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Stock Market Dispersion, Sectoral Shocks, and the German Business Cycle

by

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Abstract:

This paper elaborates on the relative importance of sectoral shocks for real economic activity in Germany. Implications of multisectoral real business cycle models are examined by resorting to testing techniques based on stock market returns. The empirical evidence is obtained by calculating cross-correlation coefficients of sectoral stock market returns with industrial production, by estimating a limited dependent variable model, and by setting up a trivariate structural vectorautoregression model including a stock market dispersion measure. The results suggest that the influence of sectoral shocks on the dynamics of real output is rather small.

Keywords: real business cycles, sectoral shocks, stock market dispersion, probit model, structural VAR

JEL classification: E32, E44

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I Introduction[1]

A heavily discussed question in the current macroeconomic debate is to what extent aggregate economic fluctuations are driven by stochastic productivity shocks as predicted by Real Business Cycle (RBC) models in the tradition of Kydland and Prescott (1982). Long and Plosser (1983) have extended this view in claiming that sectoral productivity shocks are the dominant source of movements in real gross domestic product (GDP) and other important business cycle indicators. In sharp contrast, standard macroeconomic models of either the Keynesian or the monetarist style emphasize the importance of demand side shocks for aggregate fluctuations at business cycle frequencies (Blanchard 1989).

This paper contributes to this area of research. The special focus of our empirical study is on the relevance of sectoral productivity shocks for the dynamics of the business cycle in Germany. While this issue has already been addressed by Entorf (1990, 1991) and, more recently, by Lucke (1998a) using sectorally disaggregated series of industrial production, we measure the intensity of sectoral shocks by constructing a simple stock market returns based dispersion measure. This dispersion index is defined in terms of the cross–sectional variance of returns of sectoral stock market subindeces. As reported in Loungani et al. (1990), Loungani and Trehan (1997), and Brainard and Cutler (1993) for U.S. data, this type of stock market dispersion measure helps to model the contribution of sectoral shifts to fluctuations in aggregate unemployment. The underlying economic idea motivating this line of argumentation is that the present discounted–value model implies that current stock prices reflect on current productivity shocks and thus anticipate future cash–flows. If supply side shocks predominantly affect the real output of individual sectors, this stock market based

[1] The authors thank Jan Gottschalk, Christophe Kamps and Claudia Buch for helpful comments. Remaining errors are solely in our own responsibility.

dispersion measure will be relatively high. If, in contrast, an aggregate supply or demand disturbance hits the economy as a whole, the returns across all sectors will move in the same direction so that stock market dispersion remains relatively low.

The paper assesses the relative importance of industry–specific as compared to aggregate shocks by means of three alternative procedures. We first test an implication of the sectoral real business cycle model outlined by Entorf (1990, 1991) by analyzing whether or not returns of shares of the industrial sector lead the returns of stocks belonging to consumer–related industries. The economic intuition motivating this examination procedure is that if supply shocks are the predominant source of fluctuations in economic aggregates then the output and, in our case, the returns of investment–related industries should lead the business cycle in a more pronounced fashion than the corresponding series obtained for the consumer goods related sector of the economy.

The second testing approach is stimulated by recent results reported by Campell and Lettau (1999) for the U.S. stock market. They report that a stock market dispersion measure computed by resorting to industry level returns is a leading indicator of real economic activity. While these authors use their dispersion measure to examine the forecasting power of stock market fluctuations for subsequent changes in the stance of the business cycle, their findings can also be interpreted from the perspective of real business cycle theory. Because cross–sectional stock market dispersion can serve as a measure of the extent of industry specific shocks hitting an economy, the approach suggested by Campell and Lettau (1999) provides a promising avenue of research to reconsider the importance of sectoral disturbances for real economic activity. We therefore use qualitative dependent variables technique inspired by Estralla and Mishkin (1998) to verify whether the cross–sectional variance of stock market returns provides valuable information regarding the future evolution of real output. Our results indicate that our stock market dispersion index provides some information with respect to the future stance of the business cycle. However, the evidence is rather weak.

Finally, in the tradition of Blanchard and Quah (1989), we estimate a trivariate dynamic system including our cross–sectional dispersion measure to further assess the importance of sectoral shocks for aggregate economic fluctuations in Germany. Similar to the approach recently taken by Gavosto and Pellegrini (1999) using a different set of variables, the framework of analysis estimated in the present paper renders it possible to reveal the relative importance of sectoral shocks by invoking an appropriate set of long–run neutrality restrictions.

In contrast to the predictions of the multisectoral real business cycle models tracing back to Long and Plosser (1983), we find that sectoral shocks have only a minor impact on the dynamics of German real GDP. This is in line with results reported in Lucke (1998a) who, using an alternative empirical technique, also rejects the hypothesis of sectoral productivity shocks as the main driving force behind the German business cycle. We are unable to find a clear cyclical pattern in sectoral stock market returns. In particular, non–consumer goods industries stock market returns do not lead more pronounced changed in industrial production as compared to the stock market returns computed for consumer goods industries. Furthermore, stock market dispersion provides virtually no usable information with respect to future downswings of economic activity. Finally, the fraction of the variability of real output attributable to industry–specific productivity shocks turns out be rather small. However, though sectoral shocks do not provide much information with respect to the dynamics of real GDP, our empirical analysis reveals that this type of economic fluctuations explain a significant fraction of change in the price level.

The remainder of the paper is organized as follows. We begin our analysis in section 2 with a review of the results documented in related empirical studies.

Section 3 is devoted to a discussion of the lead/ lag relationship between various sectoral stock market returns and the business cycle. In section 4, we introduce our measures of stock market dispersion and employ a qualitative dependent variables model to shed light on the forecasting performance of stock market dispersion with respect to the subsequent occurrence of recession periods. In section 5, we set up and identify a trivariate structural vectorautoregression (SVAR). Impulse response functions and a decomposition of the innovation terms are presented. The final section offers some concluding remarks.

II Existing Empirical Evidence

Stimulated by the discussion which has unfold in response to the challenge of traditional macroeconomic theory by real business cycle (RBC) theory, several empirical researchers have elaborated on the importance of real shocks for the stance of the business cycle. One of the main implications of RBC theory is that in economies with optimizing rational agents acting in a competitive Walrasian environment exogenous productivity shocks play a prominent role for the dynamics of real output. To test this hypothesis, a substantial and growing body of empirical research focuses on the so–called stylized facts regarding fluctuations in economic aggregates and examines whether or not the predictions of real business cycle models match these stylized facts.

As regards German data, the evidence documented in these studies in general contradicts the predictions of prototype RBC models. For example, Brander and Neuser (1992) argue that the stylized facts characterizing Germany’s business cycle do not indicate a prominent role for productivity shocks. Scheide (1990) uses unit root tests as suggested by Nelson and Plosser (1983) and concludes that monetary variables are more important than real disturbances in explaining movements in real output in Germany.

Using the decomposition advanced by Blanchard and Quah (1989) as well as structural VAR approaches, M. Funke (1997a,b) documents the extend to which the dynamics of real GDP can be attributed to several driving shocks. All in all, he finds that productivity shocks do exert only a minor impact on changes of real economic activity at low business cycle frequencies. However, the forecast error variance decomposition documented in Weber (1996) points to a more important role for aggregate supply shocks even in the short term. Bergmann (1996) uses a bivariate cointegrated system and confirms that a relatively large fraction of short–term and long–term movements in real GDP can be attributed to permanent shocks. Moreover, the findings reported in M. Funke (1997a) suggest that lasting technological shocks account for a significant fraction of the variability of the unemployment rate. Finally, Lucke (1997) applies the Burns–Mitchell methodology relying on the turning points of a reference cycle with the turning points of aggregate time–series to German data. The general conclusion which can be drawn from his study does not favor real business cycle theory.

While the evidence discussed so far relies on aggregate time series to examine the importance of productivity shocks for the dynamics of the business cycle, a related strand of research uses the results of Long and Plosser (1983) and resorts to sectoral data to test the impact of industry–specific disturbances on real economic activity. Using German data, Entorf (1990, 1991) argues that sectoral real business cycle models imply that the output of consumer–related sectors should lag the output of non–consumer goods related industries. Using both a cross–correlation based test and spectral analyses, he rejects this implication of the theoretical model. Lucke (1998) confirms these results using a cointegration approach. He emphasizes that sectoral real business cycle models rule out a large number of cointegration relationships between sectoral output series. Using German data, he finds more cointegration vectors than compatible with his theoretical multisectoral RBC framework.

III A Measure of Stock Market Dispersion and Its Cyclical Behavior

Stock prices respond immediately to changes in market participants' sentiment regarding the future prospects of firms and industries. They are forward looking variables by nature and can therefore be presumed to better reflect industry–specific shocks as compared to alternative measures e.g. advanced by Lilien (1982) based on unemployment data (Black 1995: pp. 213). In this section, we exploit this presupposition to test the implications of the multi–sector RBC models mentioned above. For this purpose, we use three different empirical techniques. Firstly, we utilize sectoral stock market data to reconsider the results documented in Entorf (1990, 1991). As already mentioned in the preceding section, he finds that consumer sectors lead non–consumer sectors which is in sharp contrast to the predictions of the RBC school. Secondly, we discuss how to construct a measure of industry–specific shocks based on the cross–sectional variance of stock market returns. This dispersion measure reflects the differences in the intensities with which individual sectors in an economy are hit by idiosyncratic shocks. In a third step, we calculate the cross–correlations of this measure with important macroeconomic variables. This exercise reflects that industry–specific shocks should provide information with respect to the future stance of the business cycle under the null hypothesis that RBC models provide a satisfactory explanation for aggregate real economic fluctuations.

We use quarterly data for the German stock market ranging from 1974:1 to 1998:4 and compute sectoral returns from 16 CDAX subindeces as provided by the Deutsche Börse AG. Returns are calculated as the first differences of the natural logarithms of the respective share price subindeces.

To get a first impression of the link between the stock market and real economic activity, table 1 plots cross–correlation coefficients of the respective monthly sectoral stock market returns with the change in industrial production in Germany.[2] The table reveals that there is no clear–pattern with respect to the issue whether or not the returns measured for a specific sector tend to lead changes in industrial production. Although most of the non–consumer goods sectors like the machinery lead changes in real economic activity as predicted by multi–sector RBC models, a similar proposition can also be made for several consumer sectors like, for example, utilities and the retail sector. Moreover, some cross–correlation coefficients exhibit a sign not in line with economic prejudices. Over and above, the computed correlations turn out to be rather small and hardly significant at any conventional significance level. Thus, the stock market based evidence presented in the table underpins the result reported in Entorf (1990, 1991) that there is no inherent sectoral ordering as implied by models in the tradition of Long and Plosser (1983).

To shed more light on the relevance of sector specific stock price movements for the business cycle, we now construct a measure of stock market dispersion defined as the cross–sectional variance computed over returns of sectoral stock market subindeces. More specifically, we follow Brainard and Cutler (1993) and compute industry j specific excess returns by first regressing the stock market returns of each sector $R_{j,t}$ in the sample on the returns of the market portfolio $R_{m,t}$ with the latter proxied by the CDAX index:

[1] $$R_{j,t} = \beta_{0,j} + \beta_{1,j} R_{m,t} + \varepsilon_{j,t}$$

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[2] Further information regarding the data set used in the empirical analysis can be found in the data appendix at the end of the text.

Table 1: Cross–Correlation Coefficients of Sectoral Stock Market Returns with the Change in Industrial Production

Change of Industrial Production with Returns of....	*t*-4	*t*-3	*t*-2	*t*-1	*t*-0	*t*+1	*t*+2	*t*+3	*t*+4
Automobile Industry	0.05	-0.11	-0.18	0.01	0.15	-0.11	-0.11	0.20	**0.24**
Banks	-0.19	-0.04	0.01	-0.08	-0.08	0.16	**0.24**	-0.12	-0.02
Basic Industries	0.10	-0.19	0.04	**0.20**	0.14	-0.10	0.01	0.04	0.05
Chemie	0.02	0.10	**0.37**	0.12	-0.04	-0.05	-0.18	-0.22	-0.08
Construction	-0.03	**-0.34**	-0.33	-0.08	0.04	0.00	-0.05	0.06	0.14
Finance	0.06	-0.14	-0.03	**-0.17**	0.02	0.13	-0.01	0.04	0.01
Food	0.06	**-0.16**	-0.10	-0.02	-0.10	-0.14	0.07	0.07	-0.01
Industrial	-0.10	0.03	0.12	0.08	**-0.19**	0.02	0.07	0.03	-0.06
Insurance	-0.06	0.14	0.02	-0.01	0.08	**0.17**	0.12	0.00	-0.03
Machines	-0.01	-0.05	-0.08	**0.09**	-0.01	-0.08	-0.07	0.06	-0.05
Pharma	0.09	0.23	**0.33**	0.12	0.11	-0.12	-0.16	-0.11	-0.14
Retail	0.13	-0.12	-0.22	**-0.29**	0.05	0.07	-0.12	-0.02	0.12
Technology	0.04	**0.11**	-0.13	0.03	0.05	-0.02	-0.04	-0.02	-0.01
Transport	0.26	-0.01	0.02	0.10	**0.11**	-0.06	-0.17	0.09	0.00
Utilities	0.05	-0.11	-0.02	0.08	**-0.22**	-0.10	-0.04	0.07	-0.17
Cyclical Consumer Goods	0.07	**-0.26**	-0.16	-0.03	0.11	0.07	0.05	0.07	0.12

Note: Bold figures denote the absolute maximum of the calculated cross–correlation coefficients. Stock market returns have been computed by taking the first difference of the natural logarithm of the respective stock market subindeces sampled at a monthly frequency.

The residuals $\hat{\varepsilon}_{j,t}$ of this set of equations are utilized to form the industry specific component $\Theta_{j,t}$ of return variation:

[2] $$\Theta_{j,t} = \hat{\beta}_{0,j} + \hat{\varepsilon}_{j,t}$$

The cross–sectional variance CSV_t computed over the idiosyncratic components of sector stock market returns can now be computed as:

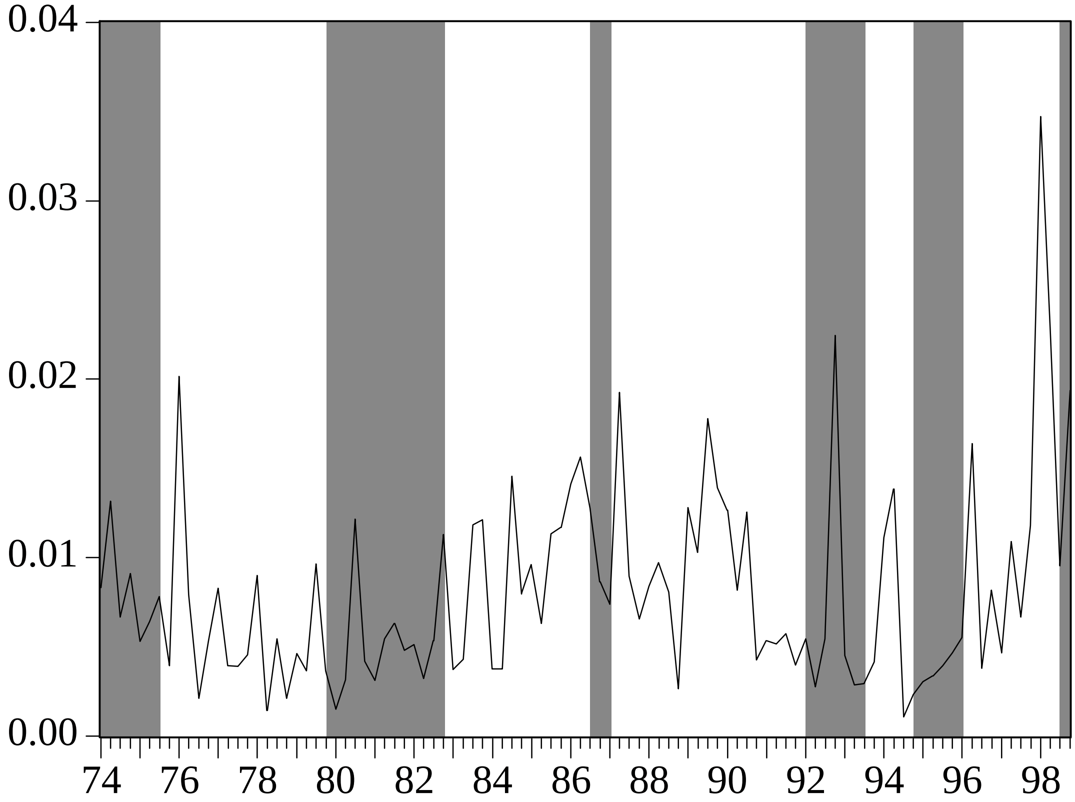
[3] $$CSV_t = \sum_{j=1}^{N} w_{j,t} \left(\Theta_{j,t} - \overline{\Theta}_t \right)$$

where N denotes the number of sectors, $w_{j,t}$ is a weighting factor, and $\overline{\Theta}_t$ reflects the mean of the sector–specific returns components in period t.

The weighting factors $w_{j,t}$ are calculated by dividing the market capitalization of the shares subsumed under a sector specific stock market index divided by the sum of the market capitalization of all sectoral subindeces under investigation. Since long time–series of market capitalizations are not available, we approximate the weights $w_{j,t}$ by taking the most recent market capitalization as well as the respective observed subindex returns as a starting point to figure out historical market capitalizations. Our specific choice of weighting factors is motivated by the notion that stock market based measures can be presumed to better reflect on current technological advances made in the various sectors of the economy than more backword–looking weights calculated e.g. from sectoral ouput or employment data. A figure plotting the evolution of the sectoral weights is contained in the data appendix at the end of the paper.

Figure 1 depicts the resulting cross–sectional variance CSV_t. Our measure of stock market returns dispersion plotted in the exhibit has several interesting properties. For example, the cross–sectional variance of sectoral stock market returns exhibited a tendency to rise in the year 1986 as a positive supply side shock emerged in the form of a pronounced reduction of oil prices. While this is

Figure 1: Cross–Sectional Stock Market Volatility at a Quarterly Frequency



Note: Shaded areas indicate recession periods defined below.

in line with economic prejudices, we also note that the first oil price shock which hit the world economy 1973 did not stimulate stock market dispersion to increase. Instead, we observe a remarkable rise of CSV_t during the year 1976 characterized by a cyclical upswing of real economic activity. A further moderate peak shows up in the cross–sectional variance of returns around the time of the stock market crash in October 1987. This reflects that the tremendous decline in the level of stock prices did not affect the prices of shares across sectors uniformly. Moreover, figure 1 reveals that the opening of the eastern European economies in the year 1989 was followed by a noticeable peak in our dispersion measure. This can be interpreted as a hint that stock market participants discounted anticipated favorite future business conditions for all those sectors which benefited most from the off–shining of the new markets in the East. A final pronounced peak in the series shows up in the years 1997/98 as the turmoils in the Asian currency and stock markets worsened and the crisis spread to the other countries in the region and the rest of the world as well. This might underscore that these disruptions hit particularly export orientated firms while prospects for companies oriented mainly towards the domestic market remained relatively stable during this period.

All in all, this informal discussion unearths that the hypothesis that the cross–sectional variance of stock market returns might provide useful information with respect to the overall course of the business cycle cannot be rejected a priori. This result encourages a closer examination of the link between our stock market dispersion measure and the fluctuation of important macroeconomic aggregates. As a first step in this direction, table 2 presents cross–correlation coefficients for CSV_t and selected time–series relevant for the characterization of the stance of the business cycle.

Table 2: Cross–correlation Coefficients of Important Macroeconomic Series with Stock Market Dispersion

Stock Market Dispersion with....	*t*-4	*t*-3	*t*-2	*t*-1	*t*-0	t+1	*t*+2	*t*+3	*t*+4
Change of Real GDP	-0.05	-0.12	-0.10	-0.05	0.03	0.00	0.04	0.13	**0.18**
Unemployment Rate	**0.39**	0.38	0.37	0.33	0.30	0.26	0.23	0.19	0.13
Inflation Rate	-0.27	-0.27	-0.26	-0.31	**-0.36**	-0.33	-0.36	-0.32	-0.26

Note: Bold figures denote the absolute maximum of the calculated cross–correlation coefficients.

Table 2 shows that stock market dispersion lags changes in real GDP. Quite in contrast, the cross–sectional variance of stock market returns tends to lead the unemployment rate, i.e. our CSV_t series exhibits an anticyclical behavior with respect to labor market prospects. This finding is in line with results documented in Loungani et al. (1990), Loungani and Trehan (1997), and Brainard and Cutler (1993). With respect to the relation between stock market dispersion and the inflation rate, a coincident link can be found. Moreover, the figures in the last row of the table indicate that an increase in CSV_t tends to be followed by a subsequent decrease in inflation. This result might be interpreted to reflect the impact of sectoral shocks on the intersectoral reallocation of resources and a concomitant decline in prices.

This section can be summarized by stating that the prima facie evidence in favor of a prominent role of industry–specific shocks for the business cycle is rather weak. However, the evidence presented so far is based on descriptive statistics and do not allow to describe the extent of sectoral and aggregate shocks hitting the economy systematically. In order to provide a more rigorous analysis, we now turn to the implementation of more formal testing procedures. On the one hand, it is examined whether stock market dispersion provides valuable information with respect to the occurrence of recessions. On the other hand, we extend a standard bivariate vectorautoregressive model advanced by Blanchard and Quah (1989) by resorting to our dispersion measure as a third state variable of the system to shed light on the importance of sector–specific shocks.

IV Stock Market Dispersion as a Leading Indicator of the Business Cycle?

As discussed by Stadler (1994), a specific challenge for RBC models is to predict recession periods. The economic intuition behind this reasoning is that the many economists questions the interpretation of recessions as an aggregate decline in productivity as supported by adherents to RBC models (Hansen and Prescott 1993). To test more formally whether sectoral productivity shocks provide valuable information with respect to subsequent changes in real economic activity, we follow Estrella and Mishkin (1998) and estimate a binary dependent variable model to assess the predictive power of widely used economic indicators with respect to the future stance of the business cycle.

The methodology is implemented by subdividing the business cycle into upswings and recessions according to the separation criterion formulated by Artis et al. (1997). This concept relies on the tradition of the National Bureau of Economic Research dating of business cycles. The classification methodology can be carried out by following three steps: In the first step, extreme values are identified and replaced. Secondly, the time series is smoothed to reduce the importance of short-run irregular fluctuations. A business cycle turning point is identified as a point in time with a higher or lower economic activity than observed during any other point within a two–sided 12 months window. In the third and final step, it is checked which dates of the original time series correspond to the turning points of the smoothed data. Applying this concept, we obtain the recession phases graphed as shaded areas in figure 1.

To transform this classification scheme into a time–series which can be used as input in a formal model, we assign the numerical value 1 to recessions and use the value 0 to catch expansions. The resulting dichotomous variable can be used to examine the predictive power of stock market dispersion with respect to upswings and downswings of real economic activity by implementing the following Probit model.

Let the unobservable latent variable R_t* denote the probability that a recession will take place in period t. Assuming that the conditional mean of this variable is a linear function of stock market dispersion observed from period $t-k$, $k \geq 1$ up to period $t-1$, the Probit model with p lagged cross–sectional volatilities of stock market returns as explanatory variable takes the form:

[4] $$R_t^* = \beta_0 + \beta_1 \cdot \sum_{k=1}^{p} CSV_{t-k} + u_1$$

where u_t is a normally distributed disturbance term and CSV_t is the stock market dispersion measure estimated in section 3. Using the notational convention introduced above, the observable recession indicator R_t is given by:

$$[5] \qquad R_t = \begin{cases} 1 & \text{if } R_t^* > 0 \\ 0 & \text{else} \end{cases}$$

Let P_R denote the probability that a recession will take place in period t. It then follows (see e.g. Greene 1997: pp. 880):

$$[6] \qquad P_R(R_t^* > 0) = P_R(R_t = 1) = \Phi\left(\mathbf{b}_k' \, \mathbf{s}_{t,k}\right)$$

where $\Phi(\cdot)$ denotes the cumulative normal distribution function, b_k is a $(k \times 1)$ vector of coefficients to be estimated, and $s_{t,k}$ is a $(k \times 1)$ vector of lagged stock market volatilities. The goodness–of–fit of the models is evaluated by means of the MacFadden R^2 (see MacFadden 1974):

$$[7] \qquad R^2 = 1 - (L_u \, / \, L_C)$$

In equation [7], L_C is the value assumed by the maximized log-Likelihood in a regression in which the recession dummy is explained by a constant only and L_u is the log-likelihood of the unrestricted regression. The MacFadden R^2 is bounded between 0 and 1 and can thus be interpreted in the same manner as the usual R^2 in standard regressions.

Table 3 gives the results of estimating the model outlined above in various specifications. The MacFadden R^2 in the models only containing stock market dispersion as an exogenous variable is rather small. Thus, the share of the variance of the endogenous variable explained by the exogenous series is negligible. Moreover, in all but one case the Wald statistic indicates that the hypothesis that the coefficients of stock market dispersion are jointly zero cannot be rejected at virtually all conventional significance levels. An exception arises in the model constructed by utilizing eight lags of cross–sectional stock market returns volatility as explanatory variables. A closer examination of this model, however, yielded that the significant coefficients exhibit a sign not compatible with the predictions of RBC models, i.e. an increase of stock market dispersion reduces the probability of a recession to come rather than increasing it. Indeed, such an outcome fits better into a model in which recession periods are characterized by strong structural change and a corresponding reallocation of resources.

Table 3: The Predicative Power of Stock Market Dispersion in a Probit Model

Model specification	*MacFadden* R^2	*Wald–test*
Constant, CSV_t	0.02	2.61
Constant, $CSV_{t-1},\ldots CSV_{t-4}$	0.05	6.13
Constant, $CSV_{t-1},\ldots CSV_{t-8}$	0.17	11.89*
Constant, $CSV_{t-1},\ldots CSV_{t-12}$	0.19	16.92
Constant, CSV_t, R_{t-1}	0.51	0.12
Constant, $CSV_{t-1},.CSV_{t-4}$, R_{t-1}	0.57	7.61
Constant, $CSV_{t-1},.,CSV_{t-8}$, R_{t-1}	0.61	9.06
Constant, $CSV_{t-1},.CSV_{t-12}$, R_{t-1}	0.64	11.08

Following Duecker (1997), we have also checked the forecasting power of stock market dispersion in binary dependent variables models featuring a lagged endogenous explanatory variable. Such a framework accounts for the lack of a dynamic specification of conventional Probit models and allows for stronger tests of the predictive power of the variable under investigation. As can be seen in the table, the results do not change very much as compared to the baseline specification. Similar to the models in which a lagged dependent variable did not show up in the vector of explanatory series, there is one almost significant Wald test with a marginal probability of 11% which is now obtained for the model containing CSV_{t-4}. Again, the respective coefficient of stock market dispersion does not exhibit a sign in line with the prejudices of RBC theory. As other studies including N. Funke (1997) report that nominal variables, in particular monetary indicators, are able to help to predict recessions, this is a hint for the importance of demand side explanations of the cycle.

V Hunting Sectoral Shocks: An SVAR Approach

To gain further insights into the relative importance of sectorspecific disturbances for the German business cycle, we now set up a structural vectorautregression (SVAR) to decompose the contributions of sectoral, aggregate permanent, and aggregate transitory shocks to the variance of the time series under investigation. The framework to be estimated contains the cross–sectional variance of sectoral stock returns (CSV_t), the change of real GDP (ΔY_t) over the previous year, and the inflation rate (ΔP_t) as endogenous variables. Prices and output are expressed in natural logarithms and the first–difference operator is denoted as Δ. The inflation rate is computed by taking the first–difference of the logarithm of the consumer price index. All variables are measured at a quarterly frequency. Let the vector of endogenous variables be defined by $X_t \equiv \left(CSV_t \quad \Delta Y_t \quad \Delta P_t\right)'$. Let the reduced form representation of this trivariate system be given as below:

[8] $$X_t = \sum_{i=1}^{p} A_i X_{t-i} + e_t$$

where A_i are (3×3) matrices of coefficients and e_t represents a (3×1) disturbance vector. Using ordinary least squares, consistent and asymptotically efficient estimates of the coefficients of the reduced form representation of the trivariate system obtain. The lag length p of this system is determined by minimizing the Akaike Information Criterion (Enders 1995: p. 315). According to this criterion, two lags of the endogenous series have been included in the VAR. Alternatively, we have also looked at the Schwartz Bayesian Criterion. Though this selection criterion suggested to include only one lag in the VAR, a Portmanteau test indicated remaining joint residual autocorrelation (Lütkepohl 1991).

Regarding the degree of integration of the time–series under investigation, we have performed conventional augmented Dickey and Fuller (1979) tests, Phillips and Perron tests (1988), and KPSS (cf. Kwiatowski et. al. 1992) tests. The results obtained for stock market dispersion and real output indicate that the series are $I(0)$ and $I(1)$, respectively. As regards the price level, the Dickey and Fuller (1979) test pointed to an integrated inflation rate. However, the results of the KPSS test were mixed. However, using a lag truncation parameter typically encountered in analyses of the sample size under investigation, the test procedure suggested a stationary inflation rate. A similar result was obtained using the Phillips–Perron procedure. Taking together the evidence of the various tests, we have decided to treat the inflation rate as a stationary variable. The presence of two integrated level variable poses the question of a possible cointegration vector within the system. To further assess the dynamic long–run properties of theVAR, we have also tested for cointegration vectors within the system. An application of the Johansen (1988) technique led to the conclusion that there is one cointegration vector in the trivariate model. However, the univariate statistics have already shown that the series CSV_t is stationary. This, in turn, implies that no cointegration between prices and output exists. From this it follows, that two permanent shocks and one transitory shock drive the system. [3]

As long as the roots of the characteristic equation of the system formalized in equation [8] can be found inside the unit circle, the unrestricted trivariate vectorautoregression can be represented in its infinite vector moving average representation as:

[9] $$X_t = \sum_{i=0}^{\infty} L^i B_i e_t$$

where B_i denotes a (3×3) matrix polynomial comprising the coefficients of the reduced system and L symbolizes the lag operator. Represent the moving average representation of the underlying structural model by:

[10] $$X_t = \sum_{i=0}^{\infty} C(L) L^i \varepsilon_i$$

where $C(L)$ is a (3×3) matrix of the polynomials $C_{ij}(L)$ and $\varepsilon_t \equiv \left(\varepsilon_{CSV,t} \quad \varepsilon_{\Delta Y,t} \quad \varepsilon_{\Delta P,t}\right)'$ is the vector of orthogonal serially uncorrelated structural shocks.

To recover these structural shocks from the sequence of the residuals e_t, first note that the relation between the vectorautoregression and its moving average representation implies that $e_0 = C(0)\varepsilon_0$. The identification of the nine elements of the matrix $C(0)$ require the imposition of a set of six restrictions on the system. The first three restrictions where obtained by normalizing the variance–covariance matrix of the underlying sectoral, supply, and demand shocks to be given by an identity matrix. The remaining three restrictions are derived from

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3 The results of the unit root and the cointegration tests are available from the authors upon request.

theoretical considerations. We let shocks to the first variable in the system CSV_t exert a permanent impact on the other two variables ΔY_t and ΔP_t. Furthermore, we allow for a long–lasting impact running from shocks to real GDP growth rates to inflation. This latter restriction is similar to the one employed by Blanchard and Quah (1989) to disentangle aggregate supply and aggregate demand side shocks. So $\varepsilon_{\Delta Y,t}$ corresponds to an aggregate supply shock, whereas $\varepsilon_{\Delta P,t}$ is an aggregate demand shock. All other shocks are assumed to be transitory in nature. This implies that nominal disturbances are neutral in the long–run with respect to real output and stock market dispersion. Furthermore, we rule out lasting effects running from ΔY_t to CSV_t.

The latter restriction imposed on the system deserves some more comments. This long–run neutrality restriction implies that stock market dispersion and thus sectoral shocks might exert a permanent impact on real GDP but that aggregate innovations to real output do not exhibit a lasting impact on CSV_t. To motivate this presupposition, consider first a technological innovation in a certain branch which increases productivity in this particular sector and, thus, the prospects for long–run output growth. While this innovation might or might not leave the level of cross–sectional stock market volatility unchanged in the long–run, this event will alter the path of real output in both the short and the long–run. Now consider the implications of an aggregate shock to ΔY_t. This disturbance either can affect all sectors within an economy uniformly or in a sector–specific way. This latter industry–specific component of the shock should be captured by our measure of the cross–sectional variance of stock market returns CSV_t. The remaining fraction of the disturbance is then clearly of a pure aggregate nature. However, this aggregate shock can only unfold a temporary impact on the cross–sectional variance of sectoral stock market returns. The reason is that stock market participants more and more incorporate the discounted impact of the shock hitting the economy on the future prospects of the economy as a whole into the current share prices. After stock prices have adjusted to reflect the new information, the cross–sectional variance of stock market returns remains unchanged as compared to the situation prevailing before the emergence of the shock. This line of argumentation unearths that permanent effects running from CSV_t to real output are possible but a reversed permanent impact is ruled out. The long–run neutrality restrictions imposed on the reduced form system can therefore be summarized as follows:

$$[11] \quad \sum_{k=0}^{\infty} c_{12}(k) = 0 \ , \qquad \sum_{k=0}^{\infty} c_{13}(k) = 0 \ , \qquad \sum_{k=0}^{\infty} c_{23}(k) = 0$$

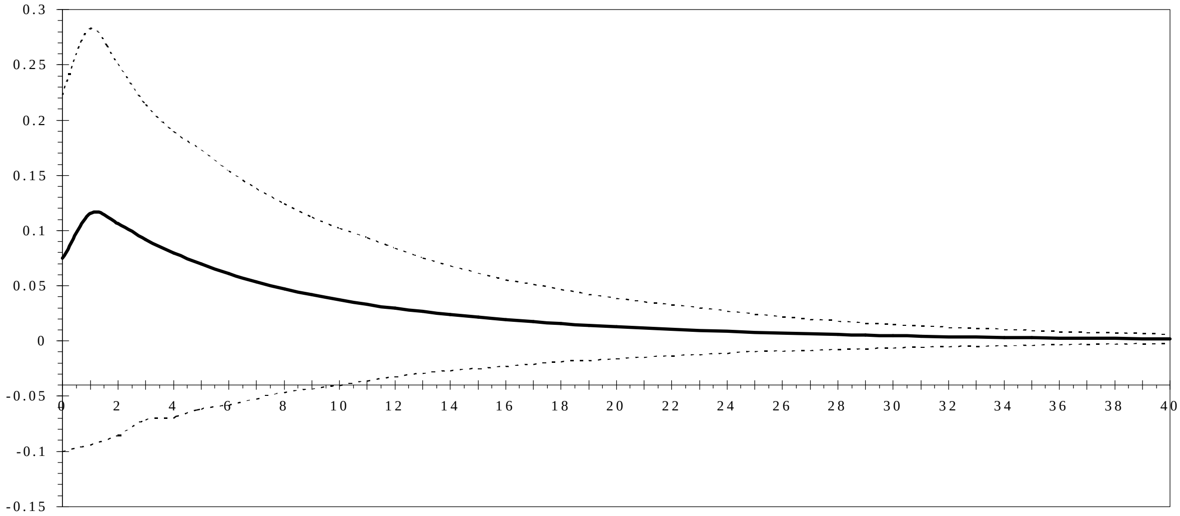
where c_{ij} represent elements of the matrix $C_{ij}(L)$ introduced above.

Figures 2 – 4 plot the accumulated impulse response functions calculated by estimating the system outlined above by OLS as well as the corresponding bootstrapped standard error bands. The figures plot the dynamic response of the model to a one–standard deviation permanent and transitory aggregate shock as well as to a one–standard deviation innovation in CSV_t. Corresponding to the identifying restrictions, demand disturbances only exert a transitory impact on real output, the graphs can also be interpreted as depicting the dynamic response of the system to an aggregate supply, an aggregate demand, and a sectoral shock hitting the economy, respectively. Note, however, that the interpretation of shocks permanently affecting output as supply shocks and disturbances which exert only a transitory impact on real GDP as demand shocks is controversial (see e.g. Sterne and Bayoumi 1995). For example, one can easily think of lasting demand side shocks like a permanent increase in government spending or only transitory supply side shocks like a temporary increase in the price of imported raw materials. Nevertheless, the estimated system can be interpreted in an economically meaningful way if the long–run neutrality restriction regarding the impact of nominal shocks on real GDP does not result in an unreasonable short–run response of inflation to the structural shocks reaching the economy (Sterne and Bayoumi 1995: 28).

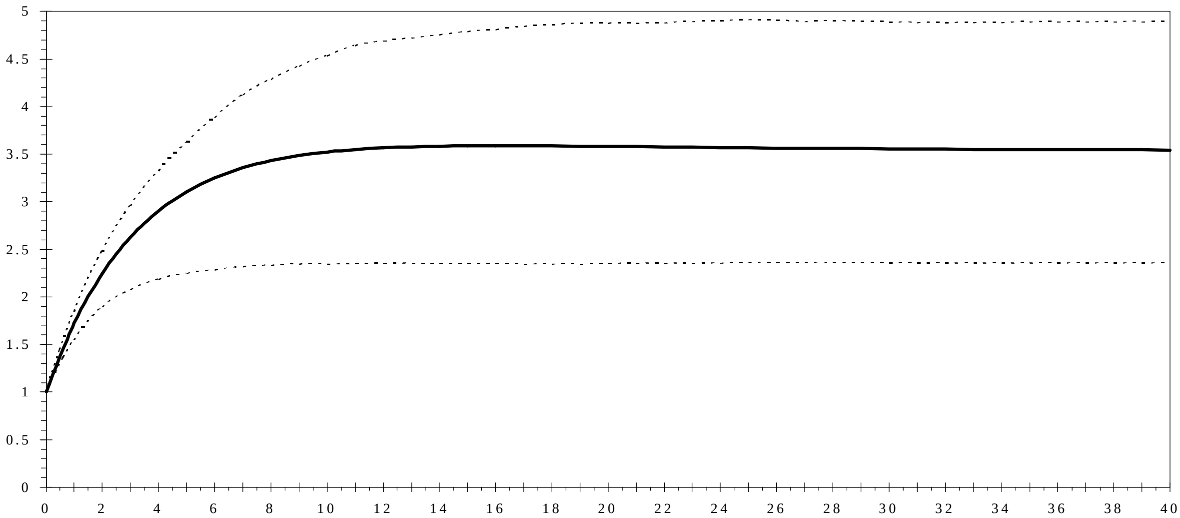
Figure 2 depicts the consequences of a one–time one–standard deviation aggregate supply side shock. Reflecting the nature of the long–run restrictions utilized to identify the underlying structural model, exhibit 2a shows that aggregate supply side shocks do not influence our measure of the cross–sectional variance of stock market returns in the long–run. In the short–run, their is very weak evidence for an amplifying impact of positive aggregate supply side shocks on CSV_t. As also reported in some of the empirical studies mentioned in section 2, we find that the aggregate supply side shock has a significant short–run and long–run impact on the path of real GDP. The respective accumulated impulse response function is shown in figure 2b. In contrast to related empirical work, however, figure 2c shows that the deflationary impact of an aggregate supply side shock is here not significantly different from zero.

To explain this surprising result, we confer to figure 4c. This graph plots the path of inflation in the aftermath of a one–standard deviation sectoral shock. The graph reveals that such a disturbance tends to dampen inflation. Combining figure 2c with the impulse response function shown in figure 4c, we conclude that in our system the deflationary pressure conventionally attributed to supply side shocks rather reflects the presence of a reallocation of resources among the various branches of the economy triggered by sectoral shocks. Another interesting result provided by figure 4b is that sectoral shocks do not tend to

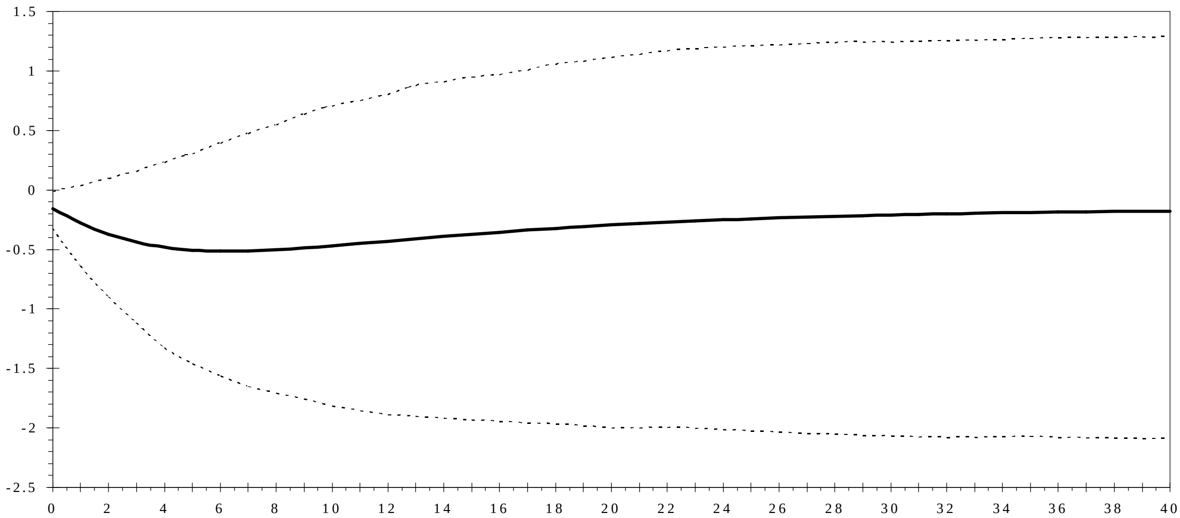
Figure 2: Accumulated Response to a Shock to a Aggregate Supply Shock



(a) Aggregate Supply Shock on CSV_t

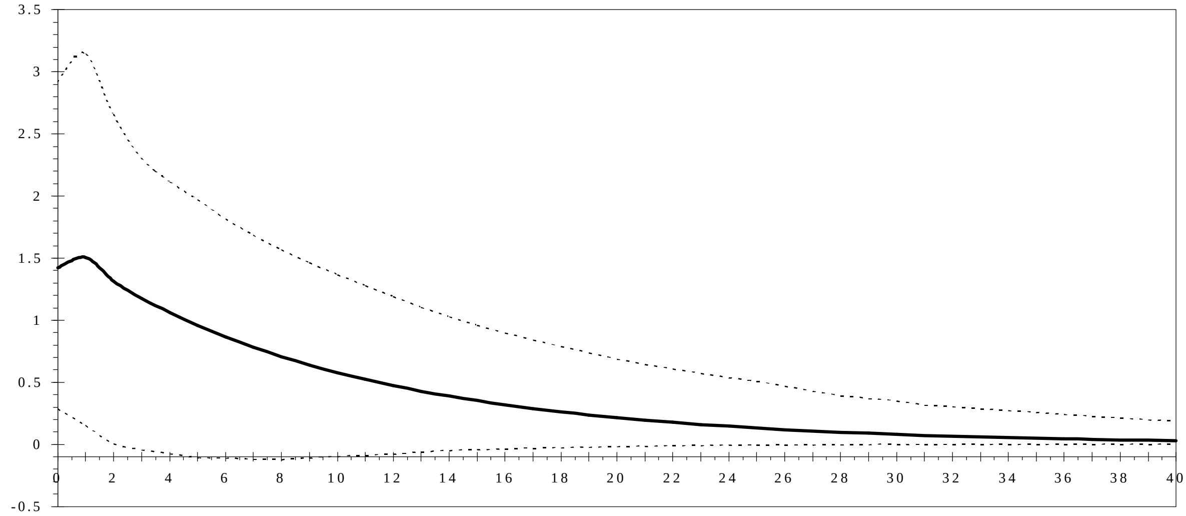


(b) Aggregate Supply Shock on ΔY_t

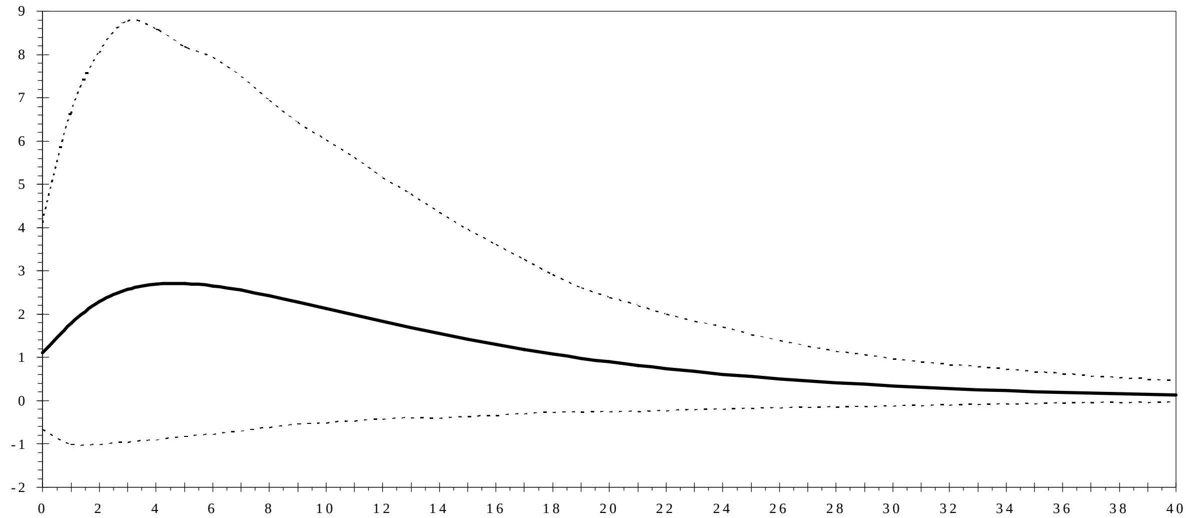


(c) Aggregate Supply Shock on ΔP_t

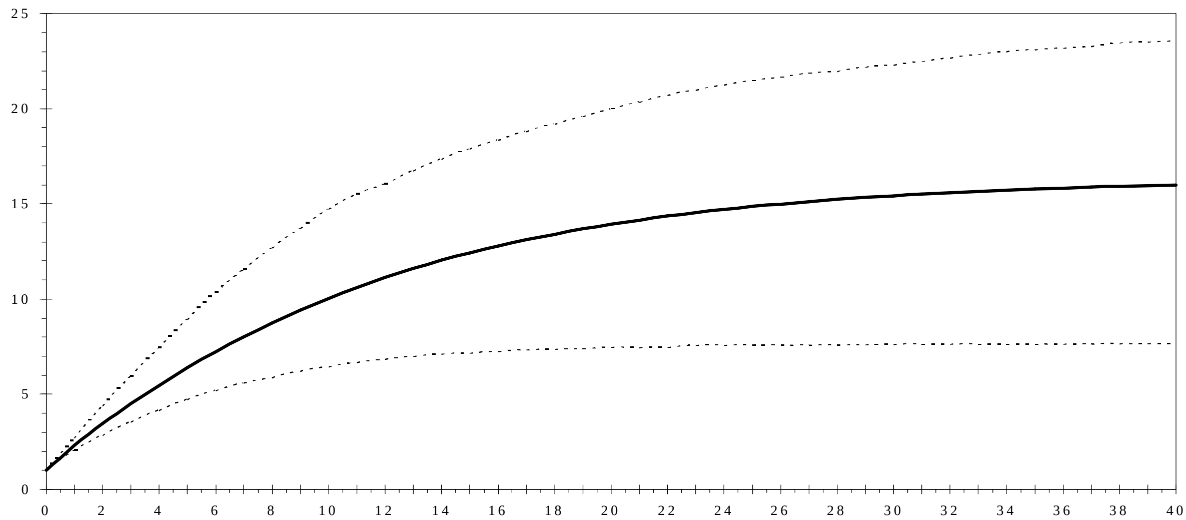
Figure 3: Accumulated Response to a Demand Shock



(a) Demand Shock on CSV_t

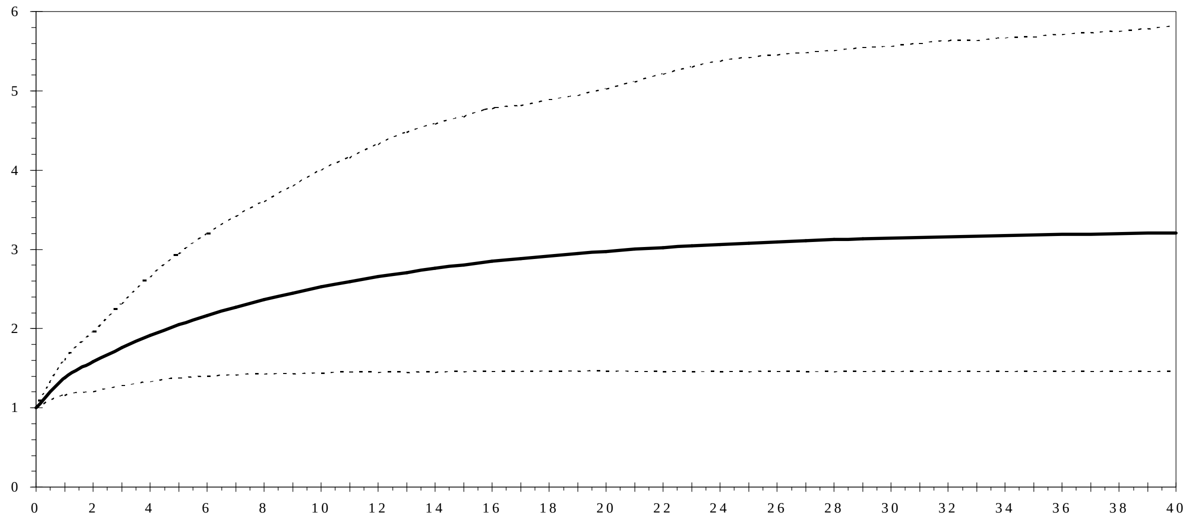


(b) Demand Shock on ΔY_t

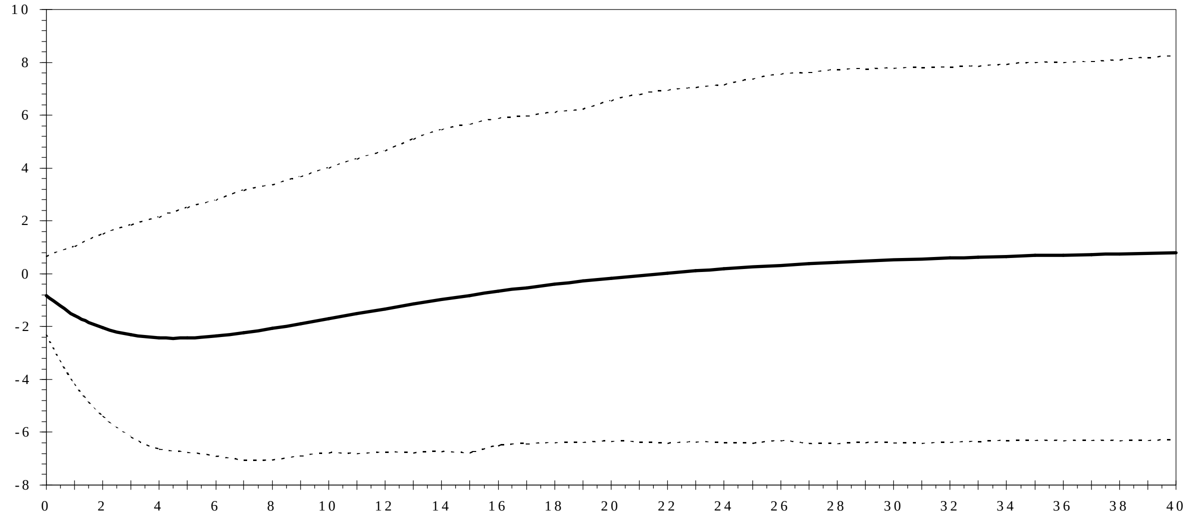


(c) Demand Shock on ΔP_t

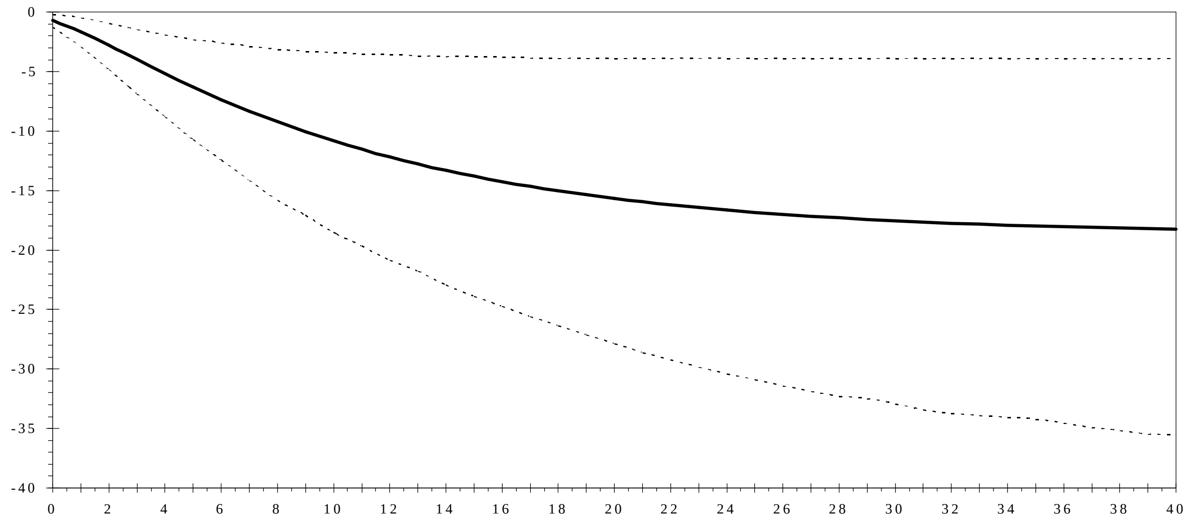
Figure 4: Accumulated Response to a Sectoral Shock



(a) Sectoral Shock on CSV_t



(b) Sectoral Shocks on ΔY_t



(c) Sectoral Shock on ΔP_t

have any significant impact on real GDP neither in the short–run nor in the long–run. This is in contrast to the prediction of the real business cycle models in the tradition of Long and Plosser (1983) mentioned above but confirms results presented by Lucke (1998a,b).

Another interesting feature of the impulse response function plotted in figure 4 is that in the immediate aftermath of the occurrence of an expansionary sectoral shock real output declines whereas in the long–run real GDP tends to increase. This is in line with the conjecture that the reallocation of resources stimulated by recessions depresses real economic activity in the short–run but, in the long–run, tends to stimulate long–run growth due to the efficiency increasing effect on the overall economy.

Finally, figure 3 gives the dynamic response of the structural VAR to aggregate demand shocks. Figure 3a reveals that their is no long–run impact of demand shocks on the cross–sectional volatility of stock market returns. While this result reflects the identifying restrictions invoked, the accumulated impulse response function also highlights that in the short–run the index variable CSV_t significantly increases. This result suggests that in the short–run demand disturbances do not affect all sectors of the economy uniformly. This implies that economic policies aiming at a management of overall demand are in this respect not neutral and might, therefore, exhibit unwanted side–effects. The accumulated impulse response functions graphed in figure 3b and 3c mimic the standard results obtained in the shock–hunting literature that an expansionary demand shock has only temporary increasing effects on real GDP but leads to a permanent higher inflation rate (see e.g. M. Funke 1997a,b).

In a nutshell, all impulse response functions exhibit a shape in line with economically motivated prejudices. We are therefore led to conclude that our framework of analysis captures the essential stylized facts of the German business cycle.

To investigate the relative importance of the underlying structural shocks for the variation of the endogenous variables, we have performed a forecast error variance decomposition of the vector autoregressive system. Table 4 plots the contribution of sectoral shocks to the variation of the time–series under investigation in per cent. As regards the cross–sectional variance of stock market returns, the figures presented in the table indicate that sectoral shocks roughly explain about 1/2 of the variation in CSV_t. Furthermore, the contribution of sectoral shocks to the variance of the forecast errors of real GDP is rather small. This is in line with previous findings reported in Lucke (1998a) and Entorf (1990, 1991). Furthermore, the variation in the inflation rate is strongly sectoral. Given the importance of sectoral shocks reported in the table, our results offer a new piece of information regarding the dynamics of inflation. This result might reflect that sectoral shocks initialize a reallocation of input factors across sectors which, in turn, might set the variation in the possibly rigid aggregate nominal price level afloat.

Table 4: Sectoral Shocks and the Variation of the Variables in the SVAR

	Percentage contribition of sectoral shocks to the variation of		
Time Horizon	CSV_t	ΔY_t	ΔP_t
t+1	0.55854	0.06961	0.48027
t+2	0.56274	0.06953	0.55833
t+3	0.56638	0.06772	0.61119
t+4	0.56942	0.06594	0.64453
t+8	0.57531	0.06547	0.69905
t+16	0.57870	0.07457	0.71927
t+24	0.57938	0.07801	0.72231
t+32	0.57952	0.07880	0.72290
t+40	0.57955	0.07898	0.72303

VI Conclusion

This paper reflects on the relative importance of sectoral shocks for business cycle fluctuations in Germany. Analyzing the lead/ lag relation of sectoral stock market returns with changes of real output, we do not find that the returns of non–consumer (consumer) related returns systematically lead (lag) the cycle. This contradicts the implications of multi–sector real business models.

We have then measured the intensity of sectoral shocks by constructing a simple index capturing the cross–sectional variance of stock market returns. The cross–correlations of this time–series with important macroeconomic aggregates have revealed that no clear–cut lead of this index with respect to subsequent changes of the overall stance of the economy can be detected. This result has been confirmed by the results of the estimation of binary dependent variable models utilized to investigate whether sectoral shocks help to predict recession phases.

Finally, stock market dispersion has been employed to enlarge the two–dimenstional structural vectorautoregressive approach pioneered by Blanchard and Quah (1989) frequently used in the empirical literature to recover aggregate supply and demand shocks and, thus, to reveal the relative importance of sectoral shocks.

In contrast to the predictions of the multisectoral real business cycle models tracing back to Long and Plosser (1983), we find that sectoral shocks exhibit only a minor impact on the dynamics of German real GDP. This is in line with the results reported in Lucke (1998a) who, using an alternative empirical technique, also rejects the hypothesis of sectoral productivity shocks as the main driving force behind the German business cycle.

Though sectoral shocks do not provide much information with respect to the dynamics of real GDP, our empirical analysis has revealed that this type of economic fluctuations can be exploited to explain a significant fraction of changes in the price level. The estimated impulse response function shows that an increase in the cross–sectional variance of stock market returns tends to be followed by a decline in the inflation rate. In line with the small temporary output decrease in the aftermath to a positive sectoral shock, this result can be interpreted as evidence that idiosyncratic disturbances induce a reallocation of resources across sectors. This reallocation might ultimately result in a more efficient use of the available production factors and, thus, exerts a depressing impact on the aggregate price level.

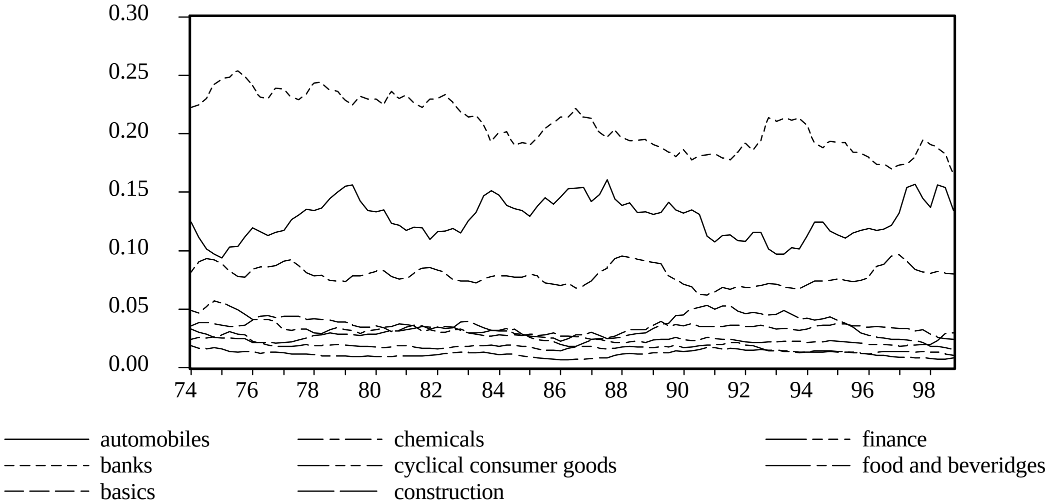
Data Appendix

Y_t	Seasonally adjusted Gross Domestic Product (GDP) denominated in 1955 prices.
P_t	Seasonally adjusted Consumer Price Index (CPI).
Unemployment rate	Seasonally adjusted umemployment rate.

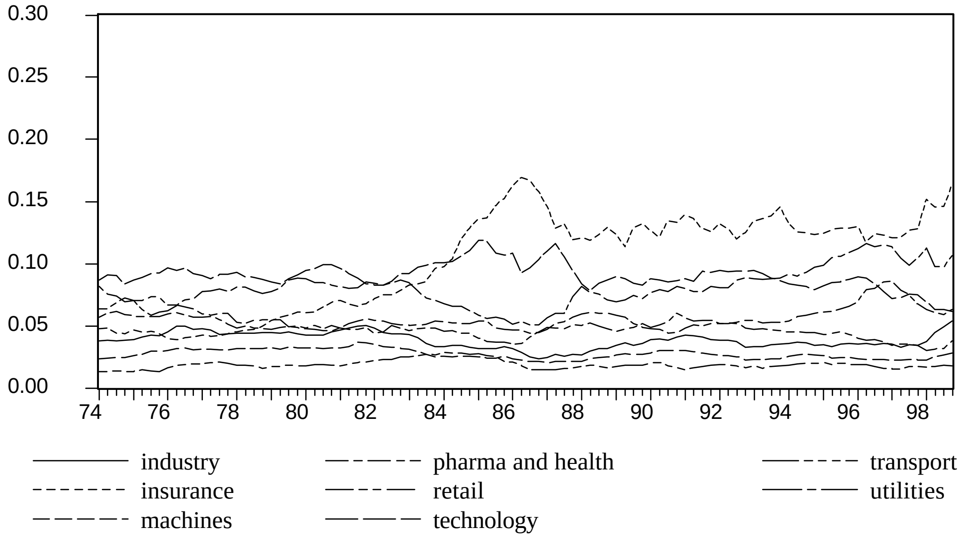
Before 1991, figures are for West Germany only. The measures have been adjusted for German unification. Source: Deutsche Bundesbank, Saisonbereinigte Wirtschaftszahlen.

$CDAX_t$	All stock market data have been taken from Datastream. The subindeces reflecting on the development of shares belonging to the sectors "Telecom" and "Media" have been excluded from the analysis because most of the firms included have not gone public before the mid–eighties.

Figure A1: Weights Utilized to Calculate Stock Market Dispersion



(a)



(b)

References

Artis, M.J., Z.G. Kontolenis and D.R. Osborn (1997). Business Cycles for G7 and European Countries. *Journal of Business* 70 (2): 249–279.

Bergmann, M. (1996). International Evidence on the Sources of Macroeconomic Shocks. *European Economic Review* 40: 1237–1258.

Black, F. (1995). *Business Cycles and Equilibrium*. New York: Basil Blackwell.

Blanchard, O., and D. Quah (1989). The Dynamic Effects of Aggregate Demand and Supply Disturbances. *American Economic Review* 79: 655–673.

Blanchard, O., (1989). A Traditional Interpretation of Macroeconomic Fluctuations. *American Economic Review* (79): 1146–1164.

Brainard, S.L., and D.M. Cutler (1993). Sectoral Shifts and Cyclical Unemployment Reconsidered. *The Quarterly Journal of Economics* 108 (1): 219–243.

Brander, P., and K. Neuser (1992). Business Cycles in Open Economies: Stylized Facts for Austria and Germany. *Weltwirtschaftliches Archiv* 128: 67–87.

Campbell, J.Y., and M. Lettau (1999). Dipersion and Volatility in Stock Returns: An Empirical Investigation. NBER Working Paper 7144. National Bureau of Economic Research, Cambridge, MA.

Dickey, D.A.A. and W.A. Fuller (1979). Distribution of the Estimators of Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association* 74: 427–431.

Dueker, M.J. (1997). Strengthening the Case for the Yield Curve as a Predictor of U.S. Recessions. Federal Reserve Bank of St. Louis. *Review* 79 (2): 41–50.

Entorf, H. (1990). *Multisektorale Konjunkturanalyse: Theorie, Empirie und Frühindikatoren realer Konjunkturzyklen*. Frankfurt am Main, New York: Campus Verlag.

Entorf, H. (1991). Real Business Cycles under Test. *European Economic Review* 35: 933–969.

Estrella, A., and F.S. Mishkin (1998). Predicting U.S. Recessions: Financial Variables as Leading Indicators. *The Review of Economics and Statistics* 80 (1): 45–61.

Funke, M. (1997a). How Important Are Demand and Supply Shocks in Explaining German Business Cycles? New Evidence on an Old Debate. *Economic Modelling* 14: 11–37.

Funke, M. (1997b). Supply Potential and Output Gaps in West German Manufacturing. *International Journal of Forecasting* 13: 211–222.

Funke, N. (1997). Predicting Recessions: Some Evidence for Germany. *Weltwirtschaftliches Archiv* 133 (1): 90–102.

Gavosto, A., and G. Pellegrini (1999). Demand and Supply Shocks in Italy: An Application to Industrial Output. *European Economic Review* 43: 1679–1703.

Greene, W.H. (1997). *Econometric Analysis*. Prentice Hall, New Jersey.

Hansen, G.D. and E.C. Prescott (1993). Did Technology Shocks Cause the 1990–1991 Recession? *American Economic Review* (83): 280–286.

Johansen, S. (1988), Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control* (12): 231–254.

Kwiatowski. D., P.C.B. Phillips, P. Schmidt, and Y. Shin (1992). Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root? *Journal Of Econometrics*, 54, 159-178.

Long, J.B., and C.I. Plosser (1983). Real Business Cycles. *Journal of Political Economy* 91 (1): 39–69.

Loungani, P., M. Rush and W. Tave (1990). Stock Market Dispersion and Unemployment. *Journal of Monetary Economics* 25 (3): 367–388.

— (1991). Stock Market Dispersion and Business Cycles. Federal Reserve Bank of Chicago. *Economic Perspectives* 15 (1): 2–8.

Loungani, P., and B. Trehan (1997). Explaining Unemployment: Sectoral vs. Aggregate Shocks. Federal Reserve Bank of San Fransico. *Economic Review* (1): 3–15.

Lucke, B. (1997). Evaluation von Real Business Cycle Modellen mit Burns-Mitchell Methodologie. *Zeitschrift für Wirtschafts– und Sozialwissenschaften* 117 (2): 167–196.

— (1998a). Productivity Shocks in a Sectoral Real Business Cycle Model for West Germany. *European Economic Review* 42 (2): 311–317.

— (1998b). *Theorie und Empirie Realer Konjunkturzyklen*. Berlin, Heidelberg: Physica Verlag.

Lütkepohl, H. (1991). *Introduction to Multiple Time Series Analysis*. Berlin: Springer–Verlag.

MacFadden, D.L. (1974). The Measurement of Urban Travel Demand. *Journal of Public Economics* 3: 303–328.

Phillips, P.C.B. and P. Perron (1988). Testing for a Unit Root in Time Series Regression. *Biometrika* (75): 335–346.

Scheide, J. (1990). Die westdeutsche Konjunktur: Nur ein „Random Walk“? *Jahrbücher für Nationalökonomie und Statistik* 207: 317–329.

Stadler, J.W. (1994). Real Business Cylces. *Journal of Economic Literature* (XXXII): 1750–1783.

Sterne, G., and T. Bayoumi (1995). Temporary Cycles or Volatile Trends? Economic Fluctuations in 21 OECD Economies. *The Manchester School of Economics* 63 (1): 23–51.

Weber, A.A. (1996). Germany Before and After Unification: A Structural VAR Analysis. *Economic Modelling* 13 (4): 575–601.