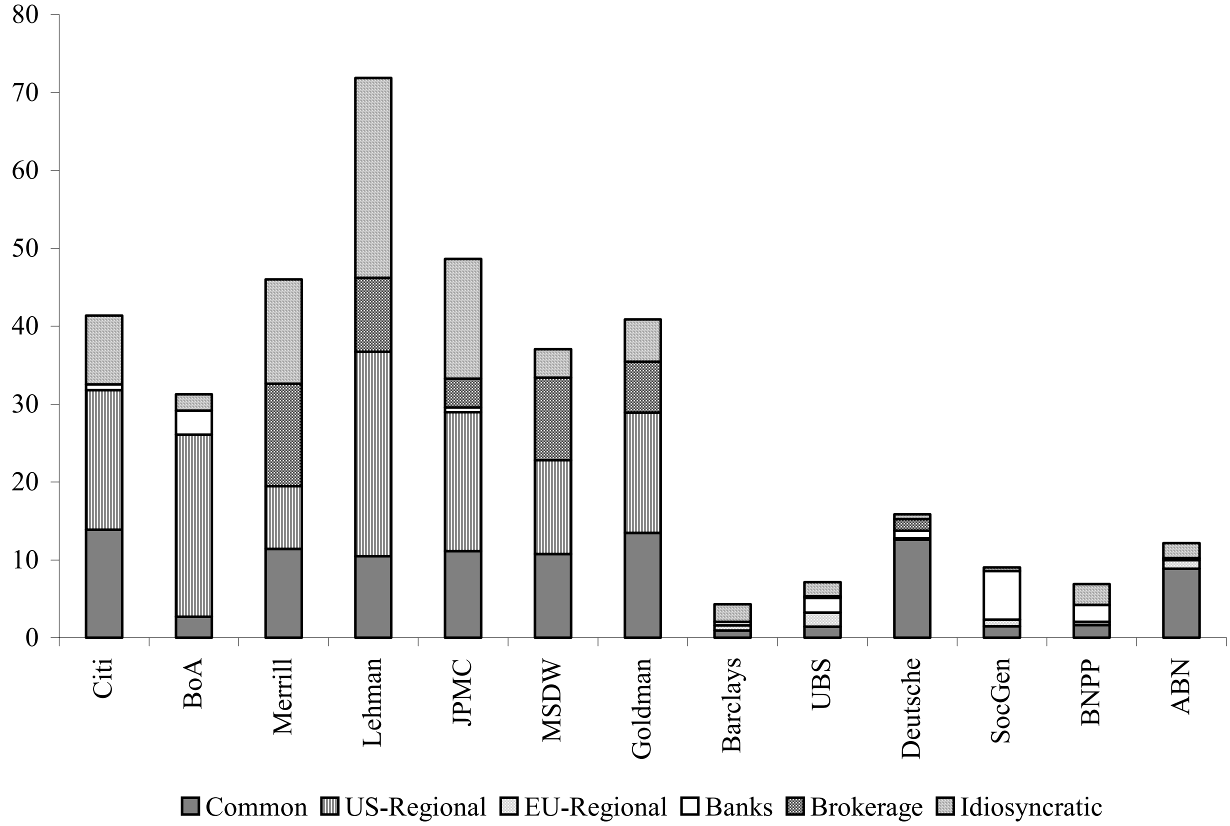


Table I. Decomposition of variance of CDS price changes with sectoral factors

	Contributions to variance				
	Common	Regional	Bank	Brokerage	Idiosyncratic
Citi	33.6%	43.3%	1.8%	0.0%	21.3%
BoA	8.7%	74.8%	9.8%		6.7%
Merrill	24.8%	17.6%		28.6%	29.1%
Lehman	14.5%	36.5%		13.2%	35.7%
JPMC	22.9%	36.6%	1.3%	7.6%	31.6%
MSDW	29.1%	32.5%		28.6%	9.9%
Goldman	32.9%	37.8%		16.0%	13.2%
Barclays	21.5%	15.9%	10.6%		52.0%
UBS	20.4%	25.2%	26.5%	2.7%	25.3%
Deutsche	79.5%	1.0%	6.3%	9.5%	3.8%
SocGen	16.5%	9.5%	69.0%		4.9%
BNPP	24.0%	5.5%	31.5%		39.0%
ABN	72.8%	9.4%	1.9%		15.9%

Figure 10. Decomposition of variance of CDS price changes with sectoral factors



7. Conclusions

In recent years, mergers, acquisitions and organic growth have meant that some of the largest and most complex financial groups have come to transcend national boundaries and traditionally defined business lines. As a result, they have become a potential channel for the cross-border and cross-market transmission of financial shocks, which is especially relevant for analysis of financial stability in an international financial centre such as London. Further, Borio's (2003) argument that common exposure to macro risk factors is a key source of systematic risk provides another incentive for macro-prudential supervisors to analyse the behaviour of large complex financial institutions.

To identify the degree to which large complex financial institutions (LCFIs) have exposures to common factors, this paper analyses the degree of comovement in the prices of securities issued by a selected group of LCFIs - more specifically, their share price returns and movements in their credit default swaps (CDSs). A number of techniques are employed to analyse information from the correlation or covariance matrices of these asset prices, including heat maps of correlations, cluster analysis, minimum spanning trees, principal component analysis and factor modelling.

Such an analysis of comovement in market prices captures both market perceptions of direct exposures between LCFIs and exposures to similar external factors. Knowledge of these common factors could help to identify potential channels for financial stability threats, such as through interlinkages between LCFIs or common vulnerabilities. The approach used does not, however, attempt to capture the degree of contagion that may occur during periods of financial stress, as the empirical estimation does not focus exclusively on such periods.

The various techniques applied to analyse comovement provide corroborating results for our peer group of LCFIs. Across the techniques employed we find, a relatively high degree of commonality in the asset price movements of LCFIs (compared to a control group of size/country matched non-financials). This emphasises the relevance for financial stability of monitoring LCFIs as a special class of financial institutions.

However, there is also clear evidence that a divide still exists between US and European institutions within the LCFI group. In the case of equity prices, this division is not caused solely by the segmentation of national equity markets. For CDS prices, it appears more likely to be due to a segmentation of US and European CDS markets, although a full discussion of this is beyond the scope of the paper. Further segmentation is evident along national lines within Europe and between pure brokerage houses and the banking oriented institutions.

Despite the liberal inclusion of unobserved factors to explain movements in the securities prices of LCFIs, some 26% of equity returns variance and 22% of the variance of CDS price changes has to be allocated to unexplained or idiosyncratic factors on average. For some LCFIs in the peer group, a large proportion of variance is unexplained, suggesting significantly different risk/return characteristics than the others. So despite recent mergers and acquisitions, LCFIs do not yet form a purely homogeneous group affected equally by common factors.

Appendix A

Table A1. Bookrunners of all international equities 1/1/2001 to 22/9/2001

Ranking	Name	Country	US$(m)
1	Merrill Lynch	US	10,657.1
2	Goldman Sachs	US	10,188.5
3	UBS	CH	8,861.9
4	MSDW	US	8,731.3
5	Citigroup	US	6,943.4
6	Credit Suisse	CH	5,847.4
7	Lehman Brothers	UC	3,250.6
8	Société Générale	FR	2,858.2
9	Deutsche Bank	DE	1,912.3
10	Dresdner Kleinwort	DE	1,836.9

Source: International Financial Review.

Table A2. Bookrunners of all international bonds 1/1/2001 to 22/9/2001

Ranking	Name	Country	US$(m)
1	Citigroup	US	150,326.4
2	MSDW	US	109,855.5
3	Merrill Lynch	US	104,453.4
4	Deutsche Bank	DE	100,540.9
5	JP Morgan Chase	US	99,695.1
6	Credit Suisse	CH	85,280.7
7	UBS	CH	83,357.5
8	Lehman Brothers	US	73,243.5
9	Goldman Sachs	US	71,044.7
10	Barclays	UK	51,669.1

Source: International Financial Review.

Table A3. Bookrunners of global syndicated loans 1/1/2001 - 30/9/2001

Ranking	Name	Country	US$(m)
1	JP Morgan Chase	US	407,377.5
2	Citigroup	US	196,689.5
3	Bank of America	US	181,895.8
4	Deutsche Bank	DE	68,453.0
5	Barclays	UK	42,253.5
6	BankOne	US	40,610.1
7	Mizuho FG	JP	39,720.0
8	Credit Suisse	CH	35,370.9
9	FleetBoston	US	27,845.3
10	HSBC	UK	19,777.0

Source: International Financial Review.

Table A4. Notional interest rate derivatives outstanding worldwide – 06/2001

Ranking	Name	Country	US$(m)
1	JP Morgan Chase	US	19,106,142
2	Deutsche Bank	DE	8,749,893
3	Bank of America	US	7,221,864
4	Citigroup	US	5,774,861
5	BNP Paribas	FR	5,614,908
6	Goldman Sachs	US	4,687,778
7	Royal Bank of Scotland	UK	4,509,828
8	Barclays	UK	3,955,503
9	Société Générale	FR	3,754,559
10	Fuji Bank	JP	3,708,853

Source: Swapsmonitor.com.

Table A5. Foreign exchange revenues - 2000

Ranking	Name	Country	US$(m)
1	Citigroup	US	1,243
2	HSBC	UK	965
3	Deutsche Bank	DE	951
4	Credit Suisse	CH	917
5	Bank of Tokyo-Mitsubishi	JP	660
6	Barclays	UK	579
7	ABN Amro	NL	536
8	Bank of America	US	524
9	United Financial of Japan	JP	469
10	Royal Bank of Canada	CA	401

Source: FX week.

Table A6. Total worldwide custody of assets - 2001

Ranking	Name	Country	US$(b)
1	Bank of New York	US	6,800
2	State Street	US	6,100
3	J.P. Morgan Chase	US	6,000
4	Citigroup	US	4,300
5	Deutsche Bank	DE	3,661
6	ABN Amro	NL	2,771
7	BNP Paribas	FR	1,800
8	Northern Trust Corporation	US	1,650
9	HSBC	UK	1,087
10	Société Générale	FR	748

Source: Globalcustody.net.

Appendix B

Figure B1. Heatmap of bivariate correlations using equity returns of non-financial corporates

	Pfizer	Intel	Bell South	Du Pont	Conoco	Sprint	Gloxo	Diageo	Roche	Richemont	E.On	Carrefour	LVMH
Pfizer													
Intel	0.17												
Bell South	0.23	0.09											
Du Pont	0.22	0.10	0.15										
Conoco	0.24	0.10	0.16	0.31									
Sprint	0.10	0.15	0.30	-0.01	0.04								
Gloxo	0.35	0.11	0.12	0.20	0.17	-0.05							
Diageo	0.22	-0.08	-0.01	0.20	0.18	-0.07	0.27						
Roche	0.28	0.17	0.15	0.25	0.13	0.08	0.33	0.20					
Richemont	0.26	0.26	0.08	0.33	0.14	0.15	0.19	0.19	0.34				
E.On	0.19	0.04	0.04	0.22	0.15	0.00	0.27	0.28	0.34	0.17			
Carrefour	0.21	0.20	0.08	0.30	0.21	0.02	0.30	0.10	0.32	0.35	0.28		
LVMH	0.22	0.30	0.08	0.25	0.18	0.07	0.27	0.12	0.25	0.42	0.21	0.44	
Philips	0.16	0.45	0.03	0.21	0.12	0.22	0.15	0.05	0.29	0.36	0.14	0.36	0.42

Correlation:

- Greater than 0.6
- Between 0.5 and 0.6
- Between 0.4 and 0.5
- Between 0 and 0.4
- Less than zero

Table B1. Likelihood ratio test for selecting number of significant principal components*

Equity returns					Residual equity residuals					Changes in CDS prices				
Eigenvalue	k	u	df	chi-prob	Eigenvalue	k	u	df	chi-prob	Eigenvalue	k	u	df	chi-prob
7.277	14	4184.542	104	0.000	3.629	14	1339.292	104	0.000	6.592	13	1028.393	90	0.000
1.771	13	1309.770	90	0.000	1.796	13	620.151	90	0.000	2.262	12	517.787	77	0.000
0.839	12	664.650	77	0.000	1.256	12	397.725	77	0.000	1.063	11	301.103	65	0.000
0.741	11	501.197	65	0.000	1.099	11	301.215	65	0.000	0.654	10	212.952	54	0.000
0.559	10	348.815	54	0.000	0.970	10	226.070	54	0.000	0.612	9	172.700	44	0.000
0.511	9	271.331	44	0.000	0.830	9	167.868	44	0.000	0.478	8	121.422	35	0.000
0.448	8	196.811	35	0.000	0.773	8	132.001	35	0.000	0.314	7	79.276	27	0.000
0.421	7	136.645	27	0.000	0.748	7	99.172	27	0.000	0.290	6	62.447	20	0.000
0.313	6	67.564	20	0.000	0.664	6	59.396	20	0.000	0.239	5	41.952	14	0.000
0.286	5	45.723	14	0.000	0.531	5	28.189	14	0.013	0.184	4	23.833	9	0.005
0.264	4	26.855	9	0.001	0.519	4	19.289	9	0.023	0.146	3	-170.842	5	-1.000
0.209	3	7.724	5	0.172	0.428	3	6.540	5	0.257	0.091	2	-285.790	2	-1.000
0.198	2	4.398	2	0.111	0.416	2	4.360	2	0.113	0.075	1			
0.162	1				0.341	1								

* This is a test of the significance of "larger or important" principal components or factors. It is based on the hypothesis that the last k population eigenvalues are small or equal. The test assumes multivariate normality and follows an asymptotic Chi-squared distribution. The null hypothesis $H_{0k}: \gamma_{p-k+1} = \gamma_{p-k+2} = \cdots = \gamma_p$; where $\gamma_1, \gamma_2, \cdots, \gamma_p$, are the population eigenvalues. p is the maximum number of eigenvalues (or factors) and k is the cut-off point. To test $H_{0k}: \gamma_{p-k+1} = \gamma_{p-k+2} = \cdots = \gamma_p$ we use the sample eigenvalues $[\lambda_i]$ and calculate the following statistic: $u = \left(n - \frac{2p+11}{6}\right)\left(k \ln \bar{\lambda} - \sum_{i=p-k+1}^{p} \ln \lambda_i\right) \sim \chi^2_{\alpha,\upsilon}$ where the average of the last k sample eigenvalues is given as $\bar{\lambda} = \sum_{i=p-k+1}^{p} \frac{\lambda_i}{k}$, n is equal to the number of observation, α is the conventional 5% critical value (chi-prob in the table is P-value of u) and υ is the degrees of freedom (df in the table); $\upsilon = \frac{1}{2}(k-1)(k+2)$. The test is carried out sequentially as shown in the table. Reject H_0 if $u \geq \chi^2_{\alpha,\upsilon}$. The results suggest that only last three eigenvalues are small or equal for all the assets. We should therefore retain the first eleven principal components for equity returns and equity returns residuals and the first ten principal components for changes in CDS prices.

Figure B2. Average clustering for 14 non-financial corporates using equity returns

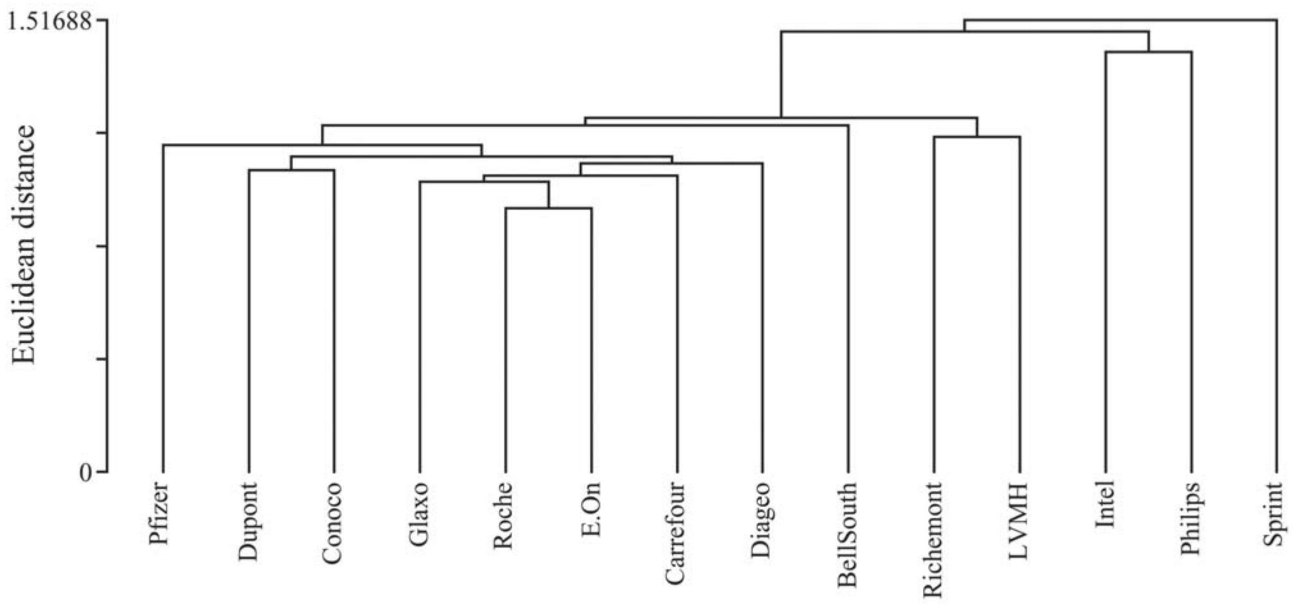
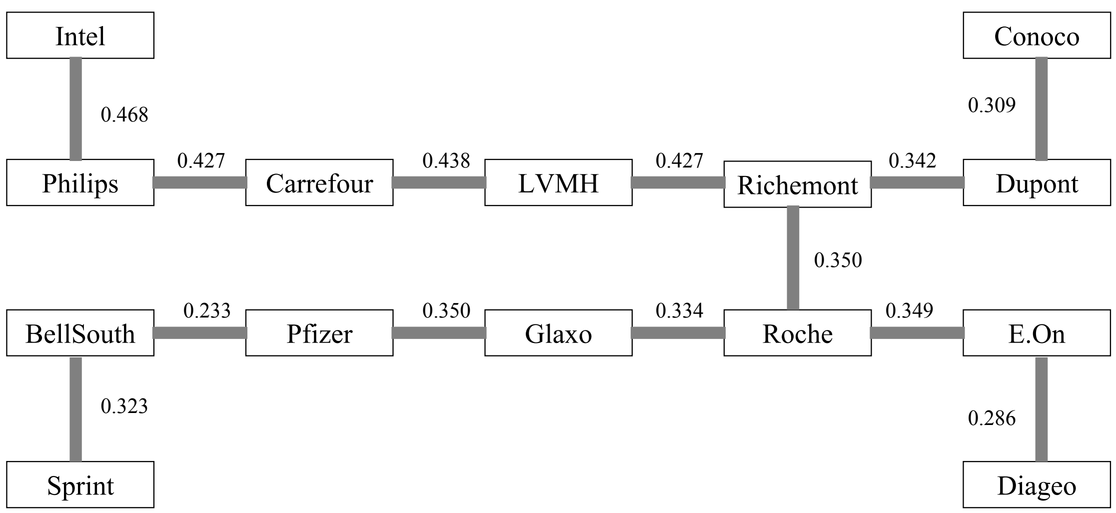


Figure B3. Minimum spanning tree for 14 non-financial corporates using equity returns



Appendix C

Table C1. Decomposition of variance of equity returns

	Variance	Contributions to variance			
		Observed	Common	Regional	Idiosyncratic
Citi	0.00279	55.7%	18.6%	0.0%	25.7%
BoA	0.00225	37.3%	29.0%	5.4%	28.4%
Merrill	0.00395	55.5%	16.4%	8.9%	19.2%
Lehman	0.00471	51.3%	15.8%	9.2%	23.6%
JPMC	0.00301	45.5%	21.6%	0.2%	32.7%
MSDW	0.00430	64.0%	11.5%	8.3%	16.3%
HSBC	0.00211	51.2%	2.0%	1.5%	45.4%
Barclays	0.00219	41.5%	4.3%	4.3%	49.9%
Cr Suisse	0.00284	54.9%	5.1%	0.6%	39.4%
UBS	0.00217	55.6%	2.8%	1.3%	40.2%
Deutsche	0.00203	54.0%	2.1%	4.0%	39.8%
SocGen	0.00294	42.0%	2.7%	37.7%	17.6%
BNPP	0.00257	43.9%	1.3%	28.5%	26.3%
ABN	0.00212	55.7%	1.5%	2.5%	40.3%

Figure C1. Decomposition of variance of equity returns

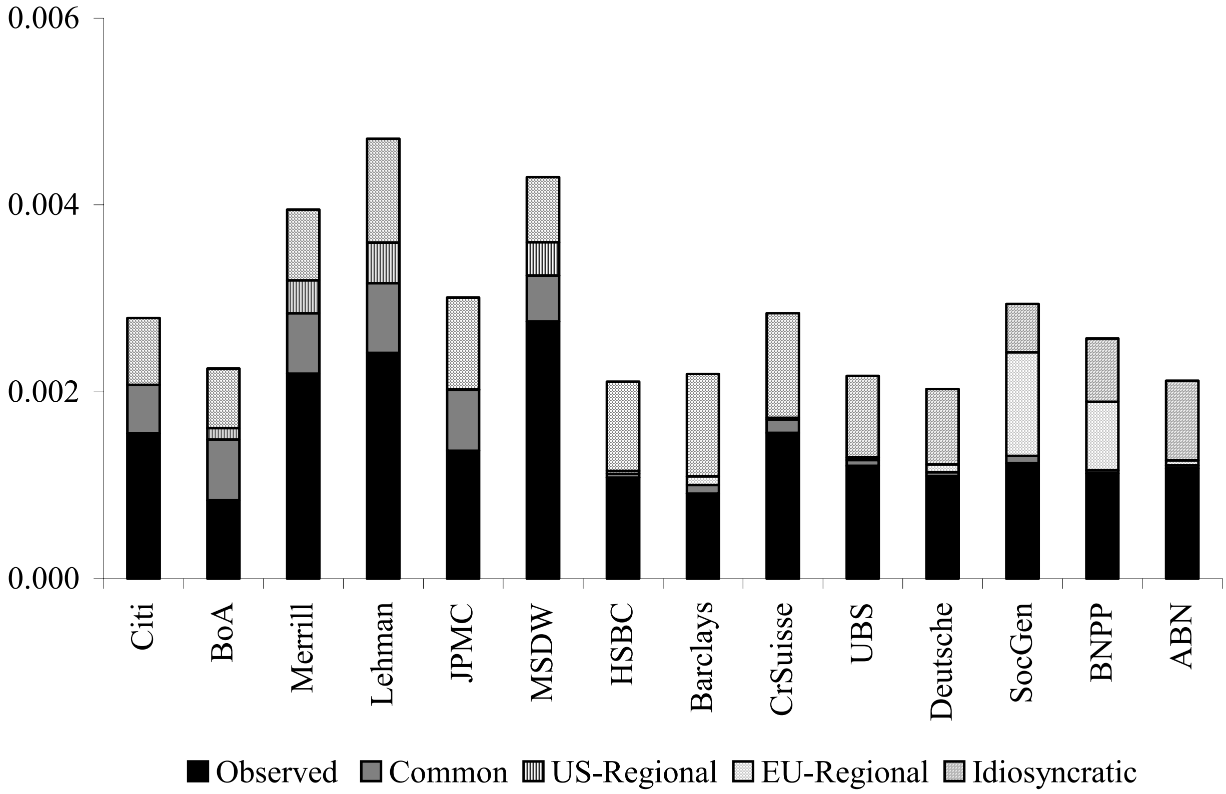


Table C2. Decomposition of variance of equity returns with sectoral factors

	Contributions to variance					
	Observed	Common	Regional	Bank	Brokerage	Idiosyncratic
Citi	55.7%	29.7%	6.0%	1.5%	7.1%	0.0%
BoA	37.3%	35.8%	23.3%	1.2%		2.5%
Merrill	55.5%	14.7%	3.2%		7.1%	19.5%
Lehman	51.3%	13.7%	2.1%		10.7%	22.2%
JPMC	45.5%	18.6%	0.0%	0.2%	0.2%	35.4%
MSDW	64.0%	10.4%	2.6%		6.0%	17.0%
HSBC	51.2%	2.1%	1.4%	0.0%		45.3%
Barclays	41.5%	3.5%	4.7%	1.9%		48.4%
Cr Suisse	54.9%	1.8%	1.4%	9.1%	2.4%	30.4%
UBS	55.6%	0.4%	2.5%	7.8%	3.8%	29.9%
Deutsche	54.0%	1.3%	4.3%	0.6%	0.3%	39.4%
SocGen	42.0%	3.3%	42.2%	1.8%		10.7%
BNPP	43.9%	1.5%	25.3%	0.6%		28.8%
ABN	55.7%	0.7%	3.3%	5.4%		34.9%

Figure C2. Decomposition of variance of equity returns with sectoral factors

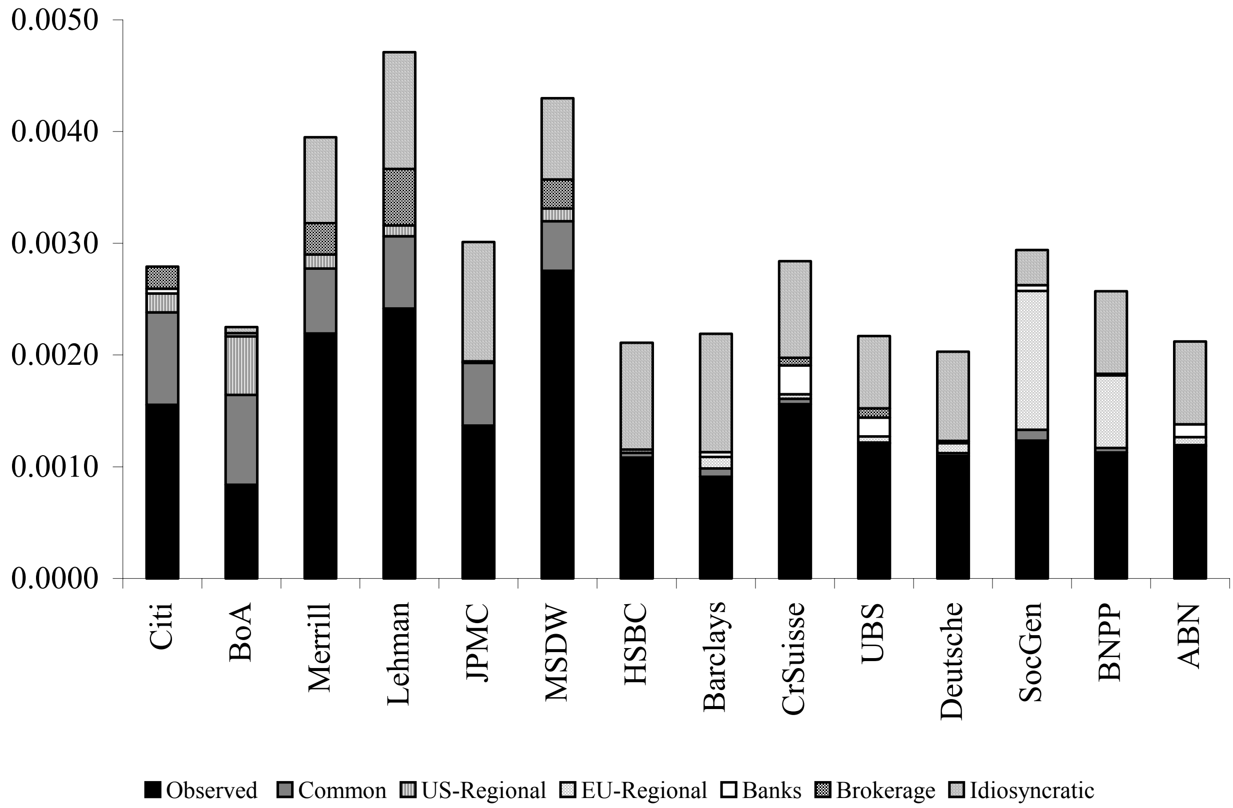


Figure C3. Decomposition of variance of equity returns for non-financial corporates

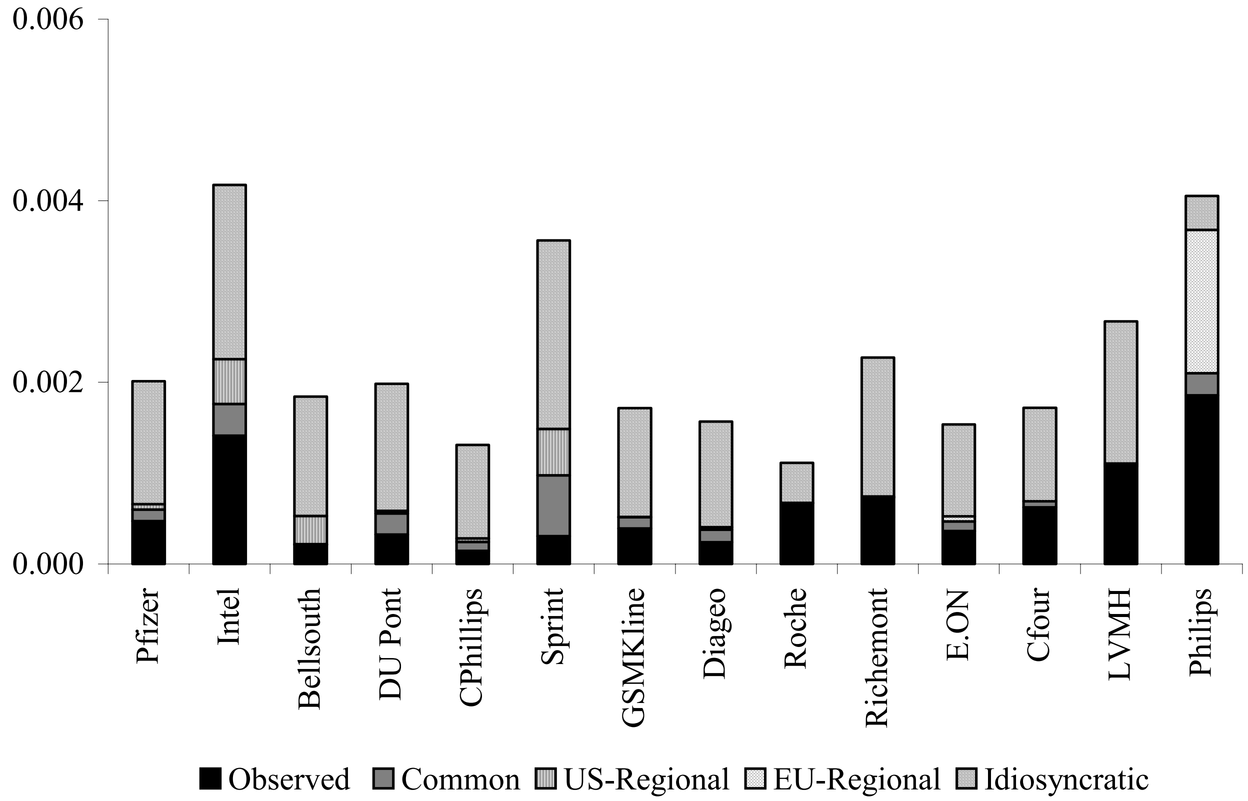
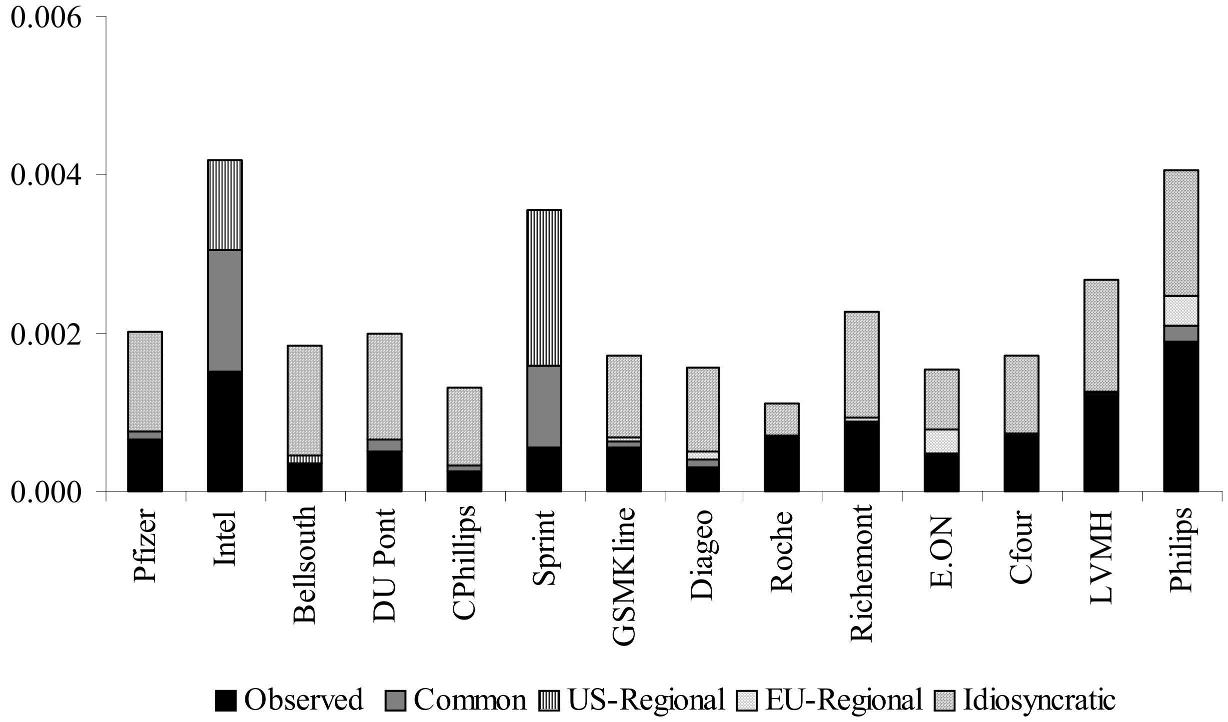


Figure C4. Decomposition of variance of equity returns for non-financial corporates (using the augmented observable factor model specification in stage one)



Appendix D

Table D1. Correlation matrix for the extracted residual idiosyncratic factors for factor models with sectoral factors using residuals from the augmented observable model

	Citi	BoA	Merrill	Lehman	JPMC	MSDW	HSBC	Barclays	Cr Suisse	UBS	Deutsche	SocGen	BNPP	ABN
Citi	1													
BoA	-0.4875	1												
Merrill	-0.0252	-0.0347	1											
Lehman	-0.19	0.1452	-0.5822	1										
JPMC	-0.6903	0.3863	0.11	0.4417	1									
MSDW	-0.083	0.3288	-0.3508	-0.3339	-0.222	1								
HSBC	-0.3345	0.1592	-0.0483	-0.0392	0.2391	0.0965	1							
Barclays	-0.4204	0.3752	0.1214	0.1345	0.5718	0.0816	-0.434	1						
Cr Suisse	0.0872	-0.0001	0.0274	-0.0327	-0.201	0.0239	0.0378	-0.0689	1					
UBS	0.2628	-0.1621	-0.0411	-0.0567	0.2246	0.0184	0.1431	0.1106	-0.5597	1				
Deutsche	0.0803	-0.0365	0.0229	-0.0226	-0.2509	-0.0325	-0.0579	-0.0621	-0.1263	-0.1871	1			
SocGen	0.1718	-0.0069	0.1043	-0.0388	0.0584	0.0202	-0.1193	0.0448	0.1629	0.1312	-0.1707	1		
BNPP	0.1311	0.0322	-0.0061	-0.0285	-0.064	0.0793	-0.1057	0.1071	0.1788	-0.0533	-0.3013	-0.7156	1	
ABN	0.01	0.0945	0.09	-0.0366	-0.1121	0.0765	-0.0721	-0.3453	-0.3822	-0.2469	-0.1521	-0.0196	0.0121	1

Table D2. Correlation matrix for the extracted residual idiosyncratic factors for factor models with sectoral factors using residuals from the standard observable model

	Citi	BoA	Merrill	Lehman	JPMC	MSDW	HSBC	Barclay	Cr Suisse	UBS	Deutsche	SocGen	BNPP	ABN
Citi	1													
BoA	0.6437	1												
Merrill	-0.091	0.2647	1											
Lehman	0.2265	0.0218	-0.3976	1										
JPMC	-0.4292	-0.743	-0.1925	-0.1812	1									
MSDW	-0.099	0.211	-0.3671	-0.3936	-0.0246	1								
HSBC	-0.2549	-0.1859	-0.0281	-0.0257	-0.1568	0.0105	1							
Barclays	-0.3943	-0.1925	0.026	0.0863	-0.0955	-0.0533	0.1056	1						
Cr Suisse	0.0459	-0.1431	-0.0416	-0.0795	0.0486	-0.0517	-0.0052	-0.1147	1					
UBS	0.5179	0.1456	-0.0595	-0.0652	0.0251	-0.0478	0.002	-0.1719	-0.5413	1				
Deutsche	0.0399	-0.0871	-0.0153	-0.0275	0.0409	-0.0637	-0.0937	-0.1195	-0.1044	-0.1482	1			
SocGen	0.2228	0.0532	0.0214	-0.03	0.0626	-0.0691	-0.2347	-0.2042	0.1481	0.1561	-0.1922	1		
BNPP	0.1585	0.1405	-0.0439	0.0018	0.0194	0.0835	-0.2212	-0.1896	0.152	0.0108	-0.2555	-0.6553	1	
ABN	-0.4445	0.0841	0.1142	0.0787	-0.0051	0.1582	0.0438	-0.1598	-0.3947	-0.3157	-0.1632	-0.0595	-0.0238	1

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