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Abhandlungen

(How) Do Stock Market Returns React to Monetary Policy? An ARDL Cointegration Analysis for Germany*

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I. Introduction

This paper deals with the impact of monetary policy on stock market returns in Germany. It sheds some light on the more general debate on monetary policy and stock market returns, that is whether: (a) the central bank as a monopolistic supplier of base money can influence stock market returns in a systematic fashion; and (b) if this is the case, whether asset prices should be used as monetary policy indicators. While part (b) of the current debate has been at the centre of theoretical and empirical research for some years now, part (a) still lacks a thorough empirical backing.[1] In principle, it is acknowledged that there are two main channels through which a central bank can influence asset prices. First, the central bank is able to determine short-term interest rates, which act as a benchmark for short-term returns and are used for discounting the assets' future income streams. Thus, the central bank is able to affect asset prices via agents' expectations about the future path of money market rates (short-run impact).

Second, the long-run perspective about future inflation has an impact on the current prices of long-term assets, since nominal long-term re-

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1 For this kind of reasoning see, for instance, *Bernanke* and *Gertler* (2001), *Bohl, Siklos* and *Werner* (2003), *Durham* (2003), *European Central Bank* (2002), and *Rigobon* and *Sack* (2004).

turns usually contain an inflation premium. Given that monetary policy determines inflation in the long run, it has a strong impact on asset prices via inflation expectations (long-run impact). However, the short run and the long run have been intertwined since, for instance, changes in inflation expectations should cause a break in the sequence of expected short-term rates. This interconnection may serve as the first hint that the use of the usual error-correction modelling framework, which enables us to model this link between the short and the long run, is highly suitable in this context.

Which policy implications would emerge from the finding of a significant and stable relationship between monetary policy and stock prices or even stock market returns? In our view, there are at least three clear implications. First, by letting short-term rates deviate from a certain level of equilibrium, the central bank may have a significant short-run impact on asset prices (short-run impact). However, indications of the change in asset prices depend on whether the long-term relationship between monetary policy and asset prices is stable, i. e. the central bank's reaction function has not changed and is still perceived to be credible by the actors (long-run impact).

Hence, and this is the second implication, only a predictable and transparent monetary policy strategy establishes a stable long-term relation between monetary policy and asset prices. However, since the long and the short run are intertwined, the sound implementation of a transparent monetary policy is an indispensable condition even in the short run. However, in the short run monetary policy intervention leads to forecastable fluctuations of asset returns around an equilibrium value.

Third, in principle the central bank is able to reduce stock price volatility by diminishing the uncertainty of future rate changes, hence volatility spillovers to other financial markets could be avoided and the option value of waiting with investment decisions would be reduced.[2] Since monetary policy exerts a significant impact on financial markets – as mirrored by the considerable attention that the ECB receives in the financial press – financial actors might also be interested in our results. Estimates of the responsiveness of stock market returns to changes in monetary policy will most likely contribute to effective investment and risk management decisions (Rigobon and Sack (2004)).

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2 See *Bean* (2004), *Dupor* and *Conley* (2004), *Domanski* and *Kremer* ((1998), pp. 24 and 41) and *European Central Bank* ((2002), pp. 39).

In order to tackle these important questions, we test for a stable cointegration relationship between the short-term interest rate (i.e., monetary policy) and stock market returns which should ultimately affect stock prices as well. For this purpose, we apply the bounds testing procedure proposed by Pesaran, Shin and Smith (1996, 2001) instead of more standard econometric procedures to estimate the impact of monetary policy on stock market returns. This methodology is particularly useful in the current application in three dimensions.

First, as claimed for instance by Durham (2003) and Rigobon and Sack (2004), estimating the response of asset prices to changes in monetary policy is complicated by the endogeneity of policy decisions and by the fact that the 'event-study' approach typically used in this context requires a much stronger set of assumptions than ours. We show that the response of asset prices to changes in monetary policy can be singled out and identified based on the procedure proposed by Pesaran, Shin and Smith (1996, 2001) and Pesaran and Shin (1999), respectively. In contrast to common instrumental variables procedures, this methodology is capable of dealing with the controversial issue of *(lack of) exogeneity* of the monetary policy variable. It enables us investigate to the up to now far less explored side of the relationship between monetary policy and the stock market: how stock market returns react to changes in monetary policy (Durham (2003) and Rigobon and Sack (2004)). In this respect, our contribution reaches beyond investigations of asset price booms and monetary policy which look at correlations leaving aside the important question of 'causality' and 'exogeneity' (see, e.g., Detken and Smets (2004)) and for this purpose use a different approach than the heteroscedasticity-based approach applied by Rigobon and Sack (2004).

Second, determining the order of integration of interest rates and stock market returns is not an issue although there is often *no clear information on the integration and cointegration properties* of the data, especially for market interest rates. While there are upper and lower bounds for the interest rate available from theory and, hence, the interest rate should be stationary, unit root tests often cannot empirically reject the I(1) hypothesis for the same variable as a sample property. Although the stationarity of stock returns is usually less debatable, the same is in principle valid for different measures of stock market returns. Thus, whether variables should be introduced in differenced or level form is highly questionable, for isntance, within the framework of the Johansen procedure. The Pesaran ARDL approach yields *consistent estimates of* *the long-run coefficients* that are asymptotically normal *irrespective of whether the underlying regressors are I(0) or I(1)* and of the extent of cointegration.

Third, the usual econometric procedures used to assess the impact of monetary policy on asset prices is that they (by estimating VARs only in differences) do not allow one to distinguish clearly between long run and short run relationships. To avoid such kind of problems, the procedure used in this paper will also allow *the correct dynamic structure* to be obtained. Although the use of an error-correction specification is especially appealing with respect to monetary policy which should have transitory impacts on asset prices it is strongly under-utilized in the relevant strand of literature and its use has only recently become popular in analysing the impacts of monetary policy on asset prices (one of the few examples is Durham, 2003). However, as far as we know, it has not yet been applied to the relation between monetary policy and stock market returns in Germany.

The paper proceeds as follows. Section II. discusses our way of modelling monetary policy impacts on stock prices. In section III., we apply the bounds testing procedure proposed by Pesaran and his co-authors on monthly data for Germany. Since the superiority of the bounds testing procedure is far from obvious, we compare the empirical results obtained from our ARDL models with those obtained from the Johansen procedure as a standard econometric approach. We move to error-correction modelling in section IV. only in cases for which the negation of a long-run relationship has been rejected in section III. In section IV., we apply the ARDL-approach to cointegration analysis and select the final error-correction model for monetary policy and German stock market returns. Section V. concludes and discusses some implications for the current debate about the impacts of monetary policy on asset prices in general.

II. Modelling Monetary Policy Impacts on Stock Market Returns

Modelling the relation between the short-term interest rate and the stock market performance, we take a rather pragmatic view. In the tradition of the Capital Asset Pricing Model (CAPM), we assume that there is a linear relation between the stock market performance measure and a risk free interest rate – which is interpreted as the central bank short-term interest rate – plus a risk premium which is assumed to be stationary (time-invariant):

$$r_t = \beta \cdot rf_t + \phi + \varepsilon_t, \tag{1}$$

where r_t is the return measure in period t, rf_t the central bank short-term interest rate, ϕ the risk premium and ε_t is the noise variable.

Assuming that the short-term interest rate of the central bank actually determines the risk free rate, and, in addition, that the risk premium is a stationary variable, the central bank can be expected to have a systematic impact on stock market returns. Put another way, equation (1) would suggest that stock returns and central bank rates are cointegrated.

While it is difficult to assign all of the weight of the β coefficient to central bank policies, it is straightforward to assume that using short-term money market rates as the rf variable monetary policy is dominating β. Although central banks do not directly set the most widely watched indicator of short-term monetary conditions, namely the one-month interest rate, they can nevertheless determine pretty much its evolution. We base our analysis on three different future stock market return measures (i. e., dependent variables r_i), namely (i) the annualised one-month continuously compounded stock market returns (h); (ii) the annualised one-month dividend growth rates in percent (Δd); and (iii) the difference between the two (h–Δd).

(i) Stock price changes ($r_i = h$)

The coefficient of the short term rate, β, should be positive if a rise in short-term interests reflects the central bank's policy of adjusting the price of money to improved growth/profit expectations as reflected by rising stock prices. With $\beta > 0$, the central bank simply responds passively to the economic environment. β, will be negative if a higher short-term rate is evidence of monetary policy efforts to slow down the economy. In such a case, the central bank takes pre-emptive action against bubbles during the upswing as emphasised for instance by Cecchetti, Genberg and Wadhwani (2002) and follows an "active", or "anti-cyclical" policy approach.

(ii) Dividend growth ($r_i = \Delta d$)

In principle, the same considerations as with respect to our proxy (i) are valid. However, in the context of dividend growth rates it is important to note that dividends as dependent variables might suffer from a drawback, namely firms' "dividend policy". In the second half of the period under review, firms reduced their share of dividend in relation to total profits quite heavily. This finding could be explained by investors expecting high returns from retained earnings. So whereas actual dividend declined, future expected cash flows might have been increased, thereby translating into rising stock prices. That is to say, firms' dividend policy might have blurred the information content of dividend (growth) in the sample under review. Hence, the estimated coefficient β might turn out to be negative in our sample.

(iii) Stock price change minus dividend growth ($r_i = h - \Delta d$)

Again, the same arguments as in (i) apply.

What does the above model show? In empirical terms, the monetary policy variable should not, a priori, be excluded when analysing a *long-term* relationship between the stock market return and its determinants. However, some readers might have a strong prior belief that monetary policy shocks cannot have permanent effects on stock returns (see, e.g., European Central Bank (2002), p. 46). Since this is not central to the analysis in this study, we choose not to take a view on this issue. Moreover, we believe the question of *short-term versus long-term* impacts of monetary policy on stock prices can only be solved empirically. The results based on empirical tests of the significance of monetary policy in the stationary and in the non-stationary parts of error-correction models which we present below are compatible with both views.

III. Testing for the Existence of Long-Run Stock Market Return Relations

1. Stylized Facts

We investigate the empirical relation between short-term interest rates (i.e. monetary policy) and stock market returns in Germany over the period August 1974 to September 2003. Following the seminal study by Rigobon and Sack (2003), we use monthly data which were in our case provided by Datastream Primark and calculated three alternative future stock market return measures: (i) the annualised one-month continuously compounded stock market returns (h); (ii) the annualised one-month dividend growth rates in percent (Δd); and (iii) the difference between these two return measures ($h - \Delta d$).[3]

The performance measures are calculated over two different holding periods, namely 3 and 12 months. Since we leave lag orders constantly at 12 in our estimations with an eye on the monthly frequency of our data set, the use of lag-orders of higher than 12, e.g. 24, 36 and 48 would be highly problematic. We use average return measures as – against the backdrop of the rational valuation formula – the forecast performance of current stock prices should generally be better for long-term return measures since these make up a larger part of the stock markets' calculated equilibrium price and, moreover, should be less susceptible to one-off shocks and "peso effects" than highly volatile short-term returns.[4]

After having ensured that there is no problem of "reverse causation", i.e. that the short-term money market rate really is the 'forcing variable' these different measures of stock market returns are then regressed on the one-month money market rate. We experimented with some other proxies of monetary policy, but we finally decided to use the one-month money market rate *i1m* (i.e., the DM rate until the end of 1998 and the euro rate from 1999 on).

A priori, if one uses market interest rate data, it becomes inherently difficult to distinguish policy maker's intentions from demand disturbances in financial markets (Bergin and Jordá (2002), p. 2). However, our inspection of the data clearly indicates that central bank rates and market rates are closely correlated. Moreover, using market rates, one has the advantage of being able to capture, albeit imperfectly, the probability of future interest rate movements by the central bank. If one uses central bank rates, one has only the realisations, not the expectations, that determine market rates; these, in turn, are the rates that influence the economy. Of course, our choice of monthly data eliminates some of the noise that might come from short-term disturbances in money markets and might be apparent in, e.g., daily data. Further details on the series are given in the annex.

To convey a broad-brush view on the data and indicate possible correlations, Figure 1 shows three scatter plots. It shows the cross-plots of our three measures of stock market returns against the one-month money market rate. The charts suggest, first, that the conjectured *positive* rela-

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3 The regressions for dividend and profit growth are potentially subject to the omitted variables problem because, in this case, expected stock market returns introduce noise. To circumvent this problem, the difference between h and Δd, $h–\Delta d$, were also calculated and used in the bounds testing procedure.

4 See *Kaul* (1996), p. 284.

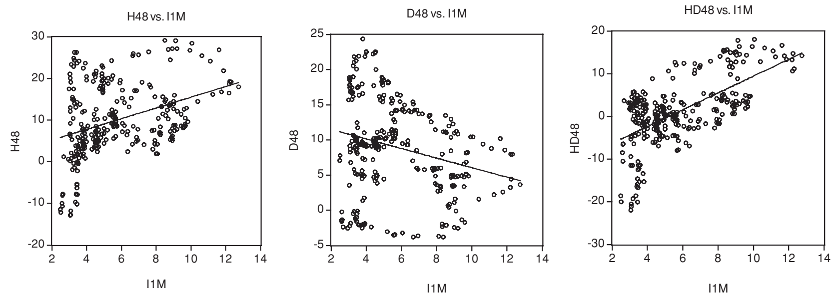
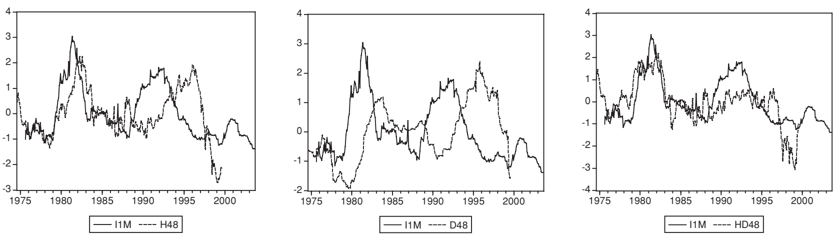


Figure 1: German Stock Market Returns and the Money Market Rate (1974M8 to 2003M9)



Source: Thomson Financials, own calculations.

Figure 2: Stock Market Returns and the Money Market Rate over Time (Normalised Scaling)

tionship between the one-month money market rate (*i1m*) and the annualised one-month continuously compounded stock market returns lagged four years (*h48*) holds for the German stock market. Second, the conjectured *positive* relationship between the one-month money market rate (*i1m*) and the four-years-lagged difference ($h–\Delta d$) between the annualised one-month continuously compounded stock market returns and the annualised one-month dividend growth rates in percent (*hd48*) is also corroborated by the visual inspection of the figures below. Third, as indicated by the theoretical considerations outlined earlier, the relation between *i1m* and $\Delta d48$ appears to be indeed negative. What matters for our empirical work, however, is that the overall relationships in these figures show a clear positive or negative relation – rather than being vertical or horizontal.

Figure 2 shows the variables under review over time. A visual inspection suggests at first sight that the short-term interest rate was leading the stock market returns by around a double-digit number of months, both when interest rates increased and when they fell. Observers might conclude from this apparent relationship that, in Germany, monetary policy "causes" stock market returns – an interesting hypothesis which is astonishingly not deeply investigated in the literature up to now but tested more rigorously in this paper.

2. *Testing for Cointegration: The Pesaran, Shin and Smith ARDL Approach*

a) Theoretical Background

An important problem inherent in the usual residual-based tests and even in some system-based tests for cointegration is given by a decisive precondition. One must know with certainty that the underlying regressors in the model, i. e. our monetary policy variable, are integrated of order one (I(1)). However, given the low power of unit root tests there will always remain a *certain degree of uncertainty with respect to the order of integration* of the underlying variables. For this reason, we now make use of the bounds testing procedure proposed by Pesaran, Shin and Smith (1996, 2001) to test for the existence of a linear long-run relationship, when the orders of integration of the underlying regressors are not known with certainty. The test is the *standard Wald- or F-statistic* for testing the significance of the lagged levels of the variables in a first-difference regression. The involved regression is an error-correction form of an ARDL model in the variables of interest.

More specifically, in the case of an unrestricted error-correction model (ECM), regressions of y on a vector x, the procedure as a first step involves estimating the following model:

$$\begin{aligned}(2)\qquad &\Delta \mathrm{y_t} = \mathrm{a_{0y}} + \mathrm{a_{1y}} \cdot \mathrm{t} + \phi \mathrm{y_{t-1}} + \delta_1 \mathrm{x_{1,t-1}} + \delta_2 \mathrm{x_{2,t-1}} + \ldots + \delta_\mathrm{k} \mathrm{x_{k,t-1}} + \\ &\sum_{\mathrm{i=1}}^{\mathrm{p-1}} \psi_\mathrm{i} \Delta \mathrm{y_{1,t-i}} + \sum_{\mathrm{i=0}}^{\mathrm{q_1-1}} \varphi_{1\mathrm{i}} \Delta \mathrm{x_{1,t-i}} + \sum_{\mathrm{i=0}}^{\mathrm{q_2-1}} \varphi_{\mathrm{i}2} \Delta \mathrm{x_{2,t-i}} + \ldots + \sum_{\mathrm{i=0}}^{\mathrm{q_k-1}} \varphi_{\mathrm{ik}} \Delta \mathrm{x_{k,t-i}} + \xi_{\mathrm{ty}}\,,\end{aligned}$$

with ϕ and δ's as the long-run multipliers, ψ's and φ's as short-run dynamic coefficients, (p,q) as the order of the underlying ARDL-model (p refers to y, q refers to x), t as a deterministic time trend, k as the number of 'forcing variables', and ξ uncorrelated with the Δx_t and the lagged values of x_t and y_t.

As a second step, one has to compute the usual F-statistic for testing the joint significance of $\phi = \delta_1 = \delta_2 = \ldots = \delta_k = 0$. However, the asymptotic distributions of the standard Wald or F statistics for testing the significance of the lagged levels of the variables are non-standard under the null hypothesis that there exists no long-run relationship between the levels of the included variables. Pesaran and his co-authors provide *two sets of* asymptotic *critical values*; one set assuming that all the regressors are I(1); and another set assuming that they are all I(0). These two sets of critical values refer to two polar cases but actually provide a band covering all possible classifications of the regressors into I(0), I(1) (fractionally integrated or even mutually cointegrated).

In view of this result, we have as a third step to use the appropriate *bounds testing procedure*. The test is consistent. For a sequence of local alternatives, it follows a non-central χ^2-distribution asymptotically. This is valid irrespective of whether the underlying regressors are I(0), I(1) or mutually cointegrated. The recommended proceedings based on the F-statistic are as follows. One has to compare the F-statistic computed in the second step with the upper and lower 90, 95 or 99 percent critical value bounds (F_U and F_L). As a result, three cases can emerge. If $F > F_U$, one has to reject $\phi = \delta_1 = \delta_2 = \ldots = \delta_k = 0$ and hence conclude that there is a long-term relationship between y and the vector of x's. However, if $F < F_L$, one cannot reject $\phi = \delta_1 = \delta_2 = \ldots = \delta_k = 0$. In this case, a long-run relationship does not seem to exist. Finally, if $F_L < F < F_U$ the inference has to be regarded as inconclusive and the order of integration of the underlying variables has to be investigated more deeply.

The above procedure should be *repeated* for ARDL regressions of *each* element of the vector of x's on the remaining relevant variables (including y) in order to select the so called 'forcing variables'. For example, in the case of k = 2, the repetition should concern the ARDL regressions of x_{1t} on (y_t, x_{2t}) and x_{2t} on (y_t, x_{1t}). If it can no longer be rejected that the linear relationship between the relevant variables is not 'spurious', one can estimate coefficients of the long-run relationship by means of the ARDL-procedure (see section 4).

b) Application to German Stock Market Data

Since the choice of the orders of the included lagged differenced variables in the unrestricted ECM specification can have a significant effect on the test results, models in the stock market returns (*h,* Δd or *h*–Δd*,* in logs) and the one-month money market rate (*i1m*) are estimated for the orders p = q = 2, 3, 4, …, 12. Finally, in the absence of a priori information about the direction of the long-run relationship between *h,* Δd or *h*–Δd and the monetary policy variables, we estimate unrestricted ECM regressions of *h,* Δd or *h*–Δd (as the respective dependent variables y) on the "vector" of monetary policy variables (x) as well as the reverse regressions of x on y. More specifically, in the case of the unrestricted ECM regressions of y on x, we re-estimate equation (2) using monthly observations over a maximum sample ranging from August 1974 to September 2003. In view of the monthly nature of observations we set the maximum orders to 12, i.e. we estimate eq. (1) for the order of $p = q_1 = q_2 = 12$ over the same sample period. It is important to note already at this early stage of investigation that we have to choose p and q *quite liberally* in order to endogenise the stock market returns.[5]

Since we are interested in the impact of the money market rate, namely of *i1m,* but take it for granted that the constant (i.e., the stationary risk premium) also influences stock market returns, we distinguish between *three different definitions of stock market returns* (cases *h,* Δd and *h*–Δd*,* in each of these cases monetary policy stance is approximated by the short-term interest rate *i1m* as implied by theory:

- *Model 1*: (*h, i1m,* intercept), means: *h, i1m* and a constant included in the long-run relation,
- *Model 2*: (Δd*, i1m,* intercept), means: Δd*, i1m* and a constant included in the long-run relation, and
- *Model 3*: (*h*–Δd*, i1m,* intercept), means: *h*–Δd*, i1m* and a constant included in the long-run relation.

The models 1, 2, and 3 each portray an important implication of the theoretical model derived in section 2, namely that there is cointegration between monetary policy and stock market returns. It is also connected with a second implicit idea inherent in the model insofar as it allows monetary policy to slow down the adjustment to a new stock market

[5] Detailed proofs can be found in *Pesaran* and *Shin* (1999) and *Pesaran, Shin* and *Smith* (1996, 2001).

equilibrium in the wake of a shock. The core implication of the model derived above is that the one-month money market rate determines German stock market returns in the short *and* in the long run. In sum, thus, our modelling approach is strictly *guided by theory*.

We now let the data tell us which of the above cases fits the German stock market data best.[6] Tables 1a to 1c display the empirical realisations of the F-statistics for testing the existence of a long-run relationship between the stock market return and the one-month money market rate (model 1: $r_i = h$, model 2: $r_i = \Delta d$, and model 3: $r_i = h{-}\Delta d$). In all of these cases, the underlying equations pass the usual diagnostic tests for serial correlation of the residuals, for functional form misspecification and for non-normal and/or heteroscedastic disturbances.

The 90, 95 and 99 percent lower and upper critical value bounds of the F-test statistic dependent on the number of regressors and dependent on whether a linear trend is included or not are originally given in Table B in Pesaran, Shin and Smith (1996) and usefully summarised in Pesaran and Pesaran (2001, Annex C, Statistical Tables, Table F). The critical value bounds for the application without trend are given in the middle panel of this Table F at the 90 percent level by 4.042 to 4.788, at the 95 percent level by 4.934 to 5.764 and at the 99 percent level by 7.057 to 7.815. However, we dispense with the specification assuming a linear trend, since it does not make sense for German interest rates and stock returns. We took the upper bound critical values from these intervals and tabulate them in Tables 1a to 1c as the relevant conservative benchmarks to check the significance of the cointegration relationships.

According to the empirical realisations of the F-values in Table 1, we find that the null hypothesis of no long-run relationship in the case of unrestricted ECM regressions of the log of stock market returns on the one-month money market rate is *rejected* in four cases at $\alpha = 0.1$ and in one of these cases even at the 5 percent level.

Overall, the results displayed in Table 1 provide *some evidence in favour of the existence of a long-run relationship* between the (future) stock market returns (as measured by h, Δd or $h{-}\Delta d$) and the one-month money market rate and the estimated constant, i.e. the risk premium. This is valid at least if we approximate stock market returns by the vari-

6 The following estimations – like all other computations in this paper – have been carried out using the program Microfit 4.11 (see *Pesaran* and *Pesaran* (2001)).

Table 1

F-Statistics for Testing the Existence of a Long-Run Relationship between the Stock Market Return and the One-Month Money Market Rate

MA-order of h	Based on regressions with the change of stock market returns as dependent variable	Based on regressions with the change of the one-month money market rate as dependent variable
Model 1: $r_i = h$		
h3	0.33054	0.68269
h12	4.1498	1.1217
Model 2: $r_i = \Delta d$		
$\Delta d3$	5.7272	.34943
$\Delta d12$	5.7826	.30969
Model 3: $r_i = h–\Delta d$		
$(h–\Delta d)3$	1.2670	.67448
$(h–\Delta d)12$	5.0548	1.1937
$F^C(0.1)$	*4.788*	*4.788*
$F^C(0.05)$	*5.764*	*5.764*
$F^C(0.01)$	*7.815*	*7.815*

Notes: Lag orders: $p = q_1 = q_2 = 12$. Maximum sample: 1974M8 to 2003M9.
Individual samples: For MA = 12 months: 1975M8 to 2002M9.

able Δd and use moving-average (MA) orders of 3 or 12. For all other specifications of the stock market returns, namely h and ($h–\Delta d$), we do not find any cointegrating relationships except for $h–\Delta d$ (MA = 12).

But in view of the potential endogeneity of monetary policy with respect to stock market performance, it is not possible to know a priori whether monetary policy, i.e. the 1-month money market rate, is the 'long-run forcing' variable for the average future stock market return performance.[7] Since we see attach highest importance to this point (although it has not been tackled frequently in the literature so far), we

[7] For instance, monetary policy could have systematically and preemptively reacted to the emergence of asset price bubbles. More generally, asset prices as predictors of the future course of the economy might have triggered some monetary policy action. See, for instance, *Bean* (2004), *Dupor* and *Conley* (2004), *European*

have considered all possible regressions and substituted the change in the stock market return dh, d(Δd) or d(h–Δd) as the dependent variable in eq. (2) by the change in the one-month money market rate d(*i1m*), in order to test whether this relationship is *spurious* in respect to not capturing the 'correct direction of causation'. Hence, we have to make sure that the future stock market return is not among the forcing variables.

The empirical results based on the reversed test equations are displayed in the second column of Table 1. In the case of $r_i = \Delta d$ and for moving averages of 3 or 12 months, we find that the *direction* of this relation is most likely to be *from the one-month money market rate to the future stock market returns*. Hence, we feel legitimized to consider the short-term interest rate *i1m* as the 'long-run forcing' variable for the stock market returns Δd. Analogously, the one-month money market rate *i1m* can be regarded as the 'long-run forcing' variable for the explanation of the variable Δd if MA = 12. As a consequence, in this case the parameters of the long-run relationship can now be estimated using the ARDL procedure discussed in Pesaran and Shin (1999). Experimenting with dummies coded as one from October 1987 on, from July 1990 on, from August 2001 on and from September 2001 on did not change the results substantially.

3. Long-run Structural Modelling – Comparison with Results from the Johansen Procedure

To check for robustness and in order to convince the reader that applying ARDL models is really worth the effort, we have also moved to some complementary tests for cointegration on the basis of model 2, the one with the best fit according to Table 1. When using cointegration analysis in the Johansen-framework (Johansen, 1991 and 1995), we first needed to establish that all the underlying variables are I(1). The main result from our standard ADF tests was that the null of a unit root in the one-month money market interest rate cannot be rejected; but the evidence of whether our measure of German stock market returns is I(1) or I(0) is borderline. Hence, it cannot be excluded a priori that German stock returns are nearly integrated of order one.

However, such pre-testing results may adversely affect the test results based on cointegration techniques (Cavanaugh, Elliot and Stock (1995)

Central Bank (2002) and *Robinson* and *Stone* (2005) for good summaries of this discussion in the literature.

and Pesaran (1997)). This insight already motivated us to use the Pesaran, Shin and Smith (1996) approach and not to display the results here. The latter are available on request. In general, the results of these quite traditional cointegration exercises not displayed here convey the impression that cointegration properties appear clearly if, and this is important in the light of the literature on monetary policy reaction functions and on the impact of monetary policy on asset prices, cointegration is indicated if exogeneity is imposed (solely) on the monetary policy variable.[8]

Let us now turn to a first brief discussion of the above mentioned unit root and cointegration test results. With respect to the interpretation of our unit root test results, we closely follow Narayan and Smyth (2004) and others who all unambiguously stress that this scenario of some variables being I(0) and others I(1) – is exactly the scenario in which the bounds testing approach to cointegration is applicable and its use reaps the greatest benefits.[9] All of these studies have in common with ours that they tested the stationarity of the variables using the Augmented Dickey-Fuller or other unit root tests and their results in general suggest that some of the investigated variables are I(0), while the other variables are I(1). Using the bounds test appears appropriate to all of them under these circumstances.[10]

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8 When we applied the standard *Johansen* (1991) system approach, we were able to confirm the above results for the one-month money market rate $i1m$ and the annualised one-month dividend growth rates in percent $\Delta d3$ within this standard framework. In addition, we were able to show based on the long-run structural modelling approach by *Pesaran, Shin* and *Smith* (1997) that, if exogeneity is imposed on the one-month money market rate, the existence of no cointegration vectors has to be rejected. If, in turn, exogeneity is imposed on the German stock market returns, the null hypothesis of no cointegration cannot be rejected any more. This clear result strongly corresponds to our results based on the ARDL approach to cointegration and again highlights that the 1-month money market rate is the 'forcing variable' of stock market returns if the latter is defined as the annualised one-month dividend growth rates in percent (Δd). Of course, the whole exercise can be interpreted as an additional robustness check of our results.

9 See among others *Bahmani-Oskooee* and *Ng* (2002), p. 150, *Faria* and *Leon-Ledesma* (2000), pp. 6, *Halicioglu* (2004), p. 3, *Morley* (2003), p. 6, and *Payne* (2003), p. 1724.

10 See *Narayan* and *Smyth* (2004), p. 5: "… We tested the stationarity of the variables using the Augmented Dickey-Fuller test and the small sample unit root tests proposed by *Elliot* et al. (1996). To save space the results are not reported, but they suggest that two of the key variables, the robbery and unemployment rates, are I(0), while the other variables are I(1). Using the bounds test is appropriate under these circumstances."

As a practical consequence, most empirical work using the ARDL bounds testing procedure totally dispenses with such kind of unit root pre-testing even if and especially if some of the included variables cannot be rejected to be I(1) and some others are classified as I(0) by the unit root tests. The procedure chosen in the seminal paper by Pesaran, Shin and Smith (2001), p. 18, in their application to the UK earnings equation is quite instructive in this respect: "Also the application of unit root tests to the five variables yields, perhaps not surprisingly, mixed results with strong evidence for the unit-root hypothesis only in the cases of real wages and productivity. … Following the methodology developed in this paper it is possible to test for the existence of a real wage equation involving the levels of these five variables …".

Does the Johansen procedure lead to similar results of how to model the impact of monetary policy on stock market returns, i.e. dividend growth rates, as the ARDL approach? If yes, what are the main merits of applying the bounds testing procedure? The results of both procedures in terms of cointegration properties are strikingly similar. Hence, it appears as if we have identified a significant long-run relation running from monetary policy on stock market returns. If exogeneity is imposed on the one-month money market rate, the existence of no cointegration vector has to be rejected. If, in turn, exogeneity is imposed on the German stock market returns, the null hypothesis of no cointegration cannot be rejected any more.

This clear result strongly corresponds to our results which are based on the ARDL approach to cointegration. The results again highlight that the one-month money market rate can be considered as the 'forcing variable' for stock market returns if defined as the annualised one-month dividend growth rate in percent (Δd). In general, the results of these traditional cointegration exercises convey the impression that cointegration properties appear clearly if, and this is important in the light of the literature on monetary policy reaction functions and on the impact of monetary policy on asset prices, cointegration is indicated if exogeneity is imposed (solely) on the monetary policy variable.

Finally, what is the value added of applying the bounds-testing procedure? It is widely known that unit root tests have low power, which is especially true in the case of the alternative that the respective time series exhibit a persistent, yet stationary pattern as often claimed for stock market returns (Canova (1994), Payne (2003)). However, the autoregressive distributed lag (ARDL) bounds testing approach set forth by

Pesaran et al. (2001) fortunately does not require any assumption as to whether the time series are I(1) or I(0).

Unlike other cointegration techniques like the Johansen procedure which require certain pre-testing for unit roots and that the underlying variables to be integrated are of order one, the ARDL model provides an alternative test for examining a long-run relationship regardless of whether the underlying variables are I(0), I(1), or fractionally integrated (Bahmani-Oskooee and Ng (2002), p. 150). Accordingly and deviating from the Johansen procedure, the ARDL bounds test procedure allows to make inferences *irrespective the absence of any knowledge concerning the actual order of integration of the series under investigation* as long as the value of the test statistic falls outside the critical bounds.

Hence, the ARDL approach is really worth the effort since the unit root tests deliver evidence that the integration properties are not a priori clear and, hence, the Johansen procedure (which actually delivers similar results after some modifications) would not have been tackled at all under the standard econometric rules. Moreover, we interpret the results from the modified Johansen procedure as a successful additional robustness check of our main empirical result.

Let us now turn to the estimation of the long-run coefficients and the associated error-correction models for the German stock market. This part of the analysis has to be interpreted as an important completion of our analysis. That is, in the following we explicitly take into account the existence of a *long-term* relationship between stock market returns and monetary policy and the *short-term deviations* from it as a driving force of short-term movements in stock market returns. By this, we allow monetary policy to have a short-term *and* a long-term (and by this, via feedback mechanisms, further short-term) impacts on the stock market return.

IV. Applying the ARDL-Approach to Cointegration Analysis

1. Theoretical Background

Let us first deal with the issue of estimating long-term coefficients. The conditional long-run model can then be produced from the reduced form solution of (2), when the first-differenced variables jointly equal zero. The long-run coefficients and error correction model are estimated by the ARDL approach to cointegration, where the conditional ECM is estimated using OLS and then the Schwarz-Bayesian criteria is used to select the optimal lag structure for the ARDL specification of the short-run dynamics.[11]

Note that the ARDL approach necessitates putting in *enough lags* of the 'forcing variables' in order to endogenise y_t (i. e., the stock market return), before estimation and inference are carried out. By this, one can simultaneously correct for the problem of endogenous regressors and for residual autocorrelation (Pesaran and Shin (1999), p. 16). We make use of two important facts resulting from appropriate augmentation of the order of the ARDL-model. First, the OLS estimators of the *short-run* parameters are $\sqrt{T}$-consistent with the asymptotically singular covariance matrix. Second, the ARDL-based estimators of the *long-run* coefficients are super-consistent. Thus, valid inferences on the long-term parameters can be made using standard normal asymptotic theory (Pesaran and Shin, 1998). We prefer this approach since it has the additional advantage of yielding consistent estimates of the long-run coefficients that are asymptotically normal irrespective of whether the underlying regressors are I(0) or I(1) or fractionally integrated (Pesaran and Shin (1999), p. 17).

Most important in our context is that the ARDL procedure is valid even if there is some doubt about the unit-root properties of some of the variables y and x (as in our context, e. g., stock market returns and short-term interest rates). Following Pesaran and Shin (1999), the ARDL procedure (in contrast to other procedures often proposed in the literature for estimation of cointegrating relations) works irrespective of whether x and y are I(1) or are near I(1) processes. This is not, however, true of the other procedures proposed in the literature for estimation of cointegrating relations.

In fact, as indicated by a visual inspection of Figure 2 and to our unit root test results there is some doubt about the unit-root properties of the stock market returns and less so of the short-term interest rates. If one considers the (non-)stationarity of a variable as a sample property and, hence, conducts unit root tests, one can check whether variables are stationary or not. Our results let the short-term interest rate best be characterized as an I(1) variable whereas evidence for the return variable was mixed and indicate a more or less borderline case between I(0) and I(1). Moreover, on a more general level, one might even argue that cumulative

[11] For technical details see *Pesaran* and *Pesaran* (2001), p. 404, and *Pesaran* and *Shin* (1999), pp. 14.

returns almost behave like I(1) processes as persistence is introduced by overlapping observations whereas the nominal interest rate could well be modelled as I(1).[12]

When estimating the long-run relationship, one of the most important issues is the *choice of the order of the distributed lag function* on y_t and the 'forcing variables' x_t for the unrestricted ECM model. One possibility would be to carry out the *two-step* ARDL estimation approach advanced by Pesaran and Shin (1999), according to which the lag orders p and q are selected at first by the *Akaike (AIC)* or the *Schwarz information criteria (SIC)*.[13] The excellent Monte Carlo results gained by Pesaran and Shin (1999) compared with the Fully-Modified OLS estimation procedure by Phillips and Hansen (1990) speak strongly in favour of this two-step estimation procedure.

Setting the maximum orders for p and the q's to 12 (monthly data), we compare the maximised values of the log-likelihood functions of the $(m+1)^{k+1}$ (with m: maximum lag and k: number of 'forcing variables') different ARDL models. Most important, all the models have to be estimated based on the same sample period, namely (m+1, m+2, … , n). We select the final model by finding those values of p and q which maximise the above mentioned selection criteria. Then the selected model is estimated by the OLS procedure as already described above. These estimates will in this paper be referred to as AIC-ARDL and SIC-ARDL.

The derivation of the error-correction model from the ARDL equation (2) involves the estimation of the error correction equation using the differences of the variables and the lagged long run solution and determines the speed of adjustment of employment equilibrium (Pesaran and Shin, 1999).

12 This case of a variable which is I(0) by construction has also been addressed by *Faria* and *Leon-Ledesma* (2000), pp. 6. They argue that in the case in which both variables are I(1) one could use the well-known cointegration tests for the existence of a long-run cointegration vector. However, taking ratios instead of levels make this approach inappropriate for the purposes of their test, since mixed orders of integration would arise. For these reasons, tests based on traditional cointegration techniques would be flawed and the bounds testing procedure has to be applied.

13 However, one drawback in practical work is that one has to set the maximum lag orders p and q *a priori* although the 'true' orders of the ARDL (p,m) model are not known *a priori*. Cf. *Pesaran* and *Shin* ((1998), pp. 3 and 16).

2. *Application to German Stock Market Data*

The estimation of the long run parameters and the associated error-correction model for the unrestricted ECM regression of the stock market returns, cases $r_i = \Delta d$, and $r_i = h - \Delta d$ (which we in the following abbreviate as Δd and hd), on the short-term interest rate *i1m* is now carried out using the two-step ARDL estimation approach as outlined above.

a) Estimating the Orders of the Distributed Lag Functions

An important issue in the application of the two-step approach is the *choice of the order of the distributed lag function* on y_t and the 'forcing variables' x_t for the unrestricted ECM model when estimating the long-run relationship. We prefer to apply the two-step ARDL estimation approach to our model 2 ($r_i = \Delta d$, without trend) which according to the preceding sections generally leads to the highest goodness-of-fit. We firstly select the lag orders p and q by the AIC or the SIC information criterion. Setting the maximum orders for p and the q's to 12 (since we use monthly data), we compare the maximised values of the log-likelihood functions of the $(m+1)^{k+1}$ different ARDL models. All models have been estimated by means of the OLS procedure.

Table 2 shows the selected lag order and the corresponding maximising empirical values of the model selection criteria, AIC and SIC, for the selected variants of the model (MA = 3 or 12 months). The sequence of the lag orders (p, q_1, q_2 ...) always corresponds to the sequence of the variables in both models.

Table 2

Empirical Values of Model Selection Criteria

ECM	*SIC-value of SIC – ARDL*	*AIC-value of AIC – ARDL*
Model 2 (MA 3 months)	–1266.9 ARDL (10,0)	–1244.2 ARDL (10,0)
Model 2 (MA 12 months)	–848.4556 ARDL (1,0)	–842.1958 ARDL (6,0)
Model 3 (MA 12 months)	–1120.4 ARDL (1,0)	–1106.0 ARDL (11,0)

Sample: For MA = 12 months: 1975M8 to 2002M9.

b) Estimating Long-Run Relationships

The estimation results for the long-run relationship between different measures of German stock market returns and the short-term interest rate rate are displayed in Tables 3a to 3c. The values in brackets represent the standard errors of the parameter estimates. Later on, the associated estimated error correction regressions are obtained.

Table 3a

Estimated Long Run Coefficients Using the ARDL Approach
(Model 2, $r_i = \Delta d$, MA = 3 months)

	SIC – *ARDL (10,0)*	AIC – *ARDL (10,0)*
Intercept (Risk premium)	14.8662 (7.2737)	14.8662 (7.2737)
one-month money market rate *i1m*	–1.3450 (1.1980)	–1.3450 (1.1980)

Sample: 1975M8 to 2002M9.

Table 3b

Estimated Long Run Coefficients Using the ARDL Approach
(Model 2, $r_i = \Delta d$, MA = 12 months)

	SIC – *ARDL (1,0)*	AIC – *ARDL (6,0)*
Intercept (Risk premium)	17.8791 (8.4560)	17.8447 (6.8485)
one-month money market rate *i1m*	–1.8966 (1.3787)	–1.8395 (1.1161)

Sample: 1975M8 to 2001M9.

Table 3c

Estimated Long Run Coefficients Using the ARDL Approach
(Model 3, r_i = hd, MA = 12 months)

	SIC – *ARDL (1,0)*	AIC – *ARDL (11,0)*
Intercept (Risk premium)	–13.3565 (12.2126)	–8.2024 (5.7312)
one-month money market rate *i1m*	2.5057 (1.9990)	1.5589 (.93621)

Sample: 1975M8 to 2001M9.

The long-run coefficients based on the selected ARDL models estimated over the maximum period August 1974 to September 2003 are listed in Tables 3a to 3c. The results show that the *long-run elasticity* of stock market returns, if defined as annualised one-month dividend growth rates in percent (Δd), with respect to the *one-month money market rate i1m* is negative. This result strongly supports our claim that in the context of dividend growth rates it is important to note that dividends as a dependent variable suffer from a serious drawback, namely firms' "dividend policy". As argued in section 2, one might observe actual dividends which decline although future expected cash flows might have increased, thereby translating into rising stock prices. That is, in our sample, the estimated coefficient β might well turn out to be negative.[14] A positive coefficient β results if stock market returns are specified as the difference ($h – \Delta d$) between the annualised one-month continuously compounded stock market returns h and the annualised one-month dividend growth rates in percent (Δd).

According to the Tables 3a to 3c, the specifications emerging from the SIC-, and AIC- model selection criteria yield very *similar point estimates*. However, the lag order specifications differ dependent on the choice of the number of months in the moving average specification. Moreover, the estimated standard errors vary dependent on the specific model selection criterion and on the order of the selected ARDL model. Most important to note, the one-month money market rate *i1m* enters the long-term relation with a rather large coefficient and the expected sign. We now finally turn to the estimated error-correction models which are by construction associated with these long-run estimates.

c) Estimating Final Error-Correction Models and Model Selection

Having determined the lag order and the long-run coefficients for each selected ARDL model, we derive the estimates for the error correction models. The results are displayed in Table 5. As a benchmark, the ECM estimates for an ARDL (12, 12) specification are added. The estimates of the error correction coefficients are sometimes highly significant as compared with the usual t-distribution.[15] In all cases, the estimated error-

[14] This kind of result is not unfamiliar in this strand of research. For instance, the results gained by *Rigobon* and *Sack* (2004) indicate that an increase in short-term interest rates might well result in a decline in stock prices. As it is well-known from cointegration theory, we should not draw any inference from the t-values of the coefficient estimates.

correction parameters have the 'correct' negative sign and turn out to take values up to a considerably high value of –6.27 in model 3. Their size which is estimated in the significant cases at a magnitude of around –0.06 suggests a moderate speed of convergence to equilibrium. The only exception here is model 2 (MA = 3) where the convergence speed is significantly higher, as indicated by the estimated error-correction parameters of between –0.22 and –0.25. For this model, also the realisation of the R-squared is by far the highest. Hence, we select it as our final empirical model.

However, it might not be appropriate to take critical t-values from the student-t-distribution in our case. The most conservative critical t-values which lead to the lowest chance of rejection of the non-cointegration hypothesis for our ECM parameter estimates can be taken from Banerjee, Dolado and Mestre (1992, 1998, Appendix Table 4). In case of model 2 (MA = 3), we could for example choose a critical value for one exogenous regressor, ECM with a constant and without a deterministic trend, around 300 observations ($\alpha = 0.05$) as falling between a range from –3.27 (100 observations) to –3.23 (500 observations). Even in this extreme case, all of the three estimated error-correction parameters are significant at $\alpha = 0.05$.

In order to select the best performing ARDL-model, the significance of the resulting ECM-parameters or, as an alternative in cases of identical samples, the empirical values of the two information criteria are compared. The advantage of the AIC lies in its property to generally lead to a higher order of the ARDL model than the SIC. This tendency in turn leads to smaller estimated standard errors and a higher chance of white-noise property of the residuals.[16] However, the SIC is again chosen as the alternative to the AIC because it asymptotically determines the true model under certain preconditions. Table 2 shows the empirical realisations of both information criteria. These values are already maximised since they refer to ARDL-models whose orders have already been selected by the respective information criterion. As already stated, we se-

15 Under the assumption that the vector of cointegrating parameters is given the distribution of the t-statistics can be approximated in many cases by the standard normal distribution. This would also legitimize the use of the student-t-distribution for a judgment on the significance of the error-correction parameter. See *Banerjee* et al. ((1993), pp. 230) and *Kremers, Ericsson* and *Dolado* ((1992), pp. 328).

16 It has already been mentioned that a less parsimonious specification is preferred on theoretical grounds.

Table 4

Error Correction Parameter Estimates and Goodness-of-Fit

ECM	*SIC – ARDL*	$\bar{R}^2$	*AIC – ARDL*	$\bar{R}^2$	*ARDL (12,12)*	$\bar{R}^2$
Model 2 (MA = 3)	**–.21708 (–3.4458)**	**.39933**	**–.21708 (–3.4458)**	**.39933**	**–.25070 (–3.5876)**	**.39068**
Model 2 (MA = 12)	–.060517 (–2.9376)	.020741	–.074045 (–3.3081)	.039832	–.079467 (–2.8900)	.039107
Model 3 (MA = 12)	–.099815 (–4.0236)	.043908	–.20418 (–6.1215)	.12359	–.23925 (–6.2706)	.11007

Model specifications and samples as denoted in tables 3a to 3e. Second and third column: t-values in brackets. $\bar{R}^2$ denotes the adjusted R-squared.

lected the model displayed in Table 3a as our final model (Model 2, r_i = Δd, MA = 3 months).

At first glance, the realisations of the R-squared measure in Table 5 appear to be generally rather low and amount to similar values as in the related study by Domanski and Kremer (1998). However, this pattern is not exceptional for an ECM modelled for financial market variables. Furthermore, our selected model *fits very well,* explaining about almost 39 percent of the variations in future stock market returns (changes in the annualised one-month dividend growth rates). This is valid independent on whether the fit is measured by the R-Bar-Squared or by the t-value of the error-correction parameter. In all cases listed in Table 5, the underlying ARDL equations also pass the diagnostic tests for the serial correlation of residuals, for functional form misspecification and for non-normal disturbances. The majority of the estimated coefficients proves to be significant (the reported standard errors allow for the sampling variations in the estimated long-run coefficients) and are of a similar magnitude across the different specifications selected by the two information criteria.

Table 6 contains the final estimation results for the error-correction model based on the only candidate for the best model, namely model 2 (MA = 3 and stock market return defined as Δd). These results give some intuition on the order of magnitude of the detected impact of monetary policy on stock market returns. An empirical assessment of the responsiveness of stock market returns to changes in monetary policy might be

Table 5

Error Correction Representation of Selected ARDL Model 2 (ECM, △d3): ARDL (10,0) Model Selected Based on Schwarz Bayesian Criterion SIC

Dependent variable is dD3; observations: 323; estimation period: 1976M8 to 2003M6

Regressor	*Coefficient*	*T-Ratio[Prob]*
dD31	.14	1.9223[.055]
dD32	.17	2.4122[.016]
dD33	–.56	–7.8967[.000]
dD34	.14	2.1439[.033]
dD35	.16	2.3849[.018]
dD36	–.4	–6.7383[.000]
dD37	.09	1.6489[.100]
dD38	–.0	–.40144[.688]
dD39	–.2	–3.9789[.000]
di1m	–.29	–1.0543[.293]
dINPT	3.23	.7020[.090]
ecm(–1)	**–.22**	**–3.4458[.001]**

with: dD3 = D3-D3(-1); dD31 = D3(-1)-D3(-2); dD32 = D3(-2)-D3(-3); dD33 = D3(-3)-D3(-4); dD34 = D3(-4)-D3(-5); dD35 = D3(-5)-D3(-6); dD36 = D3(-6)-D3(-7); dD37 = D3(-7)-D3(-8); dD38 = D3(-8)-D3(-9); dD39 = D3(-9)-D3(-10); di1m = i1m-i1m(-1); dINPT = INPT-INPT(-1); ecm = D3 + 1.3450*i1m - 14.8662*INPT

R-Squared	.41985	R-Bar-Squared	.39933
S.E. of Regression	11.1895	F-stat. F(11, 311)	20.4605[.000]
Mean of Dependent Variable	–.13397	S.D. of Dependent Variable	14.4375
Residual Sum of Squares	38938.9	Equation Log-likelihood	–1232.2
Akaike Info. Criterion	–1244.2	Schwarz Bayesian Criterion	–1266.9
DW-statistic	2.0142		

important at this stage of analysis because it will most likely contribute to effective investment and risk management decisions.

Seen on the whole, the results of those studies which support short- and long-term impacts of monetary policy on stock market returns appear to be supported from another angle, although within a limited range based on: i) a pragmatic stock market model imposing a linear relationship between stock market returns and an interest rate, ii) monthly data (which seems to be appropriate to capture the short-term dynamics), iii) an econometric procedure whose reliability is not dependent on certainty about the order of integration of the included variables and which additionally takes into account deviations from equilibrium long-term relationships between stock market variables as 'driving forces' of the short-term dynamics in German stock market returns.

As outlined earlier, the estimated coefficient β of the money market rate is significantly positive in not more than one case if the dependent variable is h–Δd and in many cases significantly negative if Δd is the dependent variable, as suggested by theoretical reasoning. In general and with an eye on avoiding too strong policy conclusions, it has to be emphasised that significant error-correction parameter estimates could be gained only for a small share of possible specifications.

V. Conclusions

By accepting our main result for the selected indicator of stock market returns and the selected lag structure, one could jump to the policy conclusion that the interest rate-setting by the central bank has a significant impact on German stock market returns. We cannot empirically reject the view that, by letting short-term rates deviate from a certain equilibrium level, the Bundesbank – and later on also the ECB – had a significant short-run impact on stock prices. Moreover, we empirically corroborate the view that monetary policy interventions lead to forecastable fluctuations of German stock market returns around an equilibrium value. Finally, the Bundesbank and also the ECB were in principle able to reduce stock price volatility by diminishing the uncertainty of future rate changes. By this, the monetary authorities relevant for Germany delivered an important positive contribution for economic growth since they were able to reduce the option value of waiting with investment decisions.

One of the main findings of the paper is that – at least for the selected error-correction model – it is a *one-way* relationship between monetary policy and stock market returns *from the first to the latter*. Hence, in this case the monetary policy variable can best be characterised as a so-called 'forcing variable' of stock market returns. Following this interpretation, one would feel inclined to conclude that the empirical results presented in this paper indicate that the monetary policy strategy followed by the Bundesbank, at least, has been able to provide a reliable medium-term orientation for actors on asset markets.

However, in the light of our empirical results, even if we limited such reasoning to the Bundesbank case it might appear to be premature at this stage of analysis. It is true that we are able to show that an increase in the one-month money market rate has a statistically significant negative impact on the German stock market returns (with one exception, i.e. one ECM specification based on $h–\Delta d$) *only if* the latter are defined as the annualised one-month dividend growth rates in percent. This result suggests that rising central bank rates – in response to improved investor profit expectations – triggered an increase in firms' retained earnings ratios, as reinvesting corporate profits were seen as more favourable compared to the pay-out of earnings.

In line with our theoretical reasoning in section 2, the sign of the impact of monetary policy on stock market returns becomes positive if these returns are measured by ($h–\Delta d$), i.e. the difference between the annualised one-month continuously compounded stock market returns h and Δd. But similar to Durham (2003) in his study for the US, we could gain significant error-correction parameter estimates only for a significant share of all possible specifications.

Anyway, most of the progress claimed by this paper is in the field of methodology. For instance, the ARDL bounds testing procedure used in this contribution is robust with respect to the uncertainty of the order of integration of the included variables. Moreover, some causality issues like, e.g., the identification of monetary policy as the long-run forcing variable of stock market returns, can be tackled in this framework. Both aspects might be important news and highly relevant for areas in which stock market return forecasts are important like, for instance, asset management. The ARDL bounds testing approach could be followed in this paper only for one country, namely Germany. Replicating it for many others like the US for which Durham (2003) applies the ordinary ECM procedure represents an important task for future research.

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Data

Stock market data for Germany was taken from the Thomson Financials' data base; we made use of TOTMKBD(PI) and TOTMKBD(MV). The stock market indices cover around 80 % of the stock market capitalisation in Germany.

The following stock market return measures were calculated:

h = holding stock market returns (capital gains plus dividend returns, presented by the stock market total performance index), expressed as the annualised one-month continuously compounded stock return in percent;

Δd = dividend growth, expressed as the annualized one-month continuously compounded stock return in percent; and

$h–\Delta d$ = holding period return minus dividend growth (as defined above).

In the text, a number behind a variable indicates the time horizon under review. For instance, $h36$ would indicate the holding period return over the coming 36-months. Averages for return measures were used as – against the backdrop of the rational valuation formula – the forecast performance of current stock prices should generally be better for long-term return measures since these make up a larger part of the stock markets' calculated equilibrium price and, moreover, should be less susceptible to one-off shocks and "peso effects" than highly volatile short-term ones.

$i1m$ = one-month-money market rate, DM until December 1998 and Euro from January 1999 (in percent).

Summary

(How) Do Stock Market Returns React to Monetary Policy? An ARDL Cointegration Analysis for Germany

Is a central bank able to influence stock market returns? In order to answer this question, we test for cointegration between stock market returns and central bank interest rates in Germany for the period 1974–2003. Problems related to spurious regression could arise from the mixed order of integration of the series used, from reverse causation between the variables and from the lack of a long run relationship among the variables of the model. We address these problems by applying the bounds testing approach and autoregressive distributed lag models developed by Pesaran and others. The empirical results are also compared with those obtained from a more standard econometric approach, the Johansen procedure. Seen on the whole, we cannot empirically reject the view that the Bundesbank – and then the ECB – have had a significant short- and long-run impact on stock market returns. We conclude that short-term rates drive stock market returns but not vice versa. But the results are confined to a single stock market return measure, namely dividend growth. (JEL C22, E52, G12)

Zusammenfassung

(Wie) Reagieren Aktien-Returns auf die Geldpolitik? Eine ARDL-Analyse für Deutschland

Sind Zentralbanken in der Lage, Aktienmarktrenditen systematisch zu beeinflussen? Um diese Frage zu beantworten, testen wir die Kointegrationsbeziehung zwischen Renditemaßen für den Aktienmarkt und dem Kurzfristzins in Deutschland für die Periode 1974–2003. Folgende Probleme sind dabei zu bewältigen: „Scheinzusammenhänge" aufgrund unterschiedlicher Integrationsgrade der Zeitreihen müssen ausgeschlossen und die Kausalitäts- und Kointegrationsbeziehungen zwischen den Variablen müssen eindeutig identifiziert werden. Diese Problemstellungen werden im Rahmen des „Bounds Testing"- und „Autoregressive Dis-

tributed Lag-(ARDL-)"Ansatzes von Pesaran et al. behandelt. Die Ergebnisse werden mit denen des Standard-Ansatzes von Johansen verglichen. Die Resultate können die Hypothese, dass die Deutsche Bundesbank – und nachfolgend die Europäische Zentralbank (EZB) – einen signifikanten Einfluss auf kurz- und langfristige Renditemaße für den deutschen Aktienmarkt in Form des Dividendenwachstums genommen hat, nicht ablehnen, während der umgekehrte Zusammenhang nicht gilt.