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Abstract

Using monthly data for Germany from 1968 through 1998, the relationship betweenfluctuations of prices in financial markets and inflation is analyzed. The results of Granger–causality tests reveal that stock market has no predictive power volatility for inflation uncertainty, *et vice versa*. Regarding the subsequent volatility of short–term and of long–term interest rate. In contrast, inflation uncertainty provides some information. The hypothesis of a causality running from the volatility of the real exchange rate to inflation uncertainty cannot be rejected.

Keywords: Inflation uncertainty; financial market volatility; GARCH models; Granger–causality

JEL-classification: E 31;C 32

1. Introduction*

Recent research has shown that financial market prices contain information regarding the future course of important macroeconomic variables including interest rates, the exchange rate, and the inflation rate (see e.g. Deutsche Bundesbank 1998). Moreover, some authors advocate to include the level of financial market variables into the set of indicators utilized by authorities to conduct monetary policy (Dornbusch et al. 1998). The primary focus of this strand of the literature is to examine whether a mutual relationship exploitable for forecasting purposes between the *level* of financial market variables and the current inflation rate can be established empirically. Some of the welfare costs of inflation like the redistribution of wealth, however, can only arise in the presence of uncertainty regarding future inflation (Friedman 1977). The main goal of monetary policy, therefore, is to limit the unsteadiness of the inflation path. Consequently, it is interesting to focus attention directly on the link between inflation uncertainty and the *variability* of prices in financial markets. In the present paper we, therefore, elaborate on possible causal relationships between inflation uncertainty and variability in financial markets.

Using monthly data for Germany from 1968 through 1998, the results of Granger–causality tests indicate that there is no predictive power of stock market volatility for inflation uncertainty, *et vice versa.* In contrast, inflation uncertainty exhibits a significant positive impact on the variability of both short–term and long–term rates of interest. The results of the test procedures further indicate that the hypothesis of a reverse causal relationship running from the volatility of the real exchange rate to inflation uncertainty cannot be rejected.

The paper is organized as follows. Section 2 provides summary statistics of the data series under investigation. In section 3, we introduce our measure of inflation uncertainty and present estimates of financial market volatility. The

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results of Granger–causality tests carried out to detect whether a link between financial market volatility and inflation uncertainty can be established are documented in section 4. In section 5, we offer some concluding remarks.

2. The Data

Our empirical analysis of the link between financial market volatility and inflation uncertainty uses monthly data for 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. Inflation is computed as the annualized monthly change of the seasonally adjusted consumer price index for West Germany. We use the change of the logarithm of the German share market index (DAX) as given at the end of each month to capture the situation on the stock market (1987:12 = 100). The exchange rate is measured by the inverse of the monthly changes of the logarithm of the index of the real external value of the DM. The situation on the capital market is represented by the yield of federal securities outstanding (*Umlaufsrendite festverzinslicher Wertpapiere*). Three months money market rate is selected to represent the short–term interest rate. Table 1 reports summary statistics for the time series utilized 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	Inflation rate
Mean	0.01	0.00	7.51	6.47	3.39
Median	0.01	0.00	7.50	5.83	2.76
Maximum	0.16	0.03	11.50	14.57	16.19
Minimum	–0.24	–0.07	4.40	3.09	–6.97
Std. Dev.	0.05	0.01	1.49	2.68	3.06
Skewness	–0.60	–1.31	0.27	0.79	1.03
Kurtosis	5.26	9.05	2.59	2.92	5.70
Observations	368	368	368	368	368

3. Empirical Measures of Financial Market Volatility and Inflation Uncertainty

In order to analyze the link between the variability of financial market prices and inflation uncertainty, empirical measures of volatility and uncertainty need to be constructed. In the present paper these tasks are accomplished by employing the autoregressive conditional heteroscedasticity framework introduced by Engle (1982) and Bollerslev (1986). This econometric framework has been frequently utilized to compute series of both financial market volatility (see the surveys of Bera and Higgins (1993) and Palm (1996) and the references therein) and of time–varying conditional variances representing a measure of inflation uncertainty (see Joyce 1997, Caporale and McKiernan 1997, and Grier and Perry 1998).

The first step in estimating a conditional variance is to specify an appropriate model for the conditional mean of the series (I_t) under investigation. In the present paper, simple univariate 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 I_t are stationary. The results of the tests proposed by Dickey and Fuller (1979) and Phillips and Perron (1988) summarized in table 2 indicate that the selected financial market 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. Though some authors have found the price level to be integrated of order two (see Wolters, Teräsvirta and Lütkepohl 1998), the results of our unit root tests lead us to conclude that the series of the annualized monthly change of the price level used in the present study is stationary.

The model given in equation (1) further requires a proper specification of the lag length. This is done using the Schwartz information criterion. Additionally, it is tested whether the residuals obtained from estimating equation (1) are white noise.

Table 2 — Results of Augmented Dickey–Fuller and Phillips–Perron Tests

Time series	Test specification	Dickey-Fuller-Statistic	Test specification	Phillips-Perron-statistic
Stock market index, level	c,t,0	0.27	c,t,5	0.43
Real exchange rate, level	c,t,2	-2,37	c,t,5	-2.24
Long-term interest rate, level	c,2	-1.58	c,5	-1.58
Short-term interest rate, level	c,1	-2.48	c,5	-2.40
Consumer prices, level	c,t,1	-1.15	c,t,5	-1.12
Stock market index, first difference	c,0	-16.34***	c,5	-16.47***
Real exchange rate, first difference	c,3	-9.03***	c,5	-13.91***
Long-term interest rate, first difference	c,1	-11.74***	c,5	-11.50***
Short-term interest rate, first difference	c,0	-12.21***	c,5	-12.47***
Inflation rate	c,3	-5.14***	c,5	-13.30***

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

c stands for a constant, t for a deterministic trend. The number gives the lags of the auto-correlation correction for the ADF-test and the lag trunctation for the PP-test, respectively.

Source: Own estimates.

Once the autoregressive process has been specified, a model capturing 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 Auto-Regressive 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} represents the set of information available in period t-1. In equation (2), σ_t^2 denotes the variance of the 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). Equations (1) and (2) can be efficiently estimated simultaneously using a non-linear maximum likelihood routine.

Table 3 summarizes the results of the estimations. The second column of Table 3 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. As concerns the inflation rate, a constant and the various lags reported in the second column of table 2 turned out to be the most appropriate specification. Breusch-Godfrey LM-tests presented in column three of Table 3 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 3 strongly reject the Null of no conditional heteroscedasticity for all series. 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 3. 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. However, normality is mostly rejected by a Jarque-Bera test as can be seen from column seven of Table 2.[1] In

[1] Visual inspection of QQ–plots scattering standardized residuals against the quantiles of the normal distribution revealed that the departure from normality is mainly attributable to some influential outliers. The QQ–plots are available from the authors upon request.

Table 3 — Testing the AR/GARCH Models for Inflation and the Financial Variables

	Testing the AR-process			Testing the GARCH(1,1) process					
Variable (1)	Model specification[a] (2)	H_0: no remaining autocorrelation of order 4 F-value[b] (3)	H_0: no ARCH-process of order not higher than 4 in the residuals (F-value)[c] (4)	α^d (5)	β^d (6)	Jarque-Bera test for normality (7)	H_0: standardized residuals have mean zero (t-value) (8)	H_0: standardized residuals have variance 1 (variance ratio) (9)	H_0: no remaining ARCH-process of order 4 (LM-test) (10)
Stock market return	C	0.22	6.33***	0.11 (3.03)***	0.86 (15.24)***	39.68***	0.51	367.26	0.68
Change of real exchange rate	AR(1)	0.30	12.81***	0.14 (1.90)**	0.61 (3.73)***	353.5***	0.42	368.13	0.06
Change of long-term interest rates	AR(1), AR(2)	0.60	4.97***	0.11 (2.24)**	0.84 (12.47)***	4.45	–0.34	366.77	0.44
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
Inflation rate	C,AR(1) to AR(4), AR(6), AR(9), AR(11), AR(12)	1.87	3.17**	0.63 (4.15)***	0.30 (3.76)***	32.16***	1.68*	352.47	1.00

[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 GARCH(β) coefficient are equal to zero. — *(**,***) denotes rejection of the null hypothesis at the 10 (5, 1) percent level.

Source: Own estimates.

spite of this rejection, the results can 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 eighth and ninth column of Table 2 do not reject the null hypotheses that the standardized residuals of the estimated models have zero mean and a variance equal to unity. Only the hypothesis that the standardized residuals of the inflation equation have zero mean is rejected at the ten per cent level.

A well–behaved process also 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 the residuals are well behaved with respect to this criterion.

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 independently identically distributed (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 4 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 4 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 4 — BDS-tests on i.i.d. Standardized Residuals of the GARCH(1,1) models

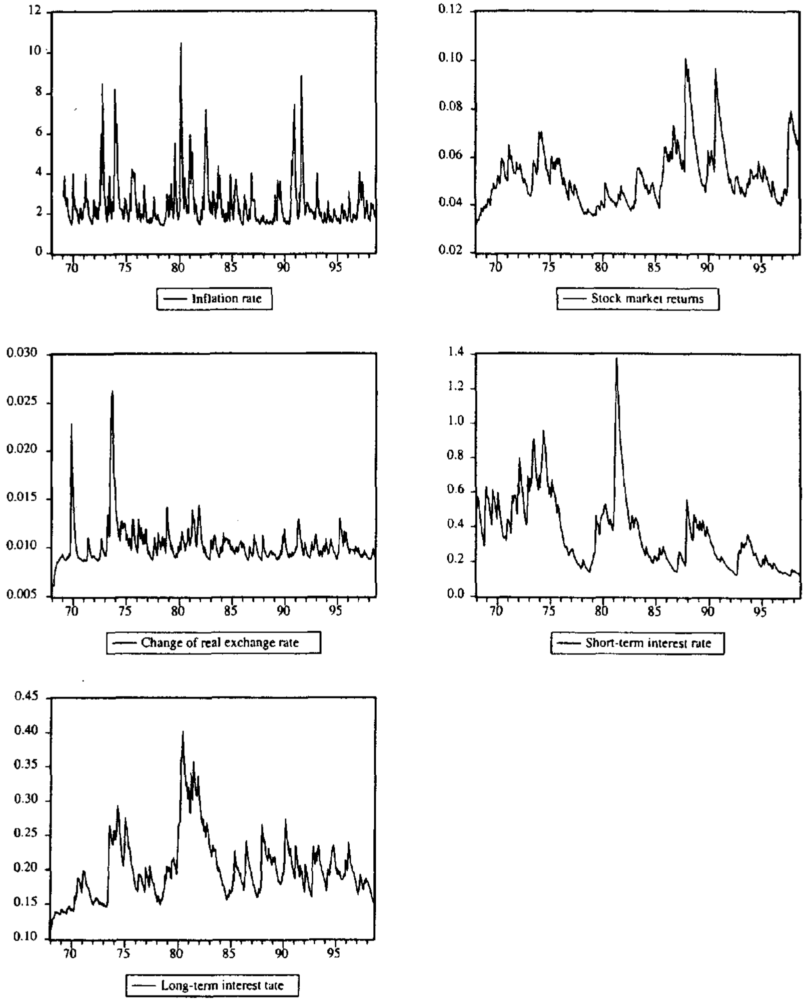
Time series	Dimension			
	2	3	4	5
Stock market return	−1.31	−1.47	−1.36	−1.01
Change of real exchange rate	−0.00	0.76	1.27	1.49
Change of long-term interest rate	−0.08	−0.69	0.09	1.27
Change of short-term interest rate	2.65*	1.86	1.23	0.78
Inflation rate	0.68	0.73	0.67	0.85

* 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).

In a nutshell, 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 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.

The models of financial market volatility produce economically reasonable results. Figure 1 shows estimates of the conditional variances of both the inflation rate and the financial market variables. All in all, the time series depicting inflation uncertainty makes sense as a measure of inflation uncertainty. There are three pronounced peaks. The first two peaks are due to the two oil price crises. The third one reflects the unification boom. 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

Figure 1 — Inflation Uncertainty and Conditional Standard Deviations of Financial Market Prices



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). 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 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 (1989).

4. Testing for Granger Causality

In this section, we elaborate on the link between the volatility of financial variables and inflation uncertainty. A frequently used statistical technique in the literature to address this kind of question is the test for Granger–causality (Granger 1969). Within a bivariate autoregressive representation, the hypothesis that the conditional variance of the financial market series does not Granger cause inflation uncertainty can be tested by a standard F-test. It will also be analyzed whether a reverse causality does exsist. If both hypotheses cannot be rejected it is a feedback relationship. Table 5 gives the results of this testing procedure. Though resorting to the Schwartz information criterion would have led to the selection of rather short lag lengths of two months, we have decided to check for the robustness of the results also by presenting the test statistics obtained for a lag of six months.[2]

Though economic theory offers several arguments in favour of a link between share prices and inflation uncertainty (see e.g. Dokko and Edelestein 1991), the results documented in table 5 demonstrate that for the data under investigation in the present study show no causal relationship between inflation uncertainty

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[2] Applying the technique outlined in Bianchi (1995), we have also tested for the stability of the results of the Granger non–causality tests over time. It turned out that the results are fairly stable. More detailed information is available from the authors upon request.

Table 5 — Testing for Granger-Causality

Time Series	H_0:Inflation Volatility does not Granger cause time series (F-value)	H_0: Time Series does not Granger cause inflation volatility (F-value)	Decision
Stock market volatility			
Three lags	0.47	1.76	(-)
Six lags	0.54	1.05	(-)
Volatility of real exchange rate			
Three lags	0.20	3.53**(+)	T→I
Six lags	0.28	2.37**(+)	T→I
Long-term interest rate volatility			
Three lags	7.01***(+)	1.20	I→T
Six lags	4.34***(+)	1.35	I→T
Short-term interest rate voltility			
Three lags	4.68***(+)	0.35	I→T
Six lags	2.54**(+)	0.69	I→T

***(**,*) denotes the rejection of the hypothesis of no Granger-causality at the 1(5,10) percent level. I→T denotes that inflation uncertainty does Granger-cause the time series, T→I stands for the reverse relationship, (-) represents no Granger-causal relationship in either direction. (+) denotes, that the sum of the coefficients of the null hypothesis is positive.

and the stock market index volatility exists, *et vice versa*. This is in line with the results reported Liljeblom and Stenius (1997) and Schwert (1989).[3] In contrast, our measure of inflation uncertainty exhibits a significant positive impact on the variability of both short–term and long–term rates of interest. Given that both economic theory predicts that real economic activity might be negatively correlated with interest rate uncertainty (Ingersoll and Ross 1992) and that the empirical evidence suggests that the level of inflation is an important determinant of inflation uncertainty (see e.g. Grier and Perry 1998), this result makes a case for low inflation rates as a target for monetary policy. With respect to the short–term interest rate, inflation uncertainty does Granger cause short–term interest rates while the reversed causation is rejected by the data. The outcomes of the tests, thus, indicate that monetary policy reacts to inflation uncertainty rather than being the source of it. In contrast to the findings discussed above, the hypothesis that the volatility of the real exchange rate causes inflation

3 Liljeblom and Stenius (1997: 423) report a significant impact of inflation uncertainty and stock market volatility using Finish data for 1946–1969 but not for the period 1970–1991.

uncertainty cannot be rejected. Hence, inflation uncertainty can be viewed to be imported to some extent. This might reflect, in part, the impact of oil price shocks which took place in 1973 and 1980. This is in line with the argument made by Artis and Zhang (1997) that the volatility of the real exchange rate can be interpreted as a measure of importance of asymmetric shocks hitting an economy.

5. Conclusion

The present empirical analysis has addressed the the question whether a link between volatility in financial markets and inflation uncertainty can be detected. After specifying GARCH models to capture the time series properties of both inflation uncertainty and financial market variability, Granger–causality tests are performed. The results of applying this testing methodology indicate that stock market volatility seems to evolve largely independently from inflation uncertainty. In addition, we find that inflation uncertainty raises short–term and long–term interest rate volatility. With respect to turbulences in the foreign exchange market, the hypothesis of a causal relationship running from the volatility of the real exchange rate to inflation uncertainty cannot be rejected. To summarize, our findings indicate that financial market volatility provides only very limited information exploitable by monetary authorities.

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