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Brokers and Business Cycles: Does Financial Market Volatility Cause Real Fluctuations?

By Jörg Döpke and Christian Pierdzioch, Kiel*

I. Introduction

It is a popular belief that the volatility of prices in financial markets is a reliable indicator for the future stance of the business cycle. The majority of academic studies in this area, however, mainly investigates whether economic fundamentals help to explain fluctuations in financial markets (cf. e.g. *Schwert* (1989a) or, for European stock market data, *Errunza* and *Hogan* (1998)). Only relatively few work has been done to examine if a reverse causality running from financial market volatility to the evolution of the business cycle can be established empirically (cf. e.g. *Romer* (1990), *Lijleblom* and *Stenius* (1997)). The present study contributes to this strand of research and uses German data to investigate whether causality in this direction can be observed and, thus, whether financial fluctuations provide any information about a coming change of the stance of the business cycle. Our study is motivated by the results of recent studies for the U.S. economy conducted by *Campbell* and *Lettau* (1999) and by *Campbell* et al. (2000) who point out that stock market uncertainty computed by using a set of industry level share price returns exhibits a clear-cut cyclical pattern and can be utilized as a leading indicator of the level of future real economic activity.

Focusing on Germany, we perform a variety of econometric tests to investigate whether the volatility of important financial time series has predictive power for subsequent changes of real economic activity. We first obtain measures of financial market volatility by applying an autoregressive conditional volatility approach to compute the conditional variance of

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the real exchange rate, of a long-term and a short-term interest rate, and of a stock market index. We then construct a measure of the stance of the business cycle and utilize several techniques to examine whether financial market volatility helps to predict subsequent real fluctuations.

The remainder of the paper is organized as follows. In Section II, we discuss possible theoretical arguments supporting the conjecture that the real sector of an economy might be linked to the volatility of financial market prices. The data utilized in our empirical analyses, descriptive statistics of the time-series under investigation, and the empirical measures of financial market volatility employed in the present paper are introduced in Section III. In Section IV, the link between financial market volatility and the business-cycle is analyzed by applying three different techniques. The first step of the analysis is to test for a potential cyclical pattern of the volatility series. We then use a signal approach to examine the forecasting power of financial market volatility. Finally, we analyze whether financial market volatility causes either the level or the volatility of real economic activity, et vice versa. Some concluding remarks are offered in Section V.

II. Theoretical Background and Empirical Evidence

The theoretical groundwork linking real economic activity to financial market volatility may be seen in recent theoretical contributions to the investment literature which emphasize that the possibility to postpone an irreversible investment project under uncertainty creates a positive option value of waiting to invest (see e.g., *Bernanke* (1983); *Ingersoll* and *Ross* (1988); *Pindyck* (1991); *Dixit* (1992); *Dixit* and *Pindyck* (1994)). If the uncertainty regarding the future realizations of important factors influencing the investment climate is sufficiently high, the value of the real option to postpone an irreversible investment project increases, and the volume of investment actually undertaken declines.

In order to test whether a negative impact of uncertainty on investment can empirically be detected, *Ferderer* (1993) defines uncertainty in terms of a risk premium on long-term bonds derived from the term structure of interest rates. He then shows for the United States that this measure of uncertainty exhibits a significant negative relationship with aggregate investment. Similar results are obtained by *Leahy* and *Whited* (1996) who use the variance of firm's daily stock returns as a measure of uncertainty. Using several important financial time series, *Episcopos* (1995) finds that the conditional annualized volatility of a stock index and of a long-term rate of interest exert a statistically significant dampening effect on investment expenditure. Empirical evidence for Germany on the link between financial market variability and investment is provided by *Mailand* (1998). The results documented in his study suggest that increasing volatility of the real exchange rate as well as a high volatility of short-term interest rates are accompanied by a slowdown of investment spending. However, the results of this author also indicate that other financial variables like stock prices or the long-term interest rate do not influence real investment significantly (*Mailand* (1998) pp. 22). *Böhm* et al. (1999), in contrast, use German firm-level data and find that stock market volatility exerts a significantly dampening impact on real investment spending. They also report that this inverse relation between stock market volatility and investment is positively related to the degree of market power of the firm under investigation.

Some authors employ the real options approach to discuss the influence of uncertainty on exports as well (see e.g., *Dixit* (1989) and *Sercu* (1992)). This theoretical discussion has stimulated empirical studies trying to clarify whether exchange rate volatility and real economic activity are linked. For example, *Scheide* and *Solveen* (1998) expand an empirical export function into an equation which also contains a variable measuring exchange rate volatility. They find only very weak evidence for an influence of the volatility variable, if any at all. Qualitatively similar results are reported in *Lastrapas* and *Koray* (1990). Using U.S. data, these authors find only very weak evidence for a quantitatively small relationship between exchange rate volatility and real economic variables. In contrast, *Bell* and *Campa* (1998) use firm level data for the U.S. chemical processing industry and find a significant impact of exchange rate volatility on investment spending. Similarly, *Campa* and *Goldberg* (1995) present evidence for the U.S. that exchange rate volatility exerts a weakly significant impact on investment spending.

Uncertainty might also influence real economic activity through its impact on consumption spending. For example, *Eberly* (1994) reports that income uncertainty influenced the decisions of U.S. households to buy durable goods in the 1980s significantly. She argues that her results are consistent with the predictions of theoretical models describing households expenditure decisions under uncertainty by means of a hysteresis band. A negative impact of uncertainty on consumption spending is also derived in *Caballero* (1992) who employs a sunk costs argument similar to the one known from the irreversibility literature to demonstrate that the consumption of durable goods can be negatively affected by uncertainty. Empirical studies relying on measures of financial market volatility to test for the link between uncertainty and the level of household consumption spending on durable goods include *Romer* (1990) and *Hassler* (1993). Hassler finds that the demand for durable goods is significantly lower during periods characterized by high financial volatility represented by the variability of the S&P-500 index. Romer argues that the significant increase in monthly squared returns on the stock market in the aftermath of the tremendous decline of stock prices in October 1929 generated substantial household uncertainty concerning the level of future income. She thus concludes that the uncertainty hypothesis might explain the substantial fall of purchases of largely irreversible durable goods observed as the Great Depression gathered steam in the fall of 1929 and in 1930.

III. Empirical Measures of Financial Market Volatility

1. The Data

Our empirical analysis of the link between financial market volatility and real economic activity uses monthly data for West Germany. The source for all variables are various issues of the monthly reports published by the Deutsche Bundesbank. The time period under investigation consists of approximately thirty years of monthly data and ranges from 1968:01 to 1998:08. More specifically, we use the German share market index (DAX) to measure the situation on the stock market (1987:12 = 100). We use the index level at the end of each month. Stock market returns are modeled as $\log(DAX/DAX_{t-1})$. The exchange rate is measured by the inverse of the index of the real external value of the DM provided by the Deutsche Bundesbank. Again, we use changes of the logarithm over the previous month. The situation on the capital market is captured by a long-term interest rate. We use the yield of Federal securities outstanding with an average time to maturity of about five years. The course of monetary policy is represented by the three months money market rate. The stance of the business cycle is measured by the seasonally adjusted index of industrial production including construction (1991 = 100). Though this index stands only for about one third of real GDP, the industrial sector shows the most pronounced business cycle behavior and is therefore a good measure for the changes of prospects of the overall economy. Moreover, monthly data for a broader measure are not available.

2. Estimation of Financial Market Volatility

In order to analyze the link between financial market volatility and real economic activity, an empirical measure of volatility is needed. Several concepts to compute series of financial market volatility have been discussed in the literature (see *Pagan* and *Schwert* (1990)). We follow the empirical literature concerned with the impact of uncertainty on irreversible investment (cf. e.g., *Episcopos* (1995); *Seppelfricke* (1996); *Mailand* (1998)) and employ the autoregressive conditional heteroscedasticity framework introduced by *Engle* (1982) and *Bollerslev* (1986) to obtain time series of the conditional variances of our financial market data. The first step in estimating a conditional variance is to specify an appropriate model for the conditional mean of the financial variables (I) under investigation. We use simple autoregressive processes (AR) for this purpose:

$$I_t = \gamma_0 + \sum_{s=1}^{S} \gamma_s I_{t-s} + \varepsilon_t \tag{1}$$

Such a specification makes sense only, if the series of the financial variables I_t are stationary. However, unit root tests[1] indicate that the level of the selected time series are integrated of order one. Therefore, we use returns in the cases of the stock market index and the real exchange rate and first differences of the interest rates. The model given in equation (1) further requires a proper specification of the lag length. This is done here using the Schwartz information criterion. Additionally, it is tested whether the residuals obtained from estimating equation (1) are white noise.

Once the autoregressive process has been specified, a model describing the dynamics of the conditional variance needs to be constructed. Trying to find a parsimonious representation for the conditional variance, a natural starting point is to model the residual series of the mean equation as a *g*eneralized *a*uto*r*egressive *c*onditional *h*eteroscedastic process (GARCH). Our equation for the conditional variance takes the form of a GARCH(1,1) model:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad \varepsilon_t \mid \Omega_{t-1}\tilde{N}(0, \sigma_t^2), \tag{2}$$

where Ω_{t-1} denotes the set of information available in period $t-1$. In equation (2), σ_t^2 denotes the variance of the financial time series condi-

[1] The detailed results of the underlying augmented Dickey-Fuller tests are available from the authors upon request. See also *Döpke* and *Pierdzioch* (1998).

tional on the information available in period $t-1$. According to this model, the conditional variance depends on a constant ω, on the lagged squared residuals ε_{t-1}^2 from the mean equation, and the last period's forecast variance σ_{t-1}^2 (the GARCH-term). The economic interpretation of these terms is straightforward. Suppose an investor assesses the risk of a given investment. Trying to get an impression of the riskiness of the investment project, he will look at the variance of the payoff series. Equation (2) states that this measure of the uncertainty of the investment depends on some kind of average (the constant), on last periods forecasted variance (the GARCH-term), and on information about the volatility of the last period. If the squared forecast error is large, the investor increases his estimate of the variance for the next period.

Equations (1) and (2) can be efficiently estimated simultaneously using a nonlinear maximum likelihood routine. To evaluate the adequacy of the simple GARCH(1,1) specification, we applied several diagnostic tests. Standard normally distributed z-values indicated that both the ARCH as well as the GARCH-terms are significant at the 1 percent level in any of the estimated equations. Moreover, the standardized residuals of the GARCH model should be independently standard normally distributed. However, normality is mostly rejected by a Jarque-Bera test as can be seen from column seven of Table 1.[2] To account for the detected departure from normality of the standardized residuals, the quasi-maximum likelihood method developed by *Bollerslev* and *Woolridge* (1992) was adopted to estimate the models.[3]

The results of the estimation are summarized in Table 1. The second column of the exhibit presents the order of the AR-terms used to model the conditional mean of the corresponding series. The stock market return was regressed on a constant. Modeling the long-term interest rate required an AR(2) specification, the dynamics of the short-term interest rate were found to be appropriately modeled as AR(1), and the real exchange rate returns were specified as an AR(1) process. Breusch-Godfrey LM-tests presented in column 3 of Table 1 indicate that there is no remaining autocorrelation in the residuals. The Lagrange multiplier (LM) tests for remaining GARCH effects presented in the fourth column strongly reject the Null of no conditional heteroscedasticity. Hence, the

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2 Visual inspection of QQ-plots (available from the authors upon request) confirmed that the departure from normality is mainly due to some influential outliers.

3 To perform the computations, the software packages Eviews 3.1 and Rats 4.2 were utilized.

Table 1

Testing the AR/GARCH Models for the Financial Variables

Variable	Testing the AR-process			Testing the GARCH(1,1) process						
	Model specification[a]	H_o: no remaining autocorrelation of order 4 (F-value)[b]	H_o: no ARCH-process of order not higher than 4 in the residuals (F-value)[c]	α^d	β^d	Jarque-Bera test for normality	H_o: standardized residuals have mean zero (t-value)	H_o: standardized residuals have variance 1 (variance ratio)	H_o: no remaining ARCH-process of order 4 (LM-test)	*z*-statistic of additional TGARCH coefficient (p-value in brackets)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Stock market returns	C	0.22	6.33***	0.11 (3.03)***	0.86 (15.24)***	39.68***	0.51	367.26	0.67	–2.09 (0.04)
Change of real exchange rate	AR(1)	0.76	15.87***	0.21 (2.82)***	0.70 (7.21)***	34002.1***	–0.38	437.73	0.05	0.85 (0.40)
Change of long-term interest rates	AR(2)	0.60	4.97***	0.11 (2.24)**	0.84 (12.47)***	4.45	–0.34	366.77	0.44	–2.03 (0.04)
Change of short-term interest rates	AR(1)	1.39	27.25***	0.19 (2.34)***	0.81 (12.01)***	90.35***	–0.10	372.67	1.42	–2.14 (0.03)

[a] C denotes a constant, AR(p) an autoregressive process of order p.
[b] Breusch/Godfrey-Test.
[c] LM-test.
[d] The number in brackets are z-statistics testing whether the ARCH(α) or GARCH(β) coefficient is equal to zero.
***(**,*) denotes rejection of the null hypothesis at the 1 (5, 10) percent level.

residuals of the regressions of the mean equations should be modeled by means of a GARCH process. The coefficient estimates for the variance equation of a parsimonious GARCH(1,1) model are presented in the fifth and sixth column of Table 1. The coefficients entering into the conditional variance equation turn out to be significantly different from zero. Moreover, the sum $\alpha + \beta$ indicates that volatility shocks are highly persistent.[4]

The rejection of the hypothesis that the standardized residuals are normally distributed led us to further analyze the results of the estimation of the GARCH models by testing whether the squared standardized residuals are at least distributed with mean zero and a standard deviation of one. Hence, we applied tests of these hypotheses. The test statistics documented in the sixth and seventh column of Table 1 do not reject the null hypotheses that the standardized residuals of the estimated models have zero mean and a variance equal to unity. Moreover, a well behaved process requires that the remaining innovations contain no autocorrelation and no additional ARCH-effects. Both hypotheses were tested using standard LM-tests. It turned out that with respect to this criterion the residuals are well behaved.

Finally, we employed the statistic developed by *Brock, Dechert*, and *Scheinkman* (henceforth BDS) (1987) to test for independence of the standardized residuals obtained from the GARCH(1,1) model. This test utilizes the concept of the correlation integral (*Grassberger* and *Procaccia* (1983)) which gives the probability to find two m-dimensional vectors within a certain radius to each other. The idea behind the BDS test is to compare the correlation integral obtained for an embedding dimension m with the correlation integral of an i.i.d. series simply computed as the correlation integral of dimension one raised to the power m. BDS show that under the null hypothesis of i.i.d. random data their statistic is asymptotically $N(0,1)$ distributed. In order to neatly equalize the empiri-

4 In the case of the short-term interest rate, the coefficients of the variance equation are very close to unity. This indicates that an integrated GARCH model might be in order. However, the volatility series depicted in figure 2 suggests that the persistence in short-term interest rate volatility is mainly caused by an individual large outburst of conditional volatility in March 1981. In order to capture this event, we also re-estimated the model including an appropriately defined dummy variable in the mean equation. However, we found that using the conditional variance obtained from this modified model in the subsequent statistical analyses does not alter the results of the respective test procedures presented below. Taking this finding into consideration, we decided to utilize the conditional volatility series obtained from the GARCH model outlined in table 1 in our empirical study.

Table 2

BDS-tests on i. i. d. Standardized Residuals of the GARCH(1,1) models

Time series	Dimension			
	2	3	4	5
Stock market returns	–0.91	–0.93	–1.00	–0.74
Change of real exchange rate	–0.24	0.51	1.19	1.52
Change of long-term interest rate	–0.75	–0.17	0.15	0.48
Change of short-term interest rate	2.67*	1.96	1.42	1.13

* denotes significance at the 5 percent level. Radius set to the standard deviation of series under investigation. See text for details. Estimates were obtained by running the program developed by *Dechert* (1988).

cal size to the nominal size of the test, we followed *De Lima* (1996) and took the natural logarithm of the squared standardized residuals of our GARCH models before testing for independence. Table 2 reports the results of the BDS test for various embedding dimensions m. Following the literature (cf. e.g., *Hsieh* (1989)), the radius was set equal to the standard deviation of the data.

The results of employing the BDS test presented in Table 2 indicate that the standardized residuals of the GARCH(1,1) model can be considered as i.i.d. The only exception is obtained in the case of the short-term interest rate when choosing an embedding dimension of two. However, the test statistic declines rapidly as the dimension of the vector space increases. Thus, the simple GARCH(1,1) model seems to capture the main characteristics of the conditional mean and conditional variance of the financial time series under investigation.

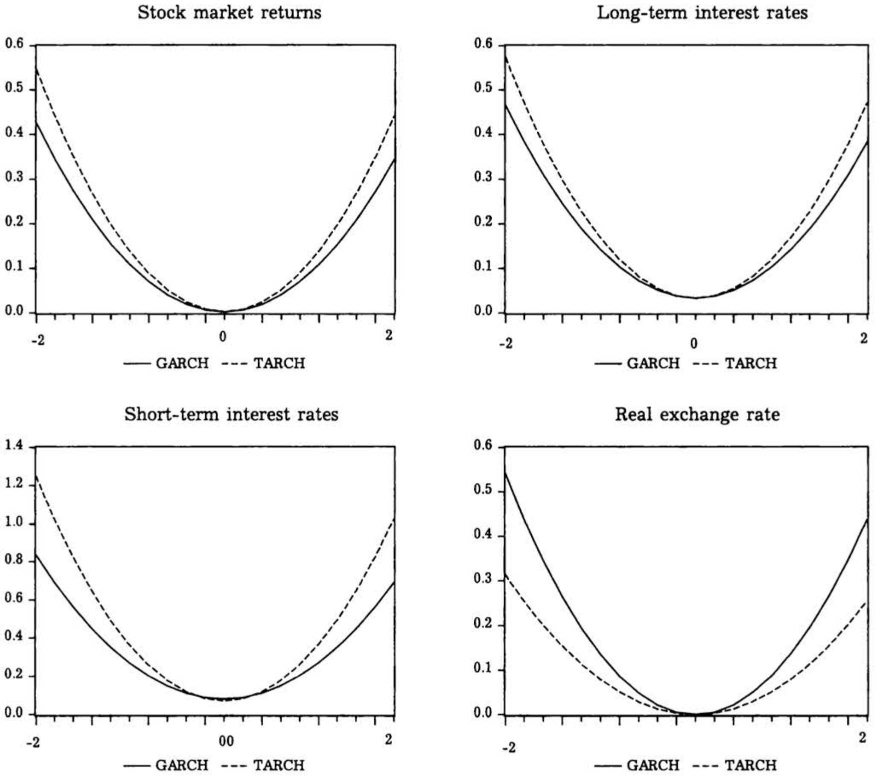
Though the results of the diagnostic tests suggest that the chosen specification of the conditional variance equation models work well we also tested whether a more sophisticated model possibly outperforms the simple GARCH(1,1) process. In order to detect possible asymmetries, we tested whether the Threshold-GARCH(1,1) model independently developed by *Glosten*, *Jagannathan* and *Runkle* (1993) and *Rabenmananjara* and *Zakoian* (1993) provides a better fit of the data than the GARCH(1,1) model. The specification for the conditional variance of the TGARCH(1,1) model is:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta D_{t-1}\varepsilon_{t-1}^2 \tag{3}$$

where $D_t = 1$ if $\varepsilon_t < 0$ and zero else. The z-values of the TGARCH coefficients reported in the eleventh column of Table 1 indicate that only the real exchange rate seems to be adequately modeled by a symmetric GARCH model. In spite of the statistically significant results obtained from the tests for asymmetric GARCH effects, the impact of allowing for asymmetric news impulse functions on the time series of the conditional variances turned out to be rather modest. The time series of the conditional variances computed by applying the competing GARCH specifications were found to be relatively close to each other. A similar proposition holds true for the news impulse functions (Figure 1) suggested by *Engle* and *Ng* (1993) to compare competing GARCH models. Thus, resorting to more sophisticated conditional variance equations results only in a slightly modified magnitude of the conditional variance estimates and leaves the qualitative characteristics of the variance series unaffected. It can thus be summarized that the parsimonious GARCH(1,1) model frequently employed in empirical work captures the essential features of the volatility processes well.

3. Characterization of the Estimated Volatility Series

Figure 2 shows estimates of the conditional variances of our series of financial market data. All in all, the models produce economically reasonable results. The volatility of the real exchange rate is considerably lower under the Bretton-Woods-System than afterwards. Not surprisingly, the end of the Bretton-Woods-System produced a sudden burst of volatility. The other peaks of the volatility series of the real exchange rate reflect realignments in the EMS system (for example 1982, 1990, 1992). The picture for the short-term interest rate volatility contrasts the result for the exchange rate. The frequency of short-term interest rate volatility peaks is clearly higher under the Bretton-Woods system than under a system of freely floating exchange rates or under the EMS exchange rate target zone. Obviously, the Bundesbank had to accept more volatile short-term interest rates to stabilize the external value of the currency. In recent years, however, the volatility of both long- and short-term interest rates has been remarkably low. This seems to reflect a steady course of monetary policy. Moreover, the volatility of short-term interest rates is considerably higher than the volatility of long-term rates. This is in line with previous studies (cf. e.g., *Sill* (1993)) and



Note: The figure plots the magnitude of responses of the conditional variance on the vertical axes and lagged shocks in the innovation term ε_t on the horizontal axes.

Figure 1: The Estimated News Impact Curves for the GARCH and TGARCH Models of the Financial Variables

sounds quite reasonable since short-term rates should be seen as a political instrument. However, the gap between the two volatility measures is obviously narrowing. The graph depicting stock market volatility exhibits two pronounced peaks in 1987 and in 1991 which reflect the bearish stock market during these episodes. For example, the burst of volatility in 1987 clearly captures the magnifying impact of the Crash in October 1987 on stock market volatility. Visual inspection of the conditional variance series also suggests that stock market volatility typically decline immediately after crashes. Such a result has also been reported by *Schwert* (1990).

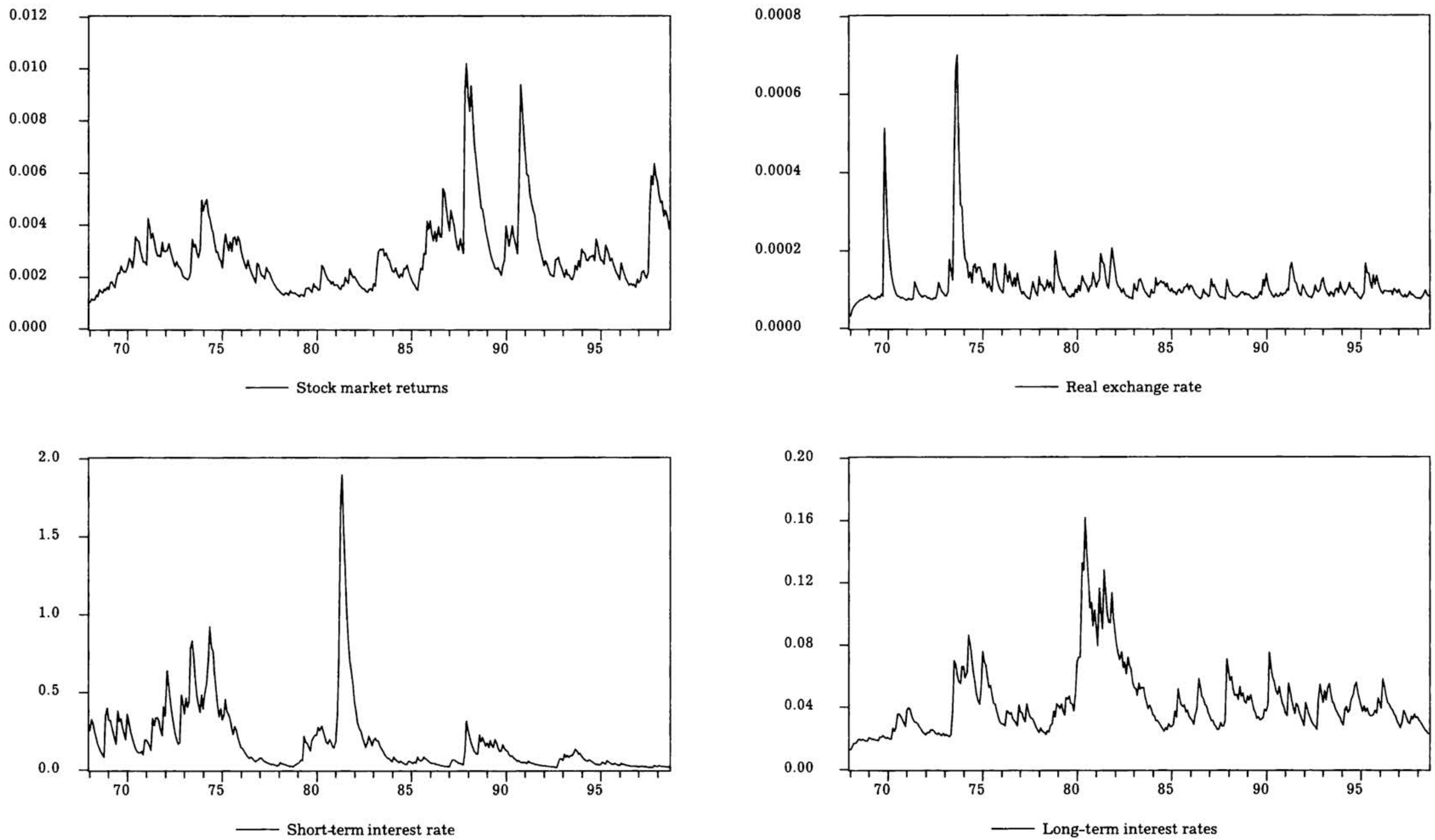


Figure 2: Conditional Variances of Financial Variables

IV. Financial Market Volatility and the Business Cycle

1. Testing for Cyclical Patterns in Financial Market Volatility

To test whether a link between financial market volatility and real economic activity exists, one first has to define the phases characterizing the cyclical movement of the business cycle in an appropriate way. There are, in general, two ways of defining the phases of the business cycle which can be found in the literature. One idea is that a business cycle should be seen as a deviation of output from a trend or a potential output variable. We use the filter developed by *Hodrick* and *Prescott* (1997) to measure the trend, choosing a smoothing parameter of $\lambda = 14400$ as it is usually done for monthly data. Declines of real economic activity, that is, recessions are then defined as a negative trend deviation of more than 1.0 percent. Alternatively, we measure the time from business cycle peaks to troughs to identify phases of downswing of real economic activity. The second approach to classify business cycle phases is to define the cycle by using absolute changes of industrial production over the previous year. A recession period is then defined as months with a negative change of industrial production as compared to the year before.[5]

If financial market volatility provides information concerning the business cycle it should have a cyclical pattern itself. In order to test for potential cyclical characteristics of our volatility series, we investigated whether financial market volatility exhibits a similar behavior in recession as compared to non-recession periods. The results of this exercise are reported in table 3. The table compares the level of conditional variances during recessions and during expansions (for similar results using U.S. data see *Schwert* (1989b)). Overall, the results of this analysis indicate that financial market volatility is significantly higher during periods of economic downswings and recessions, respectively. There are only minor exceptions: real exchange rate and long-term interest rate volatility are not higher in or prior to recessions defined on the basis of trend deviations. This difference in the results obtained by applying the two definitions of recession might reflect the fact that, given that there is some positive trend growth, an absolute decline of industrial production will indicate a relatively strong recession, whereas the trend deviation will count more months as recession months. All in all, however, these

[5] A graphical exposition of the resulting business cycle phases obtained by applying these alternative classification schemes is available from the authors upon request.

Table 3

Tests for a Similar Behavior of Financial Market Volatility in Recession as Compared to Non-recession Periods

Variable	Downswing phases defined on the basis of trend deviations		Recession defined on trend deviations		Recession defined on year on year changes	
	t-test	Mann Whitney test	*t*-test	Mann Whitney test	*t*-test	Mann Whitney test
Stock market volatility	2.27**	0.35	3.07***	2.17**	3.71***	3.26***
Real exchange rate volatility	3.13***	3.80***	1.91*	0.73	0.75	5.66***
Long-term interest rate volatility	7.68***	5.80***	1.64	0.79	9.56***	7.56***
Short-term interest rate volatility	4.30***	2.82**	0.35	3.49***	6.14***	4.73***

***(**,*) denotes that the null hypothesis of an equal mean is rejected at the 1 (5, 10) percent level.

results suggest that a link between financial market volatility and the business cycle situation may exist.

2. *Does Financial Market Volatility Send the Right Signal?*

In order to analyze the properties of the conditional variances of our financial market variables as potential leading indicators of the business cycle in more detail, we used a signal approach as outlined for example in *Kaminsky* and *Reinhart* (1998). The method works as follows (see also *Schnatz* (1998)).

Assume that an appropriate variable has been detected which is suspected to provide some information regarding the value of coming realizations of another series or the subsequent occurrence of a certain event. Say this indicator gives a "signal" and it turns out to be correct and denote this case with an A. A false signal is denoted by a B. If the indicator gives no signal and this turns out to be correct symbolize this event by a D. Finally, the letter C represents the case that the indicator does not send a signal but an event takes place. Given these definitions, it is possible to compute the following numbers:

- The share of correct signals compared to the number of all signals: $(A/(A+B))$.
- The *noise-to-signal* ratio given by $(B/(B+D)/A/(A+C))$. This number should be as small as possible since the indicator should give in the best case no false signals. For a pure random forecasting process the expected value of this ratio is 1.
- The *odds-ratio* defined as $(A^*D)/(B^*C)$. If the forecast is purely random, there will be as many correct as false signals, i.e. the odds-ratio will be equal to one. If it exceeds one the probability of receiving a correct signal is larger than the probability of receiving a false signal.

In the context of the present analysis, the indicator variables are the estimated conditional variances of the financial time series. The events which are to be predicted correctly are slowdowns of economic activity. A realization of financial market volatility is counted as a "signal" of a future slowdown of real economic activity if it exceeds its median computed for the entire sample period. In order to give the conditional financial market volatility series a fair chance to send a right signal, a warning is counted as a correct information if an "event", i.e. a downswing or a recession, respectively, indeed takes place within a period of twelve months after the financial market volatility has sent the signal.

Having already constructed time series describing the phases of the business cycle, we are now in a position to apply the signal approach to check the forecasting properties of financial market volatility. Table 4 reports the results of this exercise. The numbers plotted in Table 4 show that in almost all cases the financial market volatility series provide only very limited information about the coming business cycle situation. Comparing the results obtained for the different measures of real economic activity, it can further be seen that the forecasting power of the volatility series critically depends upon the measure of real economic activity used in the analysis. For example, the noise to signal and the odds ratio obtained for the volatility of the real exchange rate indicate a significant informational content of this indicator if real economic activity is classified utilizing downswings defined on the basis of trend deviations. In contrast, if one uses negative trend deviations of more than 1.0 percent to identify recessions the quality of a signal sent by the volatility of the real exchange rate does not exceed the quality of a signal received from a purely random variable. As regards short-term and long-term interest rate volatility, the forecasting power of these indicators reaches a maximum if a recession is defined on the basis of year-to-year changes. The quality of these indicator variables is, however, poor if the other two

Table 4

"Noise to Signal" and "Odds"-Ratio for the Volatility as a Leading Indicator for the Output Gap

Variable	Downswings defined on the basis of trend deviations			Recession defined on the basis of trend deviation			Recession defined on year on year changes		
	Number of correct signals	Noise to signal ratio	Odds ratio	Number of correct signals	Noise to signal ratio	Odds ratio	Number of correct signals	Noise to signal ratio	Odds ratio
Stock market volatility	0.45	1.34	0.55	0.55	0.83	1.47	0.50	1.01	0.99
Real exchange rate volatility	0.59	0.55	2.97	0.53	0.90	1.23	0.59	0.68	2.18
Long-term interest rate volatility	0.53	0.86	1.35	0.53	0.88	1.29	0.66	0.51	3.81
Short-term interest rate volatility	0.50	0.99	1.02	0.55	0.83	1.47	0.56	0.79	1.60

measures of the business cycle are used to compute the noise to signal and the odds ratio. Computing these ratios for stock market volatility indicates that the signals sent from this measure of financial market volatility do not provide reliable information for all measures of the business cycle. This result, thus, confirms that Samuelson's famous remark that "The stock market has predicted nine out of the last five recessions." (*Samuelson* (1966)) holds for stock market volatility as well.

In a nutshell, the results obtained by applying the signal approach suggest that our measures of financial market volatility almost always do *not* send reliable signals regarding subsequent changes of real economic activity. However, Table 4 also indicates that the forecasting power of the volatility series might depend upon the classification scheme utilized to measure the stance of the business cycle. This finding suggests that it is necessary to apply more formal techniques to test for the link between financial market volatility and the business cycle.

3. *Testing for Causality Patterns*

In this section we utilize alternative quantitative methodologies to elaborate on the possible link between the volatility of financial variables and real economic activity. In addition to an analysis of the relation between the level of real activity and financial market volatility measures as already performed in the preceding sections we now also examine whether the financial market series and the business cycle measures are linked through their conditional second moments. We thus test the hypothesis that real *volatility* and financial market volatility are interrelated.

An often used statistical technique in the business cycle literature to test for the predictive power of an economic variable with respect to future changes of the level of real economic activity is the test for Granger-non-causality. Let the (stationary) time series measuring the business cycle be denoted by Y_t. Then the following bivariate autoregressive representation is estimated:

$$
\begin{aligned}
Y_t &= \alpha_0 + \sum_{i=1}^{s} \alpha_i Y_{t-i} + \sum_{i=1}^{s} \beta_i \sigma_{t-i}^2 + \varepsilon_{1,t} \\
\sigma_t^2 &= \gamma_0 + \sum_{i=1}^{s} \gamma_i \sigma_{t-i}^2 + \sum_{i=1}^{s} \delta_i Y_{t-i} + \varepsilon_{2,t}
\end{aligned}
\tag{4}
$$

The lag length s is chosen using the minimum Schwartz-information-criterion. The hypothesis that the conditional variance does not Granger cause the output gap (i.e. $\beta_i = 0$) can be tested by performing a standard F-test. It will also be analyzed whether the output gap does not Granger-cause volatility (i.e. $\delta_i = 0$). If both hypothesis cannot be rejected it is a feedback relationship.

Table 5 gives the results of this testing procedure. It turns out that none of the financial variable volatility measures Granger-causes the *level* of the business cycle variable. The reverse relationship only occurs in the case of the volatility of long-term interest rates. Hence, the volatilities of the series under investigation provide no predictive power for the business cycle as measured by the level of industrial production.

Since the volatility series exhibit some strong peaks, one might ask whether the VARs used to implement the Granger-non-causality tests are stable over time. There are indeed several points in time at which a structural break might have taken place. For example, the influence of real exchange rate (volatility) could have changed after the breakdown of the Bretton-Woods system. The same might hold true for the volatility of the short-term interest rates since they are much more volatile under the fixed exchange rate system than afterwards. Moreover, there has been a substantial change in the direction of monetary policy in the eighties as compared to the seventies. To test for possible structural breaks reducing the power of the Granger-non-causality tests we applied a simple recursive procedure outlined in *Bianchi* (1995). Basically, a

Table 5

Testing for Granger-non-causality with Respect to the Output Gap (F-tests for block exogeneity)

Time Series	Lag-length of VAR	Schwartz criteria	H_o: Volatility does not Granger cause real	H_o: Real economic activity does not Granger cause the volatility	Decision
Stock market volatility	2	–8.33	0.08	0.15	no causality
Volatility of real exchange rate	2	–13.67	0.04	1.14	no causality
Long-term interest rate volatility	2	–3.01	1.15	4.02**	gap causes volatility
Short-term interest rate volatility	2	1.52	0.39	0.02	no causality

***(**,*) denotes that the null hypothesis of an no causality is rejected at the 1 (5, 10) percent level dummy variable is added to the two equations of the VAR which assumes the value 0 before a breakpoint and 1 afterwards. Then, beginning in January 1975, the possible breakpoint is moved forward in time and the VARs are estimated recursively. Figure 3 depicts the marginal probabilities of the resulting tests on Granger-non-causality for the output gap. As can be seen in Figure 3, the results of the tests are fairly stable. This finding helps to build up confidence in the evidence presented in Table 5.

It is also interesting to examine whether the relation between financial market volatility and the business cycle is asymmetric. For example, high stock market volatility combined with falling stock prices might exert another impact on the level of real economic activity than high volatility in times of a rising stock market. Thus, the reaction of the level of real economic activity to financial market volatility might depend on the sign of the change of the financial time series. To test this hypothesis, we reestimated the equations forming the VAR in equation (4) using dummy variables constructed in a way to capture the sign of a change of the financial market series (see Table 6). We then performed exclusion tests to study the explanatory power of the dummies (*Huh* (1998)). The tests are built on the following augmented equations:

$$\text{(5)} \quad \begin{aligned} Y_t &= \alpha_o + \Theta \cdot dummy_t + \sum_{i=1}^{S} \left(\alpha_i + \Theta_i^Y dummy_t\right) Y_{t-i} + \sum_{i=1}^{S} \left(\beta_i + \Theta_i^{\sigma^2} dummy_t\right) \sigma_{t-i}^2 + \varepsilon_{1,t} \\ \sigma_t^2 &= \gamma_o + \Theta \cdot dummy_t + \sum_{i=1}^{S} \left(\gamma_i + \Theta_i^{\sigma^2} dummy_t\right) \sigma_{t-i}^2 + \sum_{i=1}^{S} \left(\delta_i + \Theta_i^Y dummy_t\right) Y_{t-i} + \varepsilon_{2,t} \end{aligned}$$

The results of this exercise are reported in Table 6. In general, the hypothesis that the dummy is not significantly different from zero cannot be rejected. Thus, taking asymmetries into account does not alter the conclusions drawn from the baseline tests for Granger-non-causality. The only exception obtains in the case of real exchange rate volatility. The result of the corresponding dummy variable exclusion test, thus, indicates that the sign of real exchange rate changes should be taken into consideration when examining the impact of real exchange rate volatility on the level of real economic activity.

To summarize, the results of the tests for Granger-non-causality indicate – contrary to often made assumptions – that financial market turbulences do not exert a significant impact on the business cycle. A possible explanation for the lack of causality from volatility to the real sector might be that monetary authorities dampen the effect of financial market turbulences on the cycle. For example, it could be possible that the pro-

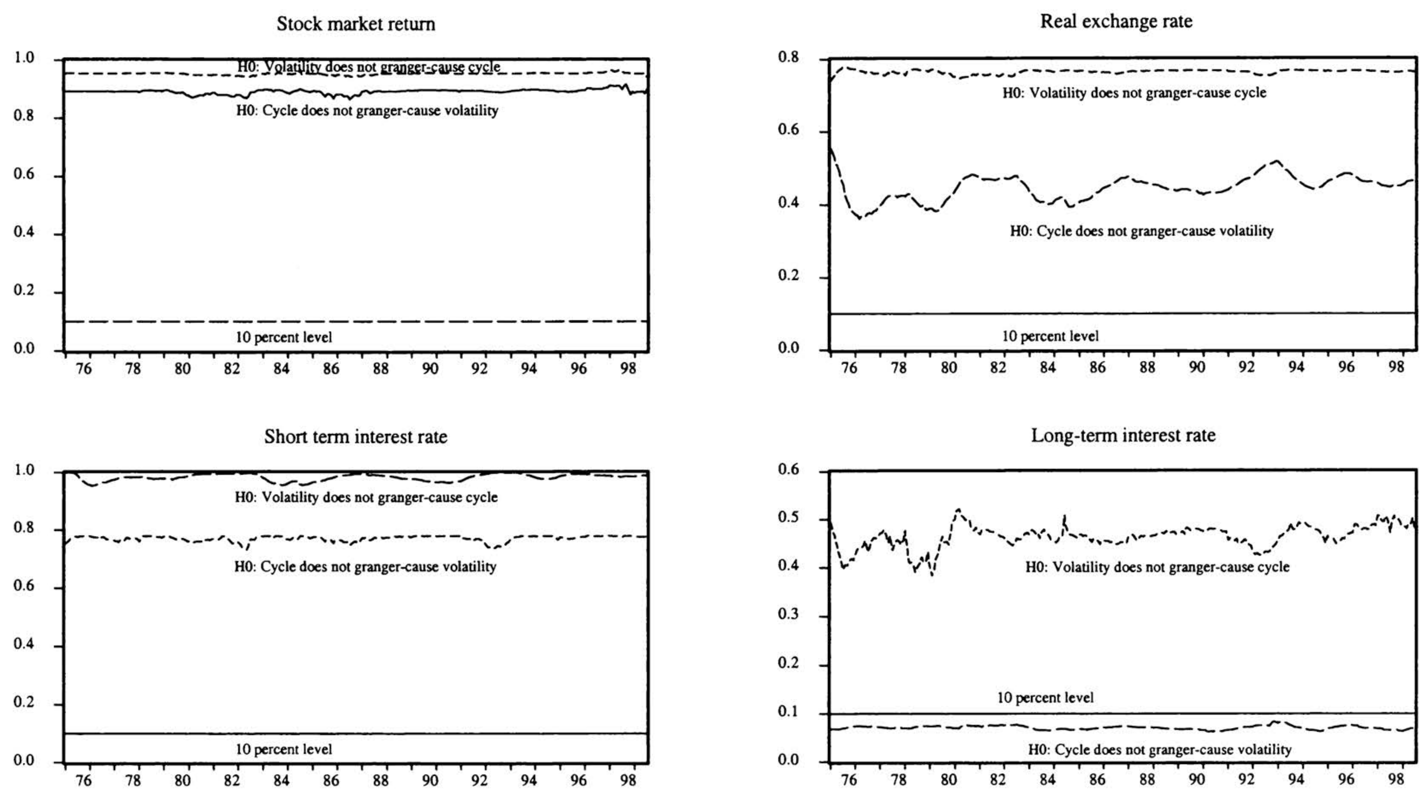


Figure 3: Recursive Tests on Granger-non-causality

Table 6

Dummy Variable Exclusion Test on Stability of the Granger-non-causality Tests

Dummy	H_o: Dummies not different from zero in equation for gap	H_o: Dummies not different from zero in equation for volatility
1 if stock-market returns < 0, 0 else	0.59 (0.77)	0.79 (0.60)
1 if change of real exchange rate < 0, 0 else	2.32 (0.04)	9.41 (0.00)
1 if change of long-term interest rate < 0, 0 else	1.62 (0.16)	0.12 (0.99)
1 if change of short-term interest rate is < 0, 0 else	0.62 (0.66)	1.84 (0.11)

F-statistic; p-value in brackets.

nounced stock market decline in the fall of 1987 induced the Bundesbank to ease monetary policy. To examine this issue in further detail, we estimated a trivariate VAR consisting of a volatility series, the output gap, and the change in the short-term interest rate as a measure of the stance of monetary policy. Table 7 reports the results of this exercise. To analyze whether our measures of financial market volatility exert no significant impact on the gap in this augmented system, we employed likelihood ratio tests on Granger non-causality. It turned out that in the cases of stock market volatility and short-term interest rate volatility the results of the bivariate analyses are confirmed. As regards long-term interest rate volatility, however, the results of the test procedure indicate a feedback relationship. Finally, real exchange rate volatility can be detected to be causal for the gap. This implies that in the trivariate framework long-term interest rate and real exchange rate volatility are either significant in the equation for the gap directly or have some indirect explanatory power for the cycle *via* their impact on the change in the short-term interest rate. From the results obtained by estimating the bivariate VARs it is clear that only the latter effect is the relevant one.

To test whether this outcome is consistent with a counteracting policy of the central bank facing a rise in the volatility of the long-term interest rate or the real exchange rate, we studied the corresponding impulse

Table 7

Testing for Granger-non-causality with Respect to the Output Gap (LR-tests for Block Exogeneity), Evidence from Trivariate Models Including the Change of Short-term Interest Rates

Time Series	Lag-length of VAR	Schwartz criteria	H_o: Volatility does not Granger cause real activity	H_o: Real economic activity does not Granger cause the volatility	Decision
Stock market volatility	2	–7.18	0.87	4.71	no causality
Volatility of real exchange rate	2	–12.62	13.10***	6.46	volatility causes cycle
Long-term interest rate volatility	2	–1.90	16.85***	12.55***	feedback
Short-term interest rate volatility	2	2.65	1.48	5.34	no causality

***(**,*) denotes that the null hypothesis of an no causality is rejected at the 1 (5, 10) percent level

reaction functions of the estimated trivariate vector autoregressions. The ordering of variables employed to carry out the impulse responses utilizing a Choleski decomposition is: volatility time series, change in the short-term interest rate, output gap. The impulse response functions are depicted in figure 4. Visual inspection of the exhibit reveals two things. Firstly, despite the significant likelihood ratio tests the impact of long-term interest rate and real exchange rate volatility on the gap is quantitatively rather small. In fact, the confidence bands include the zero line for the entire plotted post-shock horizon of twelve months. Secondly, the impact of a one standard deviation shock to the variability of the long-term interest rate and the real exchange rate on the change of the short-term interest rate is significantly different from zero but the coefficients turn out to be of opposite sign.

Thus, even in those cases where the likelihood ratio tests indicate a Granger causality, the influence of financial market volatility on the output gap is negligible. Moreover, the results are also inconsistent with a counteracting policy of the central bank. Rather, the shape of the impulse response function is more in line with the hypothesis that supply side shocks played a major role during the sample. For example,

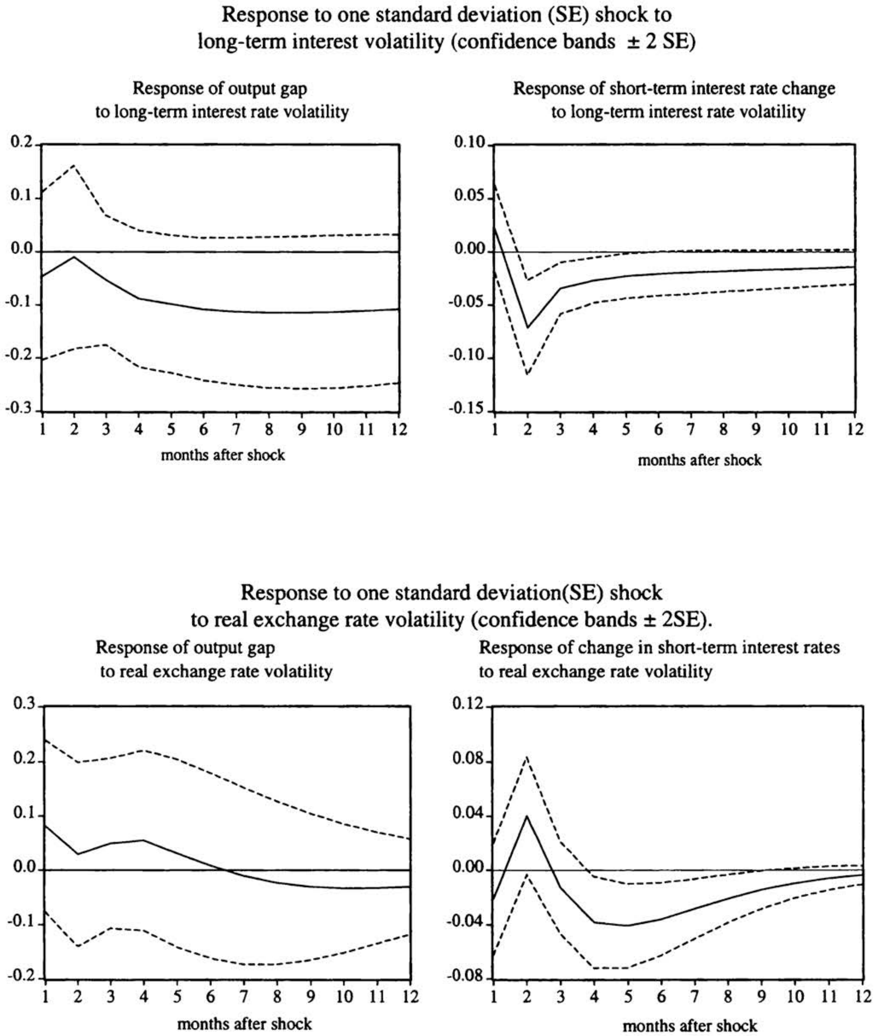


Figure 4: Impulse Response Analysis for the Trivariate VAR

the oil price crises in 1973 and 1980 resulted in both a high volatility of the long-term rate of interest and the real exchange rate and an increase in the short-term interest rate as these crises gathered steam. However, after output had declined monetary policy turned to a more expansionary course and cut the rates. This is exactly the pattern we find in the impulse response function summarizing the dynamics of the change in the short-term interest rate in the aftermath of a shock to real exchange rate volatility.

Another question is whether there is a causal relationship between the volatility of the financial variables and the volatility of industrial production (see also *Kearney* and *Daly* (1997)). To investigate this issue in more detail, we specified a parsimonious ARCH(1) model to trace out the dynamics of the volatility of the index of industrial production as well.[6] With this equation at hand, we performed causality-in-variance tests as suggested by *Cheung* and *Ng* (1996). The test statistics utilize the cross-correlation function of squared standardized residuals to identify possible links between the second moments of two series. Let $\hat{r}_{x,ip}(k)$ denote the sample cross-correlation at lag k of the squared standardized residuals obtained from the (G)ARCH models specified for the financial market series x and industrial production. Premultiplying $\hat{r}_{x,ip}(k)$ with the square root of the number of observations yields a statistic which is N(0,1) distributed under the null of non-causality in volatility at lag k. Alternatively, Cheung and Ng propose a chi-square test statistic to examine the null hypothesis of no causality from lag j to lag k: $\chi^2_{k-j-1} = T \cdot \sum_{i=j}^{k} \hat{r}_{x,ip}(i)^2$, where T symbolizes the number of observations and the scalar $(k - j + 1)$ denotes the degrees of freedom.

Table 8 depicts the results of these tests. The numbers presented in the table show that there is no causality-in-variance in either direction. Neither the test for causality at individual lags nor the chi-squared for all lags lead to a rejection of the null hypothesis of no causality in second moments. These results confirm the findings of the Granger-causality tests and provide a further piece of evidence suggesting that financial market volatility does not help to improve business cylce forecasts.

V. Conclusion

This paper used monthly data for Germany to analyze the possible link between financial market volatility and real economic activity. The findings of our empirical analyses spanning the period 1968 to 1998 strongly indicate that the hypothesis that the conditional variance obtained for

[6] To take into account the strike in the manufacturing sector, a dummy variable is added to the AR-process for IP which takes the value –1 in 1984:06 and 1 in 1984:07. The estimated equation as well as the usual diagnostic statistics are available from the authors upon request.

Table 8

Tests on Causality-in-variance

	Lags						All lags
	1	2	3	4	8	12	
H_o: Stock market volatility does not cause real volatility	–0.79	–1.30	–0.51	0.77	–1.15	–1.77	9.85
H_o: Real volatility does not cause stock-market volatility	0.59	–0.03	–0.24	0.06	–1.05	0.60	10.68
H_o: Exchange rate volatility does not cause real volatility	0.61	1.40	–0.21	–0.04	–0.80	–0.67	8.18
H_o: Real volatility does not cause exchange rate volatility	–0.30	1.38	–0.70	–0.61	–0.26	–0.61	6.09
H_o: Long-term interest rate volatility does not cause real volatility	–0.21	–0.44	–0.41	0.45	0.53	–1.38	10.77
H_o: Real volatility does not cause long-term interest rate volatility	0.01	–1.47	–0.58	0.09	0.05	–0.21	6.91
H_o: Short-term interest rate volatility does not cause real volatility	0.21	–0.16	–0.56	0.23	–0.37	–1.58	14.05
H_o: Real volatility does not cause short-term interest rate volatility	0.10	–0.72	1.39	0.56	–0.73	–0.81	8.05

*(**,***) denote rejection of the null hypotheses at the 10 (5, 1) percent level.

various important financial market variables do not predict changes of real economic activity cannot be rejected.

Our result that the business cycle is not driven by the volatility of interest rates are in line with previous estimates of *Schwert* (1989b) for American data. This suggests that it is the level of these financial variables which is important for real economic activity rather than the volatility. Our insignificant estimates regarding the impact of real exchange rate and of stock market volatility on the business cycle are in contrast to results documented in related studies. For example, *Schwert* (1989) as well as *Liljblom* and *Stenius* (1997) find that stock market volatility Granger-causes the American and the Finnish business cycle, respectively. Moreover, *Bell* and *Campa* (1997), *Campa* and *Goldberg* (1995), and *Mailand* (1998) present evidence that the real sector of the economy is negatively affected by volatile exchange rates.

There might be several reasons for these conflicting results. With respect to the stock market, some of the studies finding significant results span an observation period which includes the Great Crash of 1929. Following *Romer* (1990), it would thus be possible to claim that during the period covered by our sample period stock market volatility was just not significant and enduring enough to exhibit a noticeable impact on real economic activity. Moreover, fluctuations in financial markets might represent to some extent the influence of speculative noise trading and might, thus, be not entirely related to economic fundamentals. Such an interpretation would be in line with the findings of e.g. *Flood* and *Rose* (1995) for exchange rates. It might also be a promising direction for future research to resort to data on the firm level to highlight a potential link between stock market volatility and real economic activity. For example, *Leahy* and *Whited* (1996) use panel data for the U.S. and indeed find a link between stock market volatility and firm's investment decisions. For German data, a similar relation between the volatility of share price returns and investment spending on the level of individual firms has recently been documented by *Böhm* et al. (1999). In view of this evidence, it would be rather hasty to interprete our empirical results as a falsification of theories emphasizing the importance of uncertainty for investment and consumption decisions. Finally, our study was exclusively concerned with the impact of financial market volatility on real economic activity. Using measures designed to capture uncertainty regarding the unpredictable future evolution of real economic variables like wages and other cost determinants (*Seppelfricke* (1996)) or political factors (see e.g. *Bittlingmeyer* (1998)) it might be possible to document empirically a closer link between volatility and the business cycle.

Thus, there is ample room for further research on the relevance of uncertainty for real economic activity. However, our empirical analysis in any case suggests that it might be rather fruitless to utilize financial market volatility as a leading indicator of the business cycle.

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Summary

Brokers and Business Cycles: Does Financial Market Volatility Cause Real Fluctuations?

This paper analyzes the link between financial market volatility and real economic activity. Using monthly data for Germany from 1968 to 1998, we specify GARCH models to capture the volatility of stock market prices, of the real exchange rate, and of a long-term and of a short-term rate of interest and test for the impact of the conditional variance on the future stance of the business cycle and on the volatility of industrial production. The results of our empirical investigation lead us to reject the hypothesis that financial market volatility causes the cycle or real volatility. (JEL C32, D8, E32)

Zusammenfassung

Kurse und Konjunkturzyklen: Verursachen Finanzmarktvolatilitäten Schwankungen der realwirtschaftlichen Aktivität?

Dieser Beitrag analysiert den Zusammenhang zwischen Finanzmarktvolatilität und realer ökonomischer Aktivität. Unter Verwendung von Monatsdaten für die Bundesrepublik Deutschland für die Jahre 1968 bis 1998 werden GARCH-Modelle für den DAX, die kurz- und langfristigen Zinsen und den realen Wechselkurs der DM spezifiziert. Es wird getestet, ob die daraus abgeleiteten bedingten Varianzen einen Einfluß auf die nachfolgende konjunkturelle Entwicklung beziehungsweise die Schwankungsintensität der Industrieproduktion ausüben. Aufgrund empirischer Analysen wird diese Hypothese verworfen.

Résumé

Cours et cycles conjoncturels: La volatilité des marchés financiers provoque-t-elle des fluctuations économiques réelles?

Cet article analyse le rapport entre la volatilité des marchés financiers et l'activité économique réelle. En utilisant des données mensuelles pour l'Allemagne de 1968 à 1998, les auteurs spécifient des modèles GARCH pour déterminer la variabilité des cours de bourse, des taux d'intérêt à court et à long terme et du taux de change réel du DM. Ils testent si les variances déduites ont une influence sur l'évolution conjoncturelle future et sur l'intensité des fluctuations de la production industrielle. Les résultats des ces analyses empiriques rejettent cette hypothèse.