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Dividend Yields for Forecasting Stock Market Returns

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Dividend Yields for Forecasting Stock Market Returns

An ARDL Cointegration Analysis for Germany*

by

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Abstract

This paper empirically assesses the ability of dividend yields to predict future stock returns in Germany assuming efficient markets and rational expectations. Since the order of integration of regressors are not exactly known, a bounds procedure, namely an autoregressive distributed lag (ARDL) model, is applied to test for cointegrating relationships among future stock returns and today's dividend yield. It is also capable of dealing with the controversial issue of exogeneity of the dividend yield. ARDL and error-correction models are estimated for (future) stock returns and the dividend yield based on consistent estimates and standard normal asymptotic theory.

JEL Classifications: C22, G12, G14.

Keywords: Asset Prices, Autoregressive Distributed Lag Models, Cointegration, Dividend Yields, Long-Run Relationships, Stock Returns.

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1. Introduction

The forecasting power of the dividend yield (i.e. the ratio between dividend payments and the stock price) on future stock market returns is a hypothesis that has a long tradition among practitioners and academics (for example, Dow, 1920, Ball, 1978). The theoretical and empirical literature delivers evidence that expected stock returns are predictable. However, the predictable component of stock market returns, or equivalently the variation through time of expected returns, is a relatively small fraction of return variances (Fama and Schwert, 1977, Fama, 1981, Keim and Stambaugh, 1986, and French, Schwert and Stambaugh, 1987).

Another interesting finding is that the power of the dividend yield to forecast future stock returns, measured by the simple coefficient of determination, increases with the time horizon under review. Fama and French (1988) offer two explanations: (i) that high autocorrelation causes the variance of unexpected returns to grow faster than the return horizon, and (ii) the growth of the variance of unexpected returns with the return horizon is attenuated by a discount rate effect: shocks to expected returns generate opposite shocks to current prices.

Our analyses take the work on the information content of the dividend yield for future stock market performance as a starting point. In contrast to the literature, we apply the bounds testing and estimation procedure proposed by Pesaran, Shin and Smith (1996, 2001) and Pesaran and Shin (1999) instead of more standard econometric procedures to test for cointegration between expecially dividend yields and stock returns using monthly data from the German stock market during the 1974-2003 period.[1] The methodology applied by us is particularly useful in the current application in three dimensions.

First, estimating the response of stock returns to changes in dividend yields is complicated by the endogeneity of dividend 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 (Fama, French and Roll (1969)). We show that the response of stock prices to changes in th edividend yields 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 dividend yield variable. It enables us investigate to the up to now far less explored side of the relationship between dividend yields and the stock market: how stock market returns react to changes in the dividend yields (see, e.g., Ang and Baekert, 2004). In this respect, our contribution reaches beyond investigations of asset price booms and dividend policy which look at correlations leaving aside the important question of ‘causality’ and ‘exogeneity’.

Second, determining the order of integration of interest rates and stock market returns is not an issue within this pocedure although there is often *no clear information on the integration and cointegration properties* of the data involved. While there are upper and lower bounds for the dividend yields available from theory and, hence, the dividend yields 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. An objection raised in the empirical finance literature is that it is not clear whether stock market performance measures (such as holding period returns, dividend growth and holding period returns minus dividend growth) are stationary (I(0)) or integrated of order one (I(1)) within the specific sample chosen.

The main statistical problem that arises in regressions of returns on dividend yields is that returns are often classified a priori as stationary in empirical investigations whereas dividend yields are very persistent and often cannot be rejected to be I(1). However, economic reasoning would suggest that stock market returns might also be stationary, i.e. stock market returns should not "outperform" (world) output growth on a sustained basis. All in all then, an unbalanced regression cannot be excluded ex ante. Seen on the whole, thus, whether variables should be introduced in differenced or level form is highly questionable, for instance, within the framework of the Johansen procedure. However, we would like to stress that 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, some of the econometric procedures commonly used to assess the impact of dividend yields on stock returns (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 dividend yields which should only have transitory impacts on stock returns 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).[2] However, as far as we know, the ARDL approach has neither been applied to stock markets in industrialized countries in general, nor to the relation between dividend yields and stock returns in Germany yet. Finally, using the bounds testing approach to cointegration is generally considered to compensate for not applying structural break unit root tests to individual financial time series (Narayan and Smyth, 2004, and Narayan, 2005).

The latest studies in this field (Fama and French, 1988, and Domanski and Kremer, 1998) have not sufficiently addressed all these important issues. Hence, our motivation is to use a modern procedure to tackle these issues and to test whether dividend yields predict stock market returns based on a well-known data set for Germany. The paper proceeds as follows. Section 2 discusses our way of modelling dividend yields impacts on stock prices. In section 3, we apply the bounds testing procedure proposed by Pesaran and his co-authors on monthly data for Germany. We move to error-correction modelling in section 4 only in cases for which the negation of a long-run relationship has been rejected in section 3. In section 4, we apply the ARDL-approach to cointegration analysis and estimate the respective long-run relationship and the respective short-term dynamics are estimated. Section 5 concludes.

2. A simple model of dividend yield impacts on future stock returns

It is economically reasonable to think of a stock's fundamental value as the sum of a firm's discounted expected future cash flow. The discount rate used can be interpreted as the required (expected) rate of return that attracts investors to hold the asset in their portfolios. In an information efficient market, a stock's market price should then equal its fundamental value as calculated by all or the marginal investor depending on whether expectations are assumed to be homogenous or not. Applied to the stock market, this general valuation approach leads to the dividend discount model.

In line with Campbell, Lo and MacKinley, 1997, pp. 260, the approximation formula for the continuously compounded one-period return on stocks is:[3]

$$(1) \qquad h_{t+1} = k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t$$

where h_{t+1} = approximate continuously compounded one-period return on stocks over the holding period t+1. p_t = log of stock price at the end of t; d_{t+1} = log of dividend paid out before the end of period t+1; $\rho \equiv 1/(1 + \exp(\overline{d-p}))$, where $\overline{d-p}$ = average of log of dividend yield; and $k = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$.

Equation (1) shows a log-linear relation between stock prices, returns and dividends. It is a first-order linear difference equation in the stock price. Solving forward and imposing the terminal condition $\lim\limits_{j\to\infty} \rho^j p_{t+j} = 0$ yields:

$$(2) \qquad p_t = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^j \left[(1-\rho)d_{t+1+j} - h_{t+1+j}\right].$$

Equation (2) is an *ex post*-identity, which says that today's stock price is high if future dividends are high and/or future returns are low. Applying the conditional expectation operator $E_t x_{t+1} = E[x_{t+1} \,|\, \Omega_t]$, where Ω_t = market-wide information set available at the end of period t, and the law of iterative expectations, equation (2) be changed to an ex ante relation:

$$(3) \qquad p_t = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^j \left[(1-\rho)E_t d_{t+1+j} - E_t h_{t+1+j}\right].$$

Assuming homogenous expectations and instantaneous market clearing, the log stock price always equals its single fundamental value, which is the specifically weighted, infinite sum of expected log dividends discounted by principally time-varying expected equilibrium returns. Combined with RE, equation (3) represents the rational valuation formula (RVF).

It should be noted here that RE do not assume that people make always the right forecasts about future developments. What it says is that that forecast errors will not persistently and systematically occur. The log-linear approximation framework as outline above has two advantages. First, it allows a linear and thus simple analysis of the stock price behaviour. Second, it conforms with the empirically plausible assumption that dividends and stock return follow log-linear stochastic processes. For empirical analyses, equation (3) can be rearranged such that the log dividend yield (or log dividend–price ratio) is singled out as the left-hand variable:

$$(4) \qquad d_t - p_t = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^j \left[-E_t \Delta d_{t+1+j} + E_t h_{t+1+j} \right].$$

The current dividend yield should predict future returns if the discount rates used by forward-looking investors actually depend on expected holding period returns for subsequent periods, and if these expectations do not deviate systematically, and too much, from realised returns.[4] However, the main statistical problem that arises in such kind of regressions is that returns are stationary (I(0)) according to the usual unit root tests in empirical investigations whereas dividend yields are very persistent and often cannot be rejected to be I(1), i.e. almost an unbalanced regression.[5]

The log-linear relation between prices, dividends and returns provides an accounting framework, which provides an economic interpretation of the relationship between the dividend yields and future stock market return measures (Campbell, 1991; Cuthbertson, 1996). High prices must eventually be followed by high future dividends, low future returns, or some combination of the two. If investor expectations are consistent with this interpretation, high prices must be associated with high expected future dividends, low expected future returns, or some combination of the two. Similarly, high returns must be associated with upward revisions in expected future dividends, downward revisions in expected future returns, or some combination of the two.

3. Testing for the existence of long-run relations

3.1. Stylised facts and some benchmark regressions

The test for the existence of long-run relations between stock market returns and dividend yields was conducted for the German stock market for the period August 1974 to September 2003. We used monthly data provided by Datastream and calculated three alternative future stock market return measures (dependent variables): (i) annualised one-month continuously compounded stock returns (*h*), (ii) annualised one-month dividend growth rates in percent (Δd) and (iii) and the difference between the two ($h–\Delta d$).[6] The measures were calculated over holding periods of 1, 3, 12, 24, 36 and 48 months.

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.[7] We thereby do not included other variables which, from a theoretical viewpoint, might also be responsible for future stock market performance 8such as, for intance, short-term interest rates, investment, price-to-book ratio, etc.). By doing so, we assume that the current stock price includes the given set of information at each point in time.

These performance measures were regressed on the independent variable, that is the dividend yield (*dp*), after we have reassured that there is no problem of "reverse causation", i.e. that the dividend yield really is the 'forcing variable'.

Figure 1 shows three scatter plots for the variables over a time horizon of 12-months. It shows cross-plots of three measures of stock returns against the dividend yield, respectively. The charts suggest that the positive relationship between the dividend yield *dp* and *h* and *h–Δd* holds for the German stock market. Also, as indicated by theoretical considerations outlined earlier, the relation between *dp* and *Δd* is negative. However, what matters for our empirical analysis, is that the overall relationships in the charts show a clear positive or negative relation - rather than a vertical or horizontal one. Figure 2 shows the variables under review over time.

(Figure 1 about here)

(Figure 2 about here)

As a *first step*, we estimated the long-run relations between various stock market performance measures (measured over holding periods (*K*) ranging from one month to four years) and the dividend yield. The results in Table 1 represent baseline estimations, which will serve as benchmarks against which the results gained from the autoregressive distributed lag procedure will be evaluated later on in this paper.[8] As can be seen, the R-squared systematically increases with the forecast horizon. The same is valid for the Newey-West adjusted empirical realisations of the t-values for the dependent variable *h–Δd*. However, in the cases of $x = h$ and $x = \Delta d$ the t-values reach their maximum after three and two years, respectively. The slope coefficients reveal a positive sign with $x = h$ and $x = h–\Delta d$ and a negative one in the case of $x = \Delta d$. They tend to reach their maximum in absolute values after 3 months and decrease afterwards.

(Table 1 about here)

Although there are serious doubts about the statistical reliability of long-horizon regressions, these results seem to suggest that future stock returns, and especially future dividend growth, might contain predictable components that are reflected in the current dividend yield. On a purely statistical basis, the finding that the ability of the dividend yield to forecast future stock returns increases with the return horizon is widely attributed to the central fact that it is a rather persistent variable (Cochrane, 2001, pp. 391 and Hodrick, 1992). Economically, the finding might indicate that market agents can forecast medium- and-long-term prospects of the economy much easier than short-term fluctuations. A relatively stable monetary framework, that is, for instance, a stable reaction and objective function of the central bank and relatively few serious financial market shocks might be held responsible for this outcome. Finally, it should be noted that the predictability of future stock returns does not contradict the efficient market hypothesis, which postulates only that abnormal returns are unpredictable, not that actual returns are unpredictable.

The rather low realisations of the Durbin Watson-statistics resulting from the traditional approach described in Table 1 indicate serial autocorrelation in the residuals. We corrected for serial correlation and potential heteroskedasticity by using alternative t-statistics proposed by Newey and West (1987) to compensate the data-overlap for the forecasts beyond one month. This overlap typically leads to serial correlation of the error terms, even under the null hypothesis of no stock return predictability through the dividend yield.[9] By this correction, we also cope with the need to use asymptotic theory to generate standard errors. This need emerges from the fact that the dividend yield as the regressor is a predetermined value and is not exogenous (Campbell, Lo and MacKinley, 1997, pp. 334-336).

Following Domanski and Kremer (1998), we have dispensed with testing the order of integration of the dividend yield and the stock return at this stage of analysis. By doing so, one might interpret the results as providing preliminary evidence that future stock returns, and especially future dividend growth, contain predictable components with are reflected in the current dividend yield. Some argue, that returns typically look the more stationary the less their horizon is.[10] However, in practical work it is very difficult to distinguish a very persistent series of cumulative returns from a non-stationary one. In addition, non-stationarity of a variable is a sample property. Hence, from a purely empirical point of view, it cannot be ruled out entirely that the variables under consideration represent non-stationary series. If this is the case, cointegration theory prevents us from wrong inferences drawn from the t-values of the coefficient estimates. Therefore, it is of great interest for us to analyse if these results hold up robust when using the approach by Pesaran, Shin and Smith (1996, 2001) and Pesaran and Shin (1999), respectively, which assumes that the order of the involved series is unknown a priori.

3.2. Testing for cointegration: The ARDL bounds testing approach

3.2.1. Theoretical background

As mentioned above, an important problem inherent in the residual-based tests and in some system-based tests for cointegration is the precondition that it must be known with certainty that the underlying regressors in the model are 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 and in our case there is even some evidence of an unbalanced regression.[11] Also the visual inspection of the dividend yield and the stock return series does not help us to make a final judgment, since Figure 2 does not say too much about the unit root property. Rather it even begs the question why unit root structural tests are not used, given that it cannot be excluded ex ante that the series display some breaks (see Figure 2).[12] Given that the variables employed by us tend to be I(0) and/or I(1) and the bounds test is applicable irrespective of whether or not the variables are I(1), this test appears highly suitable in our context from this angle as well (Islam, 2004, p. 996-997, Narayan and Smyth, 2004). From this perspective, applying the bounds test procedure gives credence to the empirical analysis. Moreover, the bounds testing approach compensates for not doing the structural break unit root tests.

For these reasons, we now make use of the approach 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 autoregressive distributed lag (ARDL) model in the variables of interest.

More specifically, in the case of an unrestricted ECM, regressions of y on a vector of x's, the procedure first requires estimating the following model derived by Pesaran, Shin and Smith, 1996, pp. 2 ff.):

$$\Delta y_t = a_{0y} + a_{1y} \cdot t + \phi y_{t-1} + \delta_1 x_{1,t-1} + \delta_2 x_{2,t-1} + \ldots + \delta_k x_{k,t-1} +$$

$$\sum_{i=1}^{p-1} \psi_i \Delta y_{1,t-i} + \sum_{i=0}^{q_1-1} \varphi_{1i} \Delta x_{1,t-i} + \sum_{i=0}^{q_2-1} \varphi_{i2} \Delta x_{2,t-i} + \ldots + \sum_{i=0}^{q_k-1} \varphi_{ik} \Delta x_{k,t-i} + \xi_{ty} \quad (5)$$

with ϕ and δ as the long-run multipliers, Ψ and φ 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 $\phi = \delta_1 = \delta_2 = ... = \delta_k = 0$. However, the asymptotic distributions of the *standard Wald or F statistic* for testing the significance of the lagged levels of the variables are *non-standard* under the null hypothesis that no long-run relationship exists between the levels of the included variables. Pesaran, Shin and Smith (1996) 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 provide a band covering all possible classifications of the regressors into I(0), I(1), or even mutually cointegrated.

A third step is required in order to use the appropriate bounds testing procedure. The test proposed by Pesaran, Shin and Smith (1996, 2001) is consistent with this. For a sequence of local alternatives, it has 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 procedure based on the F-statistic is as follows. The F-statistic computed in the second step is compared 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 $\phi = \delta_1 = \delta_2 = ... = \delta_k = 0$ and conclude that there is a long-term relationship between y and the vector of x's. However, if $F < F_L$, one cannot reject either $\phi = \delta_1 = \delta_2 = ... = \delta_k = 0$ or the hypothesis that a long-run relationship does not exist. Finally, if $F_L < F < F_U$, the inference has to be regarded as inconclusive. The order of integration of the underlying variables has to be investigated more deeply.

In order to select the so-called ‘forcing variables’, 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). 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 the hypothesis of a linear relationship between the relevant variables which is not 'spurious' can no longer be rejected, one can estimate coefficients of the long-run relationship by means of the ARDL-procedure. This estimation procedure is discussed in section 4.

3.2.2. Application to German stock market data

Since the choice of the orders of the lagged differenced variables in the unrestricted ECM specification can have a significant effect on the test results, models in the log of stock market returns and the logs of the other mentioned stock market relevant variables are estimated for the orders p = q = 1, 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 other stock market variables, we estimate unrestricted ECM regressions of *h* (y) on the vector of stock market 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 model (1) using monthly observations over a maximum sample from 1974(8) to 2003(9). In view of the monthly nature of observations we set the maximum orders to 12, (i.e. we estimate eq. (5) for the order of $p = q_1 = q_2 = 12$ over the same sample period 1974(8) to 2003(9)). 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 log of stock market returns (detailed proofs can be found in Pesaran and Shin (1999) and Pesaran, Shin and Smith (1996)). In addition, first differences in the variables at order 1 are used.

Like in any long-horizon analyses, we are aware of risks that some events such as, for instance, the German reunification, the introduction of the euro area on 1 January 1999, the international financial market crisis 1997-98 and, more recently, the international stock market crash around 2000-01, might have dramatically changed the pricing action in stock markets. We decided to rely more on estimates, which take German reunification explicitly into account by means of a point dummy D901. This dummy implies a *permanent* change in the relation between the stock market return and the other stock market relevant variables. We distinguish between *three different definitions of stock returns* (cases $x = h$, $x = \Delta d$, and $x = h{-}\Delta d$). Our models are structured as follows:

- *Model 1*: the holding period return, h, the dividend yield, dp, and a constant are included in the long-term relation.
- *Model 2*: the dividend growth, Δd, the dividend yield, dp, and a constant are included in the long-term.
- *Model 3*: the holding period return minus dividend growth, $h{-}\Delta d$, the dividend yield, dp, and a constant included in the long-term.

These specifications allow the dividend yield to slow down the adjustment to a new stock market equilibrium in the wake of a shock.[13] The three models represent the core implication derived above, namely that in the long run, the dividend yield is in long-term equilibrium with the average stock market return. Thus, the modelling approach is strictly *guided by theory*.[14] We now let the data tell us which of the above models case fits the German stock market data best. Tables 1a to 1c display the empirical realisations of the F-statistics for testing the existence of a long-run relationship between stock market return measures and the dividend yield. In all 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 heteroskedastic disturbances.

The 90, 95 and 99 percent lower and upper critical values bounds of the F-test statistic that are 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 summarized in Pesaran and Pesaran (1997) (see 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. For the application with a linear trend the respective upper bound critical values can be found in the lower panel of Table F: 5.649 to 6.335 (at the 90 percent level), 6.606 to 7.423 (at the 95 percent level) and 9,063 to 9.786 (at the 99 percent level). We took the upper bound critical values from these intervals and tabulate them in Tables 2a to 2c as the relevant conservative benchmarks to check the significance of the cointegration relationships. We also experimented with the inclusion of a dummy which approximated the international stock market turbulences and took the value 1 as from 2000(1) and 0 otherwise. We finally decided to put it into the test equation including a deterministic trend in order to grasp *inter alia*, the U-turn shape of the dividend yield curve for Germany with the trough in January 2000.

According to the empirical F-values in Tables 2a to 2c, we find that the null hypothesis of no long-run relationship in the case of unrestricted ECM regressions of the log of stock returns on the dividend yield and other open economy stock market variables is *rejected* in 18 cases at $\alpha = 0.05$ and in most of the cases even at the 1 percent level. 10 of these cases emerge if a deterministic trend is excluded. However, the null hypothesis of no cointegration tends not to be rejected if the moving average of the relevant variables is below 12 months (the only exception is *h*1 with trend) or if it is higher than 24 months (except *Δd*36 and *Δd*48 without trend). This pattern is contradictory to Ang and Baekert (2004) who show that the predictive power of dividend yield is best visible at short horizons and is weak at long horizons – however with the short rate included as an additional regressor.

(Tables 2a to 2 c about here)

Overall, these results suggest *strong evidence in favour of the existence of a long-run relationship* between the (future) stock market return and the dividend yield and the constant, at least if the relevant variables are moving averages over 12 or 24 months. But in view of the high levels of cross-sectional and temporal aggregation, it is not possible to know *a priori* whether the dividend yield is the 'long-run forcing' variable for the average future stock market return performance. Therefore, we considered all possible regressions and substitute the *change* in the stock market return measures as the dependent variable in equation (5) by the *change* in the dividend yield, in order to test whether this relationship is *spurious* in the sense that we do not capture the 'correct direction of causation'. For instance, we have to ensure that the future stock market return is not among the forcing variables. The results of the reversed test equations are displayed in the final column of Tables 2a to 2c. In the case of $x = \Delta d$ and for a wide range of moving averages (12 to 48 months), we find that the *direction* of this relation is most likely to be *from the dividend yield to future stock market returns,* so that the variable *dp* can be considered as the 'long-run forcing' variable for the explanation of the variable *Δd*. 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). However, in the cases of $x = h$ and $x = h – \Delta d$ where the variables are 12-month moving averages, our bounds procedure reveals that the dividend yield and the stock returns are 'forcing variables' for each other (i.e. that there seems to be a two-way causation between them). However, in the cases of $x = h$ and $x = h–\Delta d$ where the variables are 24-month averages, future stock returns even appear to be the forcing variable' for the dividend yield. Therefore, in the following sections, we will concentrate on the case $x = \Delta d$.

However, before moving to the next step, one might ask why we did not use a more standard cointegration testing framework like, e.g., the Johansen-procedure (Johansen (1991, 1995)). In this case, we would have first needed to establish that all the underlying variables are I(1). However, such pre-testing results may adversely affect the test results based on cointegration techniques (Cavanaugh et al. (1995), Pesaran (1997)). In addition, the bounds procedure is well-suited to cope with unbalanced regressions (see section 2). These insights already motivated us to use the Pesaran, Shin and Smith (1996, 2001) approach and not to use the Johansen approach in this paper.

In the following, we *estimate the long-run coefficients* and the associated *error-correction models* for the German stock market. We consider this exercise as an important completion of the analysis by Domanski and Kremer (1998, pp. 29) who limit their analysis of the impact of dividend yield on stock markets to a battery of estimations of single equations, in levels based on monthly data. As a result, we explicitly take into account the existence of a *long-term* stock market relationship and the *short-term deviations* from it as a driving force of short-term movements in future stock returns. By this, we allow the dividend yield to have short-term *and* long-term (and by this again, additional short-term) impacts on the future stock return.

4. Applying the ARDL approach to cointegration analysis

4.1. 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.[15]

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 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).[16]

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)*.[17] 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 (5) 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).

4.2. 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 $x = h$, $x = \Delta d$, and $x = h - \Delta d$ (which we abbreviate in the following as h, d, or hd), on the dividend yield dp is now carried out using the *two-step ARDL estimation approach* proposed by Pesaran and Shin (1999).

4.2.1. Estimating the orders of the distributed lag functions and the long-run relationships

As emphasised already, the most important issue 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 carry out the two-step ARDL estimation approach by Pesaran and Shin (1999) and apply it to our model 2 (x=d, without trend), where firstly the lag orders p and q are selected by the *Akaike* or the *Schwarz information criterion*. The selected model has been estimated by the OLS procedure. 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 $(m+1)^{k+1}$ (with m: maximum lag and k: number of 'forcing variables') different ARDL models. Table 3 shows the selected lag order and the corresponding maximising empirical values of the model selection criteria, AIC and SIC (the values of the other two criteria are available on request), for each variants of the model (MA = 12, 24, 36, 48 months). The sequence of the lag orders (p, q_1, q_2 ...) always corresponds to the sequence of the variables in both models. Both selection criteria arrive at Model 2 (MA 12 months) without trend, as the best fitting model.

(Table 3 about here)

We also derived the long-run coefficients based on the selected ARDL models estimated over the maximum period 1974.8 to 2003.9. The results which hare available on request clearly show that the *long-run elasticity* of dividend growth Δd with respect to the *dividend yield dp* is negative, which is in line with our theoretical reasoning.[18] The specifications according to 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. In addition, the estimated standard errors vary depending on the specific model selection criterion and on the order of the selected ARDL model.

4.2.2. Estimating final error-correction models and model selection

After determining the lag order and the long-run coefficients for each ARDL model, we can derive the estimates for the error correction models. In these error-correction models we regress the change of our measure of x months returns on the lagged deviation of its actual level from its equilibrium level, i.e. the error-correction term, its own lags and changes of dividend growth. One further issue that needs to be addressed before the best specification can be selected is: Based on which criterion should one make the final selection? We made our final choice based on the Akaike- and the Schwarz information criterion, i.e. the AIC and the SIC.

In order to select the best performing ARDL-model, the *significance* of the resulting *ECM-parameters* or, alternatively 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 ARDL model than the SIC. This tendency leads in turn, to smaller estimated standard errors and a higher chance of white-noise property of the residuals.[19] 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 in the sense that they refer to ARDL-models whose orders have already been selected by the respective information criterion. As already stated, we selected the model 2 ($x = d$, without trend, MA = 12 months).

Taking a closer look at the estimated error correction parameter (Table 4), the main result is that the error correction coefficient is highly significant as compared with the usual t-distribution.[20] The estimated error-correction parameter has the correct negative sign. Its size, estimated at a magnitude of around -0.06 to -0.12, suggests a moderate speed of convergence to equilibrium. The most conservative critical t-values (leading to the lowest chance of rejection of the non-cointegration hypothesis) for the ECM parameter estimates can be taken from Banerjee, Dolado and Mestre (1992), Appendix Table 4. For the selected model we choose the critical value for one exogenous regressor, ECM with a constant and no deterministic trend and around 300 observations ($\alpha = 0.05$), as falling between a range from 3.27 (100 obs.) to 3.23 (500 obs.). Even in this extreme case, two of the three estimated error-correction parameters are significant at $\alpha = 0.05$.

(Table 4 about here)

At first glance, the R-squared appear to be rather low and corresponds with values observed by Domanski and Kremer (1998) and also in Table 1 of this paper. However, this pattern is not exceptional for an ECM modelled for financial market variables. The models *fit very well* on average, explaining almost 7 percent of the variations in future stock market returns (*changes* in the (logs of) h, Δd, or $h - \Delta d$). This is even valid when the fit is measured by the R-Bar-Squared. In all cases, the underlying ARDL equations also pass the diagnostic tests for the serial correlation of residuals, for functional form misspecification and for non-normal and homoskedastic disturbances. Beyond the highly significant ECM parameter, some but not all of the estimated coefficients of the selected ECMs are also 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 criteria.[21]

Tables 5 and 6 contain the detailed results for the selected error-correction model, giving some intuition on the order of magnitude of the detected impact of dividend yield on stock market returns. The dividend yield is in both selected cases (ARDL (1,0) and ARDL (3,5)) significant and reveals the correct negative sign.

(Tables 5 and 6 about here)

Overall, the results which support short- and long-term impacts of the dividend yield on future German stock returns appear to be supported from another angle: on the basis of a fully specified stock market model, of monthly data (which seem to be appropriate to capture the short-term dynamics), of an econometric procedure whose reliability is not dependent on 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 future German stock returns. As outlined earlier, the coefficient of dp is positive in the case of the dependent variables h and $h-\Delta d$, and negative if Δd is the dependent variable, as suggested by theoretical reasoning. However, it has to be kept in mind that significant error-correction parameter estimates could be gained only for a limited set of possible specifications.[22]

5. Conclusions and implications for the debate on the impacts of the dividend yield on asset prices

Our paper has applied the ARDL approach to cointegration to explore the performance of dividend yields in forecasting stock returns in Germany assuming efficient markets and rational expectations. The empirical results suggest that the role of the dividend yield is rather limited in explaining future stock returns. For a limited number of specifications, we do find that the dividend yield has a statistically significant positive impact on future stock returns in Germany. “Low” stock prices relative to dividends forecast higher subsequent returns. In these cases, and in line with previous findings and theoretical considerations, we find that the power of dividend yields to forecast future stock expected returns increases with the return horizon. We also conclude that the relationship between dividend yield and the future stock returns is *one-way from the first to the latter* if stock market returns are measured by the annualised one-month dividend growth rates in percent. Hence, (only) in this case the dividend yield variable can best be characterised as a so-called "forcing variable" of future stock returns. For other measures of the dividend yield used by us, we either find a significant co-movement with causality going into both directions or no cointegration at all, depending on the lag structure.

Our results based on the ARDL approach corroborate findings by Domanski and Kremer (1998) who detect a significant positive relationship between the magnitude of future stock returns and the level of the dividend yields in Germany. As indicated by the significant impact of the dividend yield in the I(0) part and the I(1) part of our estimated error-correction models, we find that even *short-run* increases in the dividend yield could have a temporary impact on future stock returns (i.e., the annualised one-month dividend growth) in addition to *permanent* ones. The latter finding had already been theoretically suggested by earlier studies of Fama and French (1988), Campbell, Lo and MacKinley (1997) and Domanski and Kremer (1998). Our findings are also compatible with Ang and Baekert (2004) for the US, UK and Germany who find that the predictability of dividend growth at short horizons (1 to 2 years) dominates the estimates of predictability of expected returns from dividend yields. Dividend growth predictability is even stronger when the 1990's are excluded from the sample.

We realise that the results are preliminary, not least because the questions posed in this paper have not been tackled based on the highly suitable autoregressive distributed lag approach à la Pesaran in the literature so far. The procedure used in this article is robust with respect to the uncertainty about the order of integration of the included variables and even compensates for not applying structural break unit root tests in our context.

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Data

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

The following stock market return measures were calculated:

dp = natural logarithm of the dividend yield;

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

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

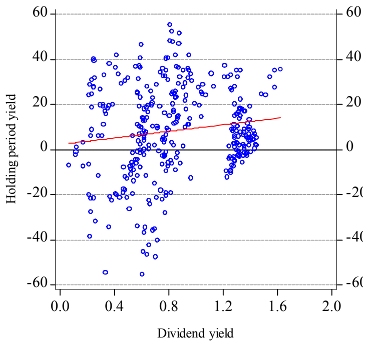
$h - \Delta d$ = holding period return minus dividend growth.

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. In the case of dp, a number would indicate the time horizon which is forecast by using the dividend yield. 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.

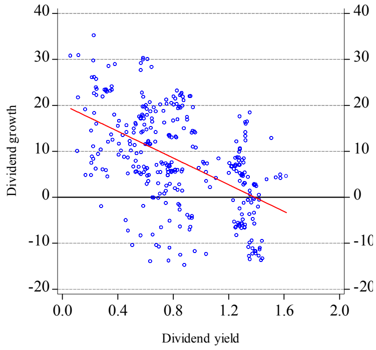
Figures and Tables

Figure 1 – *Stock returns and the dividend yield*

(a) Holding period yield against the dividend yield



(b) Dividend growth and dividend yield



(c) Holding period yield minus dividend growth against dividend yield

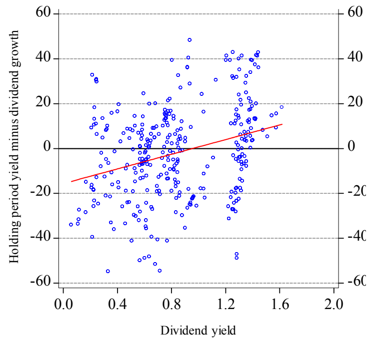
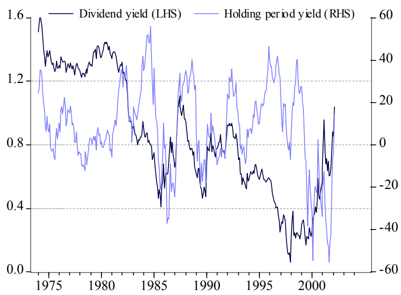
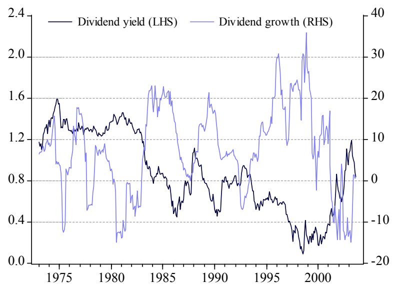


Figure 2 – *Stock returns and the dividend yield over time*

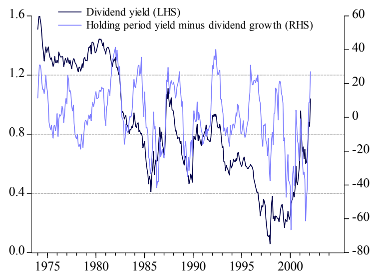
(a) Holding period yield against the dividend yield



(b) Dividend growth and dividend yield



(c) Holding period yield minus dividend growth against dividend yield



Data source: Thomson Financials; own calculations. – Time period: 1974.8 to 2003.9. Time horizon 12-month for all variables.

Table 1 – Long-horizon regressions of stock market measures on the log dividend yield and a constant for Germany

	$x = h$					
Forecast horizon K	1	3	12	24	36	48
R^2(K)	0.002	0.09	0.019	0.043	0.068	0.065
β(K)	7.943	9.556	7.361	7.704	7.512	5.786
t-value Newey West	0.833	1.100	1.280	1.622	1.763	1.660
Durbin-Watson stat.	1.872	0.579	0.125	0.057	0.042	0.042
	$x = \Delta d$					
R^2(K)	0.039	0.108	0.269	0.259	0.236	0.280
β(K)	-16.335	-16.470	-14.533	-11.388	-9.423	-9.293
t-value Newey West	-3.346	-3.752	-5.569	-4.848	-3.949	-4.437
Durbin-Watson stat	2.013	0.653	0.154	0.060	0.038	0.035
	$x = h–\Delta d$					
R^2(K)	0.016	0.054	0.184	0.353	0.471	0.546
β(K)	24.279	26.030	21.894	19.092	16.935	15.080
t-value Newey West	2.370	2.869	4.123	5.748	6.342	7.010
Durbin-Watson stat	1.933	0.621	0.196	0.129	0.113	0.115

Estimation period: August 1974 to September 2003, monthly data. h is the annualised one-month continuously compounded stock return in percent. Δd and Δp represent the annualised one-month continuously compounded dividend and profit growth rate, respectively. $\alpha(H)$ is the constant of the regression (not shown). $\beta(H)$ is the slope coefficient of the regression. Regression is estimated on the basis of OLS. $\varepsilon_{t+H,H}$ is the error term which is autocorrelated owing to data overlap for $H > 1$ under the null hypothesis of no predictability. Standard errors and t-values are corrected for serial correlation and heteroskedasticity in the equation using the New and West (1987), that is general covariance estimators that are consistent in the presence of both heteroskedasticity and autocorrelation of unknown form are used. The truncation lag, the parameter representing the number of autocorrelations used in evaluating the dynamics of the OLS residuals, has been chosen as 5.

Data source: Thomson Financials; own calculations.

Table 2a – *F-statistics for testing the existence of a long-run relationship between the stock market return and the dividend yield (model 1: x = h)*

	Based on regressions with the change of stock returns d(*h*) as dependent variable		Based on regressions with the change of the dividend yield d(*dp*) as dependent variable	
MA-order of h	*Without trend*	*With trend*	*Without trend*	*With trend*
h1	0.375	**6.432**	0.042	0.086
h3	0.379	5.009	0.287	0.319
h12	**6.452**	**10.379**	**29.380**	**40.973**
h24	1.490	4.961	**12.587**	**13.130**
h36	1.446	1.930	4.727	5.282
h48	1.166	1.723	2.162	2.688
$F^C(0.1)$	*4.788*	*6.335*	*4.788*	*6.335*
$F^C(0.05)$	*5.764*	*7.423*	*5.764*	*7.423*
$F^C(0.01)$	*7.815*	*9.786*	*7.815*	*9.786*

Table 2b – *F-statistics for testing the existence of a long-run relationship between the stock market return and the dividend yield (model 2: x = Δd)*

	Based on regressions with the change of stock returns d(Δd) as dependent variable		Based on regressions with the change of the dividend yield d(*dp*) as dependent variable	
MA-order of Δd	*Without trend*	*With trend*	*Without trend*	*With trend*
$\Delta d1$	0.345	0.255	0.058	0.067
$\Delta d3$	2.746	3.347	0.024	0.210
$\Delta d12$	**217.707**	**10.383**	0.142	0.610
$\Delta d24$	**39.919**	2.515	0.606	2.022
$\Delta d36$	**44.835**	3.400	0.638	5.160
$\Delta d48$	**48.312**	1.965	0.740	4.150
$W^C(0.1)$	*4.788*	*6.335*	*4.788*	*6.335*
$W^C(0.05)$	*5.764*	*7.423*	*5.764*	*7.423*
$W^C(0.01)$	*7.815*	*9.786*	*7.815*	*9.786*

Table 2c – *F-statistics for testing the existence of a long-run relationship between the stock market return and the dividend yield (model 3: x=h–Δd)*

	Based on regressions with the change of stock returns d(*h–Δd*) as dependent variable		Based on regressions with the change of the dividend yield d(*dp*) as dependent variable	
	Without trend	*With trend*	*Without trend*	*With trend*
(*h–Δd*)*1*	0.754	3.297	0.079	0.759
(*h–Δd*)*3*	1.269	2.950	0.033	0.324
(*h–Δd*)*12*	**30.585**	**30.983**	**18.206**	**20.318**
(*h–Δd*)*24*	1.112	2.606	**16.209**	**18.891**
(*h–Δd*)*36*	1.619	0.853	0.753	0.695
(*h–Δd*)*48*	0.620	0.383	0.101	0.070
$W^C(0.1)$	*4.788*	*6.335*	*4.788*	*6.335*
$W^C(0.05)$	*5.764*	*7.423*	*5.764*	*7.423*
$W^C(0.01)$	*7.815*	*9.786*	*7.815*	*9.786*

Notes: Maximum sample: 1974.8 to 2003.9. Lag orders: $p = q_1 = q_2 = 12$. We implemented a dummy which is coded as 1 from 2000(1) on, otherwise 0, into those regressions which also include a deterministic trend.

Table 3 – *Empirical realisations of model selection criteria*

ECM	*SIC-value of SIC - ARDL*	*AIC-value of AIC - ARDL*
Model 2 (MA 12 months)	-881.7076	-872.8644
without trend	ARDL (1,0)	ARDL (3,5)
Model 2 (MA 24 months)	-624.4295	-617.5638
without trend	ARDL (1,0)	ARDL (7,0)
Model 2 (MA 36 months)	-477.5989	-468.7692
without trend	ARDL (1,0)	ARDL (12,0)
Model 2 (MA 48 months)	-391.9962	-384.2233
without trend	ARDL (1,0)	ARDL (3,0)

Sample: For MA=12 months: 1975M8 to 2002M9. For MA=24 months: 1975M8 to 2001M9. For MA=36 months: 1975M8 to 2000M9. For MA=48 months: 1975M8 to 1999M9.

Table 4 – *Error correction parameter estimates*

ECM	***ARDL (1,0)***	$\overline{R}^2$	***ARDL (3,5)***	$\overline{R}^2$	***ARDL (12,12)***	$\overline{R}^2$
Model 2 (MA 12 months, without trend)	-.064278 (-2.9427)	.022828	-.077150 (-3.3534)	.061555.	-.12009 (-3.9385)	.069402

Sample: 1975M8 to 2002M9. Model specifications as in 3.2.2.; t-values of EC term in brackets.

Table 5 – *Error correction representation of selected ARDL model 2 (ECM without trend): ARDL (1,0) model selected based on Schwarz Bayesian Criterion (SIC)*

Dependent variable is dD12; 326 observations used for estimation from 1975M8 to 2002M9

Regressor	*Coefficient*	*Standard Error*	*T-Ratio[Prob]*
dDP12	-.47328	.63151	-.74944[.454]
dINPT	.90766	.66289	1.3692[.172]
ecm(-1)	**-.064278**	**.021844**	**-2.9427[.003]**

with: dD12 = D12-D12(-1); dDP12 = DP12-DP12(-1); dINPT = INPT-INPT(-1) (change of the intercept); ecm = D12 + 7.3630*DP12 -14.1207*INPT

R-Squared	.028841	R-Bar-Squared	.022828
S.E. of Regression	3.5384	F-stat. F(2, 323)	4.7962[.009]
Mean of Dependent Variable	-.0074529	S.D. of Dependent Variable	3.5795
Residual Sum of Squares	4044.1	Equation Log-likelihood	-873.0273
Akaike Info. Criterion	-876.0273	Schwarz Bayesian Criterion	-881.7076
DW-statistic	2.1331		

Table 6 – *Error correction representation of selected ARDL model 2 (ECM without trend): ARDL (3,5) model selected based on Akaike Information Criterion (AIC)*

Dependent variable is dD12; 326 observations used for estimation from 1975M8 to 2002M9

Regressor	*Coefficient*	*Standard Error*	*T-Ratio[Prob]*
dD121	-.059012	.056414	-1.0461[.296]
dD122	.085184	.055962	1.5222[.129]
dDP12	-9.4090	3.6077	-2.6081[.010]
dDP121	-2.5191	3.6441	-.69128[.490]
dDP122	-1.8994	3.6461	-.52095[.603]
dDP123	.31673	3.6436	.086930[.931]
dDP124	-11.3108	3.6588	-3.0914[.002]
dINPT	.99362	.67690	1.4679[.143]
ecm(-1)	**-.077150**	**.023007**	**-3.3534[.001]**

with: dD12 = D12-D12(-1); dD121 = D12(-1)-D12(-2); dD122 = D12(-2)-D12(-3); dDP12 = DP12-DP12(-1); dDP121 = DP12(-1)-DP12(-2); dDP122 = DP12(-2)-DP12(-3); dDP123 = DP12(-3)-DP12(-4); dDP124 = DP12(-4)-DP12(-5); dINPT = INPT-INPT(-1) (change of the intercept); ecm = D12 + 6.4375*DP12 -12.8791*INPT

R-Squared	.087543	R-Bar-Squared	.061555
S.E. of Regression	3.4676	F-stat. F(8, 317)	3.7897[.000]
Mean of Dependent Variable	-.0074529	S.D. of Dependent Variable	3.5795
Residual Sum of Squares	3799.7	Equation Log-likelihood	-862.8644
Akaike Info. Criterion	-872.8644	Schwarz Bayesian Criterion	-891.7989
DW-statistic	2.0100		

Notes

1. For these “standard” approaches see, for instance, Hodrick (1992), Stambaugh (1999) and Valkanov (2004).

2. If monetary policy can influence dividend yields, as is generally assumed, and if we are able to show empirically in this contribution that dividend yields help to forecast stock returns, we might have succeeded in identifying a channel for an impact of monetary policy on stock returns.

3. See Cuthbertson et al. (1997), pp. 1005.

4. See Domanski and Kremer (1998), p. 26. Note that the term $E_t h_{t+1+j}$ is the equivalent to the expected future discount rate of the RVF, a finding which will be explained in the following.

5. In the literature, these theoretical problems have been examined thoroughly by, e.g., Stambaugh (1999) with one-period ahead regressions and Hodrick (1992) and Valakanov (2004) for h-period ahead regressions. Many other authors have contributed to this discussion. See, for instance, the Campbell, Lo and MacKinley (1997) textbook.

6. Regressions for dividend and profit growth are subject to the omitted variables problem because, in that case, expected stock returns introduce noise. To circumvent this problem the differences between h and $h–\Delta d$ were also calculated.

7. See Kaul (1996), p. 284.

8. We also experimented with different truncation lags, but the results did not change materially.

9. In this case, errors are correlated with the K-1 previous error terms.

10. See, for instance, Valkanov (2004) on this issue. He claims that cumulative returns will generally not be I(1) but just more and more persistent.

11. 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.

12. For a recent application of a Sen-type unit root test that allows for a simultaneous structural break in the intercept and slope see Narayan (2005).

13. In principle, a more sophisticated specification our hypothesis could have made the impact of dividend yield dependent on the sign of the error-correction term (negative, if the latter is positive and vice versa) via e.g. the sign function. However, this way of modelling is certainly beyond the scope of this paper.

14. The following estimations, like all other computations in this paper, have been carried out using the package Microfit 4.11. See Pesaran and Pesaran (1997).

15. For technical details see Pesaran and Pesaran (2001), p. 404, and Pesaran and Shin (1999), pp. 14.

16. 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.

17. 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).

18. As it is well-known from cointegration theory, we should not draw any inference from the t-values of the coefficient estimates. However, for instance Domanski and Kremer (1998) clearly violate this key guideline when explicitly interpreting the estimation results of their Table 1 on pp. 30.

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

[20] 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 legitimise 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 ff., and Kremers, Ericsson and Dolado (1992), pp. 328 ff.

[21] Our ARDL procedure does not allow to skip the seemingly insignificant variables, since they contribute to the fit according to the empirical realisations of the information criteria.

[22] We also enacted dynamic forecasts of the growth rate of German stock returns based on an assessment of the future course of the dividend yield. The results are available on request.

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