SCHOOL OF ECONOMICS AND MANAGEMENT
Lund University

MASTER-ESSAY

Volatility and Contagion effects originating from the financial sector: An analysis of economic sectors in two different stock market downturns

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Seminar date: May 26, 2009

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Abstract

The essay applies the methodology put forward in Baur (2003) with some modifications and extensions in order to investigate on contagion and spillover effects originating from the financial sector in European and U.S. equity markets during the crisis following the "dot-com" bubble in 2000-2003 and the financial crisis of 2007-2009. A clear distinction between spillover and contagion effects is drawn and the first as well as the second moment is investigated. An EGARCH approach including a parameter to capture the leverage effect is applied to model the conditional variance.

Mean contagion is found to be negative in the U.S. and mostly positive in Europe during the financial crisis which does not provide convincing evidence for the contagion hypothesis, rather the opposite. The more central role the financial sector plays during the financial crisis is clearly reflected in terms of positive volatility contagion in most non-financial sectors. We can conclude that the turbulences in the financial sector encroached partly upon non-financial sectors expressed through positive volatility contagion. Volatility contagion is consistently significant and positive in both the U.S. and Europe for the technology, industrials, and health care sector. However, the approach taken appears not suitable to clearly distinguish between supply-side and demand-side effects.

Keywords: Spillover; Contagion; EGARCH; financial crisis; financial sector; equity markets.

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Introduction

Financial institutions are heavily under pressure from both a moral and financial point of view. The current crisis takes a huge toll on banks around the globe and many of the biggest global institutions struggle for survival and some would arguably be out of business without government assistance. It is quite common that banks suffer from losses during recessions as their clients' ability to fulfill obligations decreases. An additional aspect of the current crisis is that many blame the financial sector for having triggered the crisis with their reckless lending and lenient risk management. Much attention has recently been paid to financial institutions and their role in the current recession. Not only popular sentiment identifies them as the ones being at least partly responsible for the sharp downturn, also scholarly research has aimed at investigating on their conduct or possible misconduct. Honohan (2008, p. 1) blames the "overconfidence on the part of bankers and regulators in mechanical risk management models" for the failure of banks. The Chairman of the Federal Reserve, Ben Bernanke, acknowledges that a lack of appropriate supervision contributed to the extensive risk exposure of banks (Bernanke, 2008). The concept of systemic risk in context with financial institutions is fairly well developed. It describes the constant underlying threat of a collective bank collapse and derives the need for special treatment of the financial sector, banks in particular.[1] The mentioned developments would already justify a closer look at the impact of the financial sector on the rest of the economy, but a more comprehensive motivation for the contagion hypothesis will be put forward.

The following section is mainly based on the ideas of Hyman Minsky. Minsky is classified as a post-Keynesian economist that implies his ideas are based on the Keynesian view that the economy is not tending toward equilibrium endogenously (Whalen, 2008, p. 95f.). He applies those ideas specifically to financial markets and focuses on financial institutions and credit. The theory labeled as "financial instability theory" in Minsky (1992) regards financial institutions as profit-seeking units and not as simple mediators of the credit and savings process. As a result banks find ways to increase their earning potentials similar to any other economic actor in a capitalist economy. Such innovation leads to a deterioration of credit quality, in particular during prosperous times. It can be distinguished between three types of income-debt relations: hedge finance, speculative finance, and Ponzi finance. Hedge finance implies that all obligations, that is to say principal and interest, can be fulfilled with current

[1] See Kaufman and Scott (2005) for a recent reiteration of the subject.

cash flows. Creditors categorized as speculatively financed are able to pay interest with their generated cash flows, not the principal which has to be re-financed. Ponzi financed units are neither able to service their interest payments nor can they pay the principal out of their current cash flow. They finance payments either through additional credit or equity sales.

As financial institutions are profit seeking they find increasingly innovative ways to move the economy towards a higher ratio of speculative and Ponzi finance. Particularly in times of flourishing economic growth, credit policies of banks become increasingly lenient and promote such development. Minsky (1992, p. 9) proposes that a monetary contraction policy of the central bank to fight inflation causes a sudden shift and makes the liquidation of assets necessary. If a high proportion of the economy is financed by speculative and Ponzi credit many actors have to liquidate assets at the same time and cause a collapse of asset prices. The idea that the collapse of the system is caused by monetary policy contradicts the proposition that the crisis is created endogenously. It is, however, not difficult to imagine alternative triggering scenarios such as a sudden sentiment shift at equity markets or a default of a big, Ponzi financed unit. In a rather popular scientific work of Cooper (2008) those ideas are applied more specifically to the current crisis. Asymmetric monetary policy reacting only to negative shocks with an easing of monetary policy and not constraining in non-crisis periods is singled out to be the main driver of the crisis.

If the theory holds, it puts financial institutions in the center of interest. It explains how economic contractions could be caused by developments within the financial sector, somewhat independent of government interventions and the state of the non-financial sector. It is, of course, dangerous to use the word independent in that context. Government intervention, in particular monetary policy, can both prevent and support such developments while the rest of the economy profits from increasing asset prices and availability of credit. A possible scenario taking those considerations into account, is that the downturn originated in the financial sector and encroached upon other sectors. However, this does not necessarily have to be the case even if the theory holds. It is very well imaginable that a liquidity crisis could force non-financial firms to liquidate assets and drive them out of business first. This would mean banks would have securitized their loans sufficiently and this does not seem to reflect realities in the current crisis. It will require therefore a quite complex framework to empirically test the financial instability hypothesis as a whole and this is not the goal of this essay. This paper confines itself to investigating on potential contagion and spillover effects originating from the financial sector.

The main hypothesis of this essay proposes that the financial sector is in the epicenter of the market downturn in the period between mid 2007 and early 2009 and consequently infected other sectors in terms of mean and volatility contagion. In addition, it is of interest whether contagion effects differ across sectors. Theoretically, two main factors could explain differences in spillover and contagion effects from the financial sector (see e.g. Tong and Wei, 2008). On the one hand, non-financial firms may suffer from reduced demand caused by decreased consumer confidence and less availability of credit for consumption needs. Sectors that are particularly vulnerable if those effects are present are consumer goods and consumer services. On the other hand, firms may face increasing difficulties to gain access to funding. Such a supply-side effect would in particular affect highly leveraged companies with continuing finance needs. It requires a thorough analysis of debt and equity structures of the respective sectors and no previous research exactly matching the sectoral division chosen in this essay could be retrieved.[2] This essay will not investigate on the micro-level of firms and will focus on the development in the different sector equity markets rather than draw conclusions from balance sheets.

To put the hypothesis to a test the paper analyzes two different stock market crises: The market downturn following the so called "dot-com bubble" in 2000-2003 and the current financial crisis starting in mid 2007. The prior interest is put on the downturn of 2007-2009 and the bear market of 2000-2003 is included to compare results. The aim of this paper is to test whether there are contagion and spillover effects originating from the financial sector and whether they differ across different economic sectors. Important implications for economic policy can be derived from such analysis. It gives indications for the necessity of appropriate regulation and supervision of the financial sector. Furthermore, in case some non-financial sectors are found to be more sensitive to contagion from the financial sector, policy makers gain information on where to allocate scarce resources to mitigate effects from a credit crisis. Both the first and the second moment of equity returns are investigated and the data cover daily observations of two distinct periods from U.S. and European equity sub-indices.

The principal econometric approach is taken from Baur (2003) with some modifications and extensions. Similar research so far has mostly focused on interdependencies in an international framework, that is to say investigated on contagion and spillovers between

[2] See e.g. Fan et al. (2004) for an international comparison encompassing leverage ratios and long-term debt ratios. They focus, however, on policy factors such as taxation and institutional framework to identify potential differences in the finance structure.

different countries. It is straightforward to apply similar methodology to a sectoral contagion analysis. For both moments shocks originating from the financial sector are incorporated directly into our econometric model. We include two different specifications of the conditional volatility in the financial sector into a regular EGARCH model of every individual non-financial sector in order to test for significant volatility spillover and contagion effects. In the first specification the squared returns of the financial sector are used as a variance proxy. As an alternative approach we obtain the conditional volatility in the financial sector with a separate EGARCH estimation.

We can show that mean contagion is mostly positive in the "dot-com" bear market of 2000-2003 for both Europe and the U.S., whereas there is relatively little evidence for volatility contagion. The current financial crisis reveals more evidence for volatility contagion in both markets. The most striking difference is that mean contagion effects are negative in the U.S. market, while they are positive in Europe and more similar to the results of the first period. Overall, the hypothesis cannot be accepted unconditionally but for a majority of sectors supporting evidence can be found. The financial sector plays a more important role in the current financial crisis than in the "dot-com" downturn. We conclude that the turbulences in the U.S. financial sector do not encroach fully upon other sectors what is indicated by the negative mean contagion effects. The turbulences do, however, at least partly increase volatility in other sectors reflecting rising uncertainty. The differences in contagion across sectors do not allow clear conclusions whether supply-side or demand-side effects prevail and show that our approach is not suitable for such distinction.

The remainder of the paper is structured as the following: Section 1 gives a short overview of relevant literature on contagion and spillover analysis. Section 2 describes the analyzed data set and section 3 develops the applied empirical models. Section 4 presents the results of the empirical analysis for both the U.S. and Europe. The essay ends with an overview of the main findings and conclusions.

1. Previous literature on spillover and contagion analysis

A plethora of empirical research has been undertaken to investigate on potential contagion and spillover effects of various markets. A comprehensive overview of methodology is given by Dungey et al. (2004) and this section refers to some of the literature outlined in their work. There are a number of crucial choices involved when performing an analysis of spillover and contagion effects. The following chapter provides a selection of prior research relevant for the empirical investigations in this essay and clarifies certain terminological issues that are not consistent across the literature.

Regardless of the choice whether to investigate on the first or the second moment of market movements, it is crucial to precisely define the terms spillover and contagion. Forbes and Rigobon (2002, p. 2223) define contagion as "a significant increase in cross-market linkages after a shock". With this definition it can be distinguished between spillover and contagion effects. Interdependences of markets, which can be caused by common factors being present in both non-crisis and crisis times, lead to spillover effects. Such spillover effects could be for example expressed with simple correlation coefficients. The isolated effect of the crisis, possibly originating in one market, leads to contagion that is potentially different from regular spillover. An intuitive way to express contagion is as an increase in correlation between markets. This notion of spillover and contagion shall serve as the definition also applied in this essay.

Directly using correlation measurements can be problematic and Forbes and Rigobon (2002) show that estimates of market cross-correlations are biased in case of heteroskedastic error terms.[3] Typically, crisis periods are characterized by increasing volatility and in that case cross-correlation estimates are upward biased and hence if we test for a significant difference between crisis and non-crisis periods we tend to falsely accept this hypothesis. Although it could be adjusted for the bias, Baur (2003, p. 410) argues that the correlation coefficient is not suitable for measuring contagion effects as it is a symmetric measure whereas contagion originates in one market and is thus a non-symmetric phenomenon. Consequently, a modeling approach that incorporates the shocks directly is proposed. Dungey and Zhumabekova (2001) demonstrate that the correlation coefficient is inappropriate in case the crisis period is small in comparison to the non-crisis period.

[3] See appendix 3 for an overview of correlation with the financial sector.

It is an essential consideration whether to determine the crisis periods exogenously or implement the model in a way that determines them exogenously. In our paper the crisis periods are explicitly determined a priori and hence established exogenously.[4] Favero and Giavazzi (2002) apply a method allowing to determine the crisis by the magnitude of the shocks and define a crisis period as a point in time where shocks exceed a certain size that depends on the size of the shocks relative to the conditional variance. They initially estimate a vector autoregression (VAR) model to obtain residuals and control for interdependences. This method is suitable for investigating contagion effects between markets in general, but will most certainly not allow obtaining a connected crisis period as not all shocks will be big enough during an uninterrupted period. Other researchers investigate on contagion by defining a certain threshold return as a crisis indicator and apply a Probit/Logit approach to identify contagion effects in terms of overlapping of returns exceeding the threshold return. Examples of this approach with some differing features are proposed in Baur and Schulze (2005) and Bae et al. (2003). This has again the advantage of determining the crisis periods endogenously after establishing a certain criteria, but is not a good fit for the analyzed question. Edwards and Susmel (2000) investigate weekly interest rates in three South-American countries aiming to demonstrate volatility contagion. They apply a regime switching SWARCH model that allows determining breakpoints endogenously. They can identify periods of contagion lasting between two and seven weeks.

Investigating volatility contagion in three different financial crises, Jaque (2004) applies a T-GARCH approach for modeling time varying sovereign bond spreads of individual countries. In order to test for contagion effects the estimated conditional variance of the originator is included in the equation of the conditional variance of the potentially infected country and tested for significance. This approach does not treat the problem of endogeneity, that is to say the included estimates of the conditional variance of the originating country are simply assumed to be exogenous. This essay will partly adapt this concept and combine it with the approach in Baur (2003).

Taking those findings into account our approach for modeling spillover and contagion effects is mainly based on Baur (2003). Similar to Jaque (2004), the model assumes exogeneity of the shocks of the potentially contagious sector. Baur (2003, p. 411) postulates this as a rather

[4] Although this might seem like a sub-optimal choice, this essay aims at investigating the periods established a priori. This procedure holds the risk that if the investigated effects are present but the crisis periods are chosen incorrectly the opportunity to detect those is foregone.

weak assumption; however, it must be seen as a weakness of this approach. A main advantage of the model is that it allows testing for contagion effects in the first and second moment. In addition, it allows for a clear distinction between spillover and contagion effects. The empirical models are described in detail in chapter 3.

The research of Tong and Wei (2008) is the only scientific work that could be found covering a topic similar to our analysis. They investigate on non-financial firms and test to which extent the credit crunch spills over as a demand-side and supply-side effect. Through constructing a financial constraint and demand sensitivity index they attempt to explain stock returns. Both variables are found to be significant while the supply-side effect has a stronger impact. Contrasting our analysis, shocks are not incorporated directly and there is no sectoral division. The methodology is more suitable to distinguish directly between supply-side and demand-side effects, in particular if economic sectors are not homogeneous in those variables, which seems quite likely in particular for the financial constraint index.

2. The Data

The data comprise two different periods of daily sector returns of European and U.S. equity markets. The data are retrieved from the Datastream dataset and for Europe the DJ STOXX economic sub-index series is used and for the U.S. the FTSE NASDAQ sub-indices are used.[5] The two periods range from 01/01/1998 to 03/11/2003 (hereafter referred to as period one) and 01/03/2005 to 03/12/2009 (hereafter referred to as period two). Period one consists of 1364 observations and period two of 1095 observations. Both periods are divided in a non-crisis and a crisis period. The determination of the breakpoints is discussed in section 3. Returns are obtained taking the logarithmic difference of daily observations. The economic sectors represented by the sub-indices are basic materials, consumer goods, consumer services, health care, industrials, oil & gas, technology, utilities, telecommunication, and financials. The software package E-views is used to obtain empirical estimates.

Table 1:
Descriptive statistics, U.S.
Logarithmic returns

	Basic Materials	*Consumer Goods*	*Consumer Services*	*Health Care*	*Indus-Trials*	*Oil & Gas*	*Tele-com.*	*Finan-cials*	*Utili-ties*	*Tech-nology*
Period 1										
Non-Crisis										
Mean	0,00029	-0,00036	0,00060	0,00003	0,00026	0,00047	0,00032	0,00037	0,00042	0,00156
Std. Dev.	0,01629	0,01508	0,01343	0,01424	0,01343	0,01410	0,01430	0,01752	0,01044	0,02174
Crisis										
Mean	-0,00036	0,00014	-0,00079	-0,00052	-0,00026	-0,00053	-0,00133	-0,00039	-0,00109	-0,00183
Std. Dev.	0,01597	0,01845	0,01862	0,01761	0,01174	0,01793	0,01860	0,01672	0,01709	0,02984
Period 2										
Non-Crisis										
Mean	0,00101	0,00049	0,00038	0,00001	0,00032	0,00024	0,00065	0,00035	0,00066	0,00032
Std. Dev.	0,01408	0,01036	0,00709	0,00731	0,00599	0,00702	0,00771	0,00698	0,00791	0,00881
Crisis										
Mean	-0,00092	-0,00154	-0,00179	-0,00097	-0,00091	-0,00137	-0,00146	-0,00295	-0,00132	-0,00111
Std. Dev.	0,02995	0,02980	0,02174	0,01552	0,01652	0,02052	0,02327	0,03687	0,02030	0,02240

[5] It was not possible to retrieve the corresponding data from the same index series for the desired period. The sectoral division of both providers is the same and can be easily compared. The specific datastream codes are listed in appendix 1 and appendix 2.

Table 1 displays the mean and standard deviation of the crisis and non-crisis periods in the U.S. In period one the technology sector outperformes all other sectors in the non-crisis period and subsequently declines the most in the crisis period. Average volatility levels are higher in the crisis period for all sectors except financials which gives an early indication that the hypothesis is unlikely to be confirmed in the first period. In period two average volatility levels are higher for all sectors during the crisis. The financial sector declines by far the most and average volatility levels are the highest of all sectors.

Table 2:
Descriptive statistics, Europe
Logarithmic returns

	Basic Materials	*Consumer Goods*	*Consumer Services*	*Health Care*	*Indus-trials*	*Oil & Gas*	*Tele-com.*	*Finan-cials*	*Utili-ties*	*Tech-nology*
Period 1										
Non-										
Mean	0,00062	0,00036	0,00068	0,00035	0,00054	0,00047	0,00129	0,00039	0,00059	0,00181
Std. Dev.	0,01578	0,01199	0,01120	0,01176	0,01342	0,01200	0,01972	0,00983	0,01426	0,02267
Crisis										
Mean	-0,00069	-0,00044	-0,00129	-0,00051	-0,00083	-0,00131	-0,00156	-0,00076	-0,00104	-0,00255
Std. Dev.	0,01853	0,01512	0,01396	0,01277	0,01525	0,01581	0,02461	0,01263	0,01882	0,03338
Period 2										
Non-										
Mean	0,00053	0,00122	0,00109	0,00082	0,00044	0,00061	0,00030	0,00102	0,00070	0,00045
Std. Dev.	0,01002	0,01138	0,00880	0,00674	0,00691	0,00654	0,00867	0,00787	0,00800	0,01060
Crisis										
Mean	-0,00116	-0,00166	-0,00190	-0,00126	-0,00102	-0,00175	-0,00109	-0,00148	-0,00319	-0,00176
Std. Dev.	0,02438	0,02906	0,02298	0,01678	0,01480	0,01836	0,01863	0,01981	0,02790	0,02292

The statistics in table 2 show the same descriptive analysis for Europe. In period one, parallel to the U.S., the technology sector initially outperformes all sectors and declined with the fastest pace during the crisis. Volatility levels are slightly higher in all sectors during the crisis period. The financial sector has the lowest average volatility levels during both the non-crisis and the crisis period. This is again no sign that the hypothesis could hold for the first period. As a clear contrast to the U.S. market, the financial sector has neither strikingly high volatility levels in period two nor does it underperform as significantly during the crisis. The weakest performance is reported in the utility sector during the crisis and the highest volatility levels are found in the consumer goods sector.

3. Empirical models

This section presents the models applied in the empirical analysis. A discussion of the breakpoint determination follows. The empirical approach is mainly based on Baur (2003) and his notation is partly retained as well. Spillover and contagion effects are obtained with a single estimation using Quasi Maximum Likelihood (QML). The robust standard errors proposed by Bollerslev and Wooldrigde (1992) are computed. The mean equation is fundamentally the same for all estimations with the exception of an additional dummy variable for the second period. Using Augmented Dickey-Fuller (ADF) tests the unit root hypothesis can be rejected convincingly for all sectors and periods, which is not surprising as returns are used and there is little evidence that equity prices are integrated of order two.

The mean equation applied for the first period denotes as

$$R_{2t} = \mu_2 + \beta R_{2,t-1} + b_1 r_{F,t} + b_2 r_{F,t} D_{Crisis} + u_{2t} \tag{1}$$

where R_{2t} denotes the return of the potentially infected, non-financial sector at time t and μ_2 the mean return of that sector. $r_{F,t}$ is the return of the financial sector at time t and D_{Crisis} is a dummy variable being one in the crisis period and zero otherwise. For the second period the model includes an additional dummy variable and looks as follows

$$R_{2t} = \mu_2 + \beta R_{2,t-1} + b_1 r_{F,t} + b_2 r_{F,t} D_{Crisis(1)} + b_3 r_{F,t} D_{Crisis(2)} + u_{2t} \tag{2}$$

the only difference to equation (1) is the additional dummy variable sub-dividing the crisis period. $D_{Crisis(1)}$ is one for the first part of the crisis period and zero otherwise and $D_{Crisis(2)}$ is one for the second part of the crisis and zero otherwise.

In order to model the conditional variance the error term u_{2t} can be decomposed further

$$u_{2t} = z_{2t} \sigma_{2t} \tag{3}$$

where z_{2t} is normally distributed with mean zero and variance one and σ_{2t} is the conditional volatility of R_{2t} denoting as the following

$$\log(\sigma_{2t}^2) = c + \theta \log(\sigma_{2,t-1}^2) + \alpha \left| \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} \right| + \gamma \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} + d_1 r_{F,t-1}^2 + d_2 r_{F,t-1}^2 D_{Crisis} + \upsilon_{2t} \tag{4}$$

solving for σ_{2t}^2 yields

$$\sigma_{2t}^2 = \exp(c + \theta \log(\sigma_{2,t-1}^2) + \alpha \left| \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} \right| + \gamma \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} + d_1 r_{F,t-1}^2 + d_2 r_{F,t-1}^2 D_{Crisis} + \upsilon_{2t}) \tag{5}$$

where c expresses a constant term, $\varepsilon_{2,t-1}$ the past shocks, and $r_{F,t-1}^2$ serves as a proxy for the shocks originating from the financial sector. Analogous to the specification of the mean equation an additional dummy is included for the second period and the equation looks as follows

$$\sigma_{2t}^2 = \exp(c + \theta \log(\sigma_{2,t-1}^2) + \alpha \left| \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} \right| + \gamma \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} + d_1 r_{F,t-1}^2 + d_2 r_{F,t-1}^2 D_{Crisis(1)} + d_3 r_{F,t-1}^2 D_{Crisis(2)} + \upsilon_{2t}) \tag{6}$$

The conditional variance is an EGARCH (1,1) model. It becomes necessary to implement the EGARCH specification as the estimates for d_2 and/or d_3 can be negative. Using a standard GARCH approach would then allow for a negative conditional variance which is avoided using EGARCH. In addition, an asymmetry parameter is included as in equity markets negative shocks often increase volatility more than positive shocks do (see e.g. Engle and Ng, 1993). Baur (2003) uses the squared returns as a proxy for the variance. This has the advantage of avoiding any estimation error. It is straightforward to test for spillover and contagion effects. If b_1 and/or d_1 are different from zero then there are spillover effects in the first and/or second moment, respectively. Analogously, contagion effects can be shown if b_2/b_3 and/or d_2/d_3 are different from zero.

The alternative approach for capturing volatility dynamics integrates the method used in Jarque (2004) into the variance specification. Instead of using the squared returns as a proxy the conditional variance of the financial sector is obtained estimating a separate EGARCH regression. The mean equation for obtaining the conditional variance of the financial sector denotes as the following

$$R_{F,t} = \mu_F + \beta R_{F,t-1} + u_{F,t} \tag{7}$$

The variance equation is modeled as follows[6]

$$\sigma_{Ft}^2 = \exp(c + \theta \log(\sigma_{F,t-1}^2) + \alpha \left| \frac{\varepsilon_{F,t-1}}{\sigma_{F,t-1}} \right| + \gamma \frac{\varepsilon_{F,t-1}}{\sigma_{F,t-1}} + \upsilon_{Ft})$$

(8)

The mean equation for the contagion analysis is again represented by equation (1) for the first period and equation (2) for the second period. The EGARCH series obtained through (8) is then included in the conditional variance equation yielding two different specifications. For the first period

$$\sigma_{2t}^2 = \exp(c + \theta \log(\sigma_{2,t-1}^2) + \alpha \left| \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} \right| + \gamma \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} + d_1 r_{F,t-1}^2 + d_2 \sigma_{F,t}^2 D_{Crisis} + \upsilon_{2t})$$

(9)

And for the second period with an additional dummy variable

$$\sigma_{2t}^2 = \exp(c + \theta \log(\sigma_{2,t-1}^2) + \alpha \left| \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} \right| + \gamma \frac{\varepsilon_{2,t-1}}{\sigma_{2,t-1}} + d_1 r_{F,t-1}^2 + d_2 \sigma_{F,t}^2 D_{Crisis(1)} + d_3 \sigma_{F,t}^2 D_{Crisis(2)} + \upsilon_{2t})$$

(10)

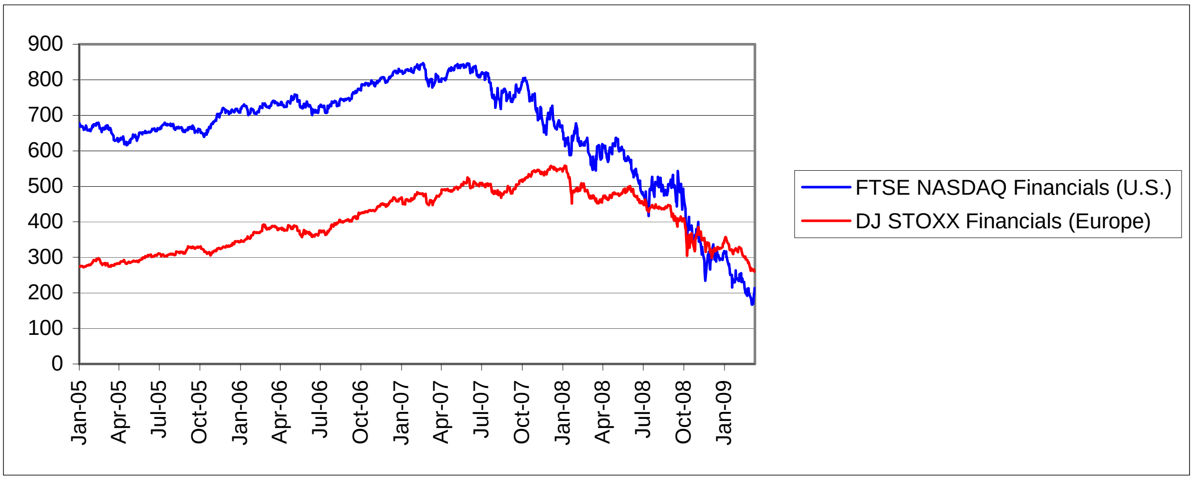
There is one crucial question left, namely the determination of the breakpoint. As stated before, the breakpoint will be determined exogenously. The notion of crisis shall be connected with a bear market period at the stock market. In general, the U.S. is taken as the leading indicator since the first signs of the crisis have evolved from the U.S. subprime mortgage market. For the "dot-com" bear market of 2000-2003 the breakpoint is chosen to be September, 24 on basis of the broad and commonly followed S&P 500 Composite Index. This is not exactly the peak, which is March 24, but observing the time series in chart 1 shows that the bear market starts only later and the period in between those two dates is characterized rather by a sideways trend than a bear market. The sample ends with the lowest point of the bear market March 11, 2003.

[6] For consistency the same EGARCH specification is applied. A simple GARCH model would also suffice to capture the dynamics.

Chart 1:
Time Series S&P 500 Composite Index

For the current financial crisis two breakpoints are chosen which sub-divide the stress period into two parts. The peak of the S&P 500 Composite Index is October 9, 2007. In order to better capture the effect of the financial sector we take the peak of the FTSE NASDAQ Financials sub-index (see chart 2), occurring June 1[7]. A second breakpoint is included when the bear market is seemingly accelerating. The second breakpoint is chosen to be October 1, 2008 based on ocular inspection of the long term S&P500 Composite Index time series. The prime interest is the combined effect of the whole crisis period and we will test both with a single dummy for the crisis period and two different dummies as described. Including an additional breakpoint also allows testing for parameter stability. The dates for the European markets are not exactly the same but for comparability the same breakpoints are chosen.

Chart 2:
Time Series Financials, period 2



[7] It only closes higher on February 20; the period in between is more a sidewards trend and as the overall market was far from being in a bear market, the later breakpoint seems more appropriate.

4. Empirical results

The results are presented and discussed separately for each period and equity market. For a better overview only parts of the estimates are reported. In general, the evidence for first order autocorrelation is not very strong and as it is not a prior interest and included as a control variable for the mean equation the results are not reported. The same holds for the constant in the mean equation μ_2, which is not significant from zero for the majority of sectors. The estimates for the constant in the conditional variance equation c, the estimates for the absolute value of the past shocks α as well as the lagged conditional variance θ are not reported. They are generally found to be significant indicating that the EGARCH model can capture the volatility dynamics quite well. This is confirmed by Q-tests which do not hint at any residual variability in the variance.

4.1 The "dot-com" crisis of 2000-2003

Table 3 depicts the estimation results for the U.S. for the first period. The estimates for b_1 indicate positive mean spillovers for all sectors and the estimates for b_2 show significant mean contagion originating in the financial sector for all sectors. The contagion effect is positive for all sectors with the exception of the health care sector and the size of the coefficient is biggest for the technology sector. Asymmetric effects are highly significant for the industrial and oil & gas sector and significant for the technology and health care sector. The coefficient γ is negative in those cases indicating that negative shocks result in a bigger increase of volatility than positive shocks do. The results for volatility spillovers and contagion are not convincing. Volatility spillovers are only significant in the technology sector and contagion effects are significant in the telecommunication and industrials sector where the sign of the effect is negative in the latter case.

Table 3:
Estimation results for the U.S., period 1
Based on equation (1) and (5), squared returns as proxy for variance

	b_1	b_2	γ	d_1	d_2
Basic Materials	0,471*	0,358*	0,001	6,22	-9,31
Consumer Goods	0,525*	0,227*	-0,042	6,59	3,47
Consumer Services	0,597*	0,259*	-0,034	12,63	-7,55
Health Care	0,487*	-0,108*	-0,068**	35,56	-27,63
Industry	0,563*	0,355*	-0,047*	7,87	-23,94
Oil & Gas	0,237*	0,174*	-0,069*	47,93	-9,05*
Technology	0,632*	0,503*	-0,059**	32,10**	-17,27
Utilities	0,219*	0,181*	-0,042	72,49	128,12
Telecommunication	0,460*	0,284*	0,000	49,16	59,80*

* significant on a 1% level ** significant on a 5% level

Table 4 tabulates the results for the same period using the EGARCH estimation instead of the squared returns. The results are quite similar with additional significant estimates in the basic materials sector for γ and d_2, indicating negative volatility contagion.

Table 4:
Estimation results for the U.S., period 1
Based on equation (1) and (9), EGARCH variance specification

	b_1	b_2	γ	d_1	d_2
Basic Materials	0,479*	0,327*	-0,021**	4,38	-11,57**
Consumer Goods	0,497*	0,269*	-0,029	1315,93	742,90
Consumer Services	0,597*	0,259*	-0,033	4,24	-8,88
Health Care	0,489*	-0,108*	-0,064**	3,82	-4,53
Industrials	0,560*	0,357*	-0,047*	5,06	-25,43*
Oil & Gas	0,239*	0,167*	-0,069*	67,02	-28,30
Technology	0,635*	0,500*	-0,064**	34,71*	-27,69
Utilities	0,217*	0,174*	-0,058	186,12	239,23
Telecommunication	0,458*	0,284*	0,002	122,41	94,39*

* significant on a 1% level ** significant on a 5% level

For the same period in Europe mean spillover effects are positive and significant as depicted in table 5. Mean contagion effects are positive and significant in all sectors except consumer goods, health care, industrials, and telecommunication. The asymmetric effects are present in the technology sector, utilities, telecom, and basic materials where in the latter case γ is positive. Significant and positive volatility spillovers are found in the basic materials, consumer goods, health care, and oil & gas sector. There are no signs of any volatility contagion in the chosen crisis period.

Table 5:
Estimation results for Europe, period 1
Based on equation (1) and (5), squared returns as proxy for variance

	b_1	b_2	γ	d_1	d_2
Basic Materials	0,632*	0,222*	0,004*	408,81**	-82,50
Consumer Goods	0,763*	0,056	-0,056	120,82**	-66,42
Consumer Services	0,742*	0,168*	-0,034	14,73	45,08
Health Care	0,816*	0,037	0,019	416,45**	-187,99
Industrials	0,683*	0,049	-0,050	137,50	-3,64
Oil & Gas	0,726*	0,286*	0,064	677,95*	-431,22
Technology	1,106*	0,363*	-0,055**	4,79	26,70
Utilities	0,911*	0,217*	-0,072*	70,69	20,27
Telecommunication	1,190*	0,005	-0,038**	40,56	-19,41

* significant on a 1% level ** significant on a 5% level

In table 6 the EGARCH variance for the volatility equation is used. The results in the first three columns are similar and the spillover effects are only found in the basic materials and the oil & gas sector. In line with the results shown in table 5, there are no signs of volatility contagion.

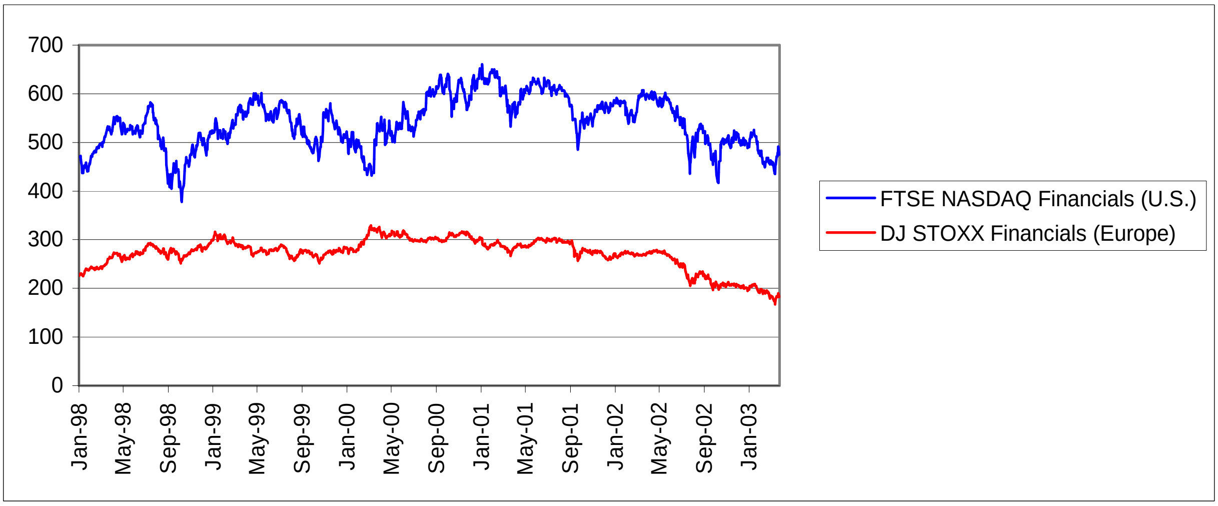
Table 6:
Estimation results for Europe, period 2
Based on equation (1) and (9), EGARCH variance specification

	b_1	b_2	γ	d_1	d_2
Basic Materials	0,647*	0,176*	0,030*	714,15**	-73,51
Consumer Goods	0,765*	0,045	-0,058	97,74	-45,98
Consumer Services	0,744*	0,167*	-0,033	-56,96	114,03
Health Care	0,781*	0,090	0,026	3506,63	-1721,05
Industrials	0,692*	0,041	-0,051	119,57	540,09
Oil & Gas	0,696*	0,341*	0,109	2744,46*	-1460,78
Technology	1,098*	0,346*	-0,058**	-51,82	89,92
Utilities	0,904*	0,221*	-0,069*	51,76	49,43
Telecommunication	1,188*	-0,006	-0,034**	-25,44	25,98

* significant on a 1% level ** significant on a 5% level

In summary, the signs for mean contagion can be shown as positive and significant for all sectors in the U.S. and for five out of nine in Europe. The implicit assumption of exogeneity has to be questioned at this point, especially when looking at the time series of the financial sector in that period. An alternative explanation is that the mean contagion effects are significant owing to the fact that other sectors decline more sharply than the financial sector in this crisis. Chart 3 illustrates that the financial sector is comparatively stable during the analyzed period. Together with the fact that there are no signs of significant volatility contagion we have to reject the hypothesis that the financial sector plays a central role in this crisis period. This result is not surprising as there was a lack of theoretical reasoning beforehand and the analysis should merely serve to complement and support the analysis of the financial crisis of 2007-2009 investigated later on.

Chart 3:
Time Series Financials, period 1



4.2 The financial crisis of 2007-2009

The presentation of the results for the second period is more complex and to make the main aspects evident not all information is included in the tables. Estimations are performed with two separate dummies sub-dividing the crisis period and a joint dummy for the whole period. This raises the question whether the two estimates for the dummy coefficients are significantly different from each other. This can be tested with a simple WALD test and shall be indicated by a "#", if significant, following the first of the two estimates. In most cases there are no signs of parameter instability and the estimation with a joint crisis dummy is easier to grasp and will be referred to if not mentioned otherwise. A "~" indicates that the estimate stems from the specification with only one dummy for the joint crisis period. Next to the omissions made for the first crisis period the coefficient $\tilde{b}_1$ is left out as the size is found to be very close to b_1.

Table 7 shows that mean spillovers are positive and significant for all sectors and mean contagion is significant for all sectors except for the later crisis period in the oil & gas sector. In contrast to the bear market starting in 2000 the contagion effect is negative, indicating that the shocks of the financial sector have less impact on the mean of other sectors during the stress period. This supports the notion that the decline in the financial sector was rather an isolated development and driven by an idiosyncratic shock. WALD tests do not hint at any differences of the parameters during the stress period except for the consumer service sector where the negative contagion effects are even bigger in the second phase of the crisis than in the first period. The asymmetry parameter γ is significant for four out of the nine sectors. In general, the volatility spillover effects are mostly negative in the non-crisis period and positive for the crisis period. They are, however, only significant from zero for the utilities, technology, and oil & gas sector. There are no signs of parameter instability for the volatility contagion effects and volatility contagion is significant for five out of the nine sectors for the joint crisis period. The evidence for the argument of decreased consumer confidence as the mechanism for contagion is mixed. The consumer goods sector volatility is not significantly affected by the financial sector, while the consumer service sector is significantly influenced. The highly significant volatility contagion effects in the utility sector could probably be better explained by a supply side effect of increasing difficulties to secure financing.

Table 7:
Estimation results for the U.S., period 2
Based on equation (1),(5) and (2),(6), squared returns as proxy for variance

	b_1	b_2	b_3	$\tilde{b}_2$	γ
Basic Materials	0,987*	-0,458*	-0,387*	-0,426*	-0,010
Consumer Goods	0,658*	-0,341*	-0,373*	-0,351*	-0,051**
Consumer Services	0,802*	-0,291*#	-0,414*	-0,320*	-0,055**
Health Care	0,620*	-0,316*	-0,303*	-0,312*	-0,003
Industrials	0,784*	-0,296*	-0,289*	-0,295*	-0,051**
Oil & Gas	0,645*	-0,271*	-0,154	-0,205**	-0,060**
Technology	0,885*	-0,429*	-0,418*	-0,419*	-0,048
Utilities	0,622*	-0,343*	-0,341*	-0,344*	-0,026
Telecommunication	0,699*	-0,232*	-0,304*	-0,254*	-0,006

	d_1	d_2	d_3	$\tilde{d}_1$	$\tilde{d}_2$
Basic Materials	-99,70	119,97	100,01	-246,15	251,60
Consumer Goods	14,40	15,22	-6,29	-50,12	64,31
Consumer Services	-161,64	199,07	174,40	-320,88**	341,69**
Health Care	-452,45**	496,77**	485,53**	-514,78**	553,02**
Industrials	-311,28	340,07	328,05	-391,50**	412,09**
Oil & Gas	-142,95	181,01	158,96	-243,84	265,01
Technology	-295,18**	319,90**	302,20**	-414,48**	425,89**
Utilities	-657,42*	701,12*	687,85*	-724,33*	758,55*
Telecommunication	-278,64	307,54	286,94	-342,87	353,62

*   significant on a 1% level   ** significant on a 5% level

The EGARCH variance specification yields less significant results for the variance spillover and contagion effects and confirms the results for the mean and asymmetry parameters.

Table 8:
Estimation results for the U.S., period 2
Based on equation (1),(9) and (2),(10), EGARCH variance specification

	b_1	b_2	b_3	$\tilde{b}_2$	γ
Basic Materials	0,984*	-0,456*	-0,425*	-0,423*	-0,006
Consumer Goods	0,662*	-0,342*	-0,378*	-0,351*	-0,052
Consumer Services	0,812*	-0,282*#	-0,419*	-0,320*	-0,083**
Health Care	0,620*	-0,316*	-0,303*	-0,314*	-0,028
Industrials	0,798*	-0,303*	-0,304*	-0,305*	-0,074**
Oil & Gas	0,640*	-0,263*	-0,144	-0,208**	-0,086*
Technology	0,897*	-0,425*	-0,421*	-0,423*	-0,067**
Utilities	0,625*	-0,318*	-0,341*	-0,339*	-0,063
Telecommunication	0,702*	-0,225*	-0,305*	-0,252*	-0,001
	d_1	d_2	d_3	$\tilde{d}_1$	$\tilde{d}_2$
Basic Materials	-345,12	692,90**	445,07	-157,71	157,41
Consumer Goods	203,46	-139,70	-186,66	39,20	-22,88
Consumer Services	-55,12	436,66	218,69	-962,02	110,69
Health Care	-452,45**	496,77**	485,53**	-140,09	165,79**
Industrials	-257,52	476,20	349,88	-451,60	496,82
Oil & Gas	103,50	19,35	-51,57	-181,74	218,37
Technology	-348,24	762,62	498,38	-544,40	581,91
Utilities	-653,95	894,13	767,12	-881,87**	965,24**
Telecommunication	-399,97	513,12**	439,67**	-543,38**	567,53**

* significant on a 1% level   ** significant on a 5% level

The results for Europe, displayed in table 9, are different particularly the ones for the mean contagion effects. Mean spillover effects are positive and significant as well, while contagion effects are less significant than for the U.S. and positive in sign contrasting the results for the U.S. equity sub-indices. Similar to the U.S., mean contagion tends to be more significant in the first part of the crisis. Volatility spillover effects during the non-crisis period are either negative or insignificant. Volatility contagion effects for the joint crisis period can be shown for six out of the nine sectors. Volatility contagion effects are significant for the first stage of the crisis for all sectors expect utilities and consumer services. The results for the second part of the crisis period are only significant for three sectors although WALD tests could not show parameter instability in any of the sectors and the size of the estimates appears close to the estimates of the first period. The insignificance may be caused by the comparatively short time span of the second part of the crisis.

Table 9:
Estimation results for Europe, period 2
Based on equation (1),(5) and (2),(6), squared returns as proxy for variance

	b_1	b_2	b_3	$\tilde{b}_2$	γ
Basic Materials	0.807*	0.263*	0.294**	0.280*	-0.047
Consumer Goods	0.592*	0.120**	0.012	0.070	-0.052
Consumer Services	0.549*	0.291*	0.102	0.174*	-0.041**
Health Care	0.414*	0.065	0.133**	0.088	0.017
Industrials	0.685*	0.315*	0.162	0.248*	-0.093*
Oil & Gas	0.687*	0.227*	0.343*	0.273*	-0.002
Technology	0.742*	0.208*	0.012	0.099	-0.042
Utilities	0.678*	0.281*	0.235**	0.264*	-0.059*
Telecommunication	0.598*	0.211*	0.111	0.157*	-0.010
	d_1	d_2	d_3	$\tilde{d}_1$	$\tilde{d}_2$
Basic Materials	-414,24*	437,05*	426,65*	-421,34*	433,61*
Consumer Goods	-342,28	414,46**	408,18**	-353,09	424,38**
Consumer Services	-200,09	177,74	191,61	-208,72	202,95
Health Care	-178,80	232,87**	206,63	-250,08**	282,01**
Industrials	-251,99	302,54**	266,32	-289,43**	302,83**
Oil & Gas	-210,74	254,41**	225,26**	-267,38**	284,85**
Technology	-234,00	259,14**	236,22	-271,93**	272,87**
Utilities	-161,09	225,89	154,02	-210,10	201,93
Telecommunication	-87,79	82,49**	83,30	-85,63	82,89

* significant on a 1% level ** significant on a 5% level

The results using the EGARCH series are similar and confirm the results using the squared returns as a proxy.

Table 10:
Estimation results for Europe, period 2
Based on equation (1),(9) and (2),(10), EGARCH variance specification

	b_1	b_2	b_3	$\tilde{b}_2$	γ
Basic Materials	0,814*	0,253*	0,276	0,264*	-0,044
Consumer Goods	0,595*	0,110**	0,010	0,055	-0,059
Consumer Services	0,552*	0,292*	0,099	0,173*	-0,040**
Health Care	0,430*	0,046	0,117**	0,078	0,026
Industrials	0,688*	0,311*	0,154	0,243*	-0,095*
Oil & Gas	0,688*	0,227*	0,338*	0,272*	-0,003
Technology	0,745*	0,203*	0,007	0,094	-0,042
Utilities	0,681*	0,279*	0,233**	0,263*	-0,058*
Telecommunication	0,609*	0,210*	0,100	0,145*	-0,012
	d_1	d_2	d_3	$\tilde{d}_1$	$\tilde{d}_2$
Basic Materials	-289,20**	293,32**	307,99**	-272,89**	292,96**
Consumer Goods	-344,39	538,29**	506,97	-372,89	541,79**
Consumer Services	-232,45**	188,06	213,82**	-231,21**	220,80
Health Care	-323,32	378,62	405,14	-288,43	368,44**
Industrials	-273,18**	290,86**	293,52**	-284,68**	307,09**
Oil & Gas	-214,25	239,67**	240,23	-216,69**	245,59**
Technology	-199,21	238,92**	208,86	-249,73**	256,49**
Utilities	-160,40	204,60	151,08	-199,86	184,89
Telecommunication	-86,91	71,32**	77,25	-89,19*	79,94*

* significant on a 1% level ** significant on a 5% level

Summarizing the results for the second period, a different impact of the financial sector comparing the U.S. and Europe is revealed. Mean contagion effects are negative in the U.S. and positive in Europe. Volatility contagion effects are significant for a majority of sectors in both the U.S. and Europe. Non-financial sectors that are consistently affected by significantly positive volatility contagion across all markets and specifications are technology, industrials, and health care. Further conclusions are drawn in the following section.

Conclusions

The empirical results suggest that the financial sector plays a different, slightly more central role in the financial crisis of 2007-2009 comparing it to the “dot-com” induced downturn of 2000-2003. Mean contagion effects are mostly positive in Europe for both periods and in the U.S. for the first period, whereas in the U.S. they are negative during the credit crunch affected crisis. This provides evidence that the decline in the financial sector in the U.S. is sharper than in all other sectors and, taking the corresponding significant mean contagion effects into consideration, an isolated development. On the back of the analysis of the first moment the initial hypothesis of the financial sector as the originator of the market downturn of 2007-2009 has to be clearly rejected for the U.S. market. Although contagion effects are positive for Europe during the financial crisis this is no strong evidence for our hypothesis as contagion is equally positive in the 2000-period.

Volatility contagion effects can be shown for a majority of sectors during the financial crisis of 2007-2009 in both the U.S. and Europe, standing in clear contrast to the findings of the downturn of 2000-2003 where they are insignificant for most sectors. This allows the conclusion that the instability of the financial sector partly encroaches on other economic sectors what leads to an increase of insecurity expressed in terms of higher volatility in most non-financial sectors. Hence, in the second moment evidence is provided that the initial hypothesis can be accepted for most non-financial sectors.

Analyzing the second topic of interest, namely whether economic sectors are affected differently by the crisis, reveals that volatility contagion is consistently positive and significant for the technology, industrials, and health care sector. As those sectors have limited direct exposure to consumer confidence fluctuations the results tend to confirm the findings of Tong and Wei (2008) who show a stronger effect of supply-side effects resulting from the credit crunch. However, our analysis is not suitable to clearly distinguish between those two effects as the sectors do not seem to be homogenous when it comes to the degree of leverage and sensitivity to consumer demand.

Other findings worth mentioning are that there is little evidence that the estimates for the contagion effects change during the crisis period of 2007-2009 and evidence of asymmetric effects of shocks can be found for less than half of the analyzed sectors.

In terms of policy implications the essay adds to the stream of arguments that appropriate regulation and supervision of the financial sector is necessary as it finds positive volatility contagion caused by the financial sector. It could not provide clear indications on how to guide economic policy on a sectoral level.

Future research could extend the sectoral analysis by paying more attention to the actual sensitiveness towards supply-side and demand-side effects of the financial crisis. By including such variables closer insight for distinct policy reactions could be gained, that is to say which sectors need additional government support to mitigate the effects of a credit crisis.

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Appendix:

Appendix 1:
Summary statistics for the U.S., complete period returns

	Basic Materials	*Consumer Goods*	*Consumer Services*	*Health Care*	*Indus-trials*	*Oil & Gas*	*Tele-com.*	*Finan-cials*	*Utili-ties*	*Tech-nology*
Period 1:										
Mean	-6,66E-05	-7,4E-05	-0,0004	-0,0002	-9,1E-05	-0,0003	-4,0E-05	-0,0003	-0,0001	-0,0002
Median	0,0000	0,0002	-1,8E-05	0,0000	0,0000	0,0000	0,0000	0,00011	0,0000	7,56E-05
Maximum	0,066901	0,05488	0,06318	0,04813	0,06979	0,05917	0,07453	0,10762	0,07629	0,0781
Minimum	-0,05924	-0,0604	-0,075	-0,0594	-0,0632	-0,0613	-0,0745	-0,1222	-0,0816	-0,098
Std. Dev.	0,013581	0,01223	0,01397	0,01125	0,01432	0,01262	0,01717	0,02838	0,02225	0,01659
Skewness	0,009657	-0,2471	-0,1086	-0,167	0,00939	-0,1437	-0,0862	-0,0105	0,10863	-0,1272
Kurtosis	5,3275	5,5949	5,1952	5,1721	5,0800	4,9338	4,5167	4,1088	3,4868	6,3375
Jarque-Bera	307,45	395,99	276,15	274,07	245,53	216,90	132,24	69,80	16,13	635,80
Probability	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0003	0,0000
Sum	-0,09068	-0,1013	-0,5426	-0,2153	-0,1235	-0,4198	-0,0551	-0,4711	-0,2031	-0,2753
Sum Sq. Dev.	0,251043	0,20369	0,26555	0,17227	0,27926	0,21679	0,40117	1,09638	0,67402	0,37436
Observations	1362	1362	1362	1362	1362	1362	1362	1362	1362	1362
Period 2:										
Mean	-6,62E-06	-6,4E-05	-3,9E-04	-4,3E-05	-1,8E-04	-0,0002	-0,0002	-0,0005	-0,0003	-0,001
Median	0,000917	0,00033	0,00011	0,0002	0,0000	0,00086	0,0000	0,0000	2,5E-05	0,0E+00
Maximum	0,132894	0,12594	0,08346	0,14858	0,08604	0,09978	0,1186	0,08515	0,09664	0,14667
Minimum	-0,12424	-0,0607	-0,0684	-0,0868	-0,0682	-0,0961	-0,1004	-0,0997	-0,0943	-0,1018
Std. Dev.	0,020862	0,01212	0,01301	0,01428	0,011	0,01646	0,01763	0,017	0,01383	0,01927
Skewness	-0,2337	0,89813	-0,0931	0,39313	0,218	-0,1305	0,04082	-0,1477	0,00318	0,2496
Kurtosis	11,3581	18,3555	8,8804	21,8575	13,5126	10,5471	12,3269	8,0288	10,9821	12,9228
Jarque-Bera	3.191,4	10.885,2	1.576,4	16.223,1	5.041,7	2.597,1	3.962,0	1.155,7	2.901,6	4.495,5
Probability	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Sum	-0,00723	0,0000	-0,4291	-0,0475	-0,1995	-0,1978	-0,2038	-0,5377	-0,3163	-1,04529
Sum Sq. Dev.	0,475279	0,16037	0,18477	0,22254	0,13211	0,29595	0,33948	0,31543	0,20882	0,40531
Observations	1093	1093	1093	1093	1093	1093	1093	1093	1093	1093

Appendix 2:
Summary statistics for Europe, complete period returns

	Basic Materials	Consumer Goods	Consumer Services	Health Care	Indus-trials	Oil & Gas	Tele-com.	Finan-cials	Utili-ties	Tech-nology
Period 1:										
Mean	-6,66E-05	-7,4E-05	-0,0004	-0,0002	-9,1E-05	-0,0003	-4,0E-05	-0,0003	-0,0001	-0,0002
Median	0,0000	0,0002	-1,8E-05	0,0000	0,0000	0,0000	0,0000	0,00011	0,0000	7,56E-05
Maximum	0,066901	0,05488	0,06318	0,04813	0,06979	0,05917	0,07453	0,10762	0,07629	0,0781
Minimum	-0,05924	-0,0604	-0,075	-0,0594	-0,0632	-0,0613	-0,0745	-0,1222	-0,0816	-0,098
Std. Dev.	0,013581	0,01223	0,01397	0,01125	0,01432	0,01262	0,01717	0,02838	0,02225	0,01659
Skewness	0,009657	-0,2471	-0,1086	-0,167	0,00939	-0,1437	-0,0862	-0,0105	0,10863	-0,1272
Kurtosis	5,3275	5,5949	5,1952	5,1721	5,0800	4,9338	4,5167	4,1088	3,4868	6,3375
Jarque-Bera	307,45	395,99	276,15	274,07	245,53	216,90	132,24	69,80	16,13	635,80
Probability	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0003	0,0000
Sum	-0,09068	-0,1013	-0,5426	-0,2153	-0,1235	-0,4198	-0,0551	-0,4711	-0,2031	-0,2753
Sum Sq. Dev.	0,251043	0,20369	0,26555	0,17227	0,27926	0,21679	0,40117	1,09638	0,67402	0,37436
Observations	1362	1362	1362	1362	1362	1362	1362	1362	1362	1362
Period 2:										
Mean	-6,62E-06	-6,4E-05	-3,9E-04	-4,3E-05	-1,8E-04	-0,0002	-0,0002	-0,0005	-0,0003	-0,001
Median	0,000917	0,00033	0,00011	0,0002	0,0000	0,00086	0,0000	0,0000	2,5E-05	0,0000
Maximum	0,132894	0,12594	0,08346	0,14858	0,08604	0,09978	0,1186	0,08515	0,09664	0,14667
Minimum	-0,12424	-0,0607	-0,0684	-0,0868	-0,0682	-0,0961	-0,1004	-0,0997	-0,0943	-0,1018
Std. Dev.	0,020862	0,01212	0,01301	0,01428	0,011	0,01646	0,01763	0,017	0,01383	0,01927
Skewness	-0,2337	0,89813	-0,0931	0,39313	0,218	-0,1305	0,04082	-0,1477	0,00318	0,2496
Kurtosis	11,3581	18,3555	8,8804	21,8575	13,5126	10,5471	12,3269	8,0288	10,9821	12,9228
Jarque-Bera	3.191,4	10.885,2	1.576,4	16.223,1	5.041,7	2.597,1	3.962,0	1.155,7	2.901,6	4.495,5
Probability	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Sum	-0,00723	0,0000	-0,4291	-0,0475	-0,1995	-0,1978	-0,2038	-0,5377	-0,3163	-1,04529
Sum Sq. Dev.	0,475279	0,16037	0,18477	0,22254	0,13211	0,29595	0,33948	0,31543	0,20882	0,40531
Observations	1093	1093	1093	1093	1093	1093	1093	1093	1093	1093

Appendix 3:
Correlations with the financial sector

	Basic Materials	*Consumer Goods*	*Consumer Services*	*Health Care*	*Indus-trials*	*Oil & Gas*	*Tele-com.*	*Utili-ties*	*Tech-nology*
U.S.									
Period 1									
Non-crisis	0,538	0,643	0,725	0,602	0,701	0,272	0,542	0,362	0,475
Crisis	0,702	0,715	0,785	0,560	0,819	0,434	0,642	0,459	0,643
Period 2:									
Non-crisis	0,679	0,717	0,821	0,719	0,794	0,337	0,650	0,581	0,722
Crisis	0,694	0,773	0,843	0,744	0,852	0,628	0,746	0,622	0,793
Europe									
Period 1									
Non-crisis	0,528	0,694	0,701	0,577	0,679	0,418	0,665	0,697	0,601
Crisis	0,710	0,824	0,741	0,745	0,666	0,669	0,605	0,792	0,542
Period 2:									
Non-crisis	0,629	0,731	0,681	0,447	0,713	0,529	0,533	0,729	0,571
Crisis	0,745	0,644	0,733	0,686	0,754	0,832	0,782	0,682	0,702