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Inter-industry contagion between UK life insurers and UK banks: an event study

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Abstract

Understanding interlinkages in a financial system is an integral part of the assessment of its stability. This paper employs an event study technique to assess the significance of interlinkages from the UK life insurance sector to the UK banking system in times of stress. The paper uses a thorough methodology to enhance standard event study techniques by adjusting for autocorrelation and heteroskedasticity when calculating the abnormal returns' forecast errors and for the offsetting effects in cumulative abnormal returns. We take an original approach by introducing the use of trading volumes to detect significant reactions not captured by the use of equity prices.

The paper shows evidence of interlinkages from the UK life insurance to the UK banking sector, and concludes that contagion is driven by banks' ownership of life insurance assets and only occurs during events that have hit the life insurance sector as a whole.

Key words: Event study, contagion, banking sector, life insurance sector, financial stability.

JEL classification: G14, G21, G22.

Summary

One of the Bank's core purposes is to detect and reduce threats to the financial system as a whole. The UK banking sector is a cornerstone of the UK financial system. Hence, contagion from one financial sector to the UK banking system may potentially have relevant implications for financial stability.

Over the past decade, correlations between equity price movements of UK banks and life insurers have increased markedly, most likely due to banks' increased involvement in the life insurance market. During the equity market decline between 2001 and 2003, UK life insurers were adversely affected. Consequently, the potential for contagion from the insurance sector to the UK banking sector became an important and much debated issue. This paper uses that period to assess the extent to which events in the life insurance sector have the potential to spillover to the banking system in times of stress.

Previous work at the Bank has identified potential channels by which shocks may be transmitted between sectors. Such interlinkages do not only originate from direct channels – ie counterparty exposures − but also from indirect channels via the impact of adverse and unexpected news on financial markets and consumers' confidence. Although accounting data provide a means to obtain a first estimate of counterparty exposures, they are less useful in measuring the magnitude of indirect channels. This paper aims to capture all three possible channels of contagion by using unexpected changes in equity price movements. In other words, we use equity prices as a tool to gauge the degree of inter-industry contagion from the UK life insurance sector to the UK banking sector.

The paper also uses information on equity trading volumes, in order to detect any significant reactions not captured by equity prices. For example, when investigating the presence of interlinkages, a mix of positive and negative reactions may lead to misleading conclusions since opposite interpretations of news can offset each other resulting in non-significant changes in equity prices. Therefore, we originally introduce the use of trading volumes to detect any significant reaction not captured by equity prices.

After undertaking a rigorous selection process to identify suitable events that originated in the life insurance sector between 2001 and 2003, we split them into two categories: events that impacted on specific life insurance companies and those that affected the life insurance sector as a whole. The results show that none of the firm-specific disturbances spilled over to the UK banking sector. There

was, however, some evidence that elements of the banking system responded to events that affected the life insurance sector as a whole – but these reactions were not uniformly pervasive. On closer inspection of the banking sector, the results show that bancassurers, defined as those banks that have large holdings of life insurance assets, were the only group whose equity prices were significantly affected by disruptions in the UK life insurance sector. These results suggest that the most significant channel for spillover to the banking sector is via UK banks' ownership of life insurers, while indirect channels were not found to be materially significant.

Our study is based upon a relatively recent period, as changes in banks' business models as well as structural changes to the economy may alter the magnitude and nature of interlinkages. Consequently, our analysis employs a relatively small sample. Further research could investigate whether the results presented in this paper can be replicated for other countries.

1 Introduction

The UK banking sector is a cornerstone of the UK financial system. Hence, contagion from one financial sector to the UK banking system may potentially have relevant implications for financial stability. Consequently, it is important to identify likely channels of contagion, in order to monitor them and help mitigate the risk of financial crises. In the past decade, correlation between the equity price of banks and life insurers has increased markedly, most likely due to banks' increased involvement in the life insurance market. During the equity market decline in the 2001-03 period, UK life insurers were seriously affected, and the potential for contagion from the insurance to the UK banking sector became an important and much debated issue. This paper employs a quantitative approach to assess the significance of spillovers from the UK life insurance sector to the UK banking system during times of stress.

Interlinkages do not only originate from direct channels – ie counterparty exposures − but also from indirect channels via the impact of adverse and unexpected news on financial markets (Kaminsky and Reinhart (2000)) and consumers' confidence (Diamond and Dybvig (1983)). Although accounting data provide a means to obtain a first estimate of counterparty exposures, they are less useful in measuring the magnitude of the remaining two channels. This paper aims to capture all three possible channels of contagion by applying an event-study approach to equity price movements. In other words, we use equity prices as a tool to gauge the degree of inter-industry contagion from the UK life insurance sector to the UK banking sector.

Looking at the UK financial system, the direct potential credit exposure of the large UK-owned banks from loans to the life insurance sector is limited.(1) But ownership interests are potentially more significant. Six of the ten largest UK-owned banks own life insurance subsidiaries, although their scale varies markedly. Therefore, there are several direct channels through which life subsidiaries might affect their parents: via reductions in banks' operating incomes, via the cost of insurance re-capitalisation and via the direct effect on banks' Tier 1 capital of any change in the 'embedded value' of a life insurance subsidiary. Furthermore, given their involvement in capital

(1) Lending to life insurance companies accounted for less than 7% of the largest ten UK-owned banks' combined Tier 1 capital over the 2001-03 period, while undrawn facilities account for a further 4%.

markets,[2] and the service they provide to households and corporations,[3] life insurers have the potential to indirectly affect UK banks through capital markets and consumer confidence channels.

During the 2001-03 period, UK life insurance companies, which traditionally invested heavily in equities, were seriously adversely affected by the prolonged fall in equity prices. On 28 June 2002, the Financial Services Authority (FSA) – the UK financial services regulatory body – amended the resilience test for life insurers. The amendment adopted allowed insurers to take account of the extent to which equity price levels were already below their average over the previous three months.[4] In January 2003, the FSA had to intervene again. Provisions were made to enable life insurers to waive some regulatory rules on the calculation of solvency, provided that they remained strong on the 'realistic' solvency measure and continued to meet EU minimum requirements. Therefore, the 2001-03 period provides an ideal opportunity to assess the degree of interlinkages between the large UK-owned banks and life insurers in times of stress.

Event studies have been used extensively in empirical finance and economics for a large variety of subjects. Examples include testing market efficiency hypotheses, initial public offers, earning announcements, wealth effects of mergers and asset price reactions to interest rate announcements. The modern methodology of event studies is based on the seminal papers of Fama (1970) and Patell (1976). In the 1980s Brown and Warner (1980, 1985) and Bernard (1987) improved the standard methodology (for an overview see MacKinlay (1997)).

More recently, event studies' methodologies were modified to estimate spillover effects from one institution to other institutions (Kaufman (1994); and Huberman and Regev (2001)). While these studies generally limit their attention to the reactions triggered from unexpected news in the same industry, ie intra-industry contagion (Docking *et al* (1997); and Akhigbe and Madura (2001)), Brewer and Jackson (2002) use an event study technique to explore the magnitude of inter-industry contagion between US commercial banks and life insurance companies. Brewer and Jackson

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(2) UK-resident life insurers have substantial holdings of marketable assets: at end-2003, they had asset holdings of £972 billion. They held approximately 20% of UK shares, 29% of UK corporate bonds and 37% of gilts. The large scale of the sector's asset holdings means that an asset reallocation by life insurers may have the potential to affect asset prices, at least temporarily.

(3) In addition to their involvement in capital markets, life insurers together with pension funds also have an important role as managers of long-term savings. During the 2001-03 period, the sector managed around 50% of UK households' financial assets and was also a provider of annuities – which are a legal requirement of private pension savings (data for the life insurers only are not available).

(4) The test required insurers to make prudent provision against the effects of possible future changes in the value of their assets, including a fall in equity prices of up to 25%.

conclude that there is evidence of inter-industry contagion and that these effects are linked to variables such as asset and liability portfolio composition.

This paper does not only contribute to the debate about inter-industry contagion, but it also introduces a thorough methodology to enhance existing event study techniques. First, we adjust for autocorrelation and heteroskedasticity when calculating the abnormal returns' forecast error. This is necessary because the assumptions of homoskedasticity and no-autocorrelation are often violated when dealing with cross-sectional and time-series data respectively. In the presence of heteroskedasticity and autocorrelation, the estimators will be inefficient and the significance tests of the abnormal returns are likely to be miscalculated, leading to potential erroneous conclusions.

Second, an unexpected negative announcement from an institution can have a positive or negative effect on the share prices of its competitors according to whether market participants believe it to be a shock specific to the institution or to its whole sector. Therefore, the sum of an institution's abnormal returns (*ARs*) across several adverse events can be insignificantly different from zero either because the *ARs* are, on average, insignificant or because positive significant *ARs* offset negative significant *ARs*. Hence, we use a combination of a chi-square and *Z*-statistic to identify whether such offsetting in cumulative abnormal returns occurred.

Third, the use of equity prices in event studies is generally characterised by the hidden assumption that there exists a broad consensus across market participants. When investigating the presence of interlinkages, a mix of positive and negative reactions may lead to misleading conclusions since opposite interpretations of news can offset each other causing a non-significant change in the equity prices. Therefore, we originally introduce the use of trading volumes to detect any significant reaction not captured by equity prices.

After undertaking a rigorous selection process to identify suitable events that originate from the life insurance sector, our results show evidence of interlinkages from life insurers to the banking sector but conclude that contagion is driven by banks' ownership of life insurers.

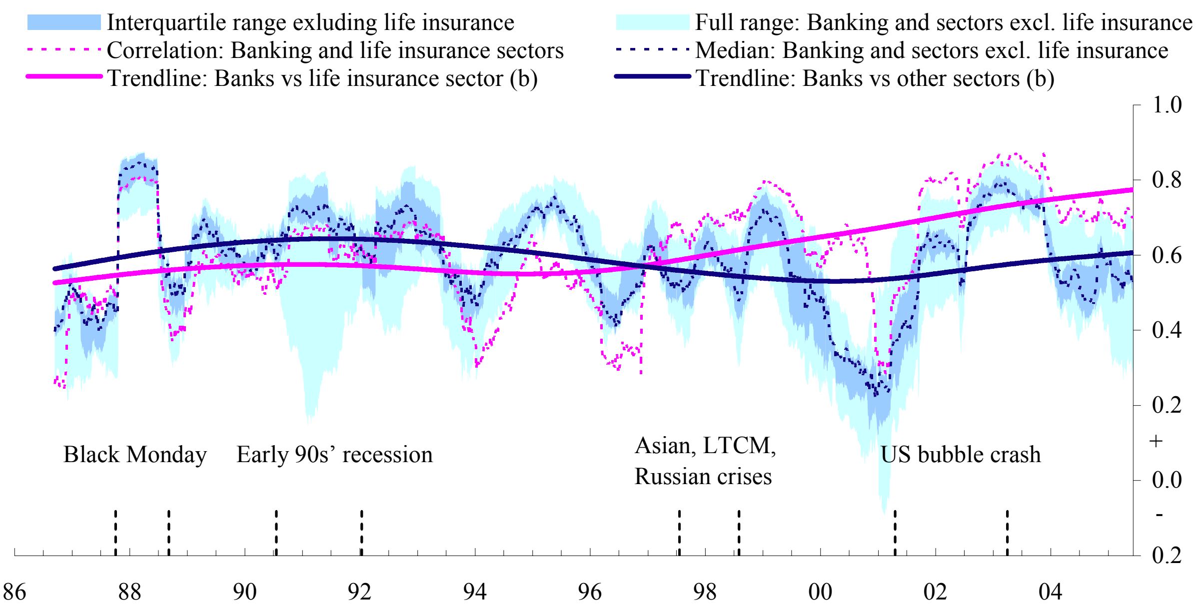
The remaining part of the paper is structured as follows. Section 2 provides a preliminary analysis of the data. In Section 3, we outline the methodology used to estimate and test the magnitude of interlinkages between the banking and life sectors. Section 4 presents the set of criteria and describes the process followed to select the events used in this study. Section 5 shows the results and Section 6 examines how sensitive these are to various modelling assumptions. Section 7 concludes.

2 A preliminary look at the data

In this paper, the ten largest UK-owned banks are used as a proxy for the UK banking system, as they accounted for more than 90% of all UK-owned banks' assets over the period studied. But, the analysis could easily be extended to cover the smaller listed UK-owned or other resident banks. As a proxy for the life insurance sector, we use all UK-owned life insurers that belonged to the FTSE 100 index at the time of the study.[5]

Correlations between equity prices are often used as a simple metric to assess the potential for contagion between sectors. In order to calculate average correlations, we divided the UK equity market into eight representative sectors.[6] In place of the financial sector we used the life insurance and banking sectors. Bilateral correlations between the UK banking sector and the remaining eight sectors were then calculated. The results are shown in Chart 1 by means of quartile ranges.

Chart 1: Correlations between UK banks and other UK sectors' equity prices[a]



Sources: Bloomberg and Thomson Financial Datastream.
(a) Correlation is calculated using a 182-day moving window.
(b) The trendlines of the correlation between banking and life insurance sectors and the correlation between banking and other sectors are calculated using the Hodrick-Prescott filter.

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[5] The ten largest UK-owned banks are: Abbey (National), Alliance & Leicester, Barclays, Bradford & Bingley, Halifax, Bank of Scotland, HBOS, Lloyds TSB, Northern Rock, Royal Bank of Scotland and Standard Chartered. The life insurers included in this study are: Aviva, Friends Provident, Legal & General, Prudential and Royal Sun Alliance.
[6] Datastream divides the UK equity market into eight sectors: Resources, Basic Industries, General Industrials, Non-Cyclical Consumer Goods, Cyclical Services, Non-Cyclical Services, Utilities, and Financials. The Financial sector was replaced by the FTSE Bank and Life indices. The FTSE UK Bank index consists of the above-listed banks with the only exception of Egg instead of Standard Chartered.

Over the period 1986-2004, the median correlation between the equity prices of UK banks and those of the non-financial UK sectors fell slightly (blue line). However, over the same period, the correlation between UK banks and the UK life insurance sector increased (pink line). The rise in correlation might partly be attributed to the increased involvement of banks such as Lloyds TSB, Abbey and HBOS in the life insurance market in the second half of the 1990s and early 2000s (Chart A1 in the appendix).

The main shortcoming of correlation analysis is that the equity returns of any two sectors may arise as a result of market-wide developments, which do not reflect any interlinkages or spillover from one sector to another. Equity returns can be affected by developments on three levels: the overall market, a specific sector, or an individual institution. While the last two are relevant for identifying specific interlinkages between two sectors, the first is not. Hence, systematic market-wide movements must be filtered out first when trying to assess the degree of spillover between the UK banking and life insurance sectors. Moreover, as Chart 1 shows correlations varying over time, average relationships might not properly reflect the potential for contagion in times of stress.

3 Methodology

We use the Sharpe-Litner market model (see Campbell *et al* (1997)) to remove market-wide changes from equity returns:

$$R_{i;t} = \alpha_i + \beta_i R_{m;t} + u_{i;t} \qquad \textbf{(1)}$$

$$E(u_{i;t}) = 0 \qquad Var(u_{i;t}) = \sigma^2_{u_{i;t}}$$

$R_{i;t}$ and $R_{m;t}$ are the period-t equity returns for institution i and the market portfolio respectively using closing prices and $u_{i;t}$ is the zero mean disturbance term where the institution-subscript accounts for heteroskedasticity. As it is common in event studies, we use a broad-based stock index – the FTSE All-Share – as an approximation for the market return. Daily equity prices for banks and insurers are obtained from Datastream.

The parameters are estimated for each institution over a period of 250 trading days – the estimation window – of daily returns data beginning 270 days before the event. As it is customary, we define $\tau = 0$ as the event day. It follows that $\tau = -270$ to $\tau = -20$ constitutes the estimation window.

For each security *i* and event day-*t*, equation **(1)** is used to calculate abnormal return ($AR_{i;t}$) as follows:

$$AR_{i;t} = R_{i;t} - \hat{\alpha}_i - \hat{\beta}_i R_{m;t} \qquad \textbf{(2)}$$

The abnormal return ($AR_{i;t}$) is characterised by:

$$E\left[AR_{i;t}\right] = 0 \qquad \textbf{(3)}$$

because $\hat{\alpha}_i$ and $\hat{\beta}_i$ are unbiased; $VaR\left(AR_{i;t}\right)$ is:

$$\sigma^2_{ARi;t} = VaR(\hat{\alpha}_i) + R^2_{m;t} VaR\left(\hat{\beta}_i\right) + 2R_{m;t}\operatorname{cov}\left(\hat{\alpha}_i;\hat{\beta}_i\right) + VaR\left(u_{i;t}\right) \qquad \textbf{(4)}$$

The variance of $AR_{i;t}$ is equal to the disturbance variance $Var(u_{i;t})$ from **(1)** plus an additional component due to sampling errors.

Following the methodology used by Patell (1976), event studies usually apply ordinary least squares to estimate the parameters of the market model. However, in the presence of heteroskedasticity and autocorrelation the estimators will be inefficient and so affect the component of $Var\left(AR_{i;0}\right)$ due to sampling errors. The consequence is that the significance test of the abnormal returns may be miscalculated.(7) We tested for autocorrelation and heteroskedasticity across institutions and events. In the vast majority of cases, both assumptions of homoskedasticity and no-autocorrelation were violated. Therefore, Newey-West *HAC* covariance estimators were used to estimate $VaR(\hat{\alpha}_i)$, $VaR\left(\hat{\beta}_i\right)$ and $cov\left(\hat{\alpha}_i;\hat{\beta}_i\right)$.

In order to assess the magnitude of the interlinkages between the banking and insurance sectors we follow three steps: first individual institutions' *ARs* are analysed, then institutions are grouped into a life insurance index and a bank index, and finally the latter index is split into three subindices.

In the **first step**, we analyse the *ARs* of individual institutions. Equation **(4)** can be used to test the significance of the impact of an event. It can be shown that standardised abnormal returns are distributed according to a *t*-distribution (Patell (1976)):

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(7) The smaller the estimation window the larger is the error. For sufficiently large estimation windows, the error is likely to be less relevant; however, the cost of correcting for autocorrelation due to the loss of observations is negligible for large estimation windows.

$$SAR_{i;t} = \frac{AR_{i;t}}{\sigma_{AR_{i;t}}} \sim t(T_i - 2) \qquad \textbf{(5)}$$

where *SARs* is the standardised prediction error and T_i is the number of days in the estimation window. Normally standardised cumulative abnormal errors (*SCAR*) are obtained as follows (MacKinlay (1997)):

$$SCAR_i = \frac{\left[\sum_{t=1}^{k_i} SAR_{i;t}\right]}{\sqrt{k_i}} \sim t(T_i - 2) \qquad \textbf{(6)}$$

where the *SARs* are accumulated over the k_i event days. However, the normalisation requires $SAR_{i;t}$ to be independently distributed. Hence, in the presence of autocorrelation it is not possible to aggregate $SAR_{i;t}$ over the event window. A partial solution can be obtained by summing $SAR_{i;t}$ on the event day, $\tau = 0$, across events:

$$SCAR_i^{\tau=0} = \frac{\left[\sum_{e=1}^{E} SAR_{i;e}^{\tau=0}\right]}{\sqrt{E}} \sim t(T_i - 2) \qquad \textbf{(6')}$$

where E is the total number of events. At this point, an important aside is necessary. The day prior to the announcement ($\tau = -1$) is often included in the event window in order to capture any news-leak, and also the day after the event ($\tau = +1$) is sometimes included in case the news was released after the market closed. In this study, we concentrate only on $\tau = 0$. As will be described in the next section, all news events have been carefully selected, making sure that the news was released when the equity market was open, and no significant news-leaks occurred at $\tau = -1$. These claims were confirmed by estimating *ARs* from $\tau = -20$ to $\tau = +20$ and paying particular attention to $\tau = \pm 1$.[8]

As mentioned in the introduction, the *SCAR* statistic in equation **(6')** can be not-significantly different from zero, either because the *ARs* are, on average, not significant, or because significant

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[8] Due to the dimensions of the output (six 40 x 20 matrices) results over the whole event window are not reported but are available by contacting the authors.

positive *ARs* offset significant negative ones. The offsetting can be eliminated by using a chi-square statistic, summing the squared *SARs* for each event day across all events.(9)

$$\sum_{e=1}^{E}\left(SAR_i^{\tau=0}\right)^2 \sim \chi_E^2 \qquad \textbf{(7)}$$

where *E* is the total number of events. We will use both statistics when interpreting our results. It is important to note the difference between the null hypotheses of the two statistics. While the rejection of the null for the *SCAR* statistic implies that *SARs* are on average significantly different from zero, the rejection of chi-square implies that at least one *SAR* is significantly different from zero.

The second step consists of determining the impact of the news on the whole banking system. When more than one event and multiple institutions are tested, some authors compute a Z-statistic(10) to demonstrate whether the release of the news is generally associated with significant abnormal returns (Brewer and Jackson (2002)). However, the Z-statistic requires the *ARs* to be independent and randomly distributed variables. When the institutions' event windows overlap, as must be the case in inter-industries contagion studies, it is not possible to assume the covariance between the institutions *ARs* is zero – as it would be equivalent to imposing that there are no interlinkages between sectors or intra-sector contagion. Therefore, we cannot compute the above statistics by aggregating *ARs* across institutions.

We accommodate this so-called 'clustering problem' (MacKinlay (1997)) by aggregating banks' abnormal returns into a portfolio, defined as the Bank index, and then replicating the above analysis as in Bernard (1987). The drawback of this approach is that positive and negative *ARs* across institutions can offset each other. However, the analysis of individual institutions' *ARs* in the first step allows us to quantify the extent of this problem.

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(9) The *SARs* on the event day are assumed to be independent because a significant amount of time elapsed between the events.

(10) Given that each *t*-statistic has an expected value of zero and a variance equals to $(T_i - 2)/(T_i - 4)$, the significance of *AR*, or *CAR*, at a chosen confidence level is often tested by using a Z-statistic:

$$Z_{ARi} = \sum_{i=1}^{n} AR_i \Bigg/ \left[\sum_{i=0}^{N}\frac{T_i - 2}{T_i - 4}\right]^{1/2} \qquad i = 1\ldots n$$

In this step, we also test whether the difference between the impact of sector-wide and idiosyncratic events – as defined in the next section – is significant. It is possible to use the above chi-square statistic to construct an F-test:

$$\frac{\sum_{b=1}^{S}(SAR_b^{\tau=0})^2 \Big/ S}{\sum_{b=1}^{Y}(SAR_b^{\tau=0})^2 \Big/ Y} \sim F_{S;Y} \qquad \textbf{(8)}$$

where S is the number of events classified as sector wide, and Y is the number of idiosyncratic events. It is important to note that the F-test requires the two chi-square statistics to be independently distributed.

In the third and last step, we investigate whether inter-industry contagion can be explained by banks' specific characteristics. In particular, we assess whether banks' reactions to life insurance events can be explained by their holding of life insurance assets. We ranked banks according to their proportion of life insurance assets over total assets. We then built three subindices by taking the highest and lowest quartiles and grouping together the two middle quartiles as shown in Table A.

Table A: Banks' life insurance assets as a proportion of total assets

Index	Banks	Percentage of assets attributable to life business		
		at Dec. 2001	*at Dec. 2002*	*at Dec. 2003*
Bancassurance (Fourth quartile)	Lloyds TSB Abbey National HBOS	19.7 14.2 12.0	17.9 14.3 10.5	19.9 16.0 10.7
International diversified banks (Second and third quartile)	Barclays HSBC RBS Standard Chartered	2.3 1.4 2.8 0.0	1.8 1.4 2.2 0.0	1.8 1.5 0.8 0.0
Mortgage banks (First quartile)	Alliance & Leicester Bradford & Bingley Northern Rock	0.0 0.0 0.0	0.0 0.0 0.0	0.0 0.0 0.0

Sources: Published accounts.

The additional benefit of this portfolio approach is the creation of three homogeneous indices: the first index groups together the bancassurers, the second domestic orientated mortgage banks and the last the international-diversified banks.

4 Events selection

In any event study the choice of events is paramount. First, the events need to meet some general criteria:

(i) The event should be unexpected, as equity prices should not react to expected events if markets are efficient.

(ii) The event should not coincide with the release of other significant but unrelated news, due to the difficulties of disentangling the impact of the two events.

Second, for the purpose of the paper, some additional criteria are required:

(iii) The event should have occurred in a relatively recent period. Structural changes in either the economy or banks' business models could result in misleading conclusions if earlier events were used.

(iv) The event should have originated from the life insurance sector.

Furthermore, given that we are interested in the transmission of adverse shocks from the life insurance to the banking sector in times of stress, only negative events are considered. As mentioned in the introduction during the 2001-03 period, UK life insurers were adversely affected by a prolonged fall in global equity prices. As equity prices fell, speculation grew about the regulatory solvency of some UK life insurers. The 2001-03 period thus provides a suitable period of stress to assess the degree of interlinkages between UK banks and UK life insurers.

The above criteria were applied to select candidate events. Initially the feasibility of two systematic approaches was examined. First, life insurers' earnings announcements that fell short of market expectations were considered. However, life insurers and banks tend to release both annual and interim results during the same periods. For example, out of the ten earnings announcements from life insurers reported during 2003, nine occurred on the same day and time of banks' earnings announcements, thereby violating the requirement of no conflicting news. Second, downgrades and negative watches were considered, but they often trail earnings announcements by a few days, and they also tended to coincide with the release of other news – which violates criterion (ii). To solve these difficulties, the final list of candidate events was compiled by drawing from news collected by the Bank of England in its financial stability surveillance role. News wires for daily reports on the life insurance sector were systematically searched in order to determine the exact event day and time of the news. The process was reiterated for the banking sector, to avoid selecting a multiple-event day.

Finally, to explore all channels of contagion, both sector-wide and idiosyncratic events were included. We define an idiosyncratic event as one that originated from a single life insurer. A sector-wide event is defined as disturbances that originate from either more than one source but regarding the same issue or an announcement from an external source with potential relevance to the whole life UK insurance sector.(11) Given the above definitions, we would expect to see the life insurance sector as a whole responding to a sector-wide event. The life insurance sector's reaction to an idiosyncratic event will depend on the magnitude of the event and on the interlinkages of the announcing institution with other institutions. The list of the accepted and rejected events is shown in Table B.

After using the criteria outlined above, six events were selected for estimation. The accepted events are numbered from one to six, and include four idiosyncratic and two sector-wide events. The other events were rejected because, after carefully examining news wires for the event day, they violated criterion (ii).(12)

(11) The reason of the additional distinction between idiosyncratic and sector-wide events may be better understood through an example. A life insurer's failure due to operational risk or poor management may boost competitors' equity prices as their market share is likely to increase. On the contrary, when the failure is due to an increase in competition or a generalised fall in consumers' demand, the sector as a whole is likely to experience negative returns.

(12) The February 2002 event was not rejected as we considered the HBOS news to be a 'life insurance event'. This interpretation follows the one given by newspapers such as the Financial Times at the time of the news (Financial Times' Lex Column of 28 February 2002 issue).

Table B: Events selection

Event	Date	Sel.	Type	Life Insurance Event Description	Bank's News Description
				Accepted events	
1	27/02/02	Accepted	Syst.	o Aviva announced a cut to its 2002 dividend. o Goldman Sachs cut their Prudential 2002 Earning-per-Share forecasts. o AMP, Australia's biggest life insurer (5th largest UK-resident life insurer as measured by with-profits assets), said earnings fell 54%. o HBOS sold new stock for £1.1bn to fund mortgages and **insurance policies**.	o HBOS: sold new stock for £1.1bn to fund **mortgages** and insurance policies.
2	11/07/02	Accepted	Syst.	o Some UK insurers were almost forced to sell stocks of equities at the FTSE 100 level of 4540, to protect their assets before the FSA changed one of its rules, FSA announced. The FTSE 100 fell to 4230 since the announcement. o Bloomberg Europe Insurance Index posted the biggest decline since 21 Sept. o Munich Re the world's largest insurer injected $2bn into its reserves. Merrill Lynch cut its rating and told investors to sell.	
3	23/0702	Accepted	Syst.	o Aviva, the No. 1 UK insurer, said it will cut final bonus rates on its with-profits policies, because of falling equity markets. o According to a Bloomberg's survey Prudential's operating profits are expected to fall by 10%. o Fortis said profit may not meet estimates due to falling equities. Moody's may cut Aegon NV's (2nd largest Dutch insurer) ratings on concern about falling earnings. o Skandia AB (largest Nordic insurer) shares posted their biggest fall since Sept. 11 as sales dropped 28% due to falling equity markets.	
4	08/08/02	Accepted	Syst.	o Schroder Salomon Smith Barney state a decline in the FTSE 100 Index to 3600 may force insurers to pump money into their UK life funds to bolster reserves. o Prudential in Singapore sold 49% less in single-premium policies in the first half, as concern over falling stock prices curbed sales. o Royal & Sun Alliance stated the need to raise £800m, close its UK life insurance business and cut 1,200 jobs. o Aegon NV said Q2 profits plunged 77% due to falling stocks.	
5	05/03/03	Accepted	Idios.	o Friends Provident reduced 2002 dividend and announced future payments may not keep in line with inflation.	
6	04/09/03	Accepted	Idios.	o Fitch Ratings, downgraded Royal & Sun Alliance to BBB from BBB+ and long-term rating to B+ from BBB- (BBB minus).	
				Rejected events	
-	12/03/01	Rejected	Idios.	o Standard & Poor's (S&P) placed Prudential and American General Group ratings on Credit Watch with negative and positive implications respectively following the announcement of an agreement to merge the two companies.	o Hong Kong's stock index fell led by concerns on HSBC. o Goldman Sachs downgraded HSBC and the target price to 850p.
-	03/07/02	Rejected	Syst.	o FTSE 100 fell to its lowest level since 21 Sept. 2001 following worse-than-expected news from US services economy.	
-	23/10/02	Rejected	Idios.	o S&P put RSA on 'Credit Watch negative' due to capital concerns. o Legal & General Group, Britain's No.4 insurer, said it raised more than £760m from sale of shares to existing investors. o Deutsche Bank AG cut the rating on Munich Re citing concern about the company's stockholdings. o Skandia said falling stock markets reduced Q3 earnings by $342m.	o West LB downgraded; RBS, Barclays, Alliance & Leicester, and cut their target prices. o Merrill Lynch said HSBC and Northern Rock may have pension-fund deficits that will force them to transfer money to meet funding requirements.
-	05/12/02	Rejected	Idios.	o S&P put the outlook of Friends Provident to negative outlook.	o WestLB cut Lloyds TSB's target price. o Effectenbank SNV downgraded Barclays' rating and cut the target price. o Merrill Lynch said HSBC's growth prospects improved. o Goldman Sachs raised 2002/03 EPS estimates for Northern Rock.
-	25/02/03	Rejected	Idios.	o Prudential, the UK's second-largest insurer, abandoned a decade-old pledge to raise its dividend as falling markets erode capital needed to write new business.	o Lloyds TSB Group rating was maintained by Merrill Lynch. o HBOS published annual results.

5 Results

The results are presented in three steps: first, institutions are analysed individually, then they are grouped into a life insurance index and a bank index, and finally the bank index is split into three subindices according to the proportion of life insurance assets held. In each case, chi-square ($\chi 2$) and *SCAR* statistics are used to provide a summary of the six events.

It is worthwhile to stress that both summary statistics are necessary complements for a correct interpretation of the results. The *SCAR* – by summing returns over the events to capture the *average* reaction – may cause two oppositely signed but significant reactions to cancel each other out.[13] The chi-square statistic avoids this problem by summing squared returns, but has the disadvantage of not distinguishing between positive and negative responses. The chi-square also differs from the *SCAR*, by testing whether *at least* one of the events is significant, rather than the *average* response across the events. The results for individual institutions are shown in Table C.

Table C: First step – Results by individual institutions[(a)]

Events	Standardised abnormal returns (*SARs*)[(a)]						Summary statistics	
	E1	E2	E3	E4	E5	E6	χ^2_6	*SCAR*
Life insurers	Sector-wide				Idiosyncratic		All events	All events
Aviva	-6.72**	-2.87**	-3.02**	-1.25	-0.02	-0.28	64.12**	-14.16**
Friends Provident	-0.51	-0.22	-0.78	-1.14	-5.49**	0.17	32.33**	-7.96**
Legal & General	-3.17**	-1.34	-0.59	-0.62	-0.92	-1.09	14.62*	-7.72**
Prudential	-2.34*	-0.01	-3.56**	-2.59**	-1.10	-0.39	26.23**	-9.98**
Royal & Sun Alliance	-2.32*	-0.77	-3.77**	-10.93**	-1.01	-3.62**	153.84**	-22.42**
Banks								
Abbey National	-1.50	-0.93	-2.01*	-0.91	-0.73	0.07	8.53	-6.02*
Alliance & Leicester	-1.51	-0.15	-0.76	-1.66	1.51	-0.44	8.12	-3.01
Barclays	-1.53	0.62	-1.75	-1.90	0.03	1.02	10.44	-3.51
Bradford & Bingley	-1.81	-1.21	-0.87	1.02	1.22	1.36	9.86	-0.29
HBOS	-2.2[(b)] *	-0.54	0.43	0.49	0.47	-0.13	5.58	-1.42
HSBC	0.87	2.88**	2.07*	-0.66	0.17	-0.58	14.13*	4.75
Lloyds TSB	-5.26**	0.93	-1.60	-3.65**	0.15	-0.17	44.52**	-11.47**
Northern Rock	-0.57	-1.60	-1.18	2.38*	0.12	-0.37	10.10	-1.22
RBS	-1.48	-0.25	-0.05	1.39	-0.05	-1.22	5.69	-1.65
Standard Chartered	-1.94	1.46	-0.98	-0.17	0.78	-1.02	8.57	-1.88

(a) *SARs* are reported for the day of the event.

(b) Reaction calculated net of the dilution of the right issue.

** Significant at the 99% level.

* Significant at the 95% level.

[13] At first glance, positive reactions to negative news might seem surprising but these reactions might be plausible were some institutions to gain competitive advantages from the news.

The first column lists all the institutions in the sample. Columns two to seven report the *SARs* for each event. The last two columns show the chi-square and *SCAR* summary statistics. Red-shaded and double-starred cells indicate a significant reaction to an event at the 99% confidence level, with orange-shaded and single-starred cells indicating significance at the 95% level.

Both summary statistics show that each of the five life insurance companies experienced a significant negative reaction to the six events as a whole. This confirms that the selected events had a significant impact on the life insurance sector, a pre-requisite for assessing spillover effects to the banking sector.

Observing the events individually, both idiosyncratic events only have a significant impact on the life insurer that the news originated from. Thus there appears to be no spillover effects to the rest of the life insurance sector from firm-specific idiosyncratic events. For sector-wide events, perhaps unsurprisingly, significant reactions appear for several insurers.

The banking sector had a more mixed reaction. Lloyds TSB shows the strongest response to the events, as evidenced by its chi-square and negative *SCAR*. Although HSBC has a marginally significant chi-square, its *SCAR* is not significant, implying a moderate and varied response to the events. According to the chi-square statistic, none of the remaining banks have been affected significantly. The *SCAR* statistic reinforces this point, with the exception of Abbey National. Abbey has a negative and significant *SCAR*, which indicates that the events were collectively significant.

Focusing on individual events (*SARs* in Table C), those defined as idiosyncratic showed no spillover to the banking sector. The sector-wide events did, however, prompt significant reactions from some banks. In a few cases – including the significant effects of HSBC – *SARs* are positive. This adds further uncertainty when trying to identify the overall impact of the events on the banking sector by using individual institutions' results.

The mixed signal coming from the banking sector can be clarified by undertaking the second step described in the methodology section. Table D, shows again the *SARs* across all six events and the summary statistics, but this time institutions have been aggregated into two portfolios representing the banking and life insurance sectors. In all sector indices in this paper we exclude the announcing firm in order to focus on the degree of spillover. The chi-square and *SCAR* statistics in the columns labelled 'All' summarise the overall impact of the six events and they have been decomposed to differentiate the impacts of sector-wide and idiosyncratic events (columns labelled 'Sector-wide' and

‘Idiosyncratic’). The F-statistic in the last column tests for a significant difference between the reactions to these two types of event. Both chi-square and *SCAR* summary statistics show that the life insurance sector reacted significantly to sector-wide events, while those events defined as idiosyncratic did not have a significant impact. The F-statistic demonstrates that this difference is significant at the 99% level.

Table D: Second step – results by sectors

Standardised abnormal returns (*SARs*)

	E1	**E2**	**E3**	**E4**	**E5**	**E6**
	Sector-wide				**Idiosyncratic**	
Banks	-2.1*	0.3	0.2	0.5	0.2	-1.2
Life Ins.	-5.9**	-1.4	-3.9**	-2.1*	-0.3	-0.3

Summary statistics

	χ_6^2	χ_4^2	χ_2^2	***SCAR***			$F_{4,2}$
	All events	**Sector-wide**	**Idiosyncratic**	**All events**	**Sector-wide**	**Idiosyncratic**	
Banks	6.4	4.9	1.5	-2.1	-1.2	-1	1.7
Life Ins.	55.2**	55.0**	0.2	-13.5**	-13.0**	-0.6	170.9**

(a) The red-shaded cells and double-starred values are significant at the 99% level. The orange-shaded cells and single-starred values are significant at the 95% level.

For the banking sector, both chi-square and *SCAR* summary statistics show that when the sector is viewed as a whole, there is no significant reaction to either the sector-wide or idiosyncratic events. As an initial conclusion, these results suggest that there is no clear evidence of contagion from the life insurance sector to the banking sector as a whole. However, while the response of the banking *sector* is not significant, Table C shows that some *individual* banks do display a significant response to the events. In particular Lloyds TSB and Abbey, the two banks with the largest proportion of life insurance assets (Table A in methodology section), showed significant negative *SCARs*.

The notion that banks with a higher proportion of holdings of life assets would react more significantly to the selected events than other banks appears to be a reasonable assumption. Thus a third step was taken to aggregate the banks according to the proportion of life assets held (Table E). The classification is best characterised as follows: ‘bancassurers’, which held the highest proportion of life assets; ‘mortgage banks’ with the lowest proportion; and ‘internationally active banks’ which fell inbetween the two extremes.

The bancassurers group reacted significantly to sector-wide events according to both summary statistics (Table E). There is thus evidence of a reaction from bancassurers’ equity prices to life insurance events, which lends support to the notion that there is a potential channel for spillover effects to the banking sector via ownership of life insurance assets.

Table E: Third step – Results according to the proportion of life assets[(a)]

Standardised abnormal returns (*SARs*)

	E1	E2	E3	E4	E5	E6
	Sector-wide				Idiosyncratic	
Internat.	-1.4	0.5	0.5	1	0.1	-1.2
Mortgage	-1.5	-0.8	-1.2	-0.3	1.3	-0.6
Bancass.	-4.0**	-1	-1.2	-1.4	0.5	-0.1
Life Ins.	-5.9**	-1.4	-3.9**	-2.1*	-0.3	-0.3

Summary Statistics

	χ_6^2	χ_4^2	χ_2^2	*SCAR*			$F_{4,2}$
	All events	Sector-wide	Idiosyncratic	All events	Sector-wide	Idiosyncratic	
Internat.	4.9	3.4	1.5	-0.6	0.6	-1.1	1.1
Mortgage	6.3	4.3	2	-3.1	-3.8	0.7	1.1
Bancass.	20.8**	20.5**	0.3	-7.3**	-7.6**	0.3	40.1*
Life Ins.	55.2**	55.0**	0.2	-13.5**	-13.0**	-0.6	170.9**

(a) The red-shaded cells and double-starred values are significant at the 99% level. The orange-shaded cells and single-starred values are significant at the 95% level.

There is no significant evidence that either the international or the mortgage banks' equity prices reacted to the events. This is thus consistent with the prior hypothesis that banks with lower proportions of life assets are less likely to be affected by the life insurance sector.

6 Sensitivity and robustness analysis

This section is divided into three parts. First, we introduce the use of trading volumes to detect any significant reaction not captured by equity prices. Second, we test the robustness of our conclusion that there is a significant link between a bank's proportion of life assets, and its reaction to events in the life insurance sector. Finally, we assess the extent to which Event 1 drives our results.

6.1 Trading volumes

The use of equity prices in event studies is generally characterised by a hidden assumption: there exists a broad consensus across market participants about how the news should be interpreted. Such an assumption is necessary when equity prices are used, a mixture of positive and negative reactions cannot be fully reflected. For example, a profits warning from a firm can have a positive or negative effect on the share prices of its competitors depending on whether market participants believe it to be a shock specific to the firm or to the whole sector. If the market is equally divided in two groups that give opposite interpretations to the event, the observed change in the share price will suggest a muted non-significant reaction while a graphical representation of the true market expectations would show a bimodal distribution.

In order to avoid any misleading conclusions, and to test the robustness of our results, we supplement our analysis of equity price returns with that of trading volumes. The intuition is that although opposite interpretations can offset each other, leading to non-significant changes in equity prices, they are likely to result in an overall increase in trading volumes. We use the following simple model to filter out market-wide movements:

$$TV_{i;t} = a_i + b_i TV_{m;t} + \varepsilon_{i;t} \qquad \textbf{(9)}$$

$$E(\varepsilon_{i;t}) = 0 \qquad Var(\varepsilon_{i;t}) = \sigma^2_{\varepsilon_{i;t}}$$

where $TV_{i;t}$ and $TV_{m;t}$ are the period-t change in trading volumes for institution i and the market index respectively, and $\varepsilon_{i;t}$ is the zero mean disturbance term. We use the FTSE 100 as broad index as the FTSE All-Share's trading volumes are more difficult to obtain. As for abnormal trading volumes, the parameters are estimated for each institution over a period of 250 trading days – the estimation window – of daily movements beginning 270 days before the event. For each institution i and event day-t, equation **(10)** is used to calculate abnormal trading volumes ($ATV_{i;t}$) and to remove market-wide changes:

$$ATV_{i;t} = TV_{i;t} - \hat{a}_i - \hat{b}_i TV_{m;t} \qquad \textbf{(10)}$$

We then compared abnormal returns with abnormal trading volumes (Table F, Panel I and Panel II respectively). The overall reactions in the two panels of the four indexes to the six events and to the sector-wide events appear very consistent. The main difference between *ARs* and *ATVs* is the idiosyncratic events columns for the life insurance sector. A possible explanation is that there was more uncertainty among market participants about the impact of idiosyncratic events on non-announcing life insurers. It is also worth noting the significant change in trading volumes for mortgage banks in the chi-square column for idiosyncratic events. However, this is only due to a sharp increase in Alliance and Leicester's trading volumes on the day of Event 5, as confirmed by the non-significant *SCAR* for idiosyncratic events.[14] Overall, the analysis of trading volumes confirms the conclusions of the previous section.

Table F: Abnormal returns and abnormal trading volumes[a]

Panel I: Abnormal equity returns

	χ_6^2	χ_4^2	χ_2^2	***SCAR***		
	All events	**Sector-wide**	**Idiosyncratic**	**All events**	**Sector-wide**	**Idiosyncratic**
Internat.	4.9	3.4	1.5	-0.6	0.6	-1.2
Mortgage	6.3	4.3	2	-3.1	-3.8	0.7
Bancass.	20.8**	20.5**	0.3	-7.3**	-7.6**	0.4
Life Ins.	56.7**	55.0**	0.1	-13.9**	-13.0**	-0.6

Panel II: Abnormal trading volumes

	χ_6^2	χ_4^2	χ_2^2	***SCAR***		
	All events	**Sector-wide**	**Idiosyncratic**	**All events**	**Sector-wide**	**Idiosyncratic**
Internat.	4.9	2.6	0.8	0.4	1.6	-1.2
Mortgage	6.3	2.3	11.9**	3	0.3	2.7
Bancass.	46.9**	46.0**	0.9	7.8**	8.9**	-1.1
Life Ins.	55.1**	10.6*	16.8**	10.2**	5.4**	4.7**

(a) The red-shaded cells and double-starred values are significant at the 99% level. The orange-shaded cells and single-starred values are significant at the 95% level.

6.2 A panel data approach

The portfolio approach taken in the third step in the results section revealed that the bancassurance group reacted more significantly to the selected events than the other two banking groups. Hence, an assertion was made that this revealed a link between an institution's proportion of life assets and its reaction to events in the life insurance sector. In order to test such assertion, we follow Brewer and Jackson (2002) by using a panel data approach.

Our sample (ten banks for six events) is more restricted than that of Brewer and Jackson (139 banks for three events). Second and perhaps even more important, our key explanatory variable, the proportion of life assets over total assets, is characterised by a very low variability as we can observe holdings of life assets only at annual frequency and our six events occur in a two-year period. The implication is that for half of the banks in our sample the ratio is constant (Table A).

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[14] Investors may have heavily traded Alliance & Leicester's share in a response to a bond issued by the bank on the day of Event 5. All other changes in trading volumes for Alliance & Leicester and the other mortgage banks are not significant.

Given the above limitations, our preferred method for estimating the unobserved effect in our panel data set is the random effects (RE) estimator as it has the advantage over fixed effects (FE) estimator or first differencing of allowing explanatory variables that are constant over time (Arellano (2003)). RE has also the advantage of 'consuming' fewer degrees of freedom than FE. We then use the Hausman test (1978) to assess whether there is correlation between the unobserved effect and the explanatory variables. The proposed model is as follows:

$$AR_{i;t} = \alpha_i + \sum_{j=1}^{5} \delta_j e_j + \beta Ratio_{i;t} + v_{i;t} \qquad \textbf{(11)}$$

where $v_{i;t} = a_i + u_{i;t}$ and a_i is the unobserved effect. The dummy variable for event *i* denoted by $e_{i,}$ and the proportion of life assets that bank *i* holds at time *t* is denoted by $Ratio_{i;t}$. Table A1 in the appendix provides estimates of the coefficients of equation **(12)**. The coefficients of *Ratio* is negative and significant (p-value 0.003) indicating that a larger holding of life assets tends to lead to larger negative returns. The Hausman specification test (Table A2), does not reject that initial hypothesis that the unobserved effects are adequately modelled by a RE model (p-value is 0.63). Therefore, these results confirm that the importance of interlinkages from the life insurers to banks depends on the proportion of life assets over total assets held by banks.

6.3 Excluding the dominant event

As shown in the results section, Event 1 caused a larger reaction in bancassurers' equity prices than the other events. The above panel data model can be used to test whether the impact of Event 1 is statistically different from those of the other events (Table A1 in the appendix). The dummy variable for the first event is negative and the only one to be significant (p-value 0.004); confirming that the Event 1 did have a larger impact than the other events.

As before, the reactions of the life insurers are significant at the 99% level, but there is less evidence of a significant reaction from the bancassurance sector. After removing the first event, the bancassurers now have non-significant chi-square statistics for the sector-wide events. The chi-square statistic has a null hypothesis that at least one event is significant, which is consistent with the removal of the event with the largest effect. The sector-wide *SCAR* statistic, on the other hand, is still significant. Given that the *SCAR* detects significance in the average response to the events, it picks up the generally weaker but consistently negative reactions of the bancassurance sector. So even after the removal of the relatively dominant effect, there is still evidence of spillover to the bancassurance sector from the other events too.

Table G: Third step excluding Event 1 – Results according to the proportion of life assets [(a)]

	χ^2_5	χ^2_3	χ^2_2	*SCAR*		
	All events	**Sector-wide**	**Idiosyncratic**	**All events**	**Sector-wide**	**Idiosyncratic**
Internat.	3.0	1.5	1.5	0.8	1.9	-1.1
Mortgage	4.2	2.2	2.0	-1.6	-2.3	0.7
Bancassurers	4.6	4.3	0.3	-3.2	-3.6*	0.3
Life Insurers	20.3**	20.1**	0.2	-7.6**	-7.0**	-0.6

(a) The red-shaded cells and double-starred values are significant at the 99% level. The orange-shaded cells and single-starred values are significant at the 95% level.

7 Conclusions

This paper employs an event study approach to assess the significance of spillover effects from the UK life insurance sector to the UK banking system in times of stress. During the 2001-03 period of global equity market decline, several life insurers were exposed to adverse conditions. This provides a period of materially important events for the life insurance sector, which are used in the event study to reveal interlinkages between institutions using equity prices.

The event study method has the benefit of being able to detect contagion from the full range of interlinkages. The same cannot, however, be said about balance sheet data, which tend to reveal only counterparty exposures. Hence, the event study provides a powerful tool that can be applied to any event, and used to extract the corresponding systemic part of an equity price reaction, helping uncover evidence of interlinkages. The paper employs a thorough methodology that adjusts for autocorrelation and heteroskedasticity in the forecast error and for offsetting effects in cumulative abnormal return. It also introduces the use of trading volumes to detect any significant reaction not captured by equity prices.

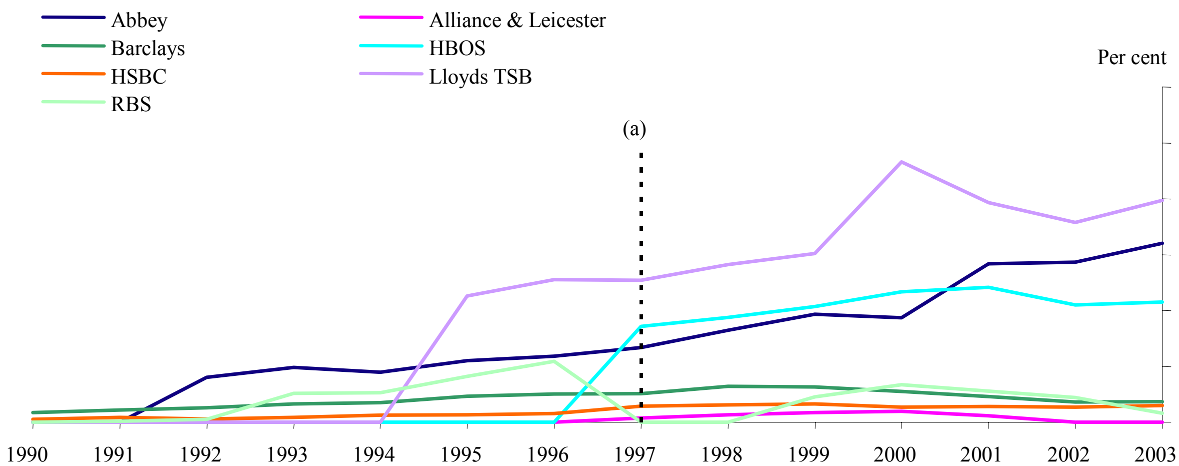
The results show that, when the events are considered collectively, each insurer experienced a significant reaction. Of these events, neither of the idiosyncratic disturbances spilled over to the UK banking sector as a whole. However, there is evidence that elements within the banking sector responded to the sector-wide events, but these reactions are not uniformly pervasive. On closer inspection of the banking sector, the results show that the bancassurers were the only group in which equity prices were significantly affected by disruptions in the UK life insurance sector. These results suggest that spillover to the banking sector came through ownership, while the links through capital markets and effects on confidence were not materially significant during the events considered.

The event study is only useful when applied to events that have the potential to reveal evidence of interlinkages. Therefore, a rigorous set of criteria was used to select the most appropriate events for analysis. Furthermore, the study had to be based on a recent period, as changes in banks' business models, as well as structural changes to the economy, can alter the magnitude and nature of interlinkages over time. Consequently we were able to select only six events. Given that relatively small sample, caution should be exercised when drawing conclusions from the results. Further research could investigate whether the results presented in this paper can be replicated for different countries.

Appendix

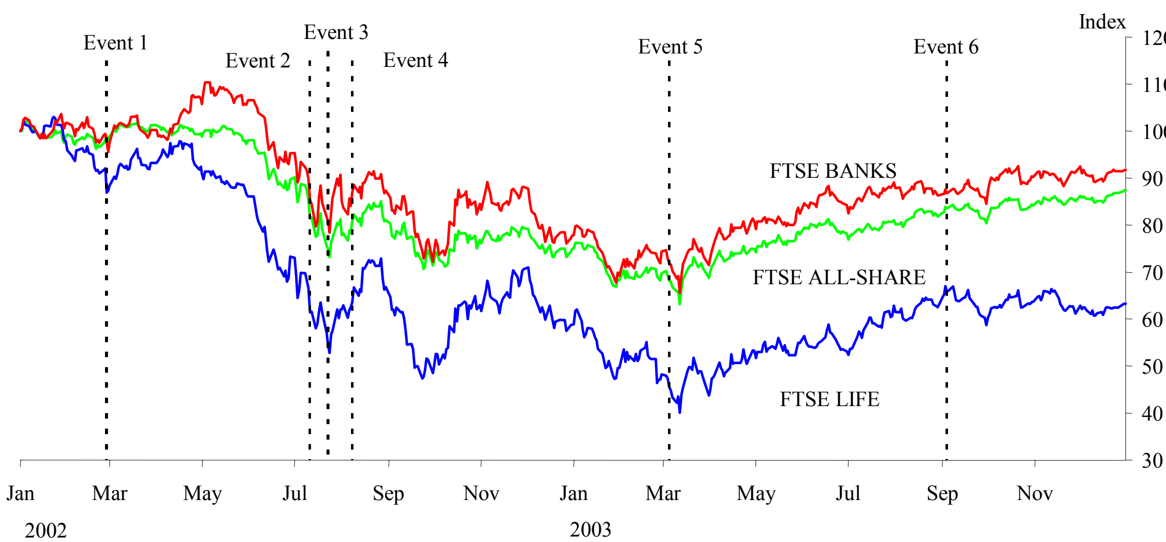
Chart A1 shows the increased involvement of Lloyds TSB, Abbey and HBOS in the life insurance market in the second half of the 1990s and early 2000s.

Chart A1: Major UK-owned banks' life insurance assets as a proportion of total assets(a)



Sources: Published accounts.
(a) Prior to 1997, life insurance data are taken from Standard & Poor's SynThesys, and total asset data are taken from Datastream. Bradford & Bingley, Northern Rock and Standard & Chartered always reported no material holdings of life insurance assets.

Chart A2: FTSE All-Share, FTSE bank and FTSE life insurance indices



Source: Thomson Financial Datastream.

Our preferred method for estimating the unobserved effect in our panel data set is the random effects estimator:

$$AR_{i;t} = \alpha_i + \sum_{j=1}^{5} \delta_j e_j + \beta Ratio_{i;t} + v_{i;t}$$

where $v_{i;t} = a_i + u_{i;t}$ and a_i is the unobserved effect. The dummy variable for event *i* denoted by e_i, and the proportion of life assets that bank *i* holds at time *t* is denoted by $Ratio_{i;t}$.

Table A1: Panel data approach – random effect estimator

R-sq: within = 0.303				Number of obs =		60
between = 0.595				Number of groups =		10
overall = 0.3612				Obs per group: min =		6
				avg =		6
Random effects u_i ~ Gaussian				max =		6
corr(u_i, X) = 0 (assumed)				Wald chi2(6) =		29.96
				Prob > chi2 =		0
ar0	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
ratio	-0.1002651	0.033197	-3.02	0.003	-0.16533	-0.0352002
e1	-2.226357	0.7700835	-2.89	0.004	-3.735692	-0.7170207
e2	0.2602098	0.7700835	0.34	0.735	-1.249126	1.769546
e3	-0.6657437	0.7700835	-0.86	0.387	-2.17508	0.8435922
e4	0.9956105	0.770133	1.29	0.196	-0.5138224	2.505043
e5	0.3186146	0.770133	0.41	0.679	-1.190818	1.828048
_cons	0.0381163	0.5674736	0.07	0.946	-1.074111	1.150344
sigma_u	0					
sigma_e	1.6847473					
rho	0	(fraction of variance due to u_i)				
F test that all u_i=0:	F(9, 44) = 1.26			Prob > F = 0.2837		

The Hausman test assesses whether there is correlation between the unobserved effect (a_i) and the explanatory variables.

Table A2: Hausman specification test

	Coefficients			
	(b)	(B)	(b)-(B)	sqrt(diag(V_b-V_B))
ar0	fixed	.	Difference	S.E.
ratio	0.9608795	-0.1002651	1.061145	0.5093196
e1	-2.226357	-2.226357	1.78E-15	.
e2	0.2602098	0.2602098	1.17E-15	.
e3	-0.6657437	-0.6657437	7.77E-16	.
e4	0.7164323	0.9956105	-0.2791782	.
e5	0.0394363	0.3186146	-0.2791782	.

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 4.34
Prob>chi2 = 0.6307

(V_b-V_B is not positive definite)

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