Dynamics of Sectoral Business Cycle Comovement*

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Abstract

Sectoral comovement is a key characteristics of business cycles. However, little is known about its time-varying aspects by now. In this paper a multivariate dynamic conditional correlation (DCC) general autoregressive conditional heteroskedasticity (GARCH) framework is employed to study dynamics of sectoral comovement across manufacturing sectors both in Germany and in the United States. Asymmetric effects both in conditional volatilities as well as in conditional correlations are being assessed. We find that comovement across sectors is not stable, but shows irregular movements. Particularly, sectoral comovement in German and US manufacturing seem to have increased considerably during some recesssion periods, especially in the recession of 2008-2009, but not during every recession. Moreover, we examine the role of stock market volatility for the fluctuations in conditional correlations and find it to have a significant effect in both countries.

JEL Classification: E32, C32

Keywords: Business cycles, sectoral comovement, time-varying correlations, DCC-GARCH

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1 Introduction

Sectoral or interindustry comovement is a key feature of business cycles. The main motivation to investigate sectoral comovement is the fact that it still cannot be fully explained by business cycle models or theories, i.e. there is no consensus about the driver(s) of the synchronized movements. A high level of sectoral comovement is traditionally interpreted as a strong propagation of common (aggregate) shocks to all sectors or pass-through of sectoral shocks due to sectoral linkages. Moreover, for understanding movements of aggregate variables it is necessary to analyse comovement across (disaggregated) industries as these sum up to the aggregate measures. Above all, the volatility of aggregate output depends on the volatility of individual sectors and correlations between them. Shea (2002) show that comovement between the sectors accounts for more than 85 percent of the variance of aggregated US manufacturing gross output. Also Foerster et al. (2011) find the covariance terms to be the main source of variation in the growth rates of aggregate US industrial production.

Although interindustry comovement has already been documented quite well (see, for example, Long and Plosser (1987), Christiano and Fitzgerald (1998), Hornstein (2000), den Haan (2000), Cassou and Vázquez (2014)), little is known about its dynamic aspects as these papers do not study patterns of comovement over the years nor depending on the state of the business cycle. Yet, there are reasons to expect that properties and dynamics of comovement might change over time in general as well as differ across the business cycle. First, there could be positive time-trend as the sectors could become more correlated over time due to better technologies and more information available for all sectors in the course of years. Also stronger interindustry linkages could lead to higher synchronization. On the other hand, there could be also a negative time trend as Foerster et al. (2011) document a decline in average pairwise correlations of sectoral growth rates in US in the 1984-2007 period (also referred as "Great Moderation") compared to the pre-1984 years. They state this finding to be a reason for the lower variance of the growth of industrial production in the same period. Second, the level of comovement might be state-dependent i.e. differ between recessions and booms. The fact that recessions seem to be more pronounced than recoveries was already noted by Keynes (1936) and Burns and Mitchell (1946), among others. This could be because of asymmetric reactions to shocks over the business cycle

(Potter, 1994) or differing reactions to positive than negative shocks. Third, it could be that correlations between sectors increase during periods of higher volatility respectively uncertainty as common factors could become more important compared to individual/sectoral shocks during these periods. One reason could be because the cost of (debt) finance tend to be higher in times of increased uncertainty as discussed by Bloom (2014). Furthermore, consumers tend to be more cautious when they are uncertain about their future income development.

However, measuring time-varying comovement is not clear-cut. If only unconditional correlation between autocorrelated series are analysed, we cannot distinguish if the changes in the correlations are due to changes in the persistence of shocks in each series or due to changes in covariances. Therefore an approach based on conditional correlations is needed. Furthermore, it is necessary to account also for the possibly non-constant volatility when modelling conditional correlations as the estimated correlations tend to be higher in times of increased volatility. Only by accounting for time-variant volatility one can distinguish if higher correlations are due to higher volatility or stronger comovement of variables.

In this study we employ a multivariate dynamic conditional correlation (DCC) general autoregressive conditional heteroskedasticity (GARCH) framework, introduced by Engle and Sheppard (2001) and Engle (2002), to study the time-varying correlations of industrial production growth rates between manufacturing sectors in Germany and the US. To our knowledge this approach has not yet been applied to study sectoral comovement. The advantage of DCC-GARCH is that we can examine possible changes in conditional correlations depending on state or circumstances of the economy as well as generally over time. Furthermore, we can account for asymmetries in the conditional volatilities as well as also in the conditional correlations. This is important because if an asymmetric process is modelled by the standard symmetric model, the estimated conditional variance respectively correlation after a negative shock would be underestimated whereas the conditional volatility respectively correlation would be too high after a positive shock.

We find some evidence for asymmetries in volatilities in growth rates of production of disaggregated manufacturing sectors, especially in the US. However, we find only little evidence for asymmetries in correlations i.e that the conditional correlations tend to react more to negative than positive shocks. Furthermore, we show that the sectoral comovement in German and US manufacturing is not constant but shows irregular movements. Especially, the correlations seem to have increased considerably during some recession periods, especially during the recession in 2008-2009, but there are also recession periods in which the comovement hardly changes. Furthermore, we examine the possible causes for the changes in comevement by studying the effects of various common factors. We asses the meaning of higher uncertainty periods, measured by stock market volatility, as well as recession periods for sectoral comovement, among others. We find that the lagged stock market volatility play a significant role for the level of sectoral comovement.

This paper is organized as follows. First, in section 2 a literature overview is given. Section 3 presents the DCC-GARCH framework. In section 4 the research methodology and data are described and in section 5 the results of DCC-GARCH approach are presented. In section 6 we address the factors explaining the irregular movements in conditional correlations. Finally, section 7 offers conclusions.

2 Literature Overview

Sectoral comovement can be studied by analysing correlation between sectoral series and corresponding aggregate variables (reference series) or through pairwise interindustry comparisons. However, the problem when using a reference series (which equals the sum of the sectoral series) is that it cannot account for the correlations between the sectors, and therefore the measures of comovement are more or less biased. In general, considerable higher level of comovement is found, if the reference series approach is applied (see, for example Christiano and Fitzgerald (1998)).

Another issue which can make great difference when examining interindustry comovement is how correlation respectively covariance is calculated. If only unconditional correlation between autocorrelated series are analysed, we cannot distinguish if the changes in the correlations are due to changes in the persistence of shocks in each series or due to changes in covariances. Furthermore, it is necessary to account also for the possibly non-constant volatility when modelling conditional correlations as the estimated correlations tend to be higher in times of increased volatility. Only by accounting for time-variant volatility one can distinguish if higher correlations are due to higher volatility or stronger comovement of variables.

One of the pioneer works of sectoral comovement is the paper of Long and Plosser (1987). They study cross-industry comovement in the US industrial production and apply factor analysis to examine the importance of aggregate versus sectoral shocks. They document the level of comovement by calculating average pairwise correlations (for the residuals from the VAR analysis) and find the level of comovement to range between 0.07 and 0.23 for seasonally adjusted series. Furthermore, they consider one- and two-factor models and find the explanatory power of the common shocks for each sector to be significant but rather weak.

Christiano and Fitzgerald (1998) study the comovement in quarterly hours worked in US two-digit industries. To measure the level of comovement they regress the business cycle component of the series on cyclical component of total hours worked at lags 0, 1 and -1 to calculate the R^2. They estimate the level of correlation to be on average 0.55 among all industries. Furthermore, Christiano and Fitzgerald (1998) show that the comovement of hours worked with total hours worked is higher across the durable goods manufacturing sectors (0.82) than across the nondurable manufacturing sectors (0.46)[1]. Also service sectors are comoving less with the general business cycle than the durable manufacturing but more than the nondurable goods manufacturing. Furthermore, Christiano and Fitzgerald (1998) analyse also some possible explanations for comovement without any definite findings. Hornstein (2000) documents also sectoral comovement in the US in the yearly data using both reference series as well as direct cross-industry measures with basic correlation measures. They consider besides the contemporaneous correlations also once-lagged respectively once-lead correlations. In most cases, however, the contemporaneous correlations tend to be the highest, what is not surprising as they use yearly data.

A framework to assess comovement not only contemperaneously but also in short and long term was introduced by den Haan (2000). He applies a method based on vector autoregressions (VARs) to calculate correlation coefficients at different forecast horizons. With this methodology it is possible to study not only contemporaneous correlations but also leads and lags in correlations. Cassou and Vázquez (2014) apply this methodology to study employment comovements at the sectoral level. However, this approach cannot be used to analyse dynamics of comovement

[1] Usually, following sectors are considered to be durable goods sectors: Wood, Metal, Machinery, Electronics, GlassStone, Electricals, Vehicles, Transportation, Furniture, Other. On the other hand, non-durable goods sectors include FoodTobacco, Textile, Apparel, Leather, Paper, Print, Petroleum, Chemicals, Rubber

at different stages of the business cycle nor over time but only at different forecast horizons.

To investigate changes in correlations over time various methodologies have been applied. A rather simple approach is the rolling window methodology, see for example Inklaar et al. (2008) and Papageorgiou et al. (2010). However, this approach is sensitive to the choice of the window length and cannot be applied to pinpoint (exact) time points when correlations change. Moreover, Croux et al. (2001) introduce a measure of dynamic comovement which is defined in frequency domain and can be used to investigate short-run and long-run properties at different frequencies.

Generalized autoregressive conditional heteroskedasticity (GARCH) framework can model processes with non-constant variance and its multivariate extension can also be applied to study time-variant correlations. Ho et al. (2009b) apply multivariate GARCH to study the asymmetric volatility and time-varying correlations between sectors of US industrial production. They find that negative shocks have greater impact on future volatilities. Furthermore, they find that evidence for time-varying conditional correlations. In Ho et al. (2009a) also a multivariate asymmetric GARCH approach is used to analyse volatility dynamics in the UK business cycle. They find evidence that conditional volatilities as well as correlations tend to be higher during UK recession periods.

Yet, during the last decade an extension of (multivariate) GARCH, the dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) framework, which was introduced by Engle and Sheppard (2001) and Engle (2002), based on the earlier works of Engle (1982), Bollerslev (1986) and Bollerslev (1990), has become more popular. The advantage of DCC-GARCH framework is that it has the flexibility of univariate GARCH but is not as complex as convential multivariate GARCH as noted by Engle (2002). The DCC-GARCH framework accounts for the time-varying volatility of the series and the conditional correlation matrix is time-dependent and therefore, it can be applied to study the dynamics in correlations. It has been applied to investigate, for instance, dynamic comovement between stock market returns and policy uncertainty (Antonakakis et al., 2013) as well as output and prices (Lee, 2006). To our knowledge this approach has not yet been applied to study sectoral comovement. The advantage of DCC-GARCH is that we can examine possible changes in conditional correlations depending on state or circumstances of the economy. Furthermore, with this approach we are also able study the asymmetric reactions of correlations to negative respectively positive shocks.

3 DCC-GARCH framework

Let u_t be a data series with mean zero or residuals from a filtered time series.

$$u_t \sim N(0, H_t).$$

For easier interpretation of the DCC-GARCH framework, H_t can be rewritten as:

$$H_t = D_t R_t D_t \tag{1}$$

where $D_t = diag\left\{\sqrt{h_{i,t}}\right\}$ is a diagonal matrix of time-varying standard deviations and R_t is a correlation matrix comprising conditional correlation coefficients. The standard deviations in matrix D_t are typically modeled to follow a univariate GARCH(1,1) (Bollerslev, 1986) of:

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1} \tag{2}$$

However, the model does not necessarily need to be the symmetric GARCH model; also other GARCH models can be incorporated. In this paper we consider also the following models: exponential GARCH (Nelson, 1991), Asymmetric power ARCH (Ding et al., 1993) and The Glosten-Jagannathan-Runkle GARCH (Glosten et al., 1993)[1]. Furthermore, each series can have their own individual GARCH model as it is not necessary to model all with the same process. We get the standardized residuals then by $\varepsilon_t = u_t/\sqrt{h_t}$. This is also called *DE-GARCHING*.

The correlation process in standard DCC model of Engle (2002) is given by

$$Q_t = (1 - a - b)S + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} \tag{3}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

[1] For exact specifications see the Appendix

where $S = E[\varepsilon_t \varepsilon_t']$ is the unconditional covariance matrix of the standardized residuals, Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t and a and b are scalars. This is the *mean-reverting* DCC(1,1) model as long as $a + b < 1$.

In the mean-reverting DCC model correlation targeting is being applied in order to keep the number of parameters to be estimated small, i.e. the intercept matrix Ω is replaced by $(1 - a - b)S$. However, as Engle (2009) and Aielli (2013) note, this is only an approximation as S is not exactly $\bar{Q}$. Therefore, R_t contains the conditional *quasicorrelations* in the form:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{5}$$

The normality assumption gives rise to a likelihood function. As Engle and Sheppard (2001) and Engle (2002) notes, the assumptions of multivariate normality is not necessary for consistency and asymptotic normality of the estimated parameters. Without this assumption, the DCC estimator will still have the quasi-maximum-likelihood interpretation.

The estimation procedure of this system has two stages: first, univariate GARCH processes are estimated for u_t and second, the standardized residuals are used to estimate the conditional quasicorrelation matrix.

A useful extension of this model is the *asymmetric* DCC (aDCC) of Cappiello et al. (2006). In this model reactions of correlations to negative shocks can be greater than to positive shocks. Here the correlation process can be written as

$$Q_t = (1 - a - b)S + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} + \gamma\eta_{t-1}\eta_{t-1}' \tag{6}$$

where $\eta_t = min[\varepsilon_t, 0]$.

Since the correlation process is modelled as a scalar process in the basic DCC framework only a single news impact parameter a and a single smoothing parameter b are being estimated. Therefore, estimating one big model with all series would mean that the dynamics in correlations would be the same for all series. Furthermore, Engle (2009) notes that estimating large models might be somewhat problematic. Therefore, he proposes the *MacGyver method* to estimate models with a large number of series. This is a simple method which takes the mean or median of these bivariate estimates. It assumes that the bivariate DCC models are correctly specified. However, the disadvantage of this method is that no inference is possible.

4 Research methodology and data

In this paper we use seasonally adjusted, monthly industrial production index (IPI) data for German manufacturing sectors (NACE 2-digit level) from January 1991 to April 2015 from Eurostat. The industrial production data for US manufacturing on NAICS 3-digit level is retrieved from Federal Reserve Economic data and it covers a period from January 1972 to April 2015. Even though manufacturing sector accounts for about 25 % of the total value added, it is responsible for most cyclical movements. Therefore it is well suited for sectoral comovement analysis. The data contains 21 subsectors (for exact definitions see Tables A1 and A3 in the Appendix). These series are transformed to first order log differences. To examine the stationarity characteristics of the log first-differenced series, we apply Augmented Dickey Fuller test. All the series seem to be stationary as the results in Tables A2 and A4 in the Appendix show.

As we expect that the growth rates of industrial production index in different subsectors are driven by different processes, we model each series by autoregressive moving average (ARMA) process chosen by the Bayesian Information Criterion (BIC)[1]. The diagnostic tests for the ARMA(l,k)-residuals are shown in Tables A5 and A5 in the Appendix. The first two columns show the weighted Ljung-Box test (lag order of 20) for serial correlation of the residuals and mean-adjusted squared residuals. In most cases, serial correlation is still present in the squares of the residuals, i.e. in the variance, which is evidence for conditional heteroskedasticity. The third column reports the results of a Lagrange multiplier (LM) test for ARCH with 10 lags and indicates also the presence of conditional heteroskedasticity for most of the residual series. Columns 4 to 6 show the results of normality tests. The null hypothesis of the Jarque-Bera test can be rejected at 5% significance level and indicates that all but one residual series are non-normal.

As most of the residual series seem to be heteroscedastic, a framework accounting for non-constant volatility is necessary for the analysis. As it is possible that the volatility dynamics

[1]In some cases manual changes where taken if the chosen order did not seem to fit well

differ across the business cycle, i.e. volatility reacts differently to negative and positive shocks, also asymmetric GARCH-models are considered: exponential GARCH (eGARCH), Asymmetric power ARCH (apARCH) and The Glosten-Jagannathan-Runkle GARCH (GJR-GARCH). If an asymmetric process is modeled by the standard symmetric model, the estimated conditional variance after a negative shock would be underestimated whereas the conditional volatility would be too high after a positive shock. The optimal GARCH(p,q)-order, model and residual distribution is chosen by BIC, however adjusted manually in some cases if the chosen model did not properly fit. Considered residual distribution assumptions include normal, skewed normal, t-student and skewed t-student distribution. The estimated coefficients for ARMA-GARCH models are presented in Tables A7 and A8 in the Appendix. Altogether, in German data there does not seem to be much asymmetry in the volatilities, as the symmetric GARCH is in most cases the more appropriate choice. For the US data, however, the asymmetric models are chosen more than half of the time.

5 Results of DCC-GARCH approach

We estimate bivariate DCC(1,1)-(G)ARCH model with t-student distributed errors for all combinations of the series. Furthermore, we also account for the possible asymmetries in the conditional correlation and choose the asymmetric DCC(1,1) if the log likelihood is significantly higher than the one of the symmetric model. As we have 21 sectors there are $21 \times 20/2 = 210$ bivariate models and thus also 210 series of dynamic correlations for each country. Therefore, we will examine the average correlation and calculate the mean and median for the dynamic correlation coefficients following Engle (2009).

The parameter a of the equation (3) captures the effect of news on the correlation process and the higher the effect, the higher the variance of the correlation process. The closer the sum of a and b is to unity, the stronger the mean-reversion of the time-varying correlations. In the asymmetric model (Equation (6)), the γ measures the asymmetric effect. A positive value of γ indicates that the correlations increase more in response to negative than positive shocks.

5.1 Results for Germany

The descriptive statistics of the estimated parameters of the bivariate DCC models are presented in Table 1. The results are satisfactory as the estimates for a are always between 0 and 0.344 and b estimates are also non-negative and smaller than unity. For numerous models the estimates for a and b are significant, indicating that the correlation process is time-varying. However, not all combinations of the series seem to have a dynamic correlation process as the estimated coefficient for a equals zero in some cases. For some sector pairs the a estimate is relatively large and thus, the correlation process is quite erratic. This could indicate that these sector-pairs are rather weakly integrated.

Table 1: Descriptive statistics of the bivariate DCC model estimates for German data

Statistic	N	Mean	St. Dev.	Min	Median	Max
a	208	0.040	0.061	0.000	0.011	0.344
b	208	0.742	0.320	0.000	0.908	0.990
gamma	9	0.414	0.201	0.034	0.450	0.733
mshape	208	8.470	6.170	4.000	7.050	50.000

Only for few sector-pairs the asymmetric model was significantly better than the symmetric one according to the likelihood ratio test. For these cases the γ is estimated to be positive, that indicates a higher reaction of the conditional correlations to negative news than positive news. The median for a is 0.011 and the median for b is 0.908 and the sum is thus 0.919. This implies a rather moderate level of persistence in the correlation process.

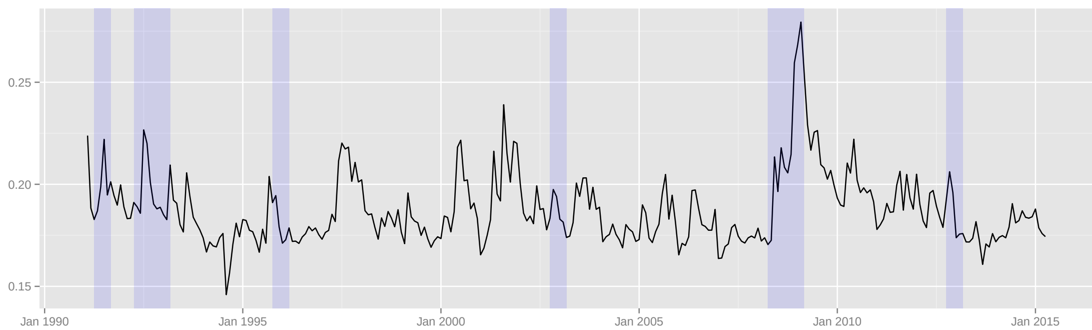

Figure 1: Average conditional correlation and German recession periods

In order to examine the interindustry comovement of the manufacturing sectors altogether, the mean of the pairwise conditional correlations is calculated. In Figure 1 the average conditional correlation is plotted together with the recession periods in Germany (defined as at least two quarters of negative growth of real GDP in a row). First of all, the mean of the average dynamic correlation over the whole time period is moderate and around 0.188. Nevertheless, we can observe that the mean dynamic correlation is not constant over the years but fluctuates somewhat. However, we cannot observe neither a positive nor negative time trend. Furthermore, the average conditional correlation seems to have increased considerably during the recession period in 2008-2009 and since then gradually normalised back to the pre-financial crises level again. Yet, during the other recession periods in Germany the comovement across the manufacturing sectors did not change substantially; only around 1992-1993 there was also a small rise in conditional correlations.

Nevertheless, there are also some periods of higher correlations which do not overlap with German recession phases. These might be periods of higher volatility due to some global events, for example. The somewhat higher comovement around 1997 could be due to the Asian currency crisis, whereas the increased correlation at the beginning of 2000 is probably accountable for the burst of the dotcom bubble. We address this issue in more detail in section 6.

A further issue that we can address with the disaggregated manufacturing data is, whether and how the dynamics differ between non-durable and durable goods sectors. Already Lucas (1977) states that the production of durable goods have more amplitude than the non-durable goods. Also Mankiw (1985) assesses the role of durable goods sectors for business cycles and states that the sectors producing durable goods are essential for business cycle fluctuations and therefore, understanding movements in durable goods sectors is important for understanding business cycles at large. Christiano and Fitzgerald (1998) show also that the comovement of hours worked with total hours worked is in durable goods manufacturing higher than across the non-durable manufacturing sectors. Moreover, Vukotic (2011) find that news shocks propagate business cycle fluctuations mainly through durable goods sectors.

For this purpose, we calculate the average conditional correlation across non-durable goods sectors respectively durable goods sectors separately. The results are plotted in Figure 2. We can observe that the conditional correlation across sectors producing durable goods is higher and more erratic than the one of non-durable goods sectors. The increase in the correlations during the recession of 2008-2009 is also observable among non-durable goods sectors, however less pronounced. These findings supports the fact that durable good sectors tend in general to comove stronger than non-durable goods sectors. Yet, not only the level of comovement is higher but also the comovement across durable goods sectors fluctuates more.

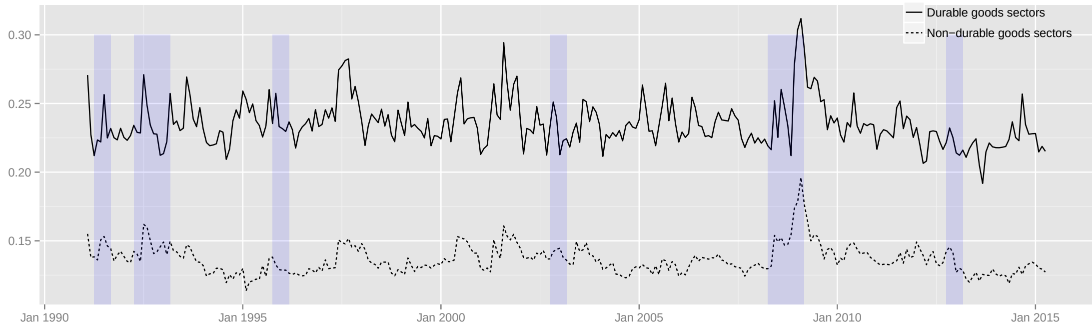

Figure 2: Average conditional correlations among durable goods and non-durable goods sectors and German recession periods

5.2 Results for the US

For the US data the results are similar to those for Germany. The descriptive statistic of the pairwise DCC model estimates are reported in Table 2. Here, the asymmetric version of the model is preferred in 21 cases by the log-likelihood criterion.

Table 2: Descriptive statistics of the all DCC model estimates for US data

Statistic	N	Mean	St. Dev.	Min	Median	Max
a	210	0.030	0.037	0.000	0.016	0.149
b	210	0.736	0.302	0.000	0.882	0.999
g	21	0.184	0.078	0.068	0.180	0.386
mshape	210	11.700	6.400	4.860	9.680	50.000

In Figure 3 the average conditional correlation across all the US manufacturing sectors is presented with the shaded areas indicating US recession as defined by the National Bureau of Economic Research. Again, in some recession periods the correlations seem to jump and we can observe the notable increase in the correlation during the recession in 2008-2009 also in the US data. A similar markable rise in the comovement is also evident mid 1970s. Altogether, the fluctuations in average conditional correlation seem to be quite similar in both Germany and in the US.

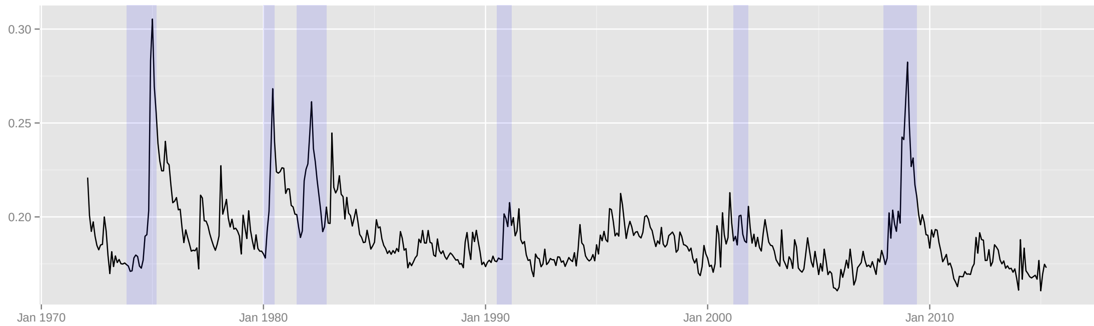

Figure 3: Average conditional correlation and US recession periods

6 Explaining dynamics of sectoral comovement

In the previous chapter we could find evidence for movements in the conditional correlations between monthly growth rates of IPI in manufacturing sectors both in Germany in the US. However, with DCC-GARCH analysis we cannot explain what are the causes for the non-constant sectoral correlations. In general, sectors comove because of common (aggregate) shocks and/or pass-through of sectoral shocks due to sectoral linkages. The time-varying inter-sectoral comovement of growth rates of manufacturing production could therefore indicate altering impact of common shock(s) as sectoral linkages tend to be rather constant.

To assess the possible factors for fluctuations in sectoral comovement, we conduct a regression analysis. We include nominal short-term (3 months) interest rates (in levels) to account for monetary policy changes. To consider effects of aggregate demand changes we include also a measure of (aggregate) activity. Total hours worked could be used as a measure, however, as this variable is available for Germany monthly only since 1995, we use the aggregate industrial production index (log change). Furthermore, stock prices (in logs) are included to be able to account for anticipated changes (often referred as *news shocks*). Moreover, we are interested to find out if and how higher volatility respectively uncertainty and recession periods influence the comovements between the sectoral IP growth rates.

Therefore, we regress the average dynamic conditional correlation on these variables, which might have an effect on comovement. The lagged value of stock market volatility is combined series from annualized monthly standard deviation of the daily returns and implied volatility index (demeaned and standardized), as implied volatility index is not available for the whole time period. We also include one lag of the dependent variable to account for serial correlation. Furthermore, we estimate various specification of the baseline model using US stock market volatility as an alternative measure for volatility, a recession dummy or dummies for each recession in the model. The data sources are reported in Table A9 in Appendix.

Table 3 presents the results of the estimated models with the mean dynamic conditional correlation as the dependent variable for German data. We report the heteroskedasticity robust standard errors. In the baseline model we include a constant, one lag of the dynamic correlation (DC), one period lagged value of stock market volatility ($volDAX$) as well as lagged values of interest rates *IntR*, (log) stock prices DAX and (log change of) industrial production *IP*. We find that stock market volatility has a positive significant effect whereas the growth rate of industrial production impacts interindustry comovement negatively. Interest rates and stock prices seem to be unrelated for the correlations between the sectors. In the second model we use the US stock market volatility instead of DAX volatility measure, and find it to have an even greater effect on sectoral comovement in German manufacturing. Next we assess the meaning of the recession periods. A recession dummy variable $d.rec.GE$ is defined to take 1 during German recession periods and zero otherwise. Also dummy variables for each recession are defined to be able to examine possible differences between the recessions. The recession dummy is positve but not significant as the variable IP is already capturing the effects of general economic situation. When examining the effects of each recession period separately (column 4), it becomes visible that some recessions periods (1992-1993 and 2008-2009) affect the mean dynamic correlation significantly positive, whereas during the economic slowdown in 2002-2003 the comovement even decreased somewhat. In the last model we leave the economic activity variable away and include instead the recession dummy. As the adjusted R^2 is almost as high, we conclude that the variable IP captures mainly the effects of economic slowdowns.

Table 3: Estimation results of regression models for German data

	Mean dynamic correlation (DC)				
	(1)	(2)	(3)	(4)	(5)
Constant	0.0345**	0.0503***	0.0504***	0.0779***	0.0521***
	(0.0165)	(0.0167)	(0.0169)	(0.0189)	(0.0179)
DC_{t-1}	0.7040***	0.6710***	0.6600***	0.6220***	0.6590***
	(0.0398)	(0.0402)	(0.0407)	(0.0427)	(0.0439)
$volDAX_{t-1}$	0.0018**				
	(0.0008)				
$volSP_{t-1}$		0.0027***	0.0027***	0.0030***	0.0031***
		(0.0009)	(0.0009)	(0.0010)	(0.0009)
$IntR_{t-1}$	0.0005	0.0003	0.0002	−0.0005	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
DAX_{t-1}	0.0023	0.0012	0.0015	−0.0007	0.0012
	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0018)
IP_{t-1}	−0.1720***	−0.1560**	−0.1370**	−0.1060*	
	(0.0653)	(0.0632)	(0.0644)	(0.0635)	
d.rec.GE			0.0034		0.0047**
			(0.0022)		(0.0023)
d.rec.91				0.0085	
				(0.0066)	
d.rec.9293				0.0088*	
				(0.0046)	
d.rec.9596				−0.0021	
				(0.0023)	
d.rec.0203				−0.0065*	
				(0.0035)	
d.rec.0809				0.0103*	
				(0.0053)	
d.rec.1213				0.00005	
				(0.0045)	
AIC	-1776.6	-1784.4	-1782.1	-1766.2	-1778.9
BG-test(3) p-value	0.6	0.74	0.89	0.59	0.94
Observations	290	290	290	290	290
R^2	0.6290	0.6390	0.6430	0.6580	0.6320
Adjusted R^2	0.6230	0.6330	0.6360	0.6450	0.6250

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Estimation results of regression models for US data

	Mean dynamic correlation (DC)			
	(1)	(2)	(3)	(4)
Constant	0.0514***	0.0519***	0.0536***	0.0460***
	(0.0102)	(0.0102)	(0.0100)	(0.0094)
DC_{t-1}	0.7670***	0.7630***	0.7560***	0.7820***
	(0.0375)	(0.0374)	(0.0391)	(0.0375)
$volSP_{t-1}$	0.0018***	0.0015***	0.0015***	0.0015***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$IntR_{t-1}$	0.0002	0.0002	0.0002	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SP500_{t-1}$	−0.0013*	−0.0013*	−0.0014**	−0.0010
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
IP_{t-1}	−0.3280**	−0.2890*	−0.2800**	
	(0.1410)	(0.1470)	(0.1420)	
d.rec.US		0.0021		0.0048***
		(0.0015)		(0.0018)
d.rec.us.7375			0.0013	
			(0.0041)	
d.rec.us.80			0.0071	
			(0.0065)	
d.rec.us.8182			0.0021	
			(0.0033)	
d.rec.us.9091			−0.0006	
			(0.0029)	
d.rec.us.01			0.0004	
			(0.0031)	
d.rec.us.0709			0.0038	
			(0.0034)	
AIC	-3377.3	-3373.3	-3346.2	-3358.3
BG-test(3) p-value	0.3	0.35	0.31	0.34
Observations	518	518	518	518
R^2	0.7760	0.7770	0.7790	0.7670
Adjusted R^2	0.7740	0.7740	0.7740	0.7650
Note:		*p<0.1; **p<0.05; ***p<0.01		

For US data we conduct similar analysis. The results are presented in Table 4. The data definition and sources can be taken from Table A10 in Appendix. Again the stock market volatility has a positive and significant effect on the mean dynamic conditional correlations. The variable *IP* affects negatively sectoral comovement as well as stock prices also. The variable *IntR*, however, does not seem to play a role for the mean dynamic correlation. As for the German data, also here the recession dummy has a positive, but not significant, effect. However, none of the individual recession dummies have significant coefficient in the model 3. Again the recession dummy seems to be able to account more and less for the same effects as the variable IP (model 4).

Altogether, these results indicate that stock market volatility plays an important role in the comovement of growth rates of industrial production across manufacturing sectors. This could indicate that stock market volatility itself causes stronger comovement or that during periods of higher uncertainty the propagation of other shocks (not captured in our analysis) is stronger.

7 Conclusions

In this paper we examine dynamics of sectoral comovement among disaggregated German and the US manufacturing sectors. We employ a multivariate dynamic conditional correlation (DCC) general autoregressive conditional heteroskedasticity (GARCH) framework to assess the time-varying and asymmetric aspects in volatilities as well as in correlations of growth rates of production. The advantage of DCC-GARCH is that we can examine possible changes in conditional correlations depending on state or circumstances of the economy as well as generally over time. We find some evidence for asymmetries in volatilities in growth rates of production of disaggregated manufacturing sectors, especially in the US. However, we find only little evidence for asymmetries in correlations i.e that the conditional correlations tend to react more to negative than positive shocks.

Our analysis reveals that the conditional correlations on average are not constant but show irregular movements, even though between some sector pairs the correlations seem to be stable. Nevertheless, no time trend can be observed. However, the level of sectoral comovement seem to have increased considerably in German as well as in the US manufacturing sectors during the recession of 2008-2009. Also during some other recessions increases in conditional correlations are observed, but not during every recession period. There are also some periods of higher correlations which do not overlap with the recession phases. Altogether, these results imply that assuming constant correlation between disaggregated (manufacturing) sectors when modelling business cycles is inappropriate.

Moreover, we examine the impact of various aggregate variables for the comovement. We find evidence that lagged stock market volatility, a measure of uncertainty, affects significantly the mean dynamic conditional correlations, also when controlling for economic downturns. On the other hand, only some specific recessions seem to have a significant effect on the level of sectoral comovement. This indicates that stock market volatility respectively uncertainty seems to be meaningful for the level of sectoral comovement and therefore, play a role in emphasizing business cycles. This could indicate that stock market volatility itself causes stronger comovement or that during periods of higher uncertainty the propagation of other shocks is stronger. However, further research is needed to explore this issue in more detail.

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A Appendix

Table A1: German data definition

NACE Code	Description	Short Label
C10-C12	Manufacture of food products; beverages and tobacco products	FoodBevTob
C13	Manufacture of textiles	Textiles
C14	Manufacture of wearing apparel	Apparel
C15	Manufacture of leather and related products	Leather
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Wood
C17	Manufacture of paper and paper products	Paper
C18	Printing and reproduction of recorded media	Print
C19	Manufacture of coke and refined petroleum products	Petroleum
C20-C21	Manufacture of chemicals and chemical products; basic pharmaceutical products and pharmaceutical preparations	ChemicalsPharma
C22	Manufacture of rubber and plastic products	Rubber
C23	Manufacture of other non-metallic mineral products	GlassStone
C24	Manufacture of basic metals	MetalPri
C25	Manufacture of fabricated metal products, except machinery and equipment	MetalFab
C26	Manufacture of computer, electronic and optical products	Electronics
C27	Manufacture of electrical equipment	Electricals
C28	Manufacture of machinery and equipment n.e.c.	Machinery
C29	Manufacture of motor vehicles, trailers and semi-trailers	Vehicles
C30	Manufacture of other transport equipment	Transport
C31	Manufacture of furniture	Furniture
C32	Other manufacturing	Other
C33	Repair and installation of machinery and equipment	Repair

Table A2: Augmented Dickey-Fuller test results for German data

	Dickey-Fuller	p-value	Lag Order
FoodBevTob	−12.10	0.01	3
Textiles	−7.01	0.01	3
Apparel	−6.39	0.01	5
Leather	−18.50	0.01	1
Wood	−9.82	0.01	4
Paper	−14.90	0.01	1
Print	−18.90	0.01	1
Petroleum	−9.74	0.01	5
ChemicalsPharma	−7.41	0.01	5
Rubber	−14.40	0.01	1
GlassStone	−10.40	0.01	4
MetalPri	−7.63	0.01	2
MetalFab	−6.25	0.01	3
Electronics	−7.35	0.01	2
Electricals	−7.38	0.01	2
Machinery	−4.66	0.01	5
Vehicles	−14.20	0.01	1
Transport	−6.22	0.01	5
Furniture	−20.40	0.01	1
Other	−19.20	0.01	1
Repair	−14.30	0.01	2

Table A3: US data definition

NAICS 2012 Code	Description	Short Label
311	Nondurable Goods: Food	Food
312	Nondurable Goods: Beverage and tobacco product	BevTob
313	Nondurable Goods: Textile mills	Textile
314	Nondurable Goods: Textile product mills	Textileprod
315	Nondurable Goods: Apparel	Apparel
316	Nondurable Goods: Leather and allied product	Leather
321	Durable manufacturing: Wood product	Wood
322	Nondurable manufacturing: Paper	Paper
323	Nondurable manufacturing: Printing and related support activities	Print
324	Nondurable manufacturing: Petroleum and coal products	Petroleum
325	Nondurable manufacturing: Chemical	Chemical
326	Nondurable manufacturing: Plastics and rubber products	Rubber
327	Durable manufacturing: Nonmetallic mineral product	Mineral
331	Durable manufacturing: Primary metal	MetalPri
332	Durable manufacturing: Fabricated metal product	MetalFab
333	Durable manufacturing: Machinery	Machinery
334	Durable manufacturing: Computer and electronic product	Electronics
335	Durable manufacturing: Electrical equipment, appliance, and component	Electricals
336	Durable Goods: Transportation equipment	Transportation
337	Durable manufacturing: Furniture and related product	Furniture
339	Durable manufacturing: Miscellaneous	Miscellaneous

Table A4: Augmented Dickey-Fuller test results for US data

	Dickey-Fuller	p-value	Lag Order
Food	−10.90	0.01	3
BevTob	−10.30	0.01	5
Textile	−8.16	0.01	4
Textileprod	−7.15	0.01	5
Apparel	−5.79	0.01	5
Leather	−9.17	0.01	2
Wood	−10.20	0.01	3
Paper	−10.30	0.01	2
Print	−8.36	0.01	3
Petroleum	−19	0.01	1
Chemical	−9.75	0.01	2
Rubber	−7.96	0.01	5
Mineral	−7.17	0.01	4
MetalPri	−10.20	0.01	3
MetalFab	−6.15	0.01	2
Machinery	−5.47	0.01	5
Electronics	−3.21	0.01	5
Electricals	−7.13	0.01	3
Transportation	−15.70	0.01	1
Furniture	−10.50	0.01	1
Miscellaneous	−7.63	0.01	4

Table A5: Diagnostic test for ARMA(p,q)-residuals for German data

	w LB (20)	w LBˆ2 (20)	Arch LM (10)	Skewness	Kurtosis	Jarque-Bera
FoodBevTob	42.85 ***	25.57	8.43	0.05	−0.04	0.14
Textiles	20.25	40.45 ***	28.9 ***	−0.37	2.92	109.57 ***
Apparel	11.99	18.41	7.6	−0.31	0.55	8.29 **
Leather	22.42	39.88 ***	29.75 ***	−0.23	2.47	76.81 ***
Wood	30.03 *	47.34 ***	36.96 ***	0.08	1.39	23.7 ***
Paper	31.16 **	32.14 **	17.29 *	−0.56	1.47	41.04 ***
Print	13.94	14.9	4.19	−0.08	1.16	16.66 ***
Petroleum	22.08	24.87	7.76	−0.67	1.78	60.06 ***
ChemicalsPharma	26.77	32.81 **	28.22 ***	−0.38	3.32	140.49 ***
Rubber	21	38.36 ***	25.73 ***	−1.20	8.88	1026.61 ***
GlassStone	26.39	62.98 ***	16.86 *	−0.81	4.97	330.79 ***
MetalPri	14.53	78.34 ***	61.43 ***	−0.37	1.63	38.79 ***
MetalFab	21.8	55.4 ***	47.65 ***	−0.62	2.70	106.77 ***
Electronics	12.34	7.38	5.57	−0.90	9.28	1083.45 ***
Electricals	40 ***	39.69 ***	31.6 ***	0.15	2.24	61.91 ***
Machinery	30.26 **	47.7 ***	41.45 ***	−0.36	7.74	732.1 ***
Vehicles	11.82	67.67 ***	36.9 ***	−0.35	3.16	126.92 ***
Transport	21.19	73.87 ***	32.91 ***	−0.41	0.87	17.51 ***
Furniture	31.46 **	32.23 **	31.53 ***	−0.54	5.35	360.48 ***
Other	17.63	37.2 ***	19.37 **	−0.39	0.88	16.53 ***
Repair	28.23 *	18.82	9.15	1.43	6.02	538.6 ***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A6: Diagnostic test for ARMA(p,q)-residuals for US data

	w LB (20)	w LBˆ2 (20)	Arch LM (10)	Skewness	Kurtosis	Jarque-Bera
Food	21.59	89.2 ***	23.29 ***	−0.07	0.95	20.56 ***
BevTob	27.22 **	70.95 ***	28.07 ***	−0.02	0.69	10.76 ***
Textile	32.92 ***	186.87 ***	81.56 ***	0.07	3.04	203.89 ***
Textileprod	15	34.21 ***	23.62 ***	0	1.06	24.88 ***
Apparel	24.59	98.85 ***	59.36 ***	0.06	1.56	54.09 ***
Leather	13.47	50.85 ***	19.31 **	−0.68	4.08	404.34 ***
Wood	20.25	24.58 **	11.31	−1.60	15.20	5252.9 ***
Paper	38.92 ***	144.65 ***	68.62 ***	0	2.01	88.84 ***
Print	32.52 **	129.02 ***	57.97 ***	−0.15	0.54	8.56 **
Petroleum	15.15	79.49 ***	75.74 ***	−0.09	6.12	820.62 ***
Chemical	19.52	145.29 ***	96.69 ***	−0.77	5.96	827.52 ***
Rubber	41.49 ***	159.22 ***	76.57 ***	0.13	11.70	3007.57 ***
Mineral	20.43	124.1 ***	49.2 ***	−0.03	0.94	19.75 ***
MetalPri	24.66	75.51 ***	58.9 ***	−0.26	1.33	45.38 ***
MetalFab	29.74 **	66.1 ***	45.42 ***	−0.31	1.63	66.71 ***
Machinery	36.56 ***	24.27 *	19.92 **	−0.08	0.69	11.46 ***
Electronics	25.26 *	174.11 ***	67.99 ***	−0.04	2.13	99.7 ***
Electricals	51.38 ***	99.15 ***	35.34 ***	0.01	1.72	65.34 ***
Transportation	9.53	39.48 ***	34.11 ***	−0.29	6.29	871.57 ***
Furniture	23.22	41.72 ***	28.06 ***	−0.06	2.27	113.35 ***
Miscellaneous	18.85	48.49 ***	26.76 ***	−0.14	1.76	69.98 ***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A7: Univariate ARMA-GARCH models for German data

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
mu	0.00^{*}	-0.00^{***}	-0.01^{***}	-0.00^{***}	0.00	0.00^{*}	-0.00	0.00	0.00^{**}	0.00^{*}	-0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ar1			0.82^{***}	0.70		-0.37^{***}	-0.55^{***}		-0.32^{***}	-0.31^{***}	
			(0.03)	(0.43)		(0.05)	(0.06)		(0.06)	(0.06)	
ar2			-0.90^{***}				-0.25^{***}				
			(0.10)				(0.06)				
ar3											
ar4											
ma1	-0.65^{***}	-0.47^{***}	-1.32^{***}	-1.26^{***}	-0.36^{***}			-0.46^{***}			-0.22^{***}
	(0.05)	(0.08)	(0.06)	(0.43)	(0.06)			(0.08)			(0.06)
ma2		0.05	1.21^{***}	0.45^{**}				-0.23^{***}			
		(0.04)	(0.21)	(0.21)				(0.07)			
ma3		0.11^{**}	-0.43^{***}								
		(0.04)	(0.14)								
ma4											
omega	0.00^{**}	0.00^{***}	-4.19^{**}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00	0.00^{***}
	(0.00)	(0.00)	(1.84)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
alpha1	0.01	0.52^{***}	0.05	0.44^{***}	0.21^{***}	0.32^{**}	0.11^{*}	0.16^{*}	0.10^{**}	0.31^{*}	0.63^{**}
	(0.01)	(0.14)	(0.10)	(0.15)	(0.08)	(0.15)	(0.06)	(0.09)	(0.05)	(0.18)	(0.25)
beta1	0.98^{***}		0.36	0.22						0.47^{*}	
	(0.01)		(0.28)	(0.16)						(0.24)	
delta											
gamma1			0.45^{***}								0.82^{*}
			(0.14)								(0.49)
skew	0.95^{***}	0.91^{***}		0.77^{***}							0.84^{***}
	(0.11)	(0.11)		(0.09)							(0.08)
shape			7.51^{**}	5.73^{***}	100.00^{***}	7.20^{***}	8.30^{**}	5.57^{***}	6.76^{***}	4.74^{***}	3.03^{***}
			(3.27)	(2.05)	(37.19)	(2.56)	(3.50)	(1.52)	(2.43)	(1.14)	(0.43)
Num. obs.	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00

	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
mu	0.00^{**}	0.00^{***}	0.00^{**}	0.00	0.00	0.00^{**}	0.00	-0.00	0.00^{***}	0.00^{**}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ar1	0.85^{***}	-0.31^{***}	-0.25^{***}	-0.21^{***}	0.83^{***}	-0.45^{***}	0.83^{***}	-0.49^{***}	-0.63^{***}	-0.43^{***}
	(0.05)	(0.07)	(0.06)	(0.08)	(0.06)	(0.05)	(0.11)	(0.07)	(0.06)	(0.05)
ar2		-0.08	0.11^{**}	0.08				-0.16^{***}	-0.31^{***}	-0.22^{***}
		(0.07)	(0.05)	(0.07)				(0.05)	(0.05)	(0.06)
ar3		0.13^{***}	0.30^{***}	0.18^{***}						
		(0.04)	(0.04)	(0.06)						
ar4		0.15^{***}								
		(0.06)								
ma1	-1.20^{***}				-1.36^{***}		-1.32^{***}			
	(0.00)				(0.07)		(0.12)			
ma2	0.35^{***}				0.56^{***}		0.50^{***}			
	(0.06)				(0.05)		(0.08)			
ma3	0.06									
	(0.06)									
ma4	-0.17^{***}									
	(0.05)									
omega	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00	0.00^{***}	0.00	0.00^{***}	0.00^{***}	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
alpha1	0.27^{**}	0.32^{**}	0.29^{***}	0.30^{**}	0.04	0.36^{***}	0.14	0.94^{***}	0.02^{**}	0.17^{**}
	(0.11)	(0.14)	(0.11)	(0.12)	(0.05)	(0.11)	(0.11)	(0.22)	(0.01)	(0.08)
beta1	0.46^{***}				0.90^{***}	0.38^{***}	0.80^{***}	0.06		0.63^{***}
	(0.10)				(0.10)	(0.13)	(0.14)	(0.06)		(0.17)
delta									3.50^{***}	
									(0.04)	
gamma1									0.96^{***}	
									(0.02)	
skew										1.53^{***}
										(0.34)
shape	7.19^{***}	7.79^{***}	5.33^{***}	6.68^{***}	5.46^{***}	6.72^{***}		3.47^{***}	7.83^{***}	5.99^{***}
	(2.33)	(2.93)	(2.02)	(2.39)	(1.77)	(2.48)		(0.67)	(0.64)	(1.91)
Num. obs.	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00	291.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A8: Individual ARMA-GARCH models for US data

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
mu	0.00***	0.00	−0.00	0.00	−0.00*	−0.00***	0.00	−0.00	0.00	0.00	0.00***	0.00***	0.00	0.00	0.00	0.00*	0.01***	0.00	0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ar1		−0.64***	−1.54***	−1.21***	0.82***	0.04	−1.08***	−0.26***	0.61***		0.78***		0.65**	0.03	0.19***	0.30	0.91***	0.86***	−0.06	0.18***	−0.00
		(0.03)	(0.01)	(0.01)	(0.06)	(0.03)	(0.06)	(0.06)	(0.11)		(0.07)		(0.28)	(0.07)	(0.06)	(0.18)	(0.03)	(0.06)	(0.07)	(0.07)	(0.05)
ar2		−0.96***	−0.36***	−0.98***		0.15***	−0.84***	0.11*	0.25***					0.18***	0.18***	0.36***				0.15***	0.14***
		(0.03)	(0.03)	(0.02)		(0.03)	(0.01)	(0.06)	(0.05)					(0.04)	(0.06)	(0.13)				(0.06)	(0.04)
ar3			0.52***	0.13***		0.21***	0.15***	0.23***							0.28***						0.19***
			(0.03)	(0.02)		(0.04)	(0.02)	(0.04)							(0.06)						(0.04)
ar4			0.15***	0.19***			0.06														
			(0.02)	(0.02)			(0.08)														
ar5				0.11***																	
				(0.02)																	
ma1	−0.15***	0.18***	1.76***	1.16***	−0.76***		1.15***		−0.77***	−0.15***	−0.70***	0.14**	−0.71***			−0.36*	−0.62***	−0.93***			
	(0.05)	(0.07)	(0.01)	(0.02)	(0.08)		(0.05)		(0.07)	(0.05)	(0.08)	(0.06)	(0.27)			(0.19)	(0.06)	(0.08)			
ma2		0.72***	0.94***	0.93***	0.15***		0.98***					0.09*	0.15***			−0.17	−0.00	0.25***			
		(0.03)	(0.01)	(0.01)	(0.04)		(0.00)					(0.05)	(0.06)			(0.13)	(0.07)	(0.04)			
ma3		−0.37***										0.20***				0.16***					
		(0.05)										(0.04)				(0.06)					
omega	0.00	0.00***	0.00***	−2.19**	−0.22	−2.73*	0.00	0.00***	0.00	0.00	0.00***	0.00***	0.00***	0.00***	−0.77***	0.00***	−2.15	0.00	−1.74	−1.38	0.00***
	(0.00)	(0.00)	(0.00)	(0.97)	(0.14)	(1.56)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(1.63)	(0.00)	(1.43)	(1.17)	(0.00)
alpha1	0.02	0.05***	0.33***	0.01	−0.13**	−0.13*	0.05	0.01	0.08	0.03	0.23***	0.05	0.05	0.41***	−0.15***	0.07	−0.19***	0.00	−0.25***	−0.18***	0.12***
	(0.05)	(0.01)	(0.07)	(0.07)	(0.05)	(0.08)	(0.08)	(0.05)	(0.21)	(0.04)	(0.08)	(0.03)	(0.08)	(0.10)	(0.03)	(0.11)	(0.07)	(0.04)	(0.06)	(0.05)	(0.02)
beta1	0.97***	0.93***	0.59***	0.72***	0.97***	0.66***	0.91***	0.79***	0.91***	0.67***	0.35***	0.77***	0.51***		0.92***	0.33**	0.77***	0.92***	0.77***	0.84***	0.80***
	(0.06)	(0.01)	(0.08)	(0.12)	(0.02)	(0.20)	(0.02)	(0.04)	(0.22)	(0.16)	(0.08)	(0.04)	(0.12)		(0.00)	(0.16)	(0.18)	(0.06)	(0.19)	(0.13)	(0.03)
gamma1				0.42***	0.15	0.55***		0.21**		0.28***	0.25	0.24***	0.41***		0.10***	0.34**	0.45***	0.12**	0.41*	0.22*	
				(0.13)	(0.33)	(0.18)		(0.09)		(0.09)	(0.19)	(0.07)	(0.09)		(0.03)	(0.14)	(0.15)	(0.06)	(0.23)	(0.12)	
skew						0.90***	0.88***	0.89***				0.89***	0.93***		0.83***				0.81***		0.94***
						(0.05)	(0.05)	(0.05)				(0.05)	(0.06)		(0.06)				(0.05)		(0.05)
shape	10.80*		5.74***	8.13**	6.85***	8.81***	4.39***	10.51**		7.00***	8.28***	7.40***	8.39**	8.03***			8.77***		5.16***	12.13**	4.85***
	(6.03)		(1.59)	(3.48)	(2.59)	(3.11)	(1.49)	(4.53)		(2.35)	(2.04)	(2.56)	(3.28)	(2.61)			(2.10)		(1.23)	(5.42)	(1.02)
Num. obs.	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00	519.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A9: German data sources

Variable	Description	Source
volDAX	Combined series of the annualized monthly volatility of the daily DAX returns (until 10/2005) and the implied volatility index from DAX option (VDAX) (from 11/2005 on)	Yahoo Finance
GDP	Seasonally adjusted real Gross Domestic Product	Federal Statistical Office
intR	3-Month or 90-day Rates and Yields: Interbank Rates for Germany	Federal Reserve Economic data
DAX	Level of German stock market index (DAX)	Yahoo Finance
IP	Industrial Production Index	Eurostat

Table A10: US data sources

Variable	Description	Source
volSP	Combined series of the annualized monthly volatility of the daily SP500 returns (until 12/1985) and the implied volatility index from SP500 option (VXO) (from 1/1986 on)	Yahoo Finance
GDP	Seasonally adjusted Gross Domestic Product chained values at 2009 Dollars	Federal Reserve Economic data
Hours worked	Index of Aggregate Weekly Hours: Production and Nonsupervisory Employees: Total Private Industries	Federal Reserve Economic data
Loans	Commercial and Industrial Loans, All Commercial Banks	Federal Reserve Economic data
IntR	3-Month Treasury Bill: Secondary Market Rate	Federal Reserve Economic data
SP500	Level of SP500	Yahoo Finance
IP	Industrial Production Index	Federal Reserve Economic data

B Appendix: Exact GARCH-model Specifications

Exponential GARCH (eGARCH)

$$log(h_t) = \omega + \alpha \frac{|u_{t-1|}}{\sqrt{h_{t-1}}} + \gamma \frac{u_{t-1}}{\sqrt{h_{t-1}}} + \beta log(h_{t-1})$$

GRJ-GARCH

$$h_t = \omega + \alpha u_{t-1}^2 + \gamma I[u_{t-1} < 0] u_{t-1}^2 + \beta h_{t-1}$$

APARCH

$$h_t^{\lambda/2} = \omega + \alpha |u_{t-1}|^\lambda + \gamma I[u_{t-1} < 0] |u_{t-1}|^\lambda + \beta h_{t-1}^{\lambda/2}$$