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Real-time macroeconomic data and ex ante predictability of stock returns

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Abstract:

We report results on the ex ante predictability of monthly excess stock returns in Germany using real-time and revised macroeconomic data. Our real-time macroeconomic data cover the period 1994-2005. We report three results. 1) Real-time macroeconomic data did not contribute much to ex ante stock-return predictability. 2) The performance of an investor who had to rely on noisy real-time macroeconomic data would have been comparable to the performance of an investor who had access to revised macroeconomic data. 3) In real time, it is important for an investor to know which real-time variable to use for predicting stock returns.

Keywords: Ex ante predictability of stock returns, real-time macroeconomic data, performance of investment strategies, Germany

JEL-Classification: C53, E44, G11

Non-technical summary

We use macroeconomic data to study the ex ante predictability of stock returns in Germany. While much of the early research on the predictability of stock returns has been concerned with the *ex post* predictability of stock returns using macroeconomic variables, a number of recent studies have reported evidence of *ex ante* predictability of stock returns. Ex post predictability of returns is studied by using full-period information. By contrast, ex ante predictability of returns is studied by using only information that was available to investors in real time.

Researchers who study ex ante return predictability of stock returns have access to macroeconomic data that have been revised many times. In contrast, an investor in real time has access only to preliminary first-releases of macroeconomic data. We analyze whether accounting for the differences between real-time and revised macroeconomic data should be considered when studying ex ante predictability of stock returns using macroeconomic variables.

Our contribution to the literature on ex ante return predictability is threefold. First, we compared the informational content of real-time and revised macroeconomic data with regard to ex ante return predictability. To the best of our knowledge, such a comparison has not been undertaken in the earlier literature on ex ante return predictability. Second, we used data for the German stock market to analyze ex ante return predictability. Most researchers so fare have used U.S. data to study ex ante return predictability. Third, we analyzed whether industrial production, orders inflow, and a measure of the output gap help to forecast returns in real time. Many other authors who have studied return predictability have focused on industrial production as a measure of real economic activity and the stance of the business cycle.

We report three main results. Our first main result is that the return predictability based on real-time macroeconomic data is comparable to return predictability based on revised macroeconomic data. Our second main result is that the performance of trading rules implemented by an investor who had to rely on noisy real-time macroeconomic data would have been comparable to the performance of an investor who had access to revised macroeconomic data. Our third main result is that, in real time, it is important for an investor to know which real-time macroeconomic data to use for forecasting returns.

Nicht-technische Zusammenfassung

In dieser empirischen Analyse wird der Informationsgehalt makrökonomischer Daten für die ex ante Prognostizierbarkeit von Aktienreturns in Deutschland untersucht. Während in der älteren Literatur häufig die ex post Prognostizierbarkeit von Aktienreturns analysiert wurde, wird in der jüngeren Literatur vornehmlich auf deren ex ante Prognostizierbarkeit abgestellt. Die ex post Prognostizierbarkeit von Aktienkursreturns wird untersucht, indem die gesamten Informationen, die dem Forscher in dem Zeitpunkt der empirischen Untersuchung zur Verfügung stehen, herangezogen werden. Die ex ante Prognostizierbarkeit von Aktienkursreturns hingegen wird auf der Basis der Informationen, welche einem Investor in Echtzeit zur Verfügung standen, untersucht.

Während Forschern bei der Analyse der ex ante Prognostizierbarkeit von Aktienkursreturns mehrfach revidierte makroökonomische Daten zur Verfügung stehen, können Investoren in Echtzeit nur auf vorläufige Erstveröffentlichungen makroökonomischer Daten zurückgreifen. In der vorliegenden empirischen Analyse wird untersucht, ob die Unterschiede zwischen vorläufigen und revidierten makroökonomischen Daten im Hinblick auf die ex ante Prognostizierbarkeit von Aktienkursreturns in Echtzeit berücksichtigt werden sollten.

Die vorliegende Arbeit trägt in dreifacher Hinsicht zur Literatur über die Prognostizierbarkeit von Aktienkursreturns bei. Erstens wird der Informationsgehalt von vorläufigen und revidierten makroökonomischen Daten für die ex ante Prognostizierbarkeit von Aktienkursreturns untersucht. Soweit den Autoren bekannt, wurde ein solcher Vergleich in der früheren Literatur noch nicht durchgeführt. Zweitens werden deutsche Daten herangezogen, um die ex ante Prognostizierbarkeit von Aktienkursreturns zu untersuchen. Abgesehen von einigen wenigen Ausnahmen wurden in der Literatur über die ex ante Prognostizierbarkeit von Aktienkursreturns vornehmlich U.S. amerikanische Daten untersucht. Drittens wird der Informationsgehalt der Industrieproduktion, der Auftragseingänge und einem Maß für die Produktionslücke für die Prognostizierbarkeit von Aktienkursreturns analysiert. In zahlreichen früheren Studien lag der Fokus der Analyse auf dem Informationsgehalt der Industrieproduktion für die Prognostizierbarkeit von Aktienkursreturns.

Die drei zentralen Ergebnisse der vorliegenden empirischen Studie können wie folgt zusammengefasst werden. Erstens ist die Prognostizierbarkeit von Aktienkursreturns auf der Basis vorläufiger Erstveröffentlichungen makroökonomischer Daten mit jener auf der Basis von revidierten makroökonomischen Daten vergleichbar. Zweitens dürfte der Erfolg einer von einem Investor in Echtzeit implementierten Handelsstrategie kaum dadurch verringert werden, dass der Investor in Echtzeit bei der Prognose von Aktienkursreturns nur auf vorläufige Erstveröffentlichungen makroökonomischer Daten zurückgreifen kann. Drittens hat die Entscheidung, welche vorläufigen Erstveröffentlichungen makroökonomischer Daten zur Prognose von Aktienkursreturns genutzt werden sollen, einen erheblichen Einfluss auf den Investitionserfolg eines Investors.

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Real-Time Macroeconomic Data and Ex Ante Predictability of Stock Returns [*]

1. Introduction

Macroeconomic variables represent key state variables in widely used intertemporal asset-pricing models, and they can represent priced factors in multifactor asset-pricing models. Given the importance of macroeconomic variables for modeling in finance, in the last 30 years, much empirical research has been done on the predictability of stock returns using macroeconomic variables (Fama 1981; Chen et al. 1986; McQueen and Roley 1993; Flannery and Protopapadakis 2002, to name just a few). While much of the early research on the predictability of stock returns has been concerned with the ex post predictability of stock returns using macroeconomic variables, a number of recent studies have reported evidence of ex ante predictability of stock returns. Ex post predictability of stock returns is studied by using full-period information. By contrast, ex ante predictability of stock returns is studied by using only information that was available to investors in real time. Evidence of ex ante predictability of stock returns can be used to gauge whether investors could have exploited predictability of stock return to set up a profitable investment strategy. Recent studies of ex ante predictability of stock returns include Pesaran and Timmermann (1995, 2000), Bossaerts and Hillion (1999), Goyal and Welch (2003), and Cooper et al. (2005). The results of these studies indicate that evidence of ex ante predictability of stock returns can be significantly different from, and in some cases much weaker than evidence of ex post predictability of stock returns.

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When one studies the ex ante predictability of stock returns using macroeconomic data, a key question is whether it is important to account for the fact that macroeconomic data available to a researcher are typically different from the macroeconomic data available to an investor in real time. Researchers have access to macroeconomic data that have been revised many times. In sharp contrast, when making an investment decision in real time, an investor has access to preliminary first-releases of macroeconomic data. An investor can only make inferences about the link between stock returns and macroeconomic variables by using the then latest release of publicly available macroeconomic data. In this paper, we ask whether accounting for the differences between real-time and revised macroeconomic data should be considered when studying ex ante predictability of stock returns using macroeconomic variables. Empirical evidence that may help to answer this question is, as far as we know, not yet available because the earlier literature on the ex ante predictability of stock returns using macroeconomic variables has studied only revised macroeconomic data. In fact, only a few studies are available that report evidence of the implications of using real-time data for research in empirical finance (Christoffersen et al. 2002, Andersen et al. 2003, Clark and Kozicki 2004, Guo 2003). By contrast, the analysis of the implications of using real-time macroeconomic data has a long tradition in research on macroeconomics and business-cycle fluctuations. Real-time data have been used to test business-cycle theories and important policy issues, such as the implications of using real-time macroeconomic data for measuring the output gap and conducting monetary policy (see Croushore 2001, Croushore and Stark 2003, Orphanides and van Norden 2002, Orphanides and Williams 2003, to name just a few).

Our contribution to the literature on ex ante predictability of stock returns is threefold. First, we compared the informational content of real-time and revised macroeconomic data with regard to ex ante predictability of stock returns. Such a comparison has not been undertaken in the earlier literature on ex ante predictability of stock returns. For example, Pesaran and Timmermann (1995, page 1208) have been aware of the fact that their dataset of revised macroeconomic data contains information not available to an investor in real time. However, rather than using real-time macroeconomic data, they have used 12-month backward-looking moving averages of macroeconomic variables to decrease the impact of historical revisions of macroeconomic data on their results. One study that maybe comes closest to our study is that by Christoffersen et al. (2002) who have used real-time macroeconomic data to analyze the sensitivity of stock returns to economic news.

Second, we used data for the German stock market to analyze ex ante predictability of stock returns. With a few exceptions (e.g., Bossaerts and Hillion 1999), most researchers have used U.S. data to study ex ante predictability of stock returns. Repeated studies of the same dataset, however, lead to a problem known as "model overfitting" or "data snooping" (Lo and MacKinlay 1990). Data snooping refers to the problem that a tendency to discover spurious relationships may arise when a dataset is used to conduct statistical tests that are inspired by evidence from prior studies of the same dataset. One way to address data snooping is to collect new data. We used a new monthly dataset of real-time macroeconomic data compiled by the Deutsche Bundesbank. Gerberding et al. (2005) have provided a detailed account of the ongoing work on the real-time macroeconomic data compiled by the Bundesbank. Data are available for each month in the period 1994-2005.

Third, we analyzed whether industrial production, orders inflow, and a measure of the output gap help to forecast stock returns in real time. Most of the studies of predictability of stock returns using macroeconomic variables have focused on industrial production as a measure of real economic activity and the stance of the business cycle (Rapach et al. 2005, Pesaran and Timmermann 1995, 2000). When only real-time macroeconomic data are available, however, an investor must take into account that preliminary data on industrial production may only give a noisy account of the stance of the business cycle. This warrants a closer look at the real-time forecasting ability for returns of other real-time macroeconomic measures of the stance of the business cycle, such as orders inflow and the output gap.

We report three main results. Our first main result is that the predictability of stock returns based on real-time macroeconomic data is comparable to predictability based on revised macroeconomic data. This suggests that the forecasting ability of models featuring real-time macroeconomic variables is dominated by the forecasting performance of other models featuring variables such as the price of oil or the dividend yield. Our second main result is that the performance of an investor who had to rely on noisy real-time macroeconomic data would have been comparable to the performance of an investor who had access to revised macroeconomic data. We measured performance in terms of widely used performance measures, such as Sharpe's ratio or Jensen's alpha. The result that using real-time rather than revised macroeconomic data does not much affect the performance of an investor is remarkable given that revisions of German macroeconomic data are substantial. Our third main result is that it is, in real time, important for an investor to know which real-time macroeconomic data to use for forecasting returns. We analyzed a number of different real-time macroeconomic data and found that the performance of an investor can be sensitive to the specific choice of real-time macroeconomic data considered as a candidate for forecasting returns.

We organize the remainder of this paper as follows. In Section 2, we discuss the recursive modeling approach we used to study the implications of using real-time macroeconomic data for the ex ante predictability of stock returns and the optimality of an investor's investment decisions in real time. In Section 3, we lay out the macroeconomic and financial data we considered to be relevant for forecasting stock returns. In Section 4, we provide a detailed discussion of our results. In Section 5, we offer some concluding remarks.

2. Recursive modeling of ex ante predictability of stock returns

In order to simulate how an investor may have predicted stock returns in real time, we used a recursive modeling approach. A recursive modeling approach renders it possible to trace out when the various macroeconomic and financial variables which we considered helped forecasting stock returns. A recursive modeling approach implies that, to forecast stock returns, an investor could only use a set of information available in the period of time in which the investor had to reach an investment decision. Included in this set of information is information on the macroeconomic data released in the period in which an investment decision had to be reached, but not information on later revisions of macroeconomic data. It is for this reason that we adopted a recursive modeling approach. A recursive modeling approach also makes it possible to study, in terms of an investor's financial wealth, the economic significance of using real-time macroeconomic data rather than revised macroeconomic data for forecasting stock returns. We measure the economic significance of using real-time macroeconomic data rather than revised ones by computing various performance measures for investment strategies that have been proposed in the finance literature.

2.1 Recursive forecasting of stock returns in real time

We considered an investor who uses a large set of macroeconomic and financial variables to predict future stock returns. In period of time *t*, the information set of the investor contains information on the realizations of macroeconomic and financial variables up to and including period of time *t*. With regard to macroeconomic variables, we emphasize that we assumed that the information set of the investor only contains information on macroeconomic data released in period of time *t* or earlier. In fact, we assumed that the investor in period of time *t* considers the then latest release of macroeconomic data to predict stock returns. Hence, we assumed that, in period of time *t*, the investor has no information concerning later revisions of macroeconomic data that only become known when revised macroeconomic data are released in period of time $t+1$ or later. This assumption implies that the investor can only use real-time macroeconomic data to predict stock returns in real time.

The investor's problem is to decide how to combine in an optimal way the available macroeconomic and financial variables to predict stock returns. When doing so, the investor does not know which variables to include in the optimal model, nor does the investor know the true parameters of the optimal model. Hence, in each period of time, the investor must reach a decision under uncertainty about the optimal model, and the best the investor can do is to systematically extract the informational content of the then available macroeconomic and financial data for future stock returns. In order to model the investor's decision problem, we follow Pesaran and Timmermann (1995, 2000) and Cooper et al. (2005) and assume that the investor applies a recursive modeling approach. The recursive modeling approach requires that the investor, in an attempt to find the model that best predicts stock returns, systematically searches in each period of time *t* over a large number of different models that feature different macroeconomic and financial variables. As time progresses, the investor recursively restarts this search for the optimal model as new information on financial variables and new releases of macroeconomic data become available, and this information may result in changes of the optimal prediction model. As a result, the investor's recursive modeling approach implies a permanent updating of the optimal forecasting model as the investor's set of information on the link between stock returns and macroeconomic and financial variables increases as time progresses.

We assume that, in each period of time t, the investor considers a set of K macroeconomic and financial variables that may be useful for making a one-period-ahead forecast of stock returns. The investor tries to identify the optimal forecasting model in period t by searching over all possible permutations of the K variables considered to be useful for forecasting stock returns. As a result, the investor must search over a large number of different models to identify in period t the optimal forecasting model for stock returns in period t+1. For example, as we shall describe in detail in Section 3, we assume that the investor considers nine macroeconomic and financial variables to be relevant for forecasting one-period ahead stock returns. Given these nine variables, and given the length of our sample period, we estimated, in total, more than 70,000 models for each real-time macroeconomic variable. A key problem is to conduct this search over a large number of forecasting models in an efficient and timely manner. To solve this problem, we followed Pesaran and Timmermann (1995, 2000) and assumed that the investor uses a linear regression model estimated by the ordinary least squares technique in order to search over all possible different forecasting models. Hence, we assumed that the investor studies the link between stock returns and macroeconomic and financial variables by estimating linear regression models of the following format:

$$r_{t+1} = \beta_i' X_{t,i} + \varepsilon_{t+1,i}, \tag{1}$$

where r_{t+1} denotes the vector of stock returns from period 0 up to and including period t+1. The subscript i denotes the models considered by the investor, $\varepsilon_{t+1,i}$ denotes a stochastic disturbance term, and $X_{t,i}$ denotes the set of regressors under model i. The set of regressors under model i, $X_{t,i}$, is a subset of the set of all macroeconomic and financial regressors, $X_{t,i} \in X_t$, the investor considers to be relevant for forecasting stock returns. (We assume that the vector of regressors always includes a constant.) The investor estimates the vector of parameters under model i, β_i, by the ordinary least squares technique, which yields robust parameter estimates even in the presence of non-Gaussian errors (Hamilton 1994, Chapter 8).

In order to identify the optimal forecasting model, the investor needs a model-selection criterion that helps to select, in each period of time *t*, the optimal forecasting model among the large number of estimated forecasting models. The model-selection criteria we considered are the Adjusted Coefficient of Determination (ACD), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). The ACD criterion is defined as

$$ACD_{t,i} = 1 - \frac{T_t - 1}{T_t - k_{t,i}}(1 - COD_{t,i}), \tag{3}$$

where $COD_{t,i} = \beta_{t,i}' X_{t,i}' X_{t,i} \beta_{t,i} / (e_{t,i}' e_{t,i})$ denotes the coefficient of determination of model *i* in period *t*, and $e_{t,i}$ denotes the estimated residuals under model *i* in period *t*. In Equation (3), T_t denotes the number of observations available in period *t*, and $k_{t,i}$ denotes the number of regressors, $k \in K$, considered under model *i* in period *t*. Using this notation, the AIC criterion (Akaike 1973) and the BIC criterion (Schwarz 1978) are defined as

$$AIC_{t,i} = \ln \frac{e_{t,i}' e_{t,i}}{T_t} + \frac{2k_{t,i}}{T_t}, \tag{4}$$

$$BIC_{t,i} = \ln \frac{e_{t,i}' e_{t,i}}{T_t} + \frac{k_{t,i}}{T_t} \ln T_t. \tag{5}$$

Similar to the AIC criterion is the popular Amemyia Prediction Criterion (Amemyia 1985). We also tried this criterion. The results turned out to be similar to those we obtained for the AIC criterion, indicating the robustness of our results. (Results for the Amemyia Prediction Criterion are available from the authors upon request.) A key advantage of the ACD, AIC, and BIC model-selection criteria is that an investor can easily compute these criteria. In consequence, these model-selection criteria are widely used in applied research. Even more important is the fact that these model-selection criteria, in contrast to other model-selection criteria discussed in the literature (Bossaerts and Hillion 1999), were readily available to an investor even at the beginning of our sample period. The availability of the model-selection criteria to an investor over the entire sample period is important because we plan to simulate the real-time investment decisions of an investor. In doing so, it is important for us to ensure that the investor bases investment decisions only on information available in the period of time in which these decisions had to be reached.

2.2 Recursive modeling of an investors' investment decisions in real time

The investors' recursive modeling approach implies that, in each period of time *t*, the investor selects three models out of the large number of estimated models: one model that maximizes the ACD criterion, and two models that minimize the AIC and BIC criteria, respectively. For each model-selection criterion, this gives a sequence of optimal models, and a sequence of optimal one-month-ahead stock-return forecasts. These stock-return forecasts can then be used to reach an investment decision. We considered an investor who can decide to switch between shares and bonds. For switching between shares and bonds, the investor can use period-*t* information on the optimal one-month-ahead stock-return forecasts implied by the optimal forecasting models selected on the basis of either the ACD criterion, or the AIC criterion, or the BIC criterion. Thus, when selecting the third investment strategy, the investor can choose among three different portfolio-switching strategies. When the optimal one-month-ahead stock-return forecasts implied by these criteria are positive, the investor only invests in shares, not in bonds. By contrast, when the optimal one-month-ahead stock-return forecasts are negative, the investor only invests in bonds, not in shares.

Depending on the investment strategy chosen by the investor, the financial wealth of the investor changes over time. In order to model how the financial wealth of the investor changes over time, we introduce some notation. Our notation follows Pesaran and Timmermann (1995). We denote the financial wealth of the investor at the end of period *t* by W_t, the price of shares at the end of period *t* by P_t, and the dividends per share paid during period *t* by D_t. We denote the period-*t* forecast of stock returns in period *t*+1 by $\hat{r}_{t+1}$. The number of shares held by the investor at the end of period *t* is given by N_t, and the investor's position in bonds is given by B_t. We assume that trading in stocks and bonds involves transaction costs that are (i) constant through time, (ii) the same for buying and selling stocks and bonds, and (iii) proportional to the value of a trade. We denote the percentage transaction costs on shares and bonds by c_1 and c_2, respectively. Taking account of transaction costs, the investor buys in period of time t a number of shares of $N_t = (1-c_1)W_t / P_t\ N_t$ if $\hat{r}_{t+1} > 0$, and a number of bonds of $B_t = (1-c_2)W_t$ if $\hat{r}_{t+1} < 0$. The investor that we consider does not make use of short selling, nor does our investor use leverage when deciding on the optimal investment strategy.

When considering a portfolio-switching strategy, the investor reconsiders the optimality of the investment decision made in period of time t+1 based on the forecast of stock returns for period of time t+2. Four different cases have to be considered:

- Case 1: The investor invested in shares in period t+1, and reinvests cash dividends in shares in period of time t+2.

$\hat{r}_{t+1} > 0$ and $\hat{r}_{t+2} > 0$

$$N_{t+1} = N_t + N_t D_t (1-c_1) / P_{t+1}$$

$$B_{t+1} = 0$$

- Case 2: The investor invested in shares in period t+1, but buys bonds in period of time t+2.

$\hat{r}_{t+1} > 0$ and $\hat{r}_{t+2} < 0$

$$N_{t+1} = 0$$

$$B_{t+1} = (1-c_2)[(1-c_1)N_t P_{t+1} + N_t D_{t+1}]$$

- Case 3: The investor invested in bonds in period t+1, but buys shares in period of time t+2.

$\hat{r}_{t+1} < 0$ and $\hat{r}_{t+2} > 0$

$$N_{t+1} = (1 - c_1) B_t (1 + R_t) / P_{t+1}$$

$$B_{t+1} = 0$$

- Case 4: The investor invested in bonds in period t+1, and reinvests financial wealth in bonds in period of time t+2.

$\hat{r}_{t+1} < 0$ and $\hat{r}_{t+2} < 0$

$$N_{t+1} = 0$$

$$N_{t+1} = (1 - c_2) B_t (1 + R_t).$$

The dynamics of the financial wealth of the investor can be described in terms of the following budget constraint:

$$W_{t+2} = N_{t+1}(P_{t+2} + D_{t+2}) + B_{t+1}(1 + R_{t+1}), \tag{6}$$

where a R_t denotes the risk free one-period interest rate on bonds.

2.3 Measuring the performance of investment strategies

We used four different performance measures in order to assess the performance of the different investment strategies available to our investor. The first widely used performance measure that we considered is Sharpe's ratio (Sharpe 1966). We computed Sharpe's ratio as

$$SR_S = \frac{r_{S,T} - R_T}{SD(r_{S,t})}, \tag{7}$$

where SR_S denotes the Sharpe ratio of investment strategy *S*, $r_{S,T}$ denotes the portfolio returns at the end of the investment horizon, *T*, obtained by following investment strategy *S*, and $SD(r_{S,t})$ denotes the standard deviation of portfolio returns, $r_{S,t}$, under investment strategy *S*.

The second performance measure that we analyzed is Jensen's alpha (Jensen 1968). We computed Jensen's alpha as the intercept coefficient in the following regression equation:

$$r_{S,t} - R_t = \alpha_S + \beta_S (r_{M,t} - R_t) + \varepsilon_{S,t}, \tag{8}$$

where α_S denotes Jensen's alpha for investment strategy *S*, $r_{M,t}$ denotes the returns on the market portfolio, β_S denotes the beta coefficient of investment strategy *S,* and $\varepsilon_{S,t}$ is an investment-strategy specific disturbance term.

We used the beta coefficient of investment strategy *S* in order to compute Treynor's ratio (Treynor 1965) as our third performance measure. We calculated Treynor's ratio as follows:

$$TR_S = \frac{r_{S,T} - R_T}{\beta_S}, \tag{9}$$

where TR_S denotes Treynor's ratio of investment strategy *S*.

Finally, we computed the appraisal ratio advocated by Treynor and Black (1973) as our fourth performance measure. We calculated the appraisal ratio as the ratio of Jensen's alpha to the standard deviation of the estimated residuals, $e_{S,t}$, of Equation (8):

$$AR_S = \frac{\alpha_S}{SD(e_{S,t})}. \tag{10}$$

3. The data

The description of our data comes in two parts. In the first part, we describe our real-time macroeconomic data for Germany. In the second part, we describe the other explanatory variables that we used in our empirical analysis.

3.1 Real-time macroeconomic data for Germany

In order to study excess return predictability, we used a real-time macroeconomic dataset for major macroeconomic business-cycle indicators for the German economy. The dataset was compiled by the Deutsche Bundesbank based on the publicly available information contained in the Bundesbank's monthly publications of seasonally adjusted macroeconomic data (Saisonbereinigte Wirtschaftszahlen). We used real-time data for month-to-month growth rates of industrial production (excluding construction) and orders inflow. Moreover, we used real-time data for year-to-year growth rates of industrial production (excluding construction). We also used real-time data for the growth rate of the consumer price index. In addition, we computed a real-time measure of the output gap, which is defined as the difference between actual output and potential output. In order to measure potential output, we applied the Hodrick-Prescott filter (Hodrick and Prescott 1997) to our real-time data for industrial production, where we set the smoothing parameter to 14,400. The real-time macroeconomic data are available at a monthly frequency for every month since January 1994. Our sample of real-time macroeconomic data starts in 1994 because all data releases from this period of time onwards strictly refer to the unified Germany. The data are organized in vintages. Each vintage contains data going back to May 1988. We considered data going back to 1988 because, in order to start our recursive modeling approach, we had to assume that the investor uses data from a training period to get initial estimates of the model-selection criteria. The training period that we considered is 1988/5-1993/12. Data before 1991/1 are for West Germany only.

Figure 1 shows how our real-time dataset is organized by means of vintages. Each column of the figure contains a vintage of real-time macroeconomic data. A vintage contains the data that would have been available to an investor in the period of time given in the column headers of the figure. The shaded cell of a vintage contains data that were then released for the first time. The organization of the real-time data by means of vintages implies that the rows of the figure contain information on the history of data revisions. Thus, if one moves from the left to the right of the figure, not only new macroeconomic data were published for the then most recent period of time, but historical macroeconomic data were also revised. The column on the far right of the figure contains information on the final release of macroeconomic data.

Figure 1 — Organization of the real-time macroeconomic data

Vintages of real-time macroeconomic data						Final release
	1994:1	1994:2….				2005:6
1988:5						
1988:6						
…						
1993:11						
1993:12						
…						
2005:4						

Macroeconomic data are generally published with a time lag. For example, data for industrial production in April 2005 were published in June 2005, and could be used for forecasting stock returns in July 2005. In our empirical analyses, we accounted for publication lags. We also accounted for the fact that the publication lag may have changed over time. As a rule, the production index is published 37 days after the beginning of the month for which data are being reported (Jung 2003, page 820). However, owing to conceptual changes in calculating the index and “important events”, there are exceptions to this rule. For example, in the case of industrial production, 1995 provides a notable example of irregularities with regard to the publication lag. In 1995, the German Federal Statistical Office did not publish data on industrial production from February to June because of a change in the calculation of the production time series.

From June to August 1995, it published two data per month to get back to the regular publication lag of two months. We dealt with irregularities in the publication lag by considering an investor who always used the then latest publicly available data. In case no new data were released, we assumed that the investor used the then most recent figure of the then most recently published vintage to fill any gaps in the data. Thus, if we identified any missing cells above or including the shaded cells in Figure 1, we used the last available observation of a vintage to fill gaps in the data. This way of filling gaps in the data does not distort the information set available to an investor because it implies that the investor only uses then publicly available data to forecast stock returns.

Table 1 provides some summary statistics of revisions of our real-time macroeconomic data. We provide summary statistics for revisions after one month, two months, six months, one year, and final revisions (i.e., revisions at the end of our sample period). For example, revisions after one month are computed by taking the difference between the first release and the second release of data. Ideally, revisions should have a zero mean because this would indicate that there is no systematic difference between data belonging to different vintages. The summary statistics in Table 1 indicate that, as a rule, revisions do not have a zero mean, where revisions of the consumer price index are an exception to this rule. Moreover, the std-ratios are substantial. The Std ratio (sometimes also called the noise-to-signal ratio) is defined as the ratio of the standard deviation of revisions and the standard deviation of final-release data (Orphanides and van Norden 2002). As the Std ratios given in Table 1 reveal, the standard deviations of revisions are at least about one-third as large as the standard deviation of the final-release data. In some cases, the standard deviation of revisions even exceeds the standard deviation of the final-release data. Furthermore, the minimum and maximum values of revisions reveal that, in some periods of time, revisions of our real-time macroeconomic data can be quite large. This implies that an investor who must use first releases of our macroeconomic data to forecast stock returns uses highly inaccurate macroeconomic data. This warrants a closer study of the implications of using real-time macroeconomic data for both forecasting stock returns in real time and for the performance of investment strategies in real time. Finally, the persistence of revisions as measured by their coefficient of first-order autocorrelation suggests that there might be some systematic information in revisions.

Table 1 — Summary statistics of revisions of real-time macroeconomic data

Summary statistics	Mean	Std Ratio	Mini-mum	Maxi-mum	Persis-tence
			Industrial production		
Revision after one month	0.16	0.78	-2.13	2.43	-0.26
Revision after two months	0.11	0.77	-2.02	2.12	-0.23
Revision after six months	0.18	0.80	-2.78	2.22	-0.20
Revision after one year	0.11	0.96	-2.78	3.48	-0.08
Revision compared with final release	0.14	1.01	-3.61	3.37	-0.06
			Orders inflow		
Revision after one month	0.07	0.49	-3.33	8.50	-0.11
Revision after two months	0.15	0.61	-3.43	8.50	0.29
Revision after six months	0.10	0.57	-3.54	8.29	0.05
Revision after one year	-0.04	0.75	-4.95	7.55	0.03
Revision compared with final release	-0.01	0.88	-6.87	8.95	-0.03
			Orders inflow, domestic		
Revision after one month	0.04	0.33	-2.05	3.69	-0.14
Revision after two months	-0.00	0.39	-3.71	3.48	-0.15
Revision after six months	0.04	0.46	-3.17	3.58	-0.11
Revision after one year	0.00	0.74	-5.73	7.67	-0.03
Revision compared with final release	-0.07	1.08	-7.12	12.91	0.02
			Orders inflow, foreign		
Revision after one month	0.05	0.24	-3.15	2.73	-0.18
Revision after two months	0.07	0.27	-3.15	2.73	-0.13
Revision after six months	0.04	0.32	-3.16	3.12	-0.14
Revision after one year	-0.05	0.46	-3.84	4.62	0.06
Revision compared with final release	0.06	0.82	-6.73	19.41	0.04
			CPI		
Revision after one month	-0.00	0.26	-0.24	0.10	0.06
Revision after two months	0.00	0.35	-0.29	0.19	-0.37
Revision after six months	-0.00	0.46	-0.30	0.19	-0.36
Revision after one year	0.01	0.65	-0.34	0.29	-0.32
Revision compared with final release	-0.01	0.81	-0.48	0.24	-0.09
			Output gap		
Revision after one month	0.14	0.69	-2.10	2.47	-0.17
Revision after two months	0.10	0.71	-1.91	1.96	-0.23
Revision after six months	0.15	0.72	-2.17	2.13	-0.19
Revision after one year	0.09	0.87	-2.46	3.23	-0.06
Revision compared with final release	0.13	0.90	-3.26	3.01	-0.07

Note: The Std Ratio is defined as the ratio of the standard deviation of revisions and the standard deviation of final-release data. Persistence is defined in terms of the coefficient of first-order autocorrelation of revisions.

Following Mankiw and Shapiro (1987) and Mankiw et al. (1984), we studied whether the real-time macroeconomic data are rational forecasts of the final-release data. To this end, we estimated by the ordinary least squares technique regressions of the following format:

$$I_t^{final} = \alpha + \beta I_t^{real-time} + \varepsilon_t \tag{11}$$

If forecasts are rational, the null hypothesis $H_0 : \alpha = 0 \wedge \beta = 1$ cannot be rejected. The estimation results clearly indicate that first releases of the data are not a rational forecast of final releases of the data (Table 2). Tests (*F*-tests) of rationality are rejected at all conventional levels of significance. One reason for this is that the first release of the data tends to systematically underestimate the final release of the data.

Table 2 — Mankiw regression (first release versus final release)

	Industrial production	Orders inflow	Orders inflow, domestic	Orders inflow, foreign	CPI inflation	Output gap
Constant	0.19	0.16	0.03	0.24	0.04	0.10
t-value	2.80	1.27	0.20	1.27	3.11	1.45
Slope coefficient	0.50	0.54	0.44	0.63	0.65	0.55
t-value	12.69	9.79	6.89	11.98	11.35	13.16
R^2	0.54	0.41	0.26	0.51	0.49	0.57
Test for rationality	85.08***	35.51***	39.40***	25.89***	19.58***	58.28***

Note: Tests for rationality are F-tests of the joint hypotheses that the intercept is zero and the slope coefficient is one. Asterisks *** denotes significance at the 1% level.

3.2 Other explanatory variables

In addition to real-time macroeconomic data, we considered a number of other variables to be potentially relevant for forecasting stock returns. Stock returns are defined as nominal excess returns on the DAX30 stock price index. We computed excess returns in two steps. In a first step, we computed the sum of the dividend yield and the first-difference in the natural logarithm of the DAX30 stock price index. In a second step, we subtracted from this sum the three-month Treasury bill rate. In order to select other explanatory variables, we studied the earlier literature on predictability of stock returns. We downloaded most of the data from Thomson Financial Datastream, an exception being data on the dividend yield which were kindly provided by the

Bundesbank. Our list of explanatory variables contains seven variables (abbreviations and Datastream codes are given in parentheses):

1. The relative three-month Treasury bill rate (RTB). As in Rapach et al. (2005), we computed RTB as the difference between the three-month Treasury bill rate (BDI60C..) and its 12-month backward-looking moving average.

2. The term spread (TSP). TSP is the difference between the long-term government bond yield (BDI61...) and the three-month Treasury bill rate. TSP has been considered by, for example, Chen et al. (1986), Campbell (1987), and Chen (1991) as a predictor of stock returns.

3. The annualized dividend yield on the DAX30 (DIV_YIELD). Shiller (1984), Fama and French (1988), and others have analyzed the forecasting ability of DIV_YIELD for stock returns.

4. The change in the natural logarithm of the spot price of oil (OIL; UKI76AAZA). The analysis of OIL as an important source of business-cycle fluctuations has a long tradition in the macroeconomics literature (Hamilton 1983; Hamilton and Herrara 2004). In the finance literature, Chen et al. (1986), and Pesaran and Timmermann (2000) have analyzed the forecasting ability of OIL for stock returns.

5. A January dummy (JAN). JAN plays an important role in the literature on financial market anomalies and seasonalities in stock returns. Profound surveys of this literature can be found in Thaler (1987) and Haugen and Lakonishok (1988).

6. A dummy variable (DMA200) that assumes the value one if the difference between the DAX30 (DAXINDZ) and its eight-month (~ approximately 200 trading days) backward-looking moving average is smaller than one percent, and zero otherwise. We considered DMA200 as a predictor for stock returns because simple moving-average-based trading strategies have been studied extensively in the literature on technical trading rules (Brock et al. 1992).

7. The IFO overall business climate indicator (IFO; WGIFOMXLE). Jacobs and Sturm (2004) have reported that IFO contains information with regard to revisions of the German production index. In consequence, it could have been valuable for investors who must rely on relatively inaccurate preliminary real-time macroeconomic data to include IFO in the information set they used to predict stock returns.

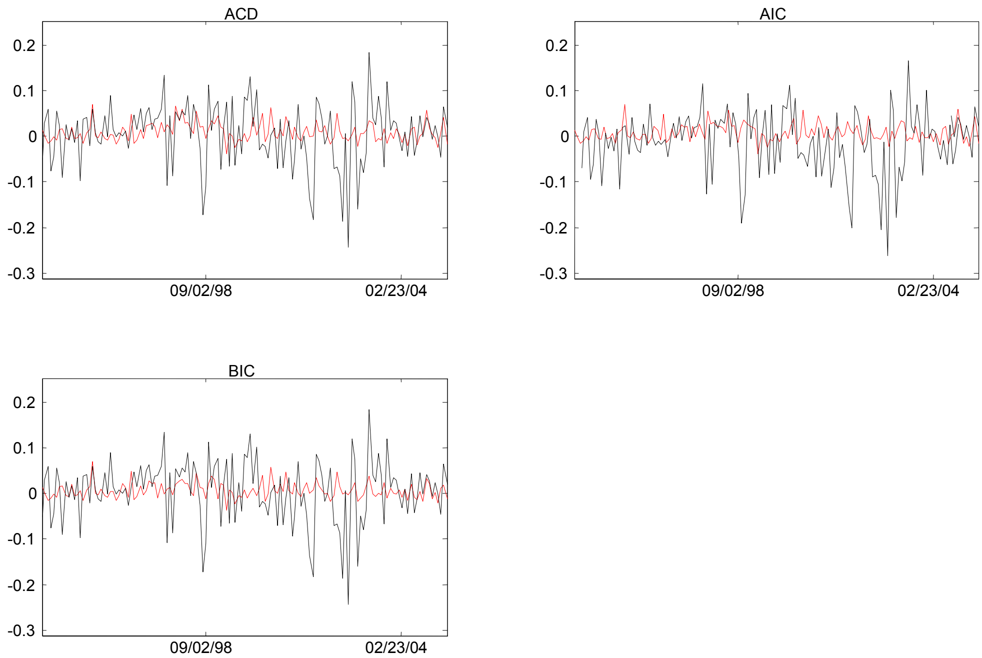
4. Results

We proceed in three steps. In a first step, we present results that summarize statistical measures of ex ante return predictability. In a second step, we present results that summarize how often both the real-time and final-release macroeconomic variables and the other explanatory variables are included in the optimal recursive excess return equations. In a third step, we report results for our economic measures of ex ante return predictability.

4.1 Statistical measures of ex ante predictability of stock returns

We use Figures 2 and 3 to give an account of the statistical properties of the recursive one-month-ahead forecasts of stock returns. In Figure 2, we compare actual returns with the one-month-ahead forecasts of stock returns under the different model selection criteria. Both actual and one-month-ahead forecasts of stock returns are quite volatile. As expected, the one-month-ahead forecasts of stock returns are much smoother than actual stock returns.

Figure 2 — Recursive stock-return forecasts and actual stock returns, 1994 – 2005

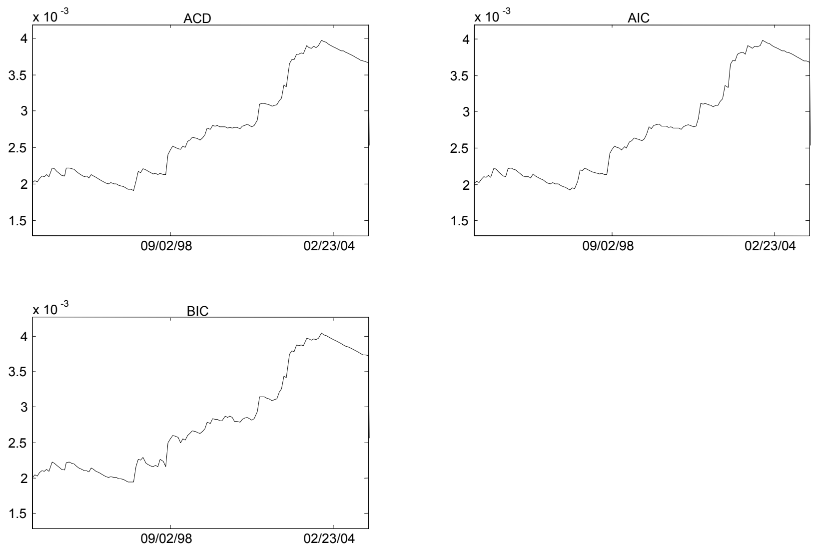


Note: The black lines show actual stock returns. The red lines show one-month-ahead forecasts of stock returns. The figure shows results for optimal forecasting models that use real-time macroeconomic data on month-to-month changes in DIPA and INF as candidates for forecasting stock returns. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

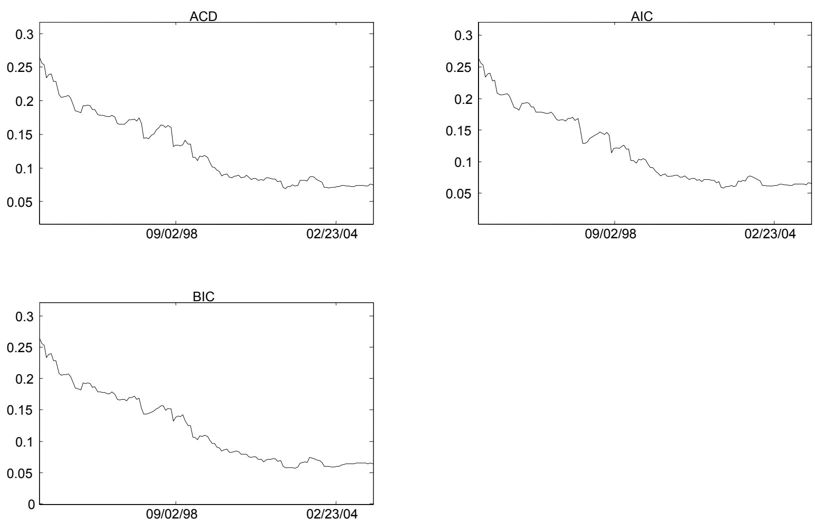
In Panel A of Figure 3, we plot the standard errors of the optimal recursive stock-return equations under the different model-selection criteria. The standard errors under the different model-selection criteria have similar patterns. Three important events are reflected in the time series of standard errors. First, the start of the substantial bull market in 1996/1997 that culminated in the “new economy” bubble led to a significant increase in standard errors. Second, the bursting of the “new economy” bubble in 2000 and the resulting large and lasting decline in stock prices resulted in a further significant increase in standard errors. Third, the terror attacks on New York that took place on September 11, 2001 led to the most pronounced and most rapid increase in standard errors in our sample. After 9/11, standard errors increased from approximately 0.003 to 0.004 in a very short period of time. The increase in standard errors is reflected in a decline in the fit of the recursive optimal stock-return equations under the different model-selection criteria.

Figure 3 — Fit of recursive stock-return equations, 1994 – 2005

PANEL A: Standard errors of recursive stock-return equations



PANEL B: Squared correlations between forecasts and actual values of stock returns



Note: This figure shows results for optimal forecasting models that use real-time macroeconomic data on month-to-month changes in DIPA and INF as candidates for forecasting stock returns. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

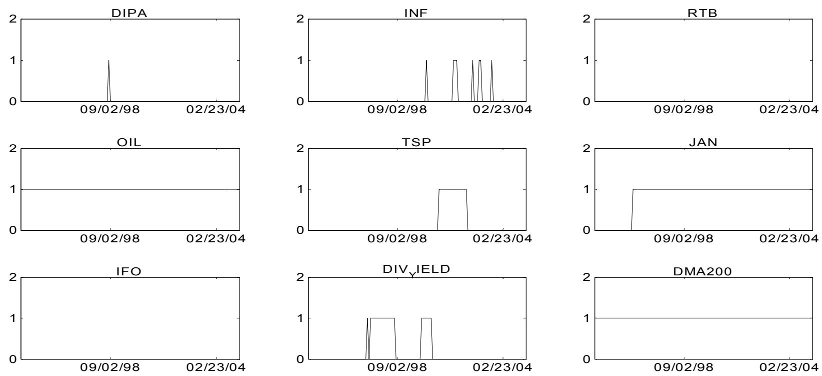
We plot the fit of the recursive optimal stock-return equations in Panel B of Figure 3. Following Pesaran and Timmermann (1995, 2000), we measured the fit of the recursive optimal stock-return equations by means of the squared coefficient of correlation between one-month-ahead forecasts of stock returns and actual stock returns. The time series of fits start at a relatively high level of between 0.25 and 0.3. This reflects the fact that we initialized the time series of squared coefficients of correlations by computing the squared coefficients of correlation between the in-sample forecasts of stock returns in the training period 5/1988-12/1993 and actual stock returns. As can be seen, when out-of-sample fits of the models are added to the time series of squared coefficients of correlations, the time series of fits of the models decrease to a level between 0.15 and 0.2. Finally, starting in 1997, the time series of fits of the models further decrease to a level between 0.05 and 0.1 as the standard errors of the recursive stock-return equations increase.

4.2 Inclusion of variables in recursive excess return equations

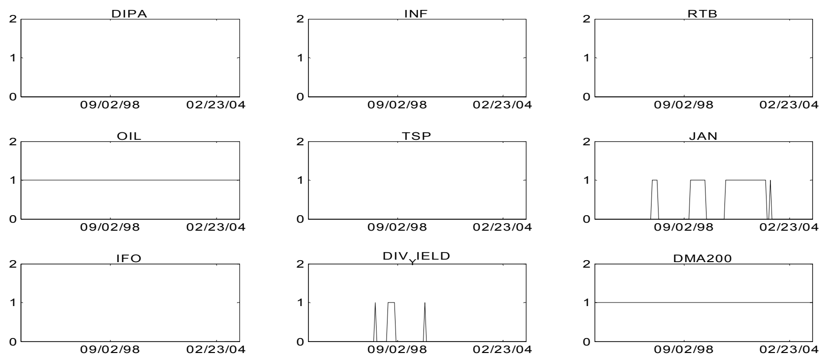
In order to illustrate our results, we defined dummy variables that assume the value one if a variable is included in the recursive stcok-return equation, and zero otherwise. In Figures 4–7, we plot these dummy variables for four different models. The models differ in two dimensions. The first dimension concerns real-time or final-release macroeconomic data, and the second dimension concerns the measure of real economic activity. As regards the first dimension, Figures 4 and 6 summarize results we obtained when we used real-time macroeconomic data, and Figures 5 and 7 summarize results we obtained when we used final-release macroeconomic data. As concerns the second dimension, Figures 4 and 5 summarize results for models that features month-to-month changes in industrial production, and Figures 6 and 7 summarize results for models that feature year-to-year changes in industrial production. Thus, the models in Figures 4 and 5 (6 and 7) are identical, except that the first was estimated using real-time data and the second was estimated using final-release data. In order to summarize in a compact way the contents of Figures 4–7, we report in Table 3 how often our variables are included under the different model-selection criteria in the optimal forecasting models.

Figure 4 — Inclusion of variables (DIPA; real time; month-to-month-changes, 1994 – 2005)

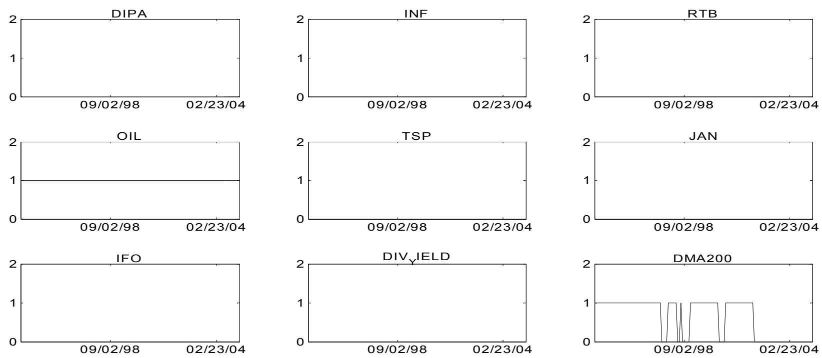
PANEL A: Inclusion of regressors under the ACD criterion



PANEL B: Inclusion of regressors under the AIC criterion



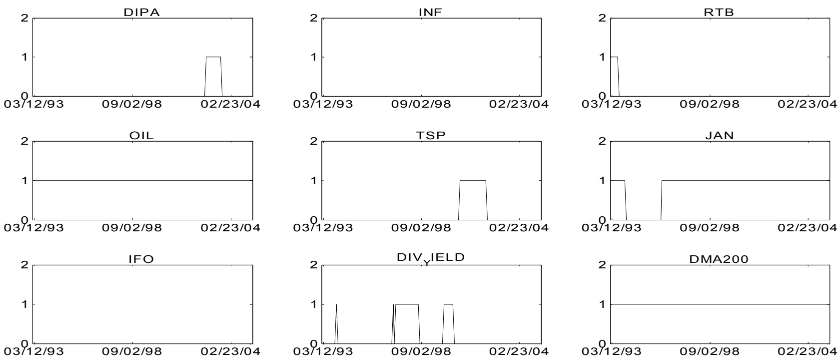
PANEL C: Inclusion of regressors under the BIC criterion



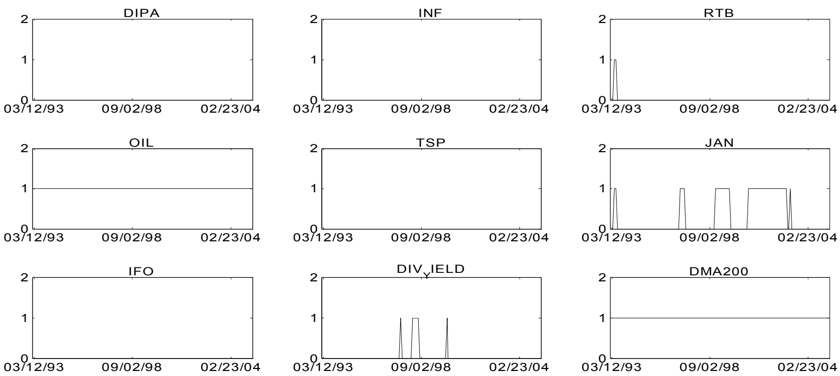
Note: The dummy variables shown in this figure are one when a variable is included in the optimal forecasting model, and zero otherwise. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

Figure 5 - Inclusion of variables (DIPA; final release; month-to-month-changes, 1994 – 2005)

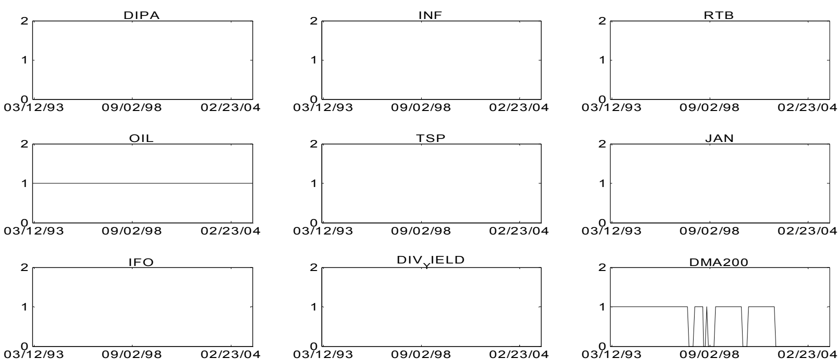
PANEL A: Inclusion of regressors under the ACD criterion



PANEL B: Inclusion of regressors under the AIC criterion



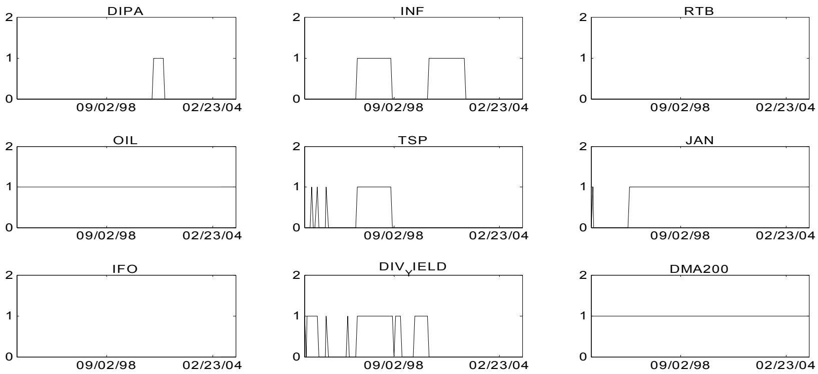
PANEL C: Inclusion of regressors under the BIC criterion



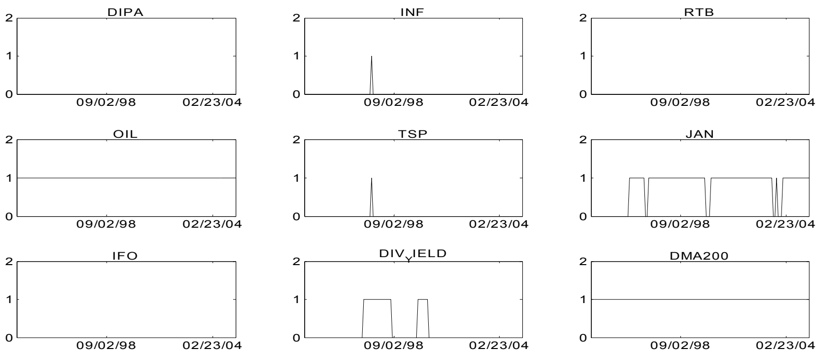
Note: The dummy variables shown in this figure are one when a variable is included in the optimal forecasting model, and zero otherwise. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

Figure 6 — Inclusion of variables (DIPA; real time; year-to-year changes, 1994 – 2005)

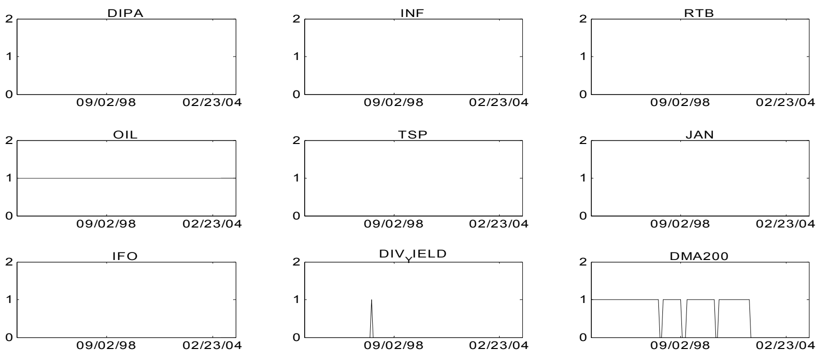
PANEL A: Inclusion of regressors under the ACD criterion



PANEL B: Inclusion of regressors under the AIC criterion



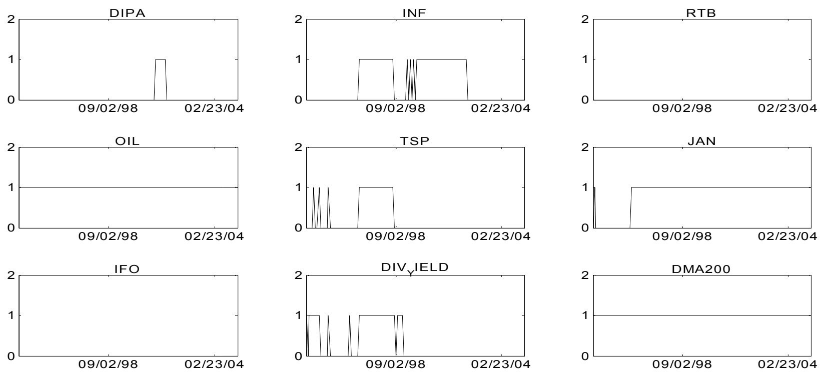
PANEL C: Inclusion of regressors under the BIC criterion



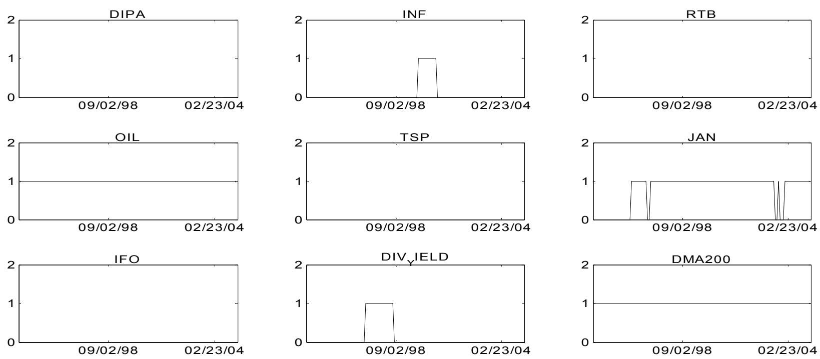
Note: The dummy variables shown in this figure are one when a variable is included in the optimal forecasting model, and zero otherwise. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

Figure 7 - Inclusion of variables (DIPA; final release; year-to- year changes, 1994 – 2005)

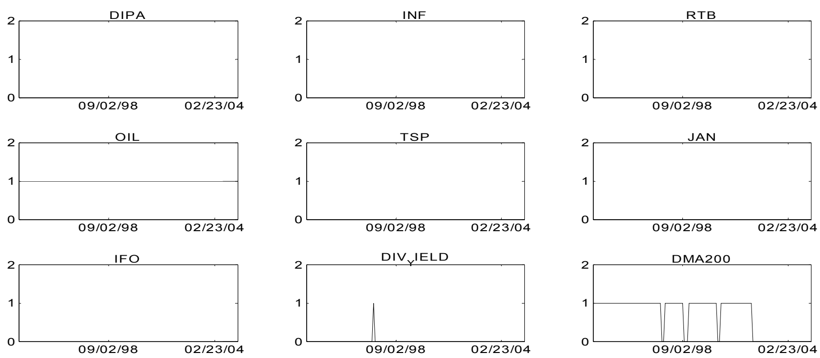
PANEL A: Inclusion of regressors under the ACD criterion



PANEL B: Inclusion of regressors under the AIC criterion



PANEL C: Inclusion of regressors under the BIC criterion



Note: The dummy variables shown in this figure are one when a variable is included in the optimal forecasting model, and zero otherwise. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

The general picture that emerges from Figures 4–7 is that irrespective of the model and the model-selection criterion considered the variables OIL and DMA200 are the most important predictors of one-month-ahead stock returns. All model-selection criteria select the variable OIL as a predictor of one-month-ahead stock returns over the entire sample period. The variable DMA200 is always included in the recursive stock-return equations under the ACD and AIC model-selection criteria. Thus, the optimal recursive forecasting model almost always features one "fundamental" factor (OIL) and one "technical" factor (DMA200). Other important predictors of one-month-ahead stock returns are JAN and DIV_YIELD although these variables are not always included in the optimal recursive forecasting model under the AIC and BIC model-selection criteria. Not surprisingly, the BIC model-selection criterion is more restrictive with regard to the inclusion of variables than the ACD and the AIC model-selection criteria are.

With regard to the macroeconomic variables, the results shown in Figures 4–7 are interesting. The overall picture that emerges from Figures 4–7 is that the differences between models based on real-time and final-release macroeconomic data are not very large. DIPA and INF are more frequently included in the optimal forecasting model when year-to-year changes of these variables are used than when month-to-month changes are used. When year-to-year changes are considered, DIPA is selected around 2000/2001 under the ACD criterion. INF is often selected as a regressor in the middle of the sample period. It is worth mentioning that we obtained results very similar to those reported in Figures 4–7 when we used other real-time macroeconomic variables (orders inflow, domestic orders inflow, and foreign orders inflow) as candidates for forecasting stock returns. The only difference is that the OUTPUT GAP is very often included in the selected forecasting model. Table 3 summarizes how often the various variables considered as candidates for forecasting stock returns are included in the optimal forecasting models under the different model-selection criteria.

Table 3 – Inclusion of variables in optimal forecasting models (in percent)

	Final-release data			Real-time data		
Industrial production (month-to-month changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
DIPA	8.03	0.00	0.00	0.73	0.00	0.00
INF	0.00	0.00	0.00	5.84	0.00	0.00
RTB	0.00	0.00	0.00	0.00	0.00	0.00
OIL	100.00	100.00	100.00	100.00	100.00	100.00
TSP	13.14	0.00	0.00	13.1	0.00	0.00
JAN	82.48	29.93	0.00	82.48	29.93	0.00
IFO	0.00	0.00	0.00	0.00	0.00	0.00
DIV_YIELD	17.52	5.11	0.00	17.52	5.11	0.00
DMA200	100.00	100.00	62.04	100.00	100.00	62.04
Industrial production (year-to-year changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
DIPA_12	5.11	0.00	0.00	5.11	0.00	0.00
INF	41.61	8.76	0.00	32.85	0.73	0.00
RTB	0.00	0.00	0.00	0.00	0.00	0.00
OIL	100.00	100.00	100.00	100.00	100.00	100.00
TSP	18.25	0.00	0.00	18.25	0.73	0.00
JAN	83.21	77.37	0.00	83.21	75.18	0.00
IFO	0.00	0.00	0.00	0.00	0.00	0.00
DIV_YIELD	27.01	13.14	0.73	33.58	18.25	0.73
DMA200	100.00	100.00	67.88	100.00	100.00	67.88
Output gap						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
GAP	98.54	78.10	1.46	94.89	53.28	0.00
INF	0.00	0.00	0.00	8.76	0.00	0.00
RTB	23.36	0.00	0.00	22.63	0.00	0.00
OIL	100.00	100.00	100.00	100.00	100.00	100.00
TSP	2.92	0.00	0.00	11.68	0.00	0.00
JAN	82.48	23.36	0.00	82.48	25.55	0.00
IFO	1.46	0.00	0.00	0.73	0.00	0.00
DIV_YIELD	5.11	2.92	0.00	8.03	5.11	0.00
DMA200	100.00	100.00	60.58	100.00	100.00	62.04

(to be continued)

(Table 3 continued)

Orders inflow (month-to-month changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
DAE	2.19	0.00	0.00	9.49	0.00	0.00
INF	0.00	0.00	0.00	5.84	0.00	0.00
RTB	0.00	0.00	0.00	0.00	0.00	0.00
OIL	100.00	100.00	100.00	100.00	100.00	100.00
TSP	13.14	0.00	0.00	13.87	0.00	0.00
JAN	82.48	29.93	0.00	82.48	29.93	0.00
IFO	0.00	0.00	0.00	0.00	0.00	0.00
DIV_YIELD	19.71	6.57	0.00	19.71	6.57	0.00
DMA200	100.00	100.00	62.04	100.00	100.00	62.04
Domestic orders inflow (month-to-month changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
DAE_IN	2.92	0.00	0.00	21.90	2.19	0.00
INF	0.00	0.00	0.00	5.84	0.00	0.00
RTB	0.00	0.00	0.00	0.00	0.00	0.00
OIL	100.00	100.00	100.00	100.00	100.00	100.00
TSP	12.41	0.00	0.00	13.87	0.00	0.00
JAN	82.48	29.93	0.00	82.48	29.93	0.00
IFO	0.00	0.00	0.00	0.00	0.00	0.00
DIV_YIELD	18.98	6.57	0.00	18.98	6.57	0.00
DMA200	100.00	100.00	62.04	100.00	100.00	62.04
Foreign orders inflow (month-to-month changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
DAE_OUT	0.00	0.00	0.00	0.00	0.00	0.00
INF	0.00	0.00	0.00	5.84	0.00	0.00
RTB	0.00	0.00	0.00	0.00	0.00	0.00
OIL	100.00	100.00	100.00	100.00	100.00	100.00
TSP	12.41	0.00	0.00	13.14	0.00	0.00
JAN	82.48	29.93	0.00	82.48	29.93	0.00
IFO	0.00	0.00	0.00	0.00	0.00	0.00
DIV_YIELD	18.98	6.57	0.00	18.98	6.57	0.00
DMA200	100.00	100.00	62.04	100.00	100.00	62.04

Note: For definitions of variables, see Section 3. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. DAE denotes the month-to-month change in the natural logarithm of orders inflow. DAE_IN denotes the month-to-month change in the natural logarithm of domestic orders inflow. DAE_OUT denotes the month-to-month change in the natural logarithm of foreign orders inflow.

It can also be seen that, in those cases in which macroeconomic variables are selected as regressors, there are in a number of cases differences between the models featuring real-time and final-release macroeconomic data. These differences concern not only the macroeconomic variables, but also the other regressors included in the optimal forecasting model. That is, whether real-time or final-release macroeconomic variables are used as predictors of stock returns can make a difference for the inclusion of the other regressors in the optimal forecasting model.

4.3 Economic measures of ex ante predictability of stock returns

Because statistical measures of forecasting ability may not be closely related to forecasts' profits (Leitch and Tanner 1991), it is important to study the implications of using real-time and final-release macroeconomic data for the performance of investment strategies. A further motivation for studying investment strategies is that Bossaerts and Hillion (1999) have shown that models selected based on information criteria might have poor out-of-sample forecasting power. In order to investigate the performance of investment strategies, we report in Tables 4–9 four performance measures for the portfolio-switching strategies that we described in Section 2.2. The performance measures are Sharpe's ratio, Jensen's α, Treynor's ratio, and the appraisal ratio. In all tables, we compare performance measures for models based on real-time macroeconomic data and final-release macroeconomic data. We report results for month-to-month changes in DIPA (Table 4), output gap (Table 5), year-to-year changes in DIPA (Table 6), month-to-month changes in orders inflow (Table 7), month-to-month changes in domestic orders inflow (Table 8), and month-to-month changes in foreign orders inflow (Table 9). Moreover, in Tables 4–9, we report results for zero, medium-sized, and high transaction costs. In order to calibrate transaction costs, we again followed Pesaran and Timmermann (1995). They assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 4 — Performance of portfolio-switching strategies (DIPA; month-to-month changes)

PANEL A: Switching strategies based on real-time macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0090	0.0498	0.2054	0.0067	0.0189	0.0174
AIC	0.0073	0.0492	0.1745	0.0051	0.0164	0.0132
BIC	0.0059	0.0492	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0064	0.0500	0.1530	0.0041	0.0141	0.0106
AIC	0.0043	0.0496	0.1140	0.0021	0.0107	0.0055
BIC	0.0027	0.0496	0.0807	0.0005	0.0074	0.0012
			High transaction costs			
ACD	0.0041	0.0502	0.1076	0.0018	0.0099	0.0047
AIC	0.0018	0.0501	0.0622	-0.0004	0.0059	-0.0011
BIC	-0.0001	0.0501	0.0259	-0.0023	0.0024	-0.0059

PANEL B: Switching strategies based on final-release macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0082	0.0519	0.1827	0.0058	0.0162	0.0151
AIC	0.0073	0.0492	0.1745	0.0051	0.0164	0.0132
BIC	0.0059	0.0492	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0055	0.0523	0.1306	0.0031	0.0116	0.0080
AIC	0.0043	0.0496	0.1140	0.0021	0.0107	0.0055
BIC	0.0027	0.0496	0.0807	0.0005	0.0074	0.0012
			High transaction costs			
ACD	0.0032	0.0527	0.0856	0.0007	0.0076	0.0018
AIC	0.0018	0.0501	0.0622	-0.0004	0.0059	-0.0011
BIC	-0.0001	0.0501	0.0259	-0.0023	0.0024	-0.0059

Note: In each period of time, the investor selects three optimal forecasting models according to the ACD, AIC, and BIC model-selection criteria. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 5 — Performance of portfolio-switching strategies (Output gap)

PANEL A: Switching strategies based on real-time macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0062	0.0535	0.1406	0.0037	0.0122	0.0096
AIC	0.0060	0.0527	0.1375	0.0035	0.0121	0.0090
BIC	0.0059	0.0527	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0035	0.0536	0.0901	0.0009	0.0078	0.0025
AIC	0.0032	0.0529	0.0852	0.0007	0.0075	0.0018
BIC	0.0027	0.0529	0.0807	0.0005	0.0074	0.0012
			High transaction costs			
ACD	0.0012	0.0538	0.0467	-0.0014	0.0041	-0.0036
AIC	0.0008	0.0532	0.0398	-0.0017	0.0035	-0.0045
BIC	-0.0001	0.0532	0.0259	-0.0023	0.0024	-0.0059

PANEL B: Switching strategies based on final-release macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0052	0.0518	0.1250	0.0028	0.0112	0.0071
AIC	0.0061	0.0527	0.1412	0.0037	0.0124	0.0095
BIC	0.0054	0.0527	0.1344	0.0032	0.0125	0.0081
			Medium-sized transaction costs			
ACD	0.0021	0.0519	0.0671	-0.0003	0.0060	-0.0006
AIC	0.0031	0.0529	0.0840	0.0006	0.0074	0.0016
BIC	0.0022	0.0529	0.0710	-0.0000	0.0066	-0.0000
			High transaction costs			
ACD	-0.0005	0.0522	0.0167	-0.0029	0.0015	-0.0073
AIC	0.0005	0.0533	0.0345	-0.0020	0.0031	-0.0052
BIC	-0.0006	0.0533	0.0159	-0.0028	0.0015	-0.0071

Note: In each period of time, the investor selects three optimal forecasting models according to the ACD, AIC, and BIC model-selection criteria. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 6 — Performance of portfolio-switching strategies (DIPA; year-to-year changes)

PANEL A: Switching strategies based on real-time macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0068	0.0517	0.1572	0.0044	0.0141	0.0115
AIC	0.0061	0.0498	0.1475	0.0038	0.0137	0.0098
BIC	0.0062	0.0498	0.1500	0.0040	0.0139	0.0101
			Medium-sized transaction costs			
ACD	0.0041	0.0521	0.1044	0.0017	0.0093	0.0044
AIC	0.0032	0.0502	0.0904	0.0010	0.0084	0.0025
BIC	0.0030	0.0502	0.0858	0.0007	0.0080	0.0018
			High transaction costs			
ACD	0.0018	0.0526	0.0593	-0.0007	0.0053	-0.0017
AIC	0.0008	0.0507	0.0423	-0.0015	0.0040	-0.0037
BIC	0.0002	0.0507	0.0304	-0.0021	0.0028	-0.0053

PANEL B: Switching strategies based on final-release macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0056	0.0514	0.1338	0.0032	0.0121	0.0083
AIC	0.0059	0.0506	0.1418	0.0036	0.0130	0.0092
BIC	0.0062	0.0506	0.1500	0.0040	0.0139	0.0101
			Medium-sized transaction costs			
ACD	0.0029	0.0518	0.0810	0.0005	0.0073	0.0012
AIC	0.0031	0.0510	0.0861	0.0008	0.0079	0.0019
BIC	0.0030	0.0510	0.0858	0.0007	0.0080	0.0018
			High transaction costs			
ACD	0.0005	0.0523	0.0359	-0.0019	0.0033	-0.0047
AIC	0.0006	0.0514	0.0389	-0.0017	0.0036	-0.0042
BIC	0.0002	0.0514	0.0304	-0.0021	0.0028	-0.0053

Note: In each period of time, the investor selects three optimal forecasting models according to the ACD, AIC, and BIC model-selection criteria. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 7 — Performance of portfolio-switching strategies (orders inflow; month-to-month changes)

PANEL A: Switching strategies based on real-time macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0084	0.0503	0.1927	0.0062	0.0176	0.0159
AIC	0.0077	0.0510	0.1750	0.0053	0.0158	0.0137
BIC	0.0059	0.0510	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0059	0.0504	0.1425	0.0036	0.0130	0.0093
AIC	0.0049	0.0514	0.1199	0.0025	0.0108	0.0064
BIC	0.0028	0.0514	0.0820	0.0005	0.0076	0.0014
			High transaction costs			
ACD	0.0037	0.0506	0.0990	0.0014	0.0091	0.0036
AIC	0.0024	0.0518	0.0728	0.0001	0.0066	0.0001
BIC	0.0001	0.0518	0.0287	-0.0022	0.0027	-0.0055

PANEL B: Switching strategies based on final-release macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0077	0.0524	0.1713	0.0052	0.0151	0.0137
AIC	0.0077	0.0510	0.1750	0.0053	0.0158	0.0137
BIC	0.0059	0.0510	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0051	0.0527	0.1213	0.0026	0.0107	0.0068
AIC	0.0049	0.0514	0.1199	0.0025	0.0108	0.0064
BIC	0.0028	0.0514	0.0820	0.0005	0.0076	0.0014
			High transaction costs			
ACD	0.0028	0.0531	0.0781	0.0003	0.0069	0.0008
AIC	0.0024	0.0518	0.0728	0.0001	0.0066	0.0001
BIC	0.0001	0.0518	0.0287	-0.0022	0.0027	-0.0055

Note: In each period of time, the investor selects three optimal forecasting models according to the ACD, AIC, and BIC model-selection criteria. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 8 — Performance of portfolio-switching strategies (domestic orders inflow; month-to-month changes)

PANEL A: Switching strategies based on real-time macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0057	0.0525	0.1331	0.0032	0.0118	0.0084
AIC	0.0065	0.0537	0.1456	0.0040	0.0126	0.0104
BIC	0.0059	0.0537	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0030	0.0525	0.0829	0.0006	0.0074	0.0015
AIC	0.0038	0.0539	0.0941	0.0012	0.0081	0.0030
BIC	0.0028	0.0539	0.0820	0.0005	0.0076	0.0014
			High transaction costs			
ACD	0.0007	0.0526	0.0387	-0.0018	0.0035	-0.0045
AIC	0.0013	0.0542	0.0495	-0.0013	0.0043	-0.0033
BIC	0.0001	0.0542	0.0287	-0.0022	0.0027	-0.0055

PANEL B: Switching strategies based on final-release macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0077	0.0524	0.1713	0.0052	0.0151	0.0137
AIC	0.0077	0.0510	0.1750	0.0053	0.0158	0.0137
BIC	0.0059	0.0510	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0051	0.0527	0.1213	0.0026	0.0107	0.0068
AIC	0.0049	0.0514	0.1199	0.0025	0.0108	0.0064
BIC	0.0028	0.0514	0.0820	0.0005	0.0076	0.0014
			High transaction costs			
ACD	0.0028	0.0531	0.0781	0.0003	0.0069	0.0008
AIC	0.0024	0.0518	0.0728	0.0001	0.0066	0.0001
BIC	0.0001	0.0518	0.0287	-0.0022	0.0027	-0.0055

Note: In each period of time, the investor selects three optimal forecasting models according to the ACD, AIC, and BIC model-selection criteria. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 9 — Performance of portfolio-switching strategies (foreign orders inflow; month-to-month changes)

PANEL A: Switching strategies based on real-time macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0085	0.0503	0.1932	0.0062	0.0176	0.0160
AIC	0.0077	0.0510	0.1750	0.0053	0.0158	0.0137
BIC	0.0059	0.0510	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0059	0.0504	0.1430	0.0036	0.0131	0.0093
AIC	0.0049	0.0514	0.1199	0.0025	0.0108	0.0064
BIC	0.0028	0.0514	0.0820	0.0005	0.0076	0.0014
			High transaction costs			
ACD	0.0037	0.0507	0.0995	0.0014	0.0091	0.0036
AIC	0.0024	0.0518	0.0728	0.0001	0.0066	0.0001
BIC	0.0001	0.0518	0.0287	-0.0022	0.0027	-0.0055

PANEL B: Switching strategies based on final-release macroeconomic data

	Mean	Standard deviation	Sharpe's ratio	Jensen's alpha	Treynor's ratio	Appraisal ratio
			Zero transaction costs			
ACD	0.0077	0.0524	0.1713	0.0052	0.0151	0.0137
AIC	0.0077	0.0510	0.1750	0.0053	0.0158	0.0137
BIC	0.0059	0.0510	0.1437	0.0037	0.0132	0.0094
			Medium-sized transaction costs			
ACD	0.0051	0.0527	0.1213	0.0026	0.0107	0.0068
AIC	0.0049	0.0514	0.1199	0.0025	0.0108	0.0064
BIC	0.0028	0.0514	0.0820	0.0005	0.0076	0.0014
			High transaction costs			
ACD	0.0028	0.0531	0.0781	0.0003	0.0069	0.0008
AIC	0.0024	0.0518	0.0728	0.0001	0.0066	0.0001
BIC	0.0001	0.0518	0.0287	-0.0022	0.0027	-0.0055

Note: In each period of time, the investor selects three optimal forecasting models according to the ACD, AIC, and BIC model-selection criteria. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

The general picture that emerges is that the performance of portfolio-switching strategies based on real-time macroeconomic data is slightly better than the performance of portfolio-switching strategies based on final-release macroeconomic data. Thus, an investor who only had access to preliminary real-time macroeconomic data would have done not worse than an investor who had access to potentially less noisy final-release macroeconomic data. The greatest differences in the performance of portfolio-switching strategies result when the ACD criterion is used for forecasting one-month-ahead stock returns. The differences in the performance of portfolio-switching strategies result because, when the ACD model-selection criterion is used, macroeconomic variables are included relatively often in the optimal forecasting model. It is also interesting to note that, when real-time macroeconomic data are considered as a candidate for forecasting one-month-ahead stock returns, portfolio-switching strategies based on DIPA, orders inflow, or foreign orders inflow perform better than portfolio-switching strategies based on domestic orders inflow, year-to-year changes in DIPA, or the OUTPUT GAP. Thus, in real time, it is important for an investor to know which real-time variable to use for predicting stock returns.

The results summarized in Table 4–9 suggest that portfolio-switching strategies based on real-time macroeconomic data tend to perform better than those based on final-release macroeconomic data. The key question is whether the differences in performances are significant. In order to answer this question, we applied the nonparametric test of market-timing ability developed by Pesaran and Timmermann (1992). This test renders it possible to study whether the optimal forecasting models have significant power to forecast the direction of change in stock returns. If the differences in performances are significant then using real-time rather than final-release macroeconomic data should significantly improve an investor's market-timing ability. The general picture emerging from the test results is that using real-time macroeconomic data does not significantly affect an investor's market-timing ability (Table 10).

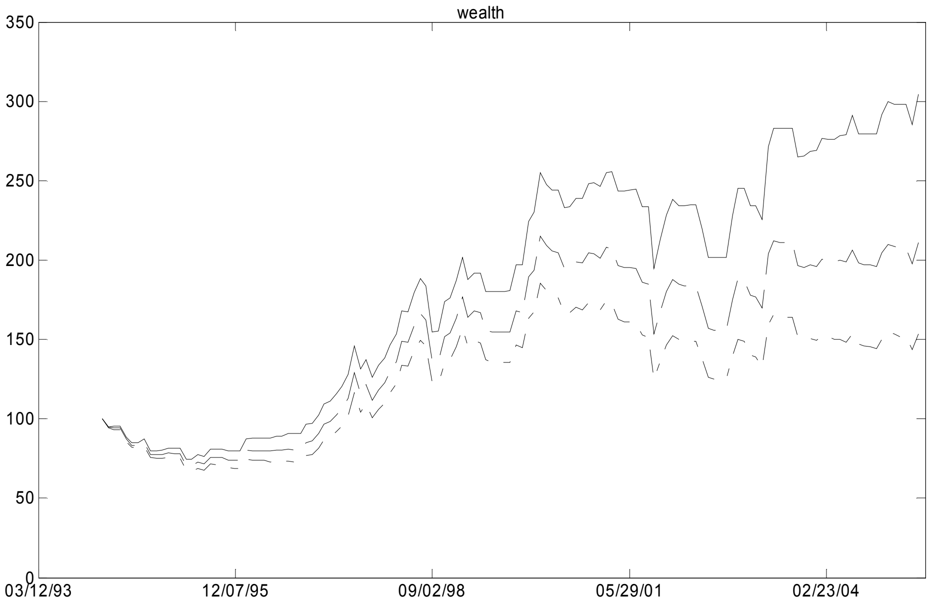
Table 10 — Nonparametric tests of market timing

	DIPA	OUTPUT GAP	DAE	DIPA_12	DAE_ IN	DAE_ OUT
			Real-time data			
ACD	-0.04	0.64	-0.26	1.30	-0.32	0.11
AIC	0.34	0.02	0.28	1.30	0.22	0.28
BIC	0.19	0.19	0.04	-0.05	0.04	0.04
			Final-release data			
ACD	0.32	0.48	0.47	1.30	0.47	0.47
AIC	0.34	0.28	0.28	1.25	0.28	0.28
BIC	0.19	0.39	0.04	-0.05	0.04	0.04

Note: In this table, we report results of nonparametric tests for market timing developed by Pesaran and Timmermann (1992). The Pesaran-Timmermann test has asymptotically a standard normal distribution. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion. DAE denotes the month-to-month change in the natural logarithm of orders inflow. DAE_IN denotes the month-to-month change in the natural logarithm of domestic orders inflow. DAE_OUT denotes the month-to-month change in the natural logarithm of foreign orders inflow. DIPA_12 denotes the year-to-year change in the natural logarithm of industrial production.

As one would have expected, higher transaction costs have an important effect on the performance of the portfolio-switching strategies. We illustrate the role played by transaction costs in Figure 8. In this figure, we plot an investor's wealth for a portfolio-switching strategy based on the ACD model-selection criterion and real-time macroeconomic data (INF and the year-to-year change in DIPA). In order to compute this figure, we assumed that the investor starts with a financial wealth of 100 monetary units. The figure illustrates that with zero (medium-sized, high) transaction costs, the financial wealth at the end of the sample period that would have been generated upon following a portfolio-switching strategy would have been approximately 300 (210, 150) monetary units. Moreover, the figure illustrates that 9/11 had a very large negative effect on an investor's wealth.

Figure 8 — The effect of transaction costs on wealth, 1994 – 2005



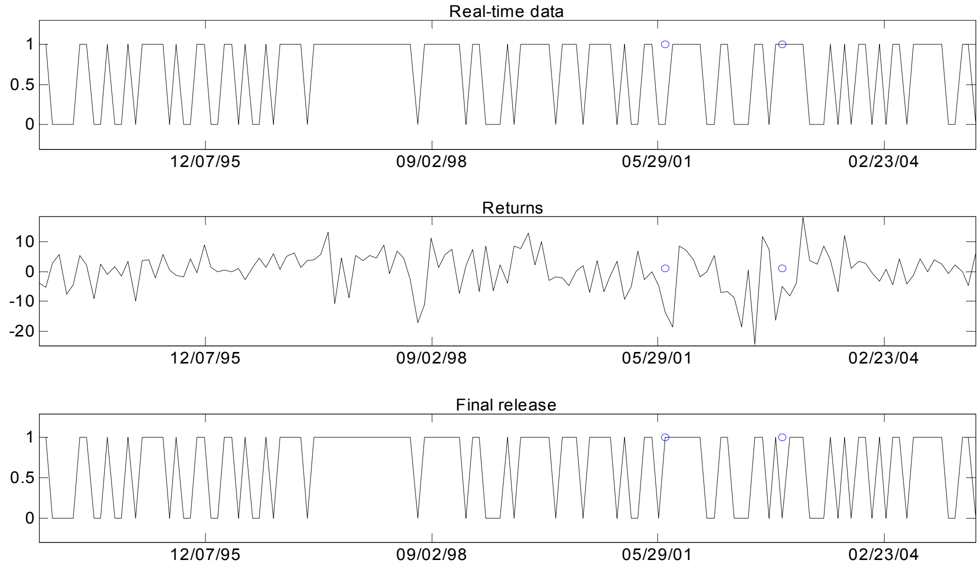
Note: The figure shows investor's wealth for optimal forecasting models that use real-time macroeconomic data on year-to-year changes in DIPA and INF as candidates for forecasting stock returns under the ACD model-selection criterion. ACD denotes the Adjusted Coefficient of Determination. The solid line shows an investor's wealth for the case of zero transaction costs. Dashed lines show an investor's wealth for the case of medium-sized and high transaction costs. Initial wealth is 100.

Figure 9 illustrates the differences between portfolio-switching strategies based on real-time versus final-release macroeconomic data (Panel A) and differences between portfolio-switching strategies based on different real-time macroeconomic data (Panel B). The portfolio-switching strategies plotted in Figure 9 were derived by applying the ACD model-selection criterion to a model that features DIPA and the OUTPUT GAP as candidates for forecasting one-month-ahead stock returns. The circles shown in the figure denote months when portfolio-switching strategies differed. Thus, when a circle appears, one portfolio-switching strategy implied an investment in stocks and the other portfolio-switching strategies implied an investment in bonds. An investment in stocks is denoted by a one and an investment in bonds is denoted by a zero.

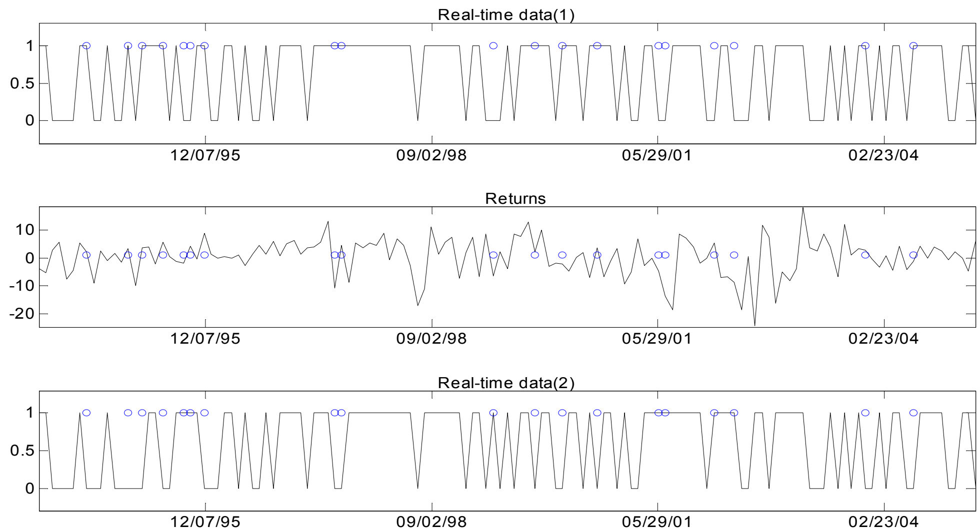
Panel A of Figure 9 reveals that portfolio-switching strategies based on real-time macroeconomic data in general closely resemble strategies based on final-release macroeconomic data. When changes in DIPA are used as a candidate for forecasting one-month-ahead stock returns, only two circles appear. When the OUTPUT GAP is used, a few more circles appear (not shown in Figure 9). We deem this to be an important result. From this result it is possible to conclude, for example, that if economists want to use German macroeconomic data to test intertemporal asset-pricing models, it does not make a great difference whether they use real-time or final-release macroeconomic data. Of course, this conclusion should not be generalized. For example, Guo (2003), using data for the United States, has shown that tests of consumption-based asset pricing models may be sensitive to whether a researcher uses real-time or final-release macroeconomic data to conduct such tests. Panel B of Figure 9 reveals that if attention is focused exclusively on real-time macroeconomic data, as an investor would do in real time, the choice of real-time macroeconomic data can be important. In Panel B, 19 circles appear. This indicates that it makes a great difference, for an investor in real time, whether a portfolio-switching strategy is based on month-to-month changes in DIPA or on the OUTPUT GAP.

Figure 9 — Differences between portfolio-switching strategies, 1994– 2005

PANEL A: DIPA, real-time vs. final-release data; ACD-criterion



PANEL B: DIPA, real-time (1) vs. OUTPUT GAP, real-time (2); ACD criterion



Note: The dummy variables shown in this figure are one for periods of investments in stocks, and zero otherwise. Circles indicate that one portfolio-switching strategy implied an investment in stocks while the other implied an investment in bonds, and vice versa. ACD denotes the Adjusted Coefficient of Determination.

5. Conclusions

In recent years, using real-time macroeconomic data has yielded interesting and important new insights for empirical macroeconomic modeling. As regards empirical modeling in finance, however, empirical research based on real-time macroeconomic data is still in its infancies. Very little research has been done to study the implications of using real-time rather than revised macroeconomic data for empirical tests of capital-market theories and asset-pricing theories. In addition, empirical research so far is been done only for the United States.

We have used a new dataset of German real-time macroeconomic data to analyze empirically the ex ante predictability of stock returns. The three main results of our empirical analysis are the following. First, stock-return predictability based on real-time macroeconomic data is comparable to predictability based on final-release macroeconomic data. Second, the performance of portfolio-switching strategies based on preliminary real-time macroeconomic data is comparable to the performance of a strategy based on final-release macroeconomic data. Third, because an investor always must use real-time macroeconomic data for forecasting stock returns, they should take into account that the specific choice of real-time macroeconomic data used for forecasting purposes can have a relatively large impact on the performances of portfolio-switching strategies.

A natural question that arises concerns the robustness of our results. We have reported results for German data only, and the sample period that we studied covered only 11 years of monthly data. For these reasons, we performed robustness checks based on U.S. real-time macroeconomic data. (The results are not reported, but are available upon request.) To this end., we analyzed data for the period 1985–2005. In addition, we used the fact that both monthly and quarterly data are available for the U.S., which implies that ex ante predictability of stock returns can be studied at different data frequencies. The U.S. data are publicly available on the internet page of the Federal Reserve Bank of Philadelphia. A detailed description of the U.S. real-time macroeconomic data is given in Croushore and Stark (2001). As in the case of German real-time macroeconomic data, we found that differences between ex ante predictability of stock returns based on real-time macroeconomic data and ex ante predictability of stock returns based on final-release macroeconomic are small. Furthermore, we found only relatively small differences between the performances of portfolio-switching strategies based on real-time and final-release macroeconomic data. Thus, our results for the

U.S. data corroborate our results for German data. These results suggest that our three main results are robust.

Because real-time macroeconomic data have only been used so far in a few studies in empirical finance, a lot of work needs to be done in future research. For example, we have been concerned exclusively with the implications of using real-time macroeconomic data for ex ante predictability of stock returns. A question of similar importance is whether the volatility of stock returns can be forecasted by using real-time macroeconomic data. Research on the potential macroeconomic sources of the volatility of stock returns has a long tradition in the finance literature (Schwert 1989). It would be interesting to analyze whether the results on the macroeconomic sources of the volatility of stock returns that have been documented in the earlier literature change when real-time rather than final-release macroeconomic data are used to study the sources of volatility. For performing such analyses, it would be natural to use the German real-time macroeconomic data that we used in this paper. This would certainly yield new and interesting insights into the macroeconomic sources of the volatility of stock returns, and it would minimize the effects of data snooping because a dataset for a country other than the U.S. would be studied. We leave this analysis for future research.

References

Akaike H. Information Theory and an Extension of the Maximum Likelihood Principle. In: Petrov B, Csake F (Eds.), Second International Symposium on Information Theory. Budapest: Akademia Kiado; 1973.

Amemyia T. Advanced Econometrics. Harvard University Press. Cambridge: Mass; 1985.

Andersen TG, Bollerslev T, Diebold FX, Vega C. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. American Economic Review 2003; 93; 38-62.

Bossaerts P, Hillion P. Implementing Statistical Criteria to Select Return Forecasting Models: What Do We Learn?. Review of Financial Studies 1999; 12; 405-428.

Brock W, Lakonishok J, LeBaron B. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. The Journal of Finance 1992; 47; 1731-1764.

Campbell JY. Stock Returns and the Term Structure. Journal of Financial Economics 1987; 18; 373-399.

Chen NF. Financial Investment Opportunities and the Macroeconomy. Journal of Finance 1991; 46; 529-554.

Chen NF, Roll R, Ross SA. Economic Forces and the Stock Market. Journal of Business 1986; 59; 383-403.

Christoffersen P, Ghysels E, Swanson NR. Let's Get "Real" about Using Economic Data. Journal of Empirical Finance 2002; 9; 343-360.

Clark TE, Kozicki S. Estimating Equilibrium Real Interest Rates in Real-Time. Bundesbank Discussion Paper No. 32/2004. Frankfurt am Main 2004.

Cooper M, Gutierrez RC Jr, Marcum B. On the Predictability of Stock Returns in Real Time. Journal of Business 2005; 78; 111-130.

Croushore D. A Real Time-Data Set for Macroeconomists. Journal of Econometrics 2001; 105; 111-130.

Croushore D, Stark T. A Real-Time Data Set for Macroeconomists: Does the Data Vintage Matter? Review of Economics and Statistics 2003; 85; 605-617.

Fama EF. Stock Returns, Real Activity, Inflation and Money. American Economic Review 1981; 71; 545-565.

Fama EF, French KR. Dividend Yields and Expected Stock Returns. Journal of Financial Economics 1988; 22; 3-25.

Flannery MJ, Protopapadakis AA. Macroeconomic Factors Do Influence Aggregate Stock Returns. Review of Financial Studies 2002; 15; 751-782.

Gerberding C, Kaatz M, Seitz F, Worms A. A Real-Time Data Set for German Macroeconomic Variables. Journal of Applied Social Science Studies 2005; 125; 337-346.

Goyal A, Welch I. Predicting the Equity Premium with Dividend Ratios. Management Science 2003; 49; 639-654.

Guo H. On the Real-Time Forecasting Ability of the Consumption-Wealth Ratio. Discussion Paper No. 2003-007B. The Federal Reserve Bank of St. Louis; 2003.

Hamilton JD. Oil and the Macroeconomy Since World War II. The Journal of Political Economy 1983; 91; 228-248.

Hamilton JD. Time Series Analysis. Princeton University Press. Princeton, New Jersey; 1994.

Hamilton JD, Herrara AM. Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy. Journal of Money, Credit, and Banking 2004; 36; 265-286.

Haugen R, Lakonishok J. The Incredible January Effect: The Stock Market's Unsolved Mystery. Dow Jones Irwin Publishers. Homewood: IL;1988.

Hodrick RJ, Prescott EC. Postwar U.S. Business Cycles: An Empirical Investigation. Journal of Money, Credit, and Banking 1997; 29; 1-16

Jacobs JPAM, Sturm JE. Do ifo Iindicators Help Explain Revisions in German Industrial Production?, Munich, CESifo Working Paper 1205; 2004.

Jensen MC. The Performance of Mutual Funds in the Period 1954-1964. Journal of Finance 1968; 23; 389-416.

Jung S. Revisionsanalyse des deutschen Produktionsindex. Wirtschaft und Statistik 9/2003; 819-826.

Leitch G, Tanner JE. Economic Forecast Evaluation: Profits Versus the Conventional Error Measures. American Economic Review 1991; 81; 580-590.

Lo A, MacKinlay C. Data-Snooping Biases in Tests of Financial Asset Pricing Models. Review of Financial Studies 1990; 3; 431-467.

Mankiw NG, Shapiro MD. News or Noise? An Analysis of GNP Revisions. NBER Working Paper, No. 1339 Cambridge: Mass; 1987.

Mankiw G, Runkle D, Shapiro M. Are Preliminary Announcements of the Money Stock Rational Forecasts? Journal of Monetary Economics 1984; 14; 15-27.

McQueen G, Roley VV. Stock Prices, News, and Business Conditions. The Review of Financial Studies 1993; 6; 683-707.

Orphanides A, van Norden S. The Unreliability of Output Gap Estimates in Real Time. Review of Economics and Statistics 2002; 84; 569-583.

Orphanides A, Williams JC. Robust Monetary Policy Rules with Unknown Natural Rates. Brookings Paper on Economic Activity 2002; 6; 3-146

Pesaran MH, Timmermann A. A Simple Nonparametric Test of Predictive Performance. Journal of Business and Economic Statistics 1992; 10; 461-465

Pesaran MH, Timmermann A. The Robustness and Economic Significance of Predictability of Stock Returns. Journal of Finance 1995; 50; 1201-1228.

Pesaran MH, Timmermann A. A Recursive Modelling Approach to Predicting UK Stock Returns. Economic Journal 2000; 110; 159-191.

Rapach DE, Wohar ME, Rangvid J. Macro Variables and International Stock Return Predictability. International Journal of Forecasting 2005; 21; 137-166.

Schwarz G. Estimating the Dimension of a Model. Annals of Statistics 1978; 6; 416-464.

Schwert WG. Why Does Stock Market Volatility Change Over Time? Journal of Finance 1989; 44; 1115-1153.

Sharpe WF. Mutual Fund Performance. Journal of Business 1966; 39; 119-138.

Shiller RJ. Stock Prices and Social Dynamics. Brookings Papers on Economic Activity 1984; 2; 457–498.

Thaler R. The January Effect. Journal of Economic Perspective 1987; 1; 197-201.

Treynor JL. How to Rate Management of Investment Funds. Harvard Business Review 1965; 43; 63-75.

Treynor JL, Black F. How to Use Security Analysis to Improve Portfolio Selection. Journal of Business 1973; 46; 66-86.

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