Macroeconomic Factors and the German Real Estate Market: A Stock-Market-Based Forecasting Experiment

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Abstract: Based on a recursive forecasting approach, this research studies whether macroeconomic factors help to forecast excess returns on a real-estate-based German stock market index. Key findings are that macroeconomic factors are often included in the optimal forecasting model, that their relative importance often differs from their importance for forecasting a broad stock-market index, and that their informational content for forecasting excess returns seems to undergo temporal shifts. This research also finds evidence of market timing.

JEL Classifications: E37, G17
Keywords: Real estate market, Stock market, Forecasting, Macroeconomic factors

1. Introduction

The U.S. subprime mortgage crisis has triggered a debate among researchers on the macroeconomic determinants of developments in real estate markets. Some researchers argue that irrational investor exuberance and market frenzies explain developments in real estate markets (Case and Shiller 2003, Brunnermeier and Julliard 2007). Other researchers argue that “fundamentals” and macroeconomic factors play a crucial role for developments in real estate markets (Goodman and Thibodeau 2008, Himmelberg et al. 2005). Yet other researchers find that macroeconomic factors affect real estate markets, but that deviations from long-term equilibrium may result in a slow adjustment process (Mikhed and Zemčik 2009, Adams and Füss 2010). Against the background of this unsettled debate, this research explores whether macroeconomic factors help to forecast the excess returns on a real-estate-based German stock-market index.

This research contributes to the large literature on forecasting real estate markets (Lui and Mei 1992, Mei and Lui 1994, Nelling and Gyourko 1998, and Nguyen and Cripps 2001, Meulen et al. 2011, to name just a few). To this end, this research uses a stock-market-based forecasting experiment to study the informational content of macroeconomic factors for real-estate-market developments. The stock-market-based forecasting experiment uses the recursive forecasting approach developed by Pesaran and Timmermann (1995, 2000) as a natural experimental setting to study the real-time investment decisions of an investor. The recursive forecasting approach is easy to implement, and it allows the out-of-sample forecasting properties of macroeconomic factors to be studied. Moreover, this approach accounts for the fact that information on macroeconomic data become available to an investor through time in a recursive way as statistical offices and government agencies release new information on macroeconomic data. Recent applications of the recursive forecasting approach include Kempe et al. (2008) and Pierdzioch et al. (2008).

The remainder of this research is organized as follows. Section 2 contains a description of the recursive forecasting approach. Section 3 contains information on the data used in the empirical

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analysis, and a summary of the empirical findings. Empirical findings show that the optimal forecasting models often feature macroeconomic factors. The relative importance of macroeconomic factors for forecasting excess returns on the real estate-based stock-market index often differs from their importance for forecasting a broad stock-market index. Empirical findings further show that the predictive power of macroeconomic factors for forecasting excess returns seems to have changed over time. Moreover, the empirical analysis recovers evidence of market timing, that is, macroeconomic variables help to forecast the direction of change of the real-estate-based stock-market index. Section 4 contains some concluding remarks.

2. The Recursive Forecasting Approach

The recursive forecasting approach developed by Pesaran and Timmermann (1995, 2000) considers an investor whose problem is to combine, when an investment decision must be reached, the then available information on $k$ macroeconomic factors to forecast excess stock returns. If an investor knew that the optimal forecasting model features all $k$ macroeconomic factors, the optimal forecasting model, under a loss function that is symmetric (quadratic) in the forecast error, could be determined by estimating the parameters, $b_j$, $j = 0, \ldots, k$, of the following regression model by the ordinary least squares technique:

$$r_{t+1} = b_0 + b_1 x_{t+1} + b_2 x_{2t+1} + \cdots + b_k x_{kt+1} + e_{t+1}$$

where $r_{t+1}$ denotes excess stock returns in period $t+1$, $x_j$, $j = 1, \ldots, k$, denotes the $k$ macroeconomic factors, and $e_{t+1}$ denotes a Gaussian stochastic disturbance term. Because an investor, however, does not know the optimal forecasting model, simply estimating the regression model given in Equation (1) does not suffice to recover the optimal forecasting model. Instead, an investor attempts to identify an optimal forecasting model by searching over all possible combinations of macroeconomic factors that are used for forecasting excess stock returns. With $k$ macroeconomic factors in hand, an investor thus searches over $2^k$ forecasting models.

In order to identify an “optimal” forecasting model among all $2^k$ estimated forecasting models, an investor needs a model-selection criterion. Given that many competing model-selection criteria could be used to identify an optimal forecasting model, this research focuses on model-selection criteria that are easy to compute and that, in consequence, are widely studied in applied research. Hence, an investor selects the optimal forecasting models from the large number of forecasting models being estimated every period on the basis of the following four model selection criteria: the Adjusted Coefficient of Determination (ACD, Theil 1971, page 178), the Akaike (1973) Information Criterion (AIC), the Schwarz (1978) Bayesian Information Criterion (SIC), and the Direction of Change (DCC, Pesaran and Timmermann 1995) criterion. The ACD model-selection criterion measures the in-sample fit of a model based on the ratio of the explained to the total variation in excess stock returns, correcting for the fact that estimation of additional parameters reduces degrees of freedom. Similarly, the AIC and the SIC model-selection criteria support forecasting models that have a good fit, as measured in terms of the residual sum of squares, but penalize forecasting models that feature many parameters to be estimated. The DCC criterion counts the number of times a forecasting model correctly predicts in sample the sign of excess stock returns. Formally, the four model-selection criteria are given by

$$ACD = 1 - \frac{(1-COD)}{(T-1)} \frac{(T-K-1)}{T}$$

$$AIC = \ln(RSS/T) + 2 (K+1)/T$$

$$SIC = \ln(RSS/T) + (K+1) \ln(T)/T$$

$$DCC = \frac{1}{T} \sum_{t=1}^{T} (I(r_{t+1}^j)I(r_{t+1}) + (1-I(r_{t+1}^j))(1-I(r_{t+1})))$$

where $K \leq k$ denotes the number of macroeconomic factors being considered for a specific forecasting model (out of all $2^k$ estimated forecasting models), $RSS$ denotes the residual sum of squares, $T$ denotes the total number of observations available in period $t$, and $COD = B'X'X, B/(B'$
\(X_t'X_t B + E_t' E_t\) denotes the coefficient of determination (in deviations from the mean), with \(B\) denoting the vector of estimated regression coefficients in Equation (1), \(X_t\) denotes the matrix of regressors, \(E_t\) denotes the vector of regression residuals from Equation (1), and a prime denotes the transpose of a vector or matrix. In Equation (5), \(I(x)\) denotes the indicator function that assumes the value one when \(x>0\), and zero otherwise, and \(r'_t\) denotes the forecast of excess stock returns. An investor computes the four model-selection criteria given in Equations (2)-(5) for all \(2^k\) forecasting models. As the optimal forecasting models, an investor selects the two models that maximize the ACD and the DCC criteria, and the two models that minimize the AIC and SIC criteria. When more than one model maximizes the DCC model-selection criterion, an investor uses the ACD model-selection criterion to select the optimal model among those models that maximize the DCC model-selection criterion. Application of the four model-selection criteria yields four optimal forecasts of excess stock returns per period of time. As new data become available, an investor recursively restarts this search for an optimal forecasting model for excess stock returns (that is, the sample size is extended stepwise). The recursive modeling approach, thus, requires a permanent updating of the optimal forecasting models, selected based on the ACD, AIC, SIC, and DCC model-selection criteria, as the investor's information on the link between excess stock returns and macroeconomic factors increases as time progresses.

In order structure this recursive search-and-updating process, an investor estimates Equation (1) by the ordinary least squares technique. The ordinary least squares technique has the advantage that it renders it possible to implement the computationally demanding recursive search-and-updating process in an efficient and timely manner. The recursive search-and-updating process is very demanding in terms of computation time needed because it requires estimation of all \(2^k\) forecasting models in every period of time. In addition to being efficient in terms of computation time, the ordinary least squares technique has the advantage that it yields robust parameter estimates even if the disturbance term, \(e_t\), is not strictly Gaussian. Once Equation (1) has been estimated by the ordinary least squares technique, and the optimal forecasting models have been selected based on the four model-selection criteria, an investor can then, in every period of time, store information on the macroeconomic factors included in the optimal forecasting models, and the forecasts of excess returns derived from the optimal forecasting models.

Given the four model-selection criteria defined in Equations (2)-(5), the recursive forecasting approach produces four sequences of optimal forecasts of excess stock returns. In order to assess the quality of the sequence of forecasts produced by the forecasting models, an investor computes a test of market timing, the noise-to-signal (NTS) ratio, and the coefficient of correlation (CORR) between forecasts and actual excess stock returns. The specific market-timing test that an investor uses is the one suggested by Pesaran and Timmermann (1992, 1994). The Pesaran-Timmermann test of market timing is a non-parametric test that informs about the informational content of forecasts of excess stock returns with regard to the sign of actual excess stock returns. The NTS ratio is defined as the ratio of the proportion of wrong negative forecasts of excess stock returns and the proportion of correct positive forecasts of excess stock returns. In terms of a trading strategy, the NTS ratio can be interpreted to compare wrong sell signals and correct buy signals. The smaller the NTS ratio is, the better are the forecasts of excess stock returns produced by the recursive forecasting approach. Finally, CORR is defined as the Brevais-Pearson coefficient of correlation. A large CORR signals a strong co-movement between forecasts and actual excess stock returns.

**3. Empirical Analysis**

This research studies monthly data for the sample period 1991/2-2011/7. The DIMAX stock-market index, compiled and provided by Bankhaus Ellwanger & Geiger, a private German bank, measures the performance of stocks of German real estate companies. As of September 2011, the market capitalization of the 76 companies in the DIMAX index was approximately 10 billion euro (see Bankhaus Ellwanger & Geiger, 2011).
Figure 1 shows the DIMAX and, to put its development into perspective, the DAX, a broad German stock-market index. Both stock-market indexes increased during the dotcom bubble to reach a peak in March 2003. After the dotcom bubble collapsed, both stock-market indexes experienced a downward trend, which only stopped in March 2003. Whereas the DAX started increasing again in 2003, the DIMAX experienced a period of stagnation in 2003, and a period of rather moderate growth in 2004. Both stock-market indexes reached a second noticeable peak in summer 2007 before the U.S. subprime mortgage crisis hit financial markets. Interestingly, the DIMAX reached its peaked in February 2007 few months earlier than the DAX, which peaked in June 2007. Both indices reached their post-crisis trough in March 2009.

![Image of graphs showing DAX and DIMAX]

**Figure 1** The graphs of DAX and DIMAX from monthly data

**Data source:** Bankhaus Ellwanger & Geiger (2011).

A natural question is whether the DIMAX reflects changes in the German real estate market. The DIMAX only represents a specific segment of the German real estate market, and its movements may also reflect international activities of the companies in the index. In order to investigate whether movements in the DIMAX are coupled to developments in the German real estate market, Figure 2 plots the DIMAX and a price index for the German real estate market.

![Image of graphs showing DIMAX and real estate price index]

**Figure 2** The DIMAX and a price index for the German Real Estate Market

**Note:** The data on the price index for the German real estate market are from the Deutsche Bundesbank (based on data provided by BulwenGesa AG; data code: I037_weitere2011q1.xls). These data are available for the sample period 1995–2010 at a yearly frequency. The data on the DIMAX (yearly averages computed from monthly data) are from Bankhaus Ellwanger & Geiger (2011). This figure shows percentage changes of both time series, scaled by their respective standard deviation.

A natural question is whether the DIMAX reflects changes in the German real estate market. The DIMAX only represents a specific segment of the German real estate market, and its movements may also reflect international activities of the companies in the index. In order to investigate whether movements in the DIMAX are coupled to developments in the German real estate market, Figure 2 plots the DIMAX and a price index for the German real estate market. Both

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the DIMAX and the price index are expressed as percentage changes from year ago and are scaled by their respective standard deviations. Figure 2 shows that movements in the DIMAX tend to reflect movements in the price index. Because stocks are forward-looking financial instruments, movements in the DIMAX often lead movements in the price index.

Excess stock returns are defined as the (continuously compounded) monthly average returns (computed from weekly data) on the DIMAX (DAX) stock-market index minus the one-month money market rate. In total, 9 macroeconomic factors and financial predictor variables are being considered, implying that an investor estimates \(2^9=512\) forecasting models in every month to identify the optimal forecasting model for a given model-selection criterion. As a result, an investor estimates for every stock-market index 95,232 forecasting models. The list of macroeconomic factors and financial predictor variables contains the following data (data source: Deutsche Bundesbank, data code in parentheses):

1) **Inflation dynamics.** The inflation rate is measured in terms of the annualized monthly log change in the consumer price index (bbk_USFB99). As an alternative measure of inflationary pressures, the inflation rate is measured in terms of the annualized monthly growth rate of real energy prices, measured in terms of the HWWI energy price index (bbk_bbxr1.m.hwwi.n.euro.energy00.indbeu.he.m00). The energy price index is deflated using the consumer price index.

2) **Interest rates.** The one-month real money-market rate measures the short-term interest rate (bbk_SU0104), where the inflation rate computed from the consumer price index serves as a deflator. In addition, the term spread is being considered as an explanatory variable. The term spread is defined as the difference between the yield on German government bonds with a time to maturity of nine to ten years (bbk_wx3950) and the short-term interest rate.

3) **Business cycle.** The stance of the business cycle is measured in terms of the annualized monthly growth rate of industrial production (including the construction sector, bbk_BBDE1.M.DE.Y.BAA1.A2P000000.G.C.I05.A). In addition, the annualized monthly rate of change of incoming orders in the construction industry (bbk_usda01) is considered as a forward-looking variable to measure the stance of the business cycle.

4) **Financial conditions.** In order to control for potential autocorrelation of returns, the list of predictor variables contains the returns on the stock-market indexes. In addition, the six month moving average of the absolute returns on the DAX controls for stock market volatility.

Two remarks are in order. First, as far as the macroeconomic factors like consumer-price inflation or the growth rate of industrial production are concerned, this research uses revised macroeconomic data. Based on the recursive forecasting approach, Döpke et al. (2008) show that, revised macroeconomic data produce forecasts of excess stock returns that are very similar to those obtained from real-time macroeconomic data. Using real-time macroeconomic data, thus, should not affect the results reported in this research qualitatively. Because no further data transformations that account for data revisions (see, for example, Pesaran and Timmermann 1995, page 1208) are used, this research sheds light, on the one hand, on an investor's recursive search-and-updating process and, on the other hand, on the potentially time-varying equilibrium links between macroeconomic factors and real-estate-market developments, as represented by the DIMAX index. Lettau and Ludvigson (2009) discuss the usefulness of real-time versus revised macroeconomic data in empirical finance and asset pricing. Second, the list of macroeconomic factors used in this research is not meant to be exhaustive. The list of macroeconomic factors merely comprises macroeconomic factors that have been often studied as predictor variables of stock returns in earlier empirical research. For example, Döpke et al. (2008) study the informational content of the inflation rate and the growth rate of industrial production for forecasting excess stock returns. They also study, following Campbell (1987) and Chen et al. (1986), the predictive power of the term spread.
Rapach et al. (2005) study in detail the informational content of a large number of macroeconomic factors for excess stock returns. Earlier research, thus, provides many important insights with respect to the links between macroeconomic factors and excess stock returns. While it is interesting to draw on earlier research to extend the list of macroeconomic factors being under study in this research, one should also account for the fact that computational time increases exponentially in the number of macroeconomic factors. On balance, for the exploratory analysis that is the subject of this research, the list of nine macroeconomic factors and financial predictor variables should suffice to shed light on the link between macroeconomic factors and developments in real estate markets.

<p>| Table 1 | Inclusion of Predictor Variables in the Optimal Forecasting Models |
|----------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|</p>
<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>ACD</th>
<th>AIC</th>
<th>SIC</th>
<th>DCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Returns on the DAX</td>
<td>100.00</td>
<td>100.00</td>
<td>75.81</td>
<td>99.42</td>
</tr>
<tr>
<td>Returns on the DIMAX</td>
<td>81.72</td>
<td>74.19</td>
<td>39.79</td>
<td>41.94</td>
</tr>
<tr>
<td>Stock-market volatility</td>
<td>22.58</td>
<td>25.27</td>
<td>19.36</td>
<td>33.87</td>
</tr>
<tr>
<td>Inflation rate</td>
<td>72.04</td>
<td>32.26</td>
<td>6.45</td>
<td>58.07</td>
</tr>
<tr>
<td>Short-term interest rate</td>
<td>80.11</td>
<td>34.95</td>
<td>6.45</td>
<td>55.91</td>
</tr>
<tr>
<td>Term spread</td>
<td>60.75</td>
<td>45.70</td>
<td>6.45</td>
<td>47.85</td>
</tr>
<tr>
<td>Growth rate of energy prices</td>
<td>95.70</td>
<td>90.86</td>
<td>46.24</td>
<td>80.11</td>
</tr>
<tr>
<td>Growth rate of production</td>
<td>12.90</td>
<td>1.08</td>
<td>0.00</td>
<td>55.15</td>
</tr>
<tr>
<td>Growth rate of incoming orders</td>
<td>75.27</td>
<td>56.99</td>
<td>23.66</td>
<td>56.99</td>
</tr>
<tr>
<td>DAX</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Returns on the DAX</td>
<td>86.02</td>
<td>88.17</td>
<td>85.48</td>
<td>60.75</td>
</tr>
<tr>
<td>Returns on the DIMAX</td>
<td>38.17</td>
<td>25.27</td>
<td>5.91</td>
<td>73.66</td>
</tr>
<tr>
<td>Stock-market volatility</td>
<td>23.12</td>
<td>3.76</td>
<td>0.00</td>
<td>65.59</td>
</tr>
<tr>
<td>Inflation rate</td>
<td>36.56</td>
<td>15.05</td>
<td>0.00</td>
<td>81.18</td>
</tr>
<tr>
<td>Short-term interest rate</td>
<td>36.56</td>
<td>10.75</td>
<td>0.00</td>
<td>80.65</td>
</tr>
<tr>
<td>Term spread</td>
<td>83.33</td>
<td>81.08</td>
<td>0.00</td>
<td>35.48</td>
</tr>
<tr>
<td>Growth rate of energy prices</td>
<td>82.80</td>
<td>18.28</td>
<td>0.00</td>
<td>87.10</td>
</tr>
<tr>
<td>Growth rate of production</td>
<td>69.36</td>
<td>64.52</td>
<td>3.23</td>
<td>73.12</td>
</tr>
<tr>
<td>Growth rate of incoming orders</td>
<td>81.72</td>
<td>62.37</td>
<td>12.90</td>
<td>59.14</td>
</tr>
</tbody>
</table>

Notes: ACD = Adjusted coefficient of determination. AIC = Akaike information criterion. SIC = Schwarz information criterion. DCC = Direction of change criterion. Empirical results reported in this research were computed using the program R (R Development Core Team 2009).

Table 1 summarizes (in percent) how often the predictor variables are included in the optimal forecasting models under the ACD, AIC, SIC, and DCC model-selection criteria (Panel A: DIMAX, Panel B: DAX). In order to compute the results, an investor uses the first five years of data to start the recursive forecasting process (that is, the training period is five years). The general picture that emerges is that the predictor variables are often included in the optimal forecasting models, where the SIC, as expected, selects parsimonious forecasting models. As for the DIMAX, the short-term interest rate and the term spread are included often in the optimal forecasting models under the ACD, AIC, and DCC model-selection criteria. This also holds for the rate of change of incoming orders in the construction industry and the inflation rate. Interestingly, the growth rate of real energy prices is also very often selected as an explanatory variable for excess returns on the DIMAX. Moreover, the returns on the DAX are often included in the optimal forecasting model. The measure of stock-market volatility is included approximately in 34% in the optimal forecasting models under the DCC model-selection criterion, but is less important under the other model-selection criterion.
The returns on the DIMAX also show up in the optimal forecasting model, indicating the presence of a certain degree of autocorrelation not captured by the macroeconomic factors.

The inflation rate and the short-term interest rate are somewhat less important for forecasting the excess returns on the DAX than for forecasting the excess returns on the DIMAX, where the results for the DCC model-selection criterion are an exception. The SIC model-selection criterion never selects these two macroeconomic factors, the term spread, and the growth rate of real energy prices for the optimal forecasting model. As in the case of the DIMAX, the rate of change of incoming orders in the construction sector seems to help to forecast the excess returns on the DAX, but not under the SIC model-selection criterion. Under the other three model-selection criteria, the growth rate of production turns out to be much more important for forecasting the excess returns on the DAX than the excess returns on the DIMAX. The measure of stock-market volatility shows up in the optimal forecasting model for the DAX often under the DCC model-selection criterion. The returns on the DAX are included quite often in the optimal forecasting model, resembling the results for the DIMAX. As expected, the returns on the DIMAX seem to be less important for forecasting excess returns on the DAX than the other way round. Notwithstanding, the returns on the DIMAX seem to have some explanatory power for excess returns on the DAX, a result that may capture potential spillover effects from the real estate market to the overall macro economy. To sum up, macroeconomic factors help to forecast excess stock-index returns, but, depending on the model-selection criterion being analyzed, their relative importance for forecasting the excess returns on the DIMAX often differs from that for forecasting the excess returns on the DAX.

![Figure 3](image)

**Figure 3** Time-varying inclusions of macroeconomic factors in the Optimal Forecasting Model

**Note:** This figure shows dummy variables that assume the value one when the inflation rate (term spread) are included in the optimal forecasting model for excess returns on the DIMAX under the AIC model-selection criterion, and zero otherwise.

It is also interesting to analyze when macroeconomic factors help to forecast excess stock-index returns. Because the recursive forecasting approach implies that an investor recursively updates the optimal forecasting model, the list of selected predictor variables can change over time. In order to illustrate this result, Figure 3 shows when the inflation rate and the term spread are included in the optimal forecasting model for the DIMAX, where the AIC is the model-selection criterion being studied. Similar graphs could be computed for the other predictor variables and for the other model-selection criteria (these graphs are available from the author upon request). The line shown in Figure 3 assumes the value one when the inflation rate (the term spread) is included in the optimal forecasting model, and zero otherwise. The key message conveyed by Figure 3 is that the importance of the macroeconomic factors for excess returns on the DIMAX changes over time. For the period from 1996 to summer 1999, the optimal forecasting model under the AIC model-
selection criterion features neither the term spread (with a short interruption in the summer of 1997) nor the inflation rate. For the period from the summer of 1999 to the winter of 2000, both macroeconomic factors are included in the optimal forecasting model. Both variables are then dropped from the optimal forecasting model, but enter again into the optimal forecasting model in the spring of 2005, but only the term spread survives, after a short interruption in early 2008, from the summer of 2008 on the recursive search-and-updating process underlying the recursive forecasting approach and, as a result, is included in the optimal forecasting model.

The changing composition of the optimal forecasting models illustrated by means of Figure 3 provides indirect evidence of temporal shifts in the links between macroeconomic factors and developments in real estate markets. In recent research, Chang et al. (2011) also report evidence of regime shifts with regard to the links between monetary policy, the term structure of interest rates, and real-estate-market developments. Specifically, they find that, as far as the U.S. real estate market is concerned, a nonlinear regime-switching model performs better than a linear model in terms of explaining REIT and housing returns. The results summarized in Figure 3 confirm the findings reported by Chang et al. (2011) insofar as the findings illustrate that the link between macroeconomic factors and excess stock returns on the DIMAX seems to vary over time. The recursive forecasting approach accounts for such temporal shifts by including macroeconomic factors during some periods, and dropping them during others. Thereby, the recursive forecasting approach is useful to identify a regime in which the link between macroeconomic factors and developments in real estate markets is strong, and a regime in which this link is weak. Kempa et al. (2008) show how the recursive forecasting approach can be modified to account explicitly for such regime shifts.

### Table 2 Analyzing forecasts

<table>
<thead>
<tr>
<th>Index</th>
<th>ACD</th>
<th>AIC</th>
<th>SIC</th>
<th>DCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>DIMAX</td>
<td>4.26**</td>
<td>4.08**</td>
<td>3.16***</td>
<td>3.41***</td>
</tr>
<tr>
<td>DAX</td>
<td>1.36</td>
<td>1.40</td>
<td>0.72</td>
<td>-0.21</td>
</tr>
<tr>
<td>NTS</td>
<td>0.62</td>
<td>0.62</td>
<td>0.63</td>
<td>0.65</td>
</tr>
<tr>
<td>DAX</td>
<td>0.87</td>
<td>0.89</td>
<td>0.93</td>
<td>1.02</td>
</tr>
<tr>
<td>CORR</td>
<td>0.36</td>
<td>0.35</td>
<td>0.29</td>
<td>0.30</td>
</tr>
<tr>
<td>DAX</td>
<td>0.17</td>
<td>0.17</td>
<td>0.10</td>
<td>0.20</td>
</tr>
</tbody>
</table>

**Note:** Table 2 provides a summary of the results of the test for market timing developed by Pesaran and Timmermann (1992). The market-timing test is based on Pesaran and Timmermann (1992). NTS = noise-to-signal ratio. CORR = coefficient of correlation between forecasts and actual excess stock returns.

The inclusion of variables in the optimal forecasting models studied in Table 1 does not inform about the quality of forecasts produced by the recursive forecasting approach. As a first check of the quality of forecasts, Table 2 summarizes the results of the test for market timing developed by Pesaran and Timmermann (1992). This nonparametric market-timing test checks whether the selected optimal forecasting models help to forecast the sign of future excess stock-market returns. The test always yields significant results in the case of the DIMAX, but is significant for the DAX only under the ACD and AIC model-selection criteria. While evidence of market timing should not be interpreted to imply a deviation from the benchmark of market efficiency (for example, transaction costs have not been factored in and forecasts are for monthly average excess returns), the evidence of market timing in the case of the DIMAX signals that macroeconomic factors produce better out-of-sample forecasts with respect to the direction of stock-market developments in the case of the DIMAX than in the case of the DAX. While the interpretation of the relatively weaker evidence of market timing in the case of the DAX perhaps should not be stretched too far,
the weaker evidence of market timing is in line with results of earlier research that indicates that forecasting broad stock-market indexes with macroeconomic factors has become rather challenging since the 1990s (Aiolfi and Favero 2005). The other measures of forecast quality (NTS and CORR) confirm the results of the market-timing test (Table 2). The selected optimal forecasting models appear to perform better in terms of the NTS ratio and CORR in the case of the DIMAX than in the case of the DAX. The link between the macroeconomic factors and financial predictor variables considered in this research and excess returns, thus, appears to be stronger for the DIMAX than for the DAX.

4. Concluding Remarks

An application of the recursive forecasting approach developed by Pesaran and Timmermann (1995, 2000) to study German stock-market data has shown that the links between macroeconomic factors and developments of a real-estate-based stock-market index may differ, also in terms of market timing, quite substantially from the links that can be detected between macroeconomic factors and a broad stock-market index. Further, the links between macroeconomic factors and developments of a real-estate-based stock-market index seem to have changed over time. The findings of this empirical research, thereby, provide information on the link between macroeconomic factors and developments in real estate markets that complement information that researchers have reported in the recent real estate literature (Mikhed and Zemčik 2009, Adams and Füss 2010) and the macroeconomics literature (Giuliodori 2005, and Goodhart and Hofmann 2008, Dreger and Wolters 2011, to name just a few).

Because the recursive modeling approach provides a natural experimental setting for studying stock-market developments, and because it can be easily adapted to analyze real-estate-market developments in other countries, it may turn out be a useful modeling alternative to other forecasting models studied in earlier real estate literature. The usefulness of the recursive modeling approach for analyzing real-estate-market developments in general and for forecasting the returns of real-estate-based stock-market indexes in particular stems from the fact that it can be easily tailored to study a broad range of macroeconomic factors, potential shifts in the link between macroeconomic factors and developments in real estate markets, and issues related to market timing and portfolio allocation.

References


