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Brokers and business cycles: Does financial market volatility cause real fluctuations?

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by

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Abstract

This paper elaborates on 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 variability 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.

Keywords: uncertainty, GARCH models, forecasting, Granger–non–causality, causality–in–variance

JEL classification: C32, D8, E32

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1. 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. Most of the academic studies in this area, however, investigate whether economic fundamentals help to explain fluctuations in financial markets (cf. e.g. Schwert 1989a). Only a few work has been done to examine if a reverse causality running from financial market volatility to the evolution of the real sector can empirically be established (Lijleblom and Stenius 1997). The present study investigates whether causality in this direction can be observed and, thus, whether financial fluctuations provide any information about a coming change of the level of economic activity.

In order to check the validity of these propositions, we perform several econometric tests to investigate whether the variability of important financial time series has predicitive power for subsequent changes of real economic activity. Focussing on Germany, we first obtain measures of financial market volatility by applying an autoregressive conditional volatility approach to compute the conditional variance of the real exchange rate, a long–term and a short–term interest rate, and a stock market index. We then construct a measure of the stance of the business cycle and perform several tests to examine whether financial market volatility helps to predict subsequent real fluctuations.

The remainder of the paper is organized as follows. In Section 2 we discuss possible theoretical arguments supporting this conjecture. 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 3. In Section 4, 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 elaborate 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 5.

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2. Theoretical Background and Empirical Evidence

The theorectical groundwork linking real economic activity to financial market volatility might 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). As the uncertainty regarding the future realizations of important factors influencing the investment climate grows, 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, Federer (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 mutual relationship with aggregate investment. Similar results are obtained in Leahy and Whited (1996) who use the variance of firm's daily stock returns as a measure of uncertainty. Using several important economic 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 by Mailand suggest that increasing variability 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).

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. In contrast, Bell and Campa (1998) use firm level data for the US chemical processing industry and find a significant impact of exchange rate volatility on investment spending. Similiarly, Campa and Goldberg (1995) present evidence for the US 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. As has been formally proven by Mirman (1971), certain types of utility functions imply that utility maximizing agents increase precautionary savings as an insurance against a possible decline of future production possibilities. 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 of 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.

3. Empirical Measures of Financial Market Volatility

3.1 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 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 modelled 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 index of industrial production including construction (1991=100). The series is seasonally adjusted using the census x-11 method. Though this index stands only for about one third of real GDP, the industrial sector shows the most pronounced business cycle behavoir 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. Table 1 reports summary statistics for the time series used in the following analyses.

Table 1 — Summary Statistics of the Time Series under Investigation 1968–1998

	Stock market return	Change of the real exchange rate	Long-term interest rate	Short-term interest rate	Percentage change of industrial production
Mean	0.01	0.00	7.51	6.47	0.00
Median	0.01	0.00	7.50	5.83	0.00
Maximum	0.16	0.03	11.50	14.57	0.11
Minimum	−0.24	−0.07	4.40	3.09	−0.09
Std. Dev.	0.5	0.01	1.49	2.68	0.02
Skewness	−0.60	−1.31	0.27	0.79	0.06
Kurtosis	5.26	9.05	2.59	2.92	8.94
Observations	368	368	368	368	368

3.2 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 examining the impact of uncertainty on irreversible investment (cf. e.g. Episcopos 1995, Seppelfricke 1996, and 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. Following Seppelfricke (1996), simple autoregressive processes (AR) are used:

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

Such a specification makes sense only, if the series of the financial variables I_t are stationary. However, unit root tests (see Appendix) 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 generalized autoregressive conditional heteroscedastic process (GARCH). Our equation for the conditional variance takes the form of a GARCH(1,1) model:

$$(2) \quad \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 , \quad \varepsilon_t|\Omega_{t-1} \sim N(0,\sigma_t)$$

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 conditional on the information available in period t-1. According to this model, the conditional variance depends on a mean 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 risk of the investment depends on some kind of average (the mean), 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 non-linear maximum likelihood routine. The results of this exercise are summarized in Table 2. The second column of Table 2 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. Modelling 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 was specified as an AR(1) process. Breusch-Godfrey LM-tests presented in column 3 of Table 2 indicate that there is no remaining autocorrelation in the residuals. The Lagrange multiplier (LM) tests for remaining GARCH effects presented in the fourth column of Table 2 strongly reject the Null of no conditional heteroscedasticity. Hence, the 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. All coefficients turn out to be significantly different from zero. Moreover, the sum $\alpha + \beta$ indicates that volatility shocks are highly persistent.

To evaluate the adequacy of the simple GARCH(1,1) specification, we applied several diagnostic tests. The z-values indicate 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 squared standardized residuals of the GARCH model should be independently standard normally distributed.

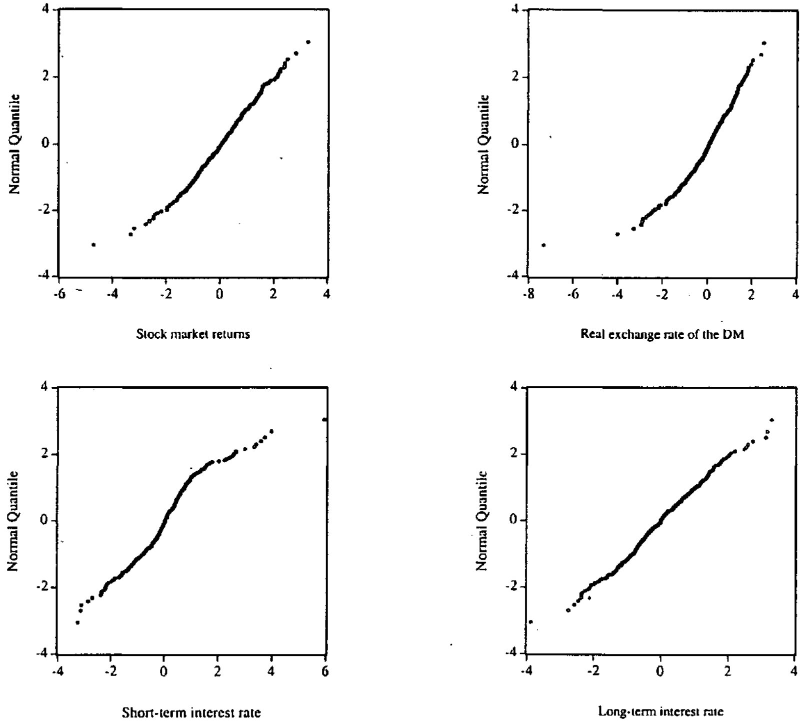
Table 2 — Testing the AR/GARCH Models for the Financial Variables

Variable	Testing the AR-process			Testing the GARCH(1,1) process						
Variable	Model specification[a]	H_0: no remaining autocorrelation of order 4 F-value[b]	H_0: no ARCH-process of order not higher than 4 in the residuals (F-value)[c]	α[d]	β	Jarque-Bera test for normality	H_0: standardized residual have mean zero (t-value)	H_0: standardized residuals have variance 1 (variance ratio)	H_0: no remaining ARCH-process of order 4 (LM-test)	z-statistic of additional TARCH coefficient (p-value in brackets)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Stock market return	C	0.22	6.33***	0.11	0.86	39.68***	0.51	367.26	0.67	–2.09
				(3.03)***	(15.24)***					(0.04)
Change of real exchange rate	AR(1)	0.76	15.87***	0.21	0.70	34002.1***	–0.38	437.73	0.05	0.85
				(2.82)***	(7.21)***					(0.40)
Change of long-term interest rates	AR(1), AR(2)	0.60	4.97***	0.11	0.84	4.45	–0.34	366.77	0.44	–2.03
				(2.24)**	(12.47)***					(0.04)
Change of short-term interest rates	AR(1)	1.39	27.25***	0.19	0.81	90.35***	–0.10	372.67	1.42	–2.14
				(2.34)***	(12.01)***					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 for a test whether the ARCH(α) or ARCH(β) coefficient are equal to zero. — *(**,***) denotes rejection of the null hypothesis at the 1 (5, 10) percent level.

Source: Own estimates.

Figure 1 — Quantile/Quantile(QQ)–Plots of the Standardized Residuals of the GARCH(1,1) Models against the Normal Distribution



However, normality is mostly rejected by a Jarque-Bera test as can be seen from column seven of Table 2. As the QQ-plots depicted in Figure 1 confirm, this is mainly due to some influential outliers. In spite of this rejection, the results can nevertheless be interpreted in a meaningful way as long the squared standardized residuals are at least distributed with mean zero and a standard deviation of one. Hence, we apply 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 have been tested using standard LM-tests. It turns out that with respect to this criterion the residuals are well behaved.

Finally, we employ 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 empirical size to the nominal size of the test, we follow De Lima (1996) and take the natural logarithm of the squared standardized residuals of our GARCH models before testing for independence. Table 3 reports the results of the BDS test for various embedding dimensions m. Following the literature (cf. e.g. Hsieh 1989), the radius has been set equal to the standard deviation of the data.

The results of employing the BDS test presented in Table 3 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.

Table 3 — BDS-tests on i.i.d. Standardized Residuals of the GARCH(1,1) models

Time series	Dimension			
	2	3	4	5
Stock market return	–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).

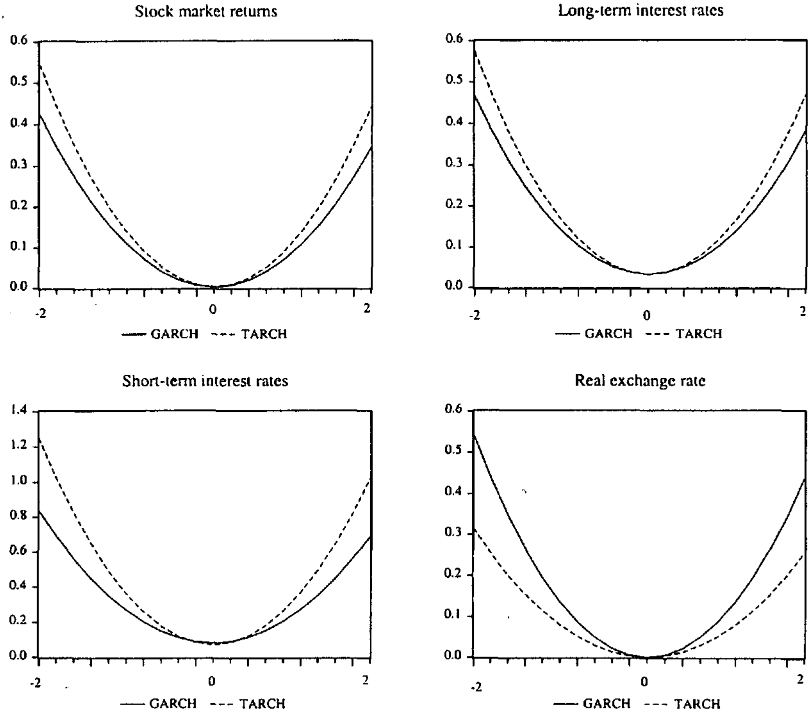
Though the results of the diagnostic tests suggest that the chosen specification of the conditional variance equations models work well we also tested whether a more sophisticated model possibly outperforms the simple GARCH(1,1) process. In order to detect possible asymmetries, we test whether the Threshold–ARCH(1,1) model independently developed by Glosten, Jagannathan and Runkle (1993) and Rabenmananjara and Zakoian (1993) outperforms the GARCH(1,1) model. The specification for the conditional variance of the TARCH(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 $\varepsilon_t < 0$. The *z*-values of the TARCH 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 variance turned out to be rather modest. The time series of the conditional variance computed by applying the competing GARCH specifications were found to be very close to each other. A similar proposition holds true for the news impulse functions (Figure 2). 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.

To summarize, the GARCH(1,1) model frequently employed in empirical work captures the essential features of the volatility processes very well. Nevertheless, the departure from normality of the standardized residuals visualized in Figure 1 suggests that it is necessary to take heteroscedasticity into account when estimating the models. In the following, the quasi–maximum likelihood method developed by Bollerslev and Woolridge (1992) is used to accomplish this task.

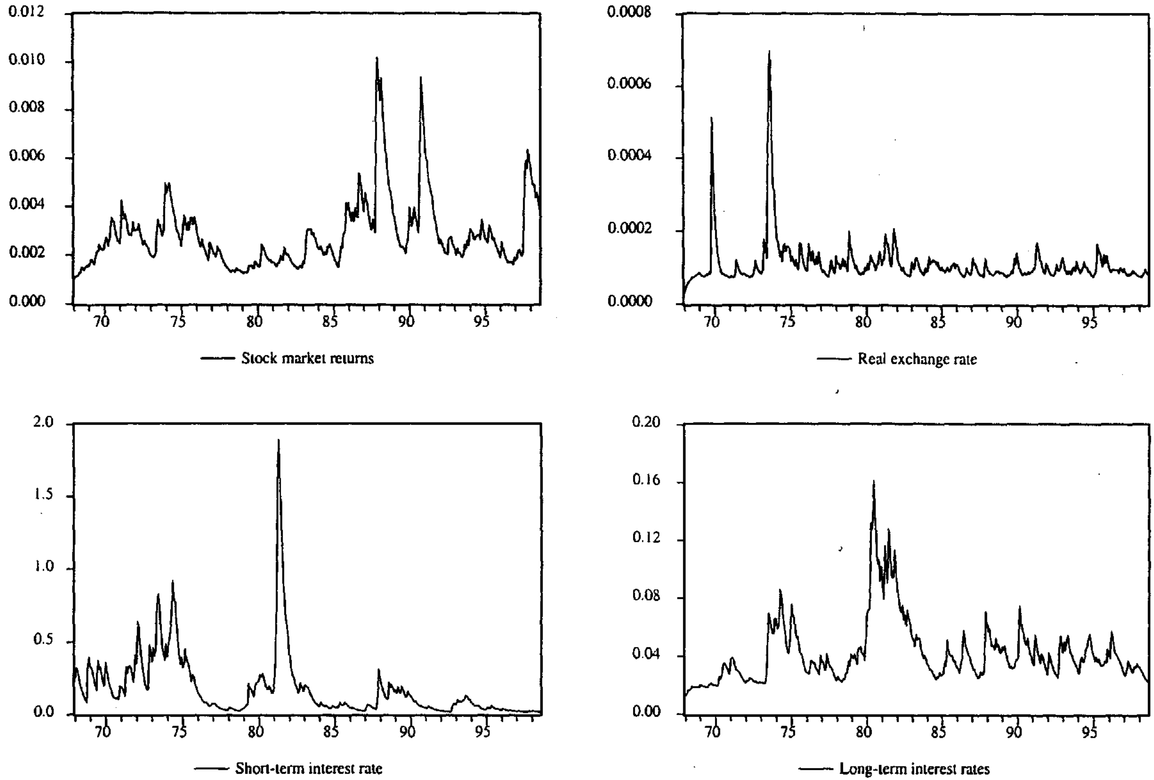
Figure 2 — The Estimated News Impact Curves for the GARCH and TARCH Models of the Financial Variables



3.3 Characterization of the Estimated Volatility Series

Figure 3 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 considerable 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

Figure 3 — Conditional Variances of Selected Financial Variables



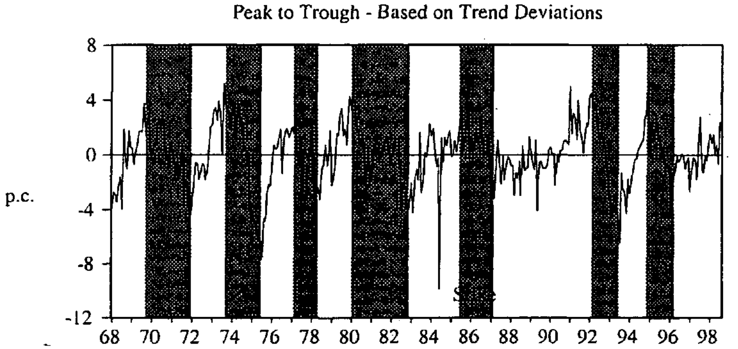
interest rate volatility peaks is clearly higher under the Bretton–Woods system than under a system of freely floating exchange rates or under the EMS exchange rate target zone. Obviously, the Bundesbank had to accept more volatile short-term interest rates to stabilize the external value of the currency. In recent years, the volatility of both long– and short–term interest rates has been remarkably low. This seems to reflect a non hectic monetary policy. Moreover, the volatility of short-term interest rates is considerably higher than the volatility of long-term rates. This in line with previous studies (cf. e.g. Sill 1993) and 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 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 found by Schwert (1990).

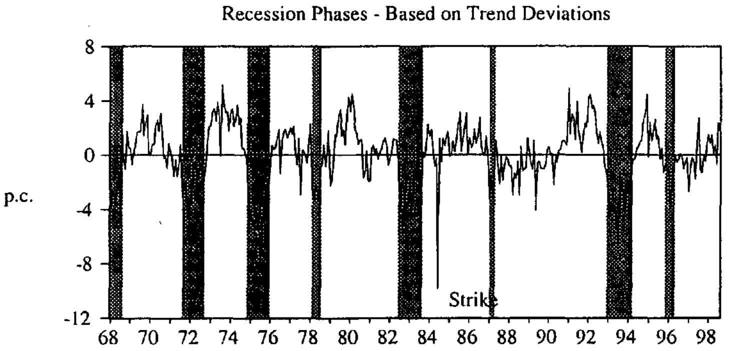
4. Financial Market Volatility and the Business Cycle

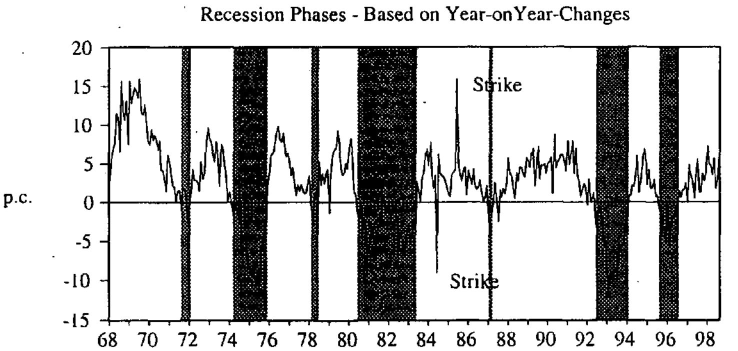
4.1 Testing for Cyclical Patterns in Financial Market Volatility

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 $\lambda = 14\,400$ 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 in classifying business cycle phases is to define

Figure 4 — Phases of West Germany's Business Cycle







Shaded areas: Downswings and Recessions, respectively.

the cycle using absolute changes 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. Applying these classification schemes, we obtain the business cycle phases depicted in Figure 3. In this figure, the shaded areas represent downswings and recessions, respectively. The large outliers in 1984 are due to a strike in the manufacturing sector.

If financial market volatility should provide 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 investigate whether financial market volatility exhibits a similar behavior in recession as compared to non-recession periods. A shortcoming of this technique is that the data are grouped according to a recession/non-recession scheme which neglects valuable information potentially provided by the chronological ordering of the data. The first test is, therefore, supplemented by the computation of the autocorrelation coefficients of the volatility variables for various lag lengths.

Table 4 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.

These results suggest that a link between financial market volatility and the business cycle situation exists. This proposition can further be tested by examining the autocorrelation functions of the volatility series. Table 5 provides the time series autocorrelation coefficients for selected lags. As can be seen from this table, the autorcorrelation functions decay slowly and are strictly positive in almost all cases. The autocorrelation functions confirm the result already obtained in Section 2 that the volatility series exhibit a remarkable degree of persistence. The results, however, do not support the notion that the conditional volatility of our financial market series show any cyclical behavior which could be claimed to match the length of a typical business cycle.

Table 4 — 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 10 (5, 1) percent level.

Table 5 — Autocorrelation Coefficients of the Volatility Variables

	ρ_1	ρ_2	ρ_3	ρ_4	ρ_8	ρ_{12}	ρ_{24}	ρ_{36}	Q(36)
Stock market volatility	0.92	0.82	0.74	0.66	0.39	0.20	0.16	0.22	1702.9***
Volatility of the real exchange rate	0.80	0.57	0.40	0.29	0.04	0.05	–0.00	–0.02	485.7***
Volatility of long-term interest rates	0.93	0.87	0.81	0.75	0.59	0.49	0.06	–0.12	2557.8***
Volatility of short-term interest rates	0.93	0.83	0.71	0.61	0.42	0.34	0.14	–0.08	1748.9***

Q(36) denotes a Liung-Box-Statistic for a test whether there is autocorrelation of order 36. — *** denotes a rejection at the 1 percent level.

4.2 Does Financial Market Volatlity 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 now use the signal approach as outlined for example in Kaminsky and Reinhard (1998). This 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 occurence 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: $(A/(A+C))$.
- 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* definded 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 6 reports the results of this exercise. The numbers plotted in Table 6 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 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 Samuelson's remark that "The stock market has predicted nine out of the last five recessions." (Samuelson 1966).

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 6 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.

Table 6 — "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

Source: Own calculations.

4.3 Testing for Causality Patterns

In this section we utilize alternative 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 the conditional second moments. We, thus, test the hypothesis that real *volatility* and financial market volatility are interrelated.

An oftenly 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 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. Then, the hypothesis that the conditional variance does not Granger cause the output gap (i.e. $\beta_i = 0$) can be tested 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.

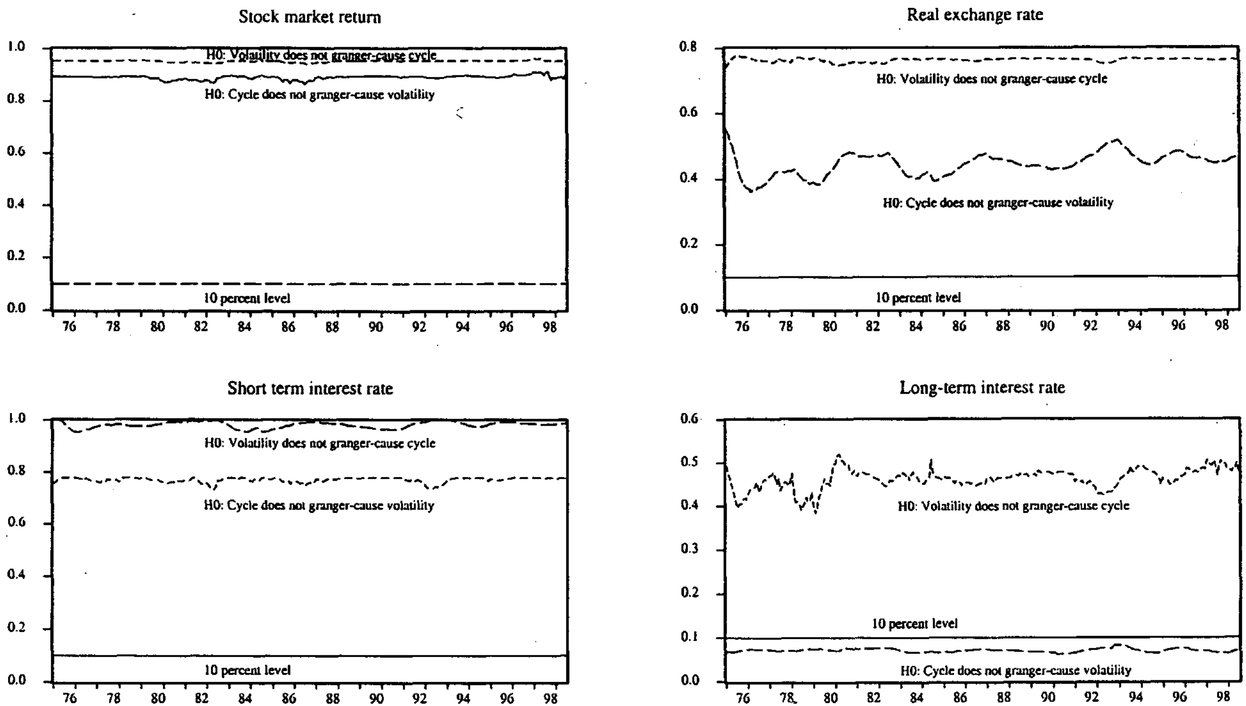
Table 7 gives the results of this testing procedure. It turns out that none of the financial variable volatility measures Granger-causes the *level* of the business cycle variable. The reverse relationship only occurs in the case of the volatility of long–term interest rates. Hence, the volatility of the series under investigation provides no predictive power for the business cycle as measured by the level of industrial production.

Table 7 — Testing for Granger-non-causality with Respect to the Output Gap

Time Series	Lag-length of VAR	Schwartz criteria	H_0: Volatility does not Granger cause real	H_0: 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

Since the volatility series exhibit some strong peaks, one might ask whether the VAR's used to estimate the Granger-non-causality 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 apply a simple recursive procedure outlined in Bianchi (1995). Basically, a dummy variable is added to the two equations of the VAR which assumes the value 0 before a breakpoint and 1 afterwards. Then, beginning at January 1970, the possible breakpoint is moved forward in time and the VAR are estimated recursively. Figure 5 depicts the marginal probabilities of the resulting tests on Granger-non-causality for the output gap. As can be read off Figure 5, the results of the tests are fairly stable.

Figure 5 — Recursive Tests on Granger-non-causality



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 reestimate the equations forming the VAR using dummy variables constructed in a way to capture the sign of a change of the financial market series (see Table 8). We then perform exclusion tests to study for the explanatory power of the dummies (Huh 1998). The tests are built on the following augmented equations:

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

The results of this exercise are reported in Table 8. In general, the hypothesis that the dummy is not significantly different from zero cannot be rejected. Thus,

Table 8 — Dummy Variable Exclusion Test on Stability of the Granger-non-causality Tests

Dummy	H_0: Dummies not different from zero in equation for gap		H_0: Dummies not different from zero in equation for volatility	
1 if stock-market return <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 1, 0 else	0.62	(0.66)	1.84	(0.11)

F-statistic; p-value in brackets.

taking asymmetries into account does not alter the conclusions drawn from the tests for Granger-non-causality. The only exception obtains in the case of real exchange rate volatility. The result of the dummy variable exclusion test 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 tests for Granger–non–causality confirm the results produced by applying the signal approach. The results of these test procedures suggest that financial market volatility has only a very limited –if any– predictive power with respect to subsequent changes of real economic activity. This finding, of course, does not imply that the *level* of important financial variables is of no relevance for the evolution of the real sector. However, our results indicate contrary to often made assumptions that financial market turbulences do not exert a significant impact on the business cycle.

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, an ARCH(1) model is specified for the index of industrial production as well. 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 following results were obtained:

$$\Delta \ln IP_t = \underset{(2.73)}{0.002} - \underset{(-6.49)}{0.304}\,\Delta \ln IP_{t-1} + \underset{(2.28)}{0.095}\,\Delta \ln IP_{t-3} - \underset{(-22.9)}{0.089}\,STRIKE + \hat{\varepsilon}_t$$

$$\sigma_\varepsilon^2 = \underset{(9.09)}{0.0002} + \underset{(2.57)}{0.223}\,\hat{\varepsilon}_{t-1}^2$$

R^2: 0.29; Jarque/Bera test for normality = 10.52; ARCH LM(4) = 1.39; standardized residual mean equal to zero –0.58; standardized residuals have standard deviation of one 336.98 BDS-test on i.i.d. (dimension = 2, radius set equal to standard deviation of squared logarithms standardized residuals): 0.29, BDS(3): 0.38, BDS(4): 0.19.

We are now in a position to perform 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 $\hat{r}_{x,p}(k)$ 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 $\hat{r}(k)$ 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: $\chi^2_{k-j-1} = T \cdot \Sigma_{i=j}^{k} \hat{r}_{x,p}(i)^2$, where T symbolizes the number of observations and the salar $(k-j+1)$ denotes the degrees of freedom.

Table 9 — Tests on Causality-in-variance

	Lags						All
	1	2	3	4	8	12	lags
H_0: Stock market volatility does not cause real volatility	–0.79	–1.30	–0.51	0.77	–1.15	–1.77	9.85
H_0: Real volatility does not cause stock-market volatility	0.59	–0.03	–0.24	0.06	–1.05	0.60	10.68
H_0: Exchange rate volatility does not cause real volatility	0.61	1.40	–0.21	–0.04	–0.80	–0.67	8.18
H_0: Real volatility does not cause exchange rate volatility	–0.30	1.38	–0.70	–0.61	–0.26	–0.61	6.09
H_0: 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_0: 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_0: 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_0: 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.

Table 9 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 t-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 result of the Granger-causality tests.

5. Conclusion

This paper has used monthly data for Germany to elaborate on 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 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 (1989a) 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.

However, 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. As noted in the introduction, 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 has just not been 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 approach to highlight a potential link between uncertainty and real economic activity to resort to data on the firm level. For example, Leahy and Whited (1996) use panel date for the US and indeed find a link between stock market volatility and firm's investment decisions. 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 has been exclusively concerned with the impact of financial market volatililty on real economic activtiy. Using measures designed to capture uncertainty regarding the unpredictable future evolution of real economic variables like wages and other cost determinants (Seppelfricke 1996), demand, or political factors it might be possible to empirically document a closer link between volatilty 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 volalitity as a leading indicator of the business cycle.

Appendix Table 1 — Unit Root Test for the Variables under Investigation

Time Series	Test specification	Dickey-Fuller statistic
Stock market index, level	C, t, 0	0.27
Real exchange rate, level	C, t, 1	–2.41
Long-term interest rate, level	C, 2	–1.58
Short-term interest rate, level	C, 1	–2.48
Industrial production, level	C, t, 1	–2.75
Stock market index, first difference	C, 0	–16.34***
Real exchange rate, first difference	C, 0	–14.02***
Long-term interest rate, first difference	C, 1	–11.74***
Short-term interest rate, first difference	C, 0	–12.21***
Industrial production, first difference	C, 0	–29.42***

***(**,*) denotes that the hypothesis of an unit root is rejected at the 1, (5, 10) percent level.

Source: Own estimates.

Appendix Figure 1 —Quantile/Quantile(QQ)-Plot of the Standardized Residuals of the ARCH(1,1) Model for Industrial Production against the Normal Distribution

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