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Forecasting stock market volatility with macroeconomic variables in real time

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Abstract:

We compared forecasts of stock market volatility based on real-time and revised macroeconomic data. To this end, we used a new dataset on monthly real-time macroeconomic variables for Germany. The dataset covers the period 1994-2005. We used a statistical, a utility-based, and an options-based criterion to evaluate volatility forecasts. Our main result is that the statistical and economic value of volatility forecasts based on real-time data is comparable to the value of forecasts based on revised macroeconomic data.

Keywords: Forecasting stock market volatility, Real-time macroeconomic data, Evaluation of forecasting accuracy

JEL-Classification: C53, E44, G11

Non Technical Summary

Studying the question of whether macroeconomic variables that capture business cycle fluctuations help to forecast stock market volatility is important for investors, macroeconomists, and policy makers. Finding an answer to this question may help investors to refine theories of derivatives pricing, to compute more exact solutions to problems of optimal portfolio selection, and to efficiently monitor and manage financial risks. Macroeconomists and policy makers can benefit from finding an answer to this question because it may help them to develop a better understanding of potential macroeconomic determinants of systematic financial-sector risk.

We studied whether it is important to account for the fact that macroeconomic data are subject to substantial historical revisions when one studies the link between macroeconomic variables and stock market volatility. Empirical research so far has not shed light on this question because, to the best of our knowledge, only revised macroeconomic data have been used to analyze macroeconomic determinants of stock market volatility.

In order to close this gap in the literature, our research contributes to the literature on the macroeconomic determinants of stock market volatility in three dimensions. First, by using a new monthly real-time macroeconomic data set for Germany that covers the period 1994-2005, we accounted for the fact that, in real time, one can only make inferences about the links between macroeconomic variables and stock market volatility by using the then available preliminary real-time macroeconomic data. Second, we applied a recursive modeling approach to analyze whether macroeconomic data help to forecast stock market volatility in real time. Third, we used three different criteria to evaluate the accuracy of forecasts of stock market volatility based on real-time macroeconomic data: a statistical criterion, a utility based criterion, and an option-based criterion.

Our main results suggests that, according to our forecast-evaluation criteria, the value of volatility forecasts based on real-time macroeconomic data is roughly comparable to the value of volatility forecasts based on revised macroeconomic data.

Nicht technische Zusammenfassung

Die Frage, ob makroökonomische Variablen hilfreich für die Prognose der Volatilität von Aktienmärkten sind, ist wichtig sowohl für Investoren einerseits als auch für Makroökonomen und Wirtschaftspolitiker andererseits. Investoren können auf Basis entsprechender Untersuchungen die Methoden der Preisfindung von Derivaten verbessern, optimale Portfolios exakter berechnen und finanzielle Risiken genauer einschätzen. Makroökonomen und Wirtschaftspolitiker sind aufgrund einschlägiger Erkenntnisse besser in der Lage, die makroökonomischen Bestimmungsgründe systematischer Risiken im Finanzsektor präziser zu analysieren.

Das vorliegende Papier analysiert, ob es bei der Untersuchung eines möglichen Zusammenhangs zwischen makroökonomischen Variablen und der Volatilität von Aktienmärkten wichtig ist, die Tatsache zu berücksichtigen, dass makroökonomische Daten in erheblicher Weise nachträglich revidiert werden. Bisherige Untersuchungen der makroökonomischen Determinanten der Volatilität von Aktienmärkten haben diesen Aspekt unseres Wissens bisher nicht berücksichtigt, da sie ausschließlich auf Basis von bereits revidierten Daten durchgeführt wurden.

Die Untersuchung geht in dreifacher Hinsicht über frühere Studien hinaus. Zum ersten verwenden wir einen neuen, monatlichen Echtzeit-Datensatz, der für den Zeitraum von 1994 bis 2005 für jeden Monat den damals jeweils vorliegenden Datenstand dokumentiert. Auf diese Weise berücksichtigen wir, dass in Echtzeit nur die vorläufigen, nicht revidierten Daten herangezogen werden können, um den Zusammenhang zwischen der Volatilität von Aktienmärkten und ihren makroökonomischen Bestimmungsgründen zu untersuchen. Zum zweiten nutzen wir einen rekursiven Ansatz, um zu prüfen, ob makroökonomische Daten zur Vorhersage der Volatilität von Aktienmärkten geeignet sind. Zum dritten verwenden wir drei Kriterien zur Beurteilung der Genauigkeit der Prognosen: ein statistisches, ein nutzentheoretisches und ein optionsbasiertes Kriterium.

Unsere Ergebnisse legen nahe, dass die Genauigkeit von Volatilitäts-Prognosen auf Basis von Echtzeitdaten in etwa jener von Vorhersagen aufgrund von revidierten Daten entspricht.

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Forecasting Stock Market Volatility with Macroeconomic Variables in Real Time [*]

1. Introduction

Macroeconomic variables play a key role in asset pricing theories. For this reason, many authors have empirically studied the link between macroeconomic variables and stock market volatility. A common finding in these studies is that stock market volatility tends to rise in periods of business cycle downturns (Errunza and Hogan 1998, Schwert 1989, Hamilton and Lin 1996). For investors, this finding raises the question of whether macroeconomic variables that capture business cycle fluctuations help to forecast stock market volatility. Finding an answer to this question may help investors to refine theories of derivatives pricing, to compute more exact solutions to problems of optimal portfolio selection, and to efficiently monitor and manage financial risks. Finding an answer to this question may also be useful for macroeconomists, politicians, and central bankers to develop a better understanding of potential macroeconomic determinants of systematic financial-sector risk.

For an investor who seeks to forecast stock market volatility based on macroeconomic variables, a key question is whether it is important to account for the fact that macroeconomic data are subject to substantial historical revisions. To the best of our knowledge, empirical evidence that may help an investor to answer this question is not yet available. In the earlier empirical literature, only revised macroeconomic data have been used to analyze macroeconomic determinants of stock market volatility. In fact, only a few studies are available that report evidence of the implications of using real-time macroeconomic data for research in empirical finance (see, for example,

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Christoffersen et al. 2002, Andersen et al. 2003, Clark and Kozicki 2004, and Guo 2003). By contrast, the analysis of real-time macroeconomic data has a long tradition in research on macroeconomics and business-cycle fluctuations (Croushore 2001, Croushore and Stark 2003, Orphanides and van Norden 2002, Orphanides and Williams 2002, and Gerberding et al. 2005, to name just a few).

Our contribution to the literature on the macroeconomic determinants of stock market volatility is threefold. First, by using a new monthly real-time macroeconomic data set for Germany that covers the period 1994-2005, we accounted for the fact that, in real time, an investor can only make inferences about the macroeconomic determinants of stock market volatility by fully exploiting the then available information set. This information set only contains the then latest release of preliminary real-time macroeconomic data, but not later releases of revised macroeconomic data. We also accounted for the fact that, in real time, an investor must take into account that preliminary real-time macroeconomic data may only give a noisy account of business cycle fluctuations. Therefore, we analyzed three different potential macroeconomic determinants of stock market volatility: the growth rate of industrial production, orders inflow, and a measure of the output gap. In the earlier literature, empirical studies of the macroeconomic determinants of stock market volatility have focused on the growth rate of industrial production as a measure of business cycle fluctuations (Schwert 1989, Campbell et al. 2001).

Second, we employed a recursive modeling approach to analyze whether macroeconomic variables help to forecast stock market volatility in real time. By doing this, we accounted for the fact that an investor's information set changes over time. In the earlier literature, it has been common practice to use an information set based on a full-sample of revised data to analyze whether macroeconomic variables help to forecast stock market volatility (Schwert 1989). Such an information set, however, is not available to an investor in real time. In consequence, it cannot be used by an investor to price derivative securities and to solve portfolio allocation problems in real time. In order to capture changes in an investor's information set over time, we employed a recursive modeling approach (Pesaran and Timmermann 1995, 2000). An advantage of using a recursive modeling approach is that it also allows the out-of-sample forecasting ability of macroeconomic variables for stock market volatility to be analyzed. Out-of-sample tests have received increasing attention in the recent empirical finance literature (Rapach et al. 2005, Sollis 2005).

Third, we used three different criteria to evaluate the accuracy of forecasts of stock market volatility. The first criterion is a statistical criterion. We used the root-mean squared error as a statistical criterion to evaluate volatility forecasts. The advantage of this statistical criterion is that it has been widely used in academic research and can easily be applied by practitioners. The second criterion is the utility-based criterion developed by West et al. (1993) and recently applied by Fleming et al. (2001) to evaluate volatility forecasts. The utility-based criterion provides a microeconomic foundation for forecast evaluation. The third criterion is an option-based criterion to evaluate volatility forecasts. Similar criteria have been developed by Engle et al. (1996) and Engle et al. (1997). The idea behind the option-based criterion is to simulate a synthetic options market in which investors trade options based on their different volatility forecasts. By comparing profits of investors, it is possible to evaluate differences between volatility forecasts in economic terms.

Our main result is that the value of volatility forecasts based on real-time macroeconomic data is roughly comparable to the value of volatility forecasts based on revised macroeconomic data. Forecasting stock market volatility by means of noisy real-time rather than reliable revised macroeconomic data does not systematically reduce investors' average utility. Furthermore, an investor who used real-time macroeconomic data for volatility forecasting would have realized profits in our synthetic options market comparable to those an investor would have reaped who based volatility forecasts on revised macroeconomic data. Our result, thus, demonstrates that an investor who wants to set up an investment strategy in real time can in general make use of results reported in the earlier literature on the macroeconomic determinants of stock market volatility that were derived by using revised macroeconomic variables.

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 forecasting stock market volatility. We also lay out the criteria we used to evaluate the accuracy of forecasts of stock market volatility. In Section 3, we describe the macroeconomic and financial data we considered to be relevant for forecasting stock market volatility. In Section 4, we present our results. In Section 5, we offer some concluding remarks.

2. Modeling and Evaluating Volatility Forecasts

In order to simulate how an investor may forecast stock market volatility in real time, we used a recursive modeling approach. In order to evaluate the accuracy of forecasts implied by our recursive modeling approach, we used a statistical, a utility-based, and an options-based criterion. We used our recursive modeling approach and the three forecast-evaluation criteria to compare forecasts of stock market volatility based on real-time macroeconomic data with forecasts based on revised macroeconomic data.

2.1 Recursive Modeling of Stock Market Volatility

We considered an investor who uses a set of macroeconomic and financial variables to predict stock market volatility. In period of time t, the information set of the investor contains real-time information on macroeconomic and financial variables up to and including period of time t. The investor seeks to combine these variables in an optimal forecasting model for stock market volatility. 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. As in Pesaran and Timmermann (1995, 2000), we assumed that the investor applies a recursive modeling approach in order to identify the optimal forecasting model. This recursive modeling approach proceeds in two steps. In a first step, the optimal forecasting model for stock market volatility is identified. This is done by searching the optimal forecasting model, in each period of time, in a systematic way over a large number of different models that feature different macroeconomic and financial variables. In a second step, this search recursively restarts in order to permanently update the optimal forecasting model as time progresses.

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 market volatility. The optimal forecasting model in period t is identified by searching over all possible permutations of the variables under consideration. From this it follows, that the number of forecasting models becomes very large as the number of variables increases. For example, we considered in our empirical analysis nine macroeconomic and financial variables to be relevant for forecasting one-period-ahead stock market volatility. In order to conduct this search over a large number of forecasting models in an efficient and timely manner, we followed Pesaran and Timmermann (1995, 2000) and used the ordinary least squares technique to estimate, in each period of time *t*, linear regression models of the following format:

$$y_{t+1} = \beta_i' X_{t,i} + \varepsilon_{t+1,i}, \qquad (1)$$

where y_{t+1} denotes the vector of changes in the natural logarithm of stock market volatility from period 0 up to and including period $t+1$. We model changes in the natural logarithm of stock market volatility because we used, as we will describe in detail in Section 2.2.3, an options-based criterion to model stock market volatility. In the options literature, it has become common practice to assume that volatility follows a geometric stochastic process (see, for example, Hull and White 1987, Heston 1993). The subscript i denotes the model the investor studies, β_i denotes the vector of parameters under model *i*, $\varepsilon_{t+1,i}$ 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 the investor considers to be relevant for forecasting stock market volatility. The vector of regressors always includes a constant.

In order to identify the optimal forecasting model, the investor needs a model-selection criterion to select, in each period of time *t*, the optimal forecasting model among the large number of estimated forecasting models. We assumed that the investor considers three alternative model-selection criteria: the Adjusted Coefficient of Determination (ACD), the Akaike Information Criterion (AIC, Akaike 1973), and the Bayesian Information Criterion (BIC, Schwarz 1978). The ACD, AIC, and BIC model-selection criteria have two key advantages. First, these model-selection criteria are widely used in applied research and an investor can easily compute them. Second, these model-selection criteria were readily available to investors during the entire sample period. This is important because our plan is to simulate how an investor forecasts stock market volatility in real time. Hence, it is important that the investor bases forecasts of stock market volatility only on information and model-selection criteria which were available in the period of time in which the forecasts had to be made.

2.2 Forecast-Evaluation Criteria

In order to evaluate and compare volatility forecasts made on the basis of real-time and revised macroeconomic data, we used three different criteria: a statistical criterion, a utility-based criterion, and an options-based criterion.

2.2.1 Statistical Criterion

We used the root-mean-squared error (RMSE) to evaluate the statistical accuracy of forecasts of stock market volatility. The RMSE is defined as the square root of the mean of the sum of the squared differences between forecasts of stock market volatility and actual stock market volatility. In addition to the RMSE, we also computed a statistic in the tradition of the U statistic that has been suggested by Theil (1966). Our version of Theil's U statistic compares the accuracy of forecasts from a forecasting model that uses real-time macroeconomic data with that from a forecasting model that uses revised macroeconomic data. We computed our U statistic as the ratio of the RMSE of a forecasting model that uses real-time macroeconomic data and the RMSE of a forecasting model that uses revised macroeconomic data. Thus, our U statistic is defined as follows:

$$U = \frac{RMSE^{real\,time}}{RMSE^{revised}} \tag{2}$$

2.2.2 Utility-Based Criterion

A utility-based criterion provides a microeconomic foundation for the evaluation of the accuracy of volatility forecasts. In order to set up a utility-based criterion, we followed West et al. (1993) and considered a mean-variance maximizing investor who maximizes the following utility function:

$$U_{t+1} = E_t(W_{t+1}) - \frac{\gamma}{2} Var_t(W_{t+1}), \tag{3}$$

where U_{t+1} denotes utility in period $t+1$, E_t denotes the conditional expectations operator, Var_t denotes the conditional variance operator, γ denotes the investor's taste for risk, and W_{t+1} denotes the wealth of the investor in period $t+1$. The dynamics of the investor's wealth can be described in terms of the following period-by-period budget constraint:

$$W_{t+1} = W_t[(1-f)R_{F,t+1} + fR_{t+1}], \tag{4}$$

where f denotes the fraction of wealth invested in stocks, R_F denotes the gross return on a riskless one-period bond, and R_{t+1} denotes the gross return on stocks in period $t+1$. For simplicity, we assume that the riskless interest rate is constant. Upon maximizing (3) with respect to f subject to (4) and assuming that the investor's coefficient of relative risk aversion, $\delta \equiv \gamma W_t / (1-\gamma W_t)$, is constant, the optimal proportion of wealth invested in stocks can be computed as

$$f = \frac{1+\delta}{\delta}\left(\frac{\mu_{t+1} - R_{F,t+1}}{h_{t+1}}\right), \tag{5}$$

where μ_{t+1} denotes the conditional mean of stock returns in period of time $t+1$. We assume that the investor knows the conditional mean of stock returns, but does not know the conditional variance, h_{t+1}. One could extend the analysis to incorporate the effects of estimation risk with regard to mean returns on the investor's investment decision (Fleming et al. 2001). However, this estimation risk would affect investment decisions based on both volatility forecasts derived from real-time and revised macroeconomic data. Thus, our utility-based measures should reliably indicate the relative value of volatility forecasts.

The investor uses the recursive estimation approach described in Section 2.1 to obtain forecasts of the conditional variance, $\hat{h}_{t+1}$. These estimates can be used in (5) to compute the conditional expectations and the conditional variance of wealth in period $t+1$. Investor's expected utility may then be written as

$$E_t(U_{t+1}) = W_t(R_{F,t+1} + d_t u_t), \tag{6}$$

where $d_t = [(1+\delta)/\delta](\mu_{t+1} - R_F)^2$ and $u_t = 1/\hat{h}_{t+1} - 0.5\, h_{t+1}/\hat{h}_{t+1}^2$. The right-hand side of (6) shows that the utility-based criterion is asymmetric insofar as underestimates of the variance of stock market returns lead to a lower expected utility than overestimates of the same magnitude.

Because the investor does not know h_{t+1}, the result given in (6) cannot be directly used to evaluate forecasts of stock market volatility. However, West et al. (1993) have proposed to get an estimate of h_{t+1} that is right on average by replacing h_{t+1} with the ex-post realized squared log difference in stock prices, h_{t+1}^r. Holding W_t fixed, average utility can be computed as

$$\overline{U} \equiv \frac{1}{TF}\sum_{t=1}^{TF} W_t (R_{F,t+1} + d_t u_t)\,, \tag{7}$$

where TF denotes the number of forecasts. In a large sample, $\overline{U}$ will be close to the average of the conditional expectation of utility, $(1/TF)\sum_{t=1}^{TF} E_t(U_{t+1})$.

Average utility as defined in (7) can be compared across models in order to evaluate the accuracy of forecasts of stock market volatility. To this end, we followed West et al. (1993) and expressed differences in the accuracy of forecasts of stock market volatility across models in terms of a wealth-sacrifice ratio. This wealth-sacrifice ratio is expressed in terms of annual basis points. Denoting average utility of an optimal model by $\overline{U}_1$, and average utility of a suboptimal model, $\overline{U}_m$, the wealth-sacrifice ratio, WSR, can be computed as

$$WSR_m = 12 \times (1 - \overline{U}_m / \overline{U}_1) \times 100 \times 100\,, \tag{8}$$

where the first 100 converts to percentage, the second one converts to basis points, and the 12 converts WSR to annual basis points. The WSR can be interpreted to represent the average fee that the investor would be willing to pay to switch from a suboptimal forecasting model, *m*, to the optimal forecasting model.

2.2.3 Options-Based Criterion

The options-based criterion we used to analyze the accuracy of forecasts of stock market volatility is similar to the options-based criteria developed by Engle et al. (1996) and Engle et al. (1997). They have suggested simulating a synthetic options market to test the relative accuracy of volatility forecasts. In the options market that we simulated, two traders interact. One trader derives forecasts of stock market volatility from a model that features real-time macroeconomic data, and the other trader from a model that features revised macroeconomic data. Both traders trade one-month options on a one euro share of the DAX30 portfolio. In each period of time, traders invest in a “straddle”, that is, they invest in one European call option and one European put option. The strike prices of both options is equal to the forward rate, $exp(R_{F,t} - 1)$. Using their forecasts of stock market volatility, both traders use the Black-Scholes formula to value options (Black and Scholes 1973). According to this formula, the price of a call (or put) option is given by

$$C_t = 2N(d_1) - 1, \; \mathrm{d}_1 \equiv 0.5\sqrt{\hat{\mathrm{h}}_{\mathrm{t+1}}\mathrm{M}}, \tag{9}$$

where C_t denotes the call (or put) price, $N(.)$ denotes the cumulative normal distribution function, M denotes the time-to-maturity of the option, and $\hat{h}_{t+1}$ denotes the forecast of the variance of monthly stock market returns. Using (9), the value of a straddle is given by $4N(d_1) - 2$.

Depending on their forecasts of stock market volatility, traders are either long or short in a straddle. The trader whose volatility forecast is larger buys one straddle, and the trader whose volatility forecast is smaller sells one straddle. If traders’ volatility forecasts are identical, we assume that both are short in one straddle. Transactions are executed at the average of the seller’s and buyer’s price. At the end of a month, buyers and sellers positions are closed and profits/losses are computed. We used the realized monthly stock market returns, $exp(R_t - 1)$, to compute the profit from each trade.

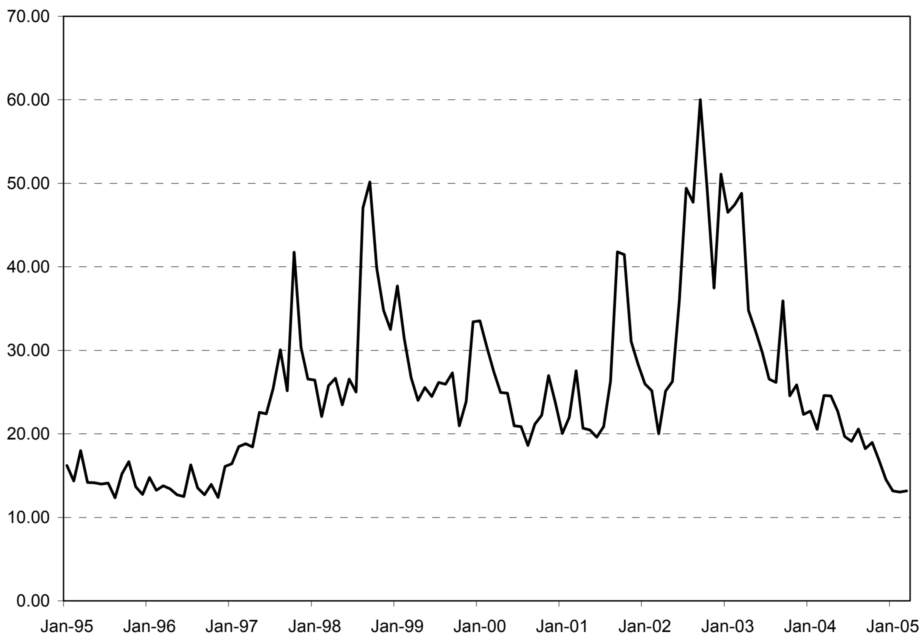
3. The Data

The description of our data comes in three parts. In the first part, we describe our data on stock market volatility. In the second part, we describe our real-time macroeconomic data for Germany. In the third part, we describe the other variables we considered to be of potential importance for forecasting stock market volatility.

3.1 Stock Market Volatility

In order to measure stock market volatility, we used data on the VDAX-NEW index collected and disseminated by the German stock exchange (Deutsche Boerse). The VDAX-NEW index is an options-based index of stock market volatility that summarizes market participants' sentiment regarding the standard deviation of returns of the DAX30. The VDAX-NEW index measures the square root of the implied variances. It has a constant time-to-maturity of 30 days. This is convenient because our macroeconomic data are available at a monthly frequency. The Deutsche Boerse computes the VDAX-NEW index based on the implied variances of at-the-money and out-of-the-money options with the same time-to-maturity. Because both at-the-money and out-of-the-money options are considered, the VDAX-NEW index summarizes information on the shape of the volatility-strike structure (the so-called "volatility smile"). Data for the VDAX-NEW index are available at a daily frequency for the period 1992/1-2005/4. We used end-of-month data in our empirical analysis in order to avoid problems due to overlapping data. Figure 1 plots the VDAX-NEW index for the period we considered in our forecasting analysis (1995-2005). A detailed description of how the VDAX-NEW index is computed can be found in Deutsche Boerse (2005).

Figure 1 — Stock Market Volatility (VDAX-NEW index, 1995/1–2005/3)



Because stock market volatility is not directly observable, various estimators have been developed in the literature. In consequence, using an options-based index is only one choice an investor can make to estimate stock market volatility. Because alternative estimators are available, an investor could ask whether the results we shall report in Section 4 are sensitive to the choice of the estimator of stock market volatility. In order to analyze the sensitivity of our results, we did not only study our options-based index of stock market volatility, but also considered two alternative estimators. The first alternative estimator is the monthly average of squared stock market returns. For an investor, it is very simple to compute this estimator in real time. The second alternative estimator is a GARCH model. To this end, we used daily data on returns of the DAX30 to estimate a GARCH(1,1) model and stored the conditional volatility of returns implied by this model. We then computed monthly averages of the estimated conditional volatility. We found that both alternative estimators yielded estimates of stock market volatility that resemble the options-based VDAX-NEW index of stock market volatility. Thus, using the two alternative estimators of stock market volatility does not affect our main result that the statistical and economic value of volatility forecasts based on real-time data is comparable to the value of forecasts based on revised macroeconomic data. We, therefore, report in Section 4 only results for our options-based volatility index. Results for the other two estimators of stock market volatility are available from us upon request.

3.2 Real-Time Macroeconomic Data for Germany

In order to study the macroeconomic determinants of stock market volatility, we used a monthly real-time macroeconomic dataset for important macroeconomic business-cycle indicators for the German economy. The dataset was provided by the Deutsche Bundesbank. Data sources are the Bundesbank's regularly published monthly publications of seasonally adjusted macroeconomic data (Saisonbereinigte Wirtschaftszahlen). We used real-time data for month-to-month growth rates of industrial production (without construction) and orders inflow. In addition, we computed a real-time measure of the output gap. The output gap is defined as the difference between actual output and potential output. We measured potential output by applying 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. Finally, we used real-time data for the annualized growth rate of the consumer-price index as a real-time measure of inflation.

Data were available 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 refer to Germany as a whole. The data are organized in vintages. A vintage contains the time series of a macroeconomic variable that was available to an investor in a given period of time. Hence, because our sample period is 1995/1-2005/3, we could use in our empirical analysis 123 vintages of each macroeconomic variable. In order to start our recursive modeling approach, we added to each vintage data that go back to November 1991. To be more specific, we started our recursive modeling approach by assuming that the investor uses the period 1991/1-1994/12 as a training period to get initial estimates of the model-selection criteria.

In our empirical analyses, we accounted for the fact that macroeconomic data are usually published with a time lag. We also accounted for the fact that the publication lag changed over time. For example, in the case of industrial production the year 1995 provides a remarkable example for irregularities with regard to the publication of macroeconomic data. In the year 1995, the German Federal Statistical Office did not publish data on industrial production from February to June. The reason for this interruption of the usual publication rhythm was a conceptual change in the calculation of the 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 of macroeconomic data 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 data of the then most recently published vintage to fill any gaps in the data. This assumption does not distort the information set available to an investor because it implies that the investor only uses then publicly available data to forecast excess returns.

Table 1 — Summary Statistics of Revisions of Real-Time Macroeconomic Data

Summary statistics	Mean	NSR	Minimum	Maximum
			Industrial production	
Revision after one month	0.16	0.78	-2.13	2.43
Revision after two months	0.11	0.77	-2.02	2.12
Revision after six months	0.18	0.80	-2.78	2.22
Revision after 1 year	0.11	0.96	-2.78	3.48
Revision compared to final release	0.14	1.01	-3.61	3.37
			Orders inflow	
Revision after one month	0.07	0.49	-3.33	8.50
Revision after two months	0.15	0.61	-3.43	8.50
Revision after six months	0.10	0.57	-3.54	8.29
Revision after 1 year	-0.04	0.75	-4.95	7.55
Revision compared to final release	-0.01	0.88	-6.87	8.95
			CPI	
Revision after one month	-0.00	0.26	-0.24	0.10
Revision after two months	0.00	0.35	-0.29	0.19
Revision after six months	-0.00	0.46	-0.30	0.19
Revision after 1 year	0.01	0.65	-0.34	0.29
Revision compared to final release	-0.01	0.81	-0.48	0.24
			Output gap	
Revision after one month	0.14	0.69	-2.10	2.47
Revision after two months	0.10	0.71	-1.91	1.96
Revision after six months	0.15	0.72	-2.17	2.13
Revision after 1 year	0.09	0.87	-2.46	3.23
Revision compared to final release	0.13	0.90	-3.26	3.01

Note: In this table, 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. The noise-to-signal, NSR, is defined as the ratio of the standard deviation of revisions and the standard deviation of final-release data. CPI is defined as the consumer price index inflation.

In order to analyze differences between real-time and revised macroeconomic data, we provide summary statistics of revisions of our real-time macroeconomic data in Table 1. The summary statistics in Table 1 indicate that, as a rule, revisions do not have a zero mean, suggesting that there are some systematic differences between data belonging to different vintages. Moreover, the noise-to-signal ratios are substantial. The noise-to-signal ratio is defined as the ratio of the standard deviation of revisions and the standard deviation of revised data (Orphanides and van Norden 2002). The noise-to-signal ratios reveal that the standard deviations of revisions are at least about one third as large as the standard deviation of the revised data. There are even some cases in which the standard deviation of revisions exceeds the standard deviation of the revised data. Furthermore, the minimum and maximum values of revisions are 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 motivates a closer look on the implications of using real-time macroeconomic data for forecasting stock market volatility.

3.3 Other Variables

In addition to real-time macroeconomic data, we considered a number of other variables to be potentially relevant for forecasting stock market volatility. We downloaded most of the data from Thomson Financial Datastream. Our list of variables is the following (abbreviations and Datastream codes are given in parentheses):

1. The relative three-month Treasury bill rate (RTB) and the term spread (TSP). RTB is defined as the difference between the three-month Treasury bill rate (BDI60C..) and its 12-month backward-looking moving average. TSP is defined as the difference between the long-term government bond yield (BDI61...) and the three-month Treasury bill rate.

2. A January dummy (JAN). JAN plays an important role in the literature on financial market anomalies and seasonalities in returns. (See Thaler (1987) and Haugen and Lakonishok (1988) for surveys of this literature.)

3. The difference between the DAX30 (DAXINDZ) and its four-month (~ approximately 100 trading days) and eight-month (~ approximately 200 trading days) backward-looking moving averages (DMA100; DMA200). We considered DMA100 and DMA200 as predictors for stock market volatility because simple moving-average-based trading strategies have been studied extensively in the literature on technical trading rules (Brock et al. 1992).
4. The IFO overall business climate indicator (IFO; WGIFOMXLE). Jacobs and Sturm (2004) have reported that IFO contains information with regard to revisions of German macroeconomic data. In consequence, it could have been valuable for investors who must rely on preliminary real-time macroeconomic data to include IFO in the information set they used to forecast stock market volatility. Moreover, in contrast to industrial production and orders inflow, there have been no irregularities with respect to the publication of the IFO index.
5. The level of the VDAX-NEW index. We used the VDAX-NEW index as a regressor to take into account that volatility may follow a mean-reverting process.

4. Results

In Table 2, we summarize how often the macroeconomic and other variables are selected by our recursive modeling approach as regressors under different model selection criteria. In the second column, we report results for models that use revised macroeconomic data as potential regressors. In the third column, we report results for models that use real-time macroeconomic data as potential regressors. As one would have expected, an investor who relied upon the BIC criterion would have used only few regressors to forecast stock market volatility. Moreover, irrespective of the model selection criterion considered, an investor would have chosen almost always the VDAX-NEW index as a regressor.

Table 2 — Inclusion of Variables (in percent)

	Revised data			Real-time data		
Industrial production (month-to-month changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
PRODUCTION	0 .00	0.00	0.00	9.02	2.46	1.64
INF	26.23	15.57	1.64	28.69	16.39	0.82
RTB	62.30	43.44	9.8361	63.93	41.80	9.02
VDAX	98.36	98.36	96.72	98.36	97.54	95.90
TSP	18.85	0.00	0.00	18.03	0.00	0.00
JAN	67.21	14.75	0.00	72.95	14.75	0.00
IFO	27.87	3.28	0.00	35.25	3.28	0.00
DMA100	30.33	16.39	1.64	32.79	9.01	0.00
DMA200	25.41	18.03	0.00	24.59	18.03	0.00
Orders inflow (month-to-month changes)						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
ORDERS	19.67	0.00	0.00	16.39	0.00	0.00
INF	27.05	15.5738	1.64	28.69	16.39	0.82
RTB	62.30	43.4426	9.84	63.93	41.80	9.02
VDAX	98.36	98.3607	96.72	98.36	97.54	96.72
TSP	18.85	0.00	0.00	18.03	0.00	0.00
JAN	66.39	14.75	0.00	71.31	14.75	0.00
IFO	27.87	3.28	0.00	35.25	3.28	0.00
DMA100	30.33	16.39	1.64	32.79	9.84	0.82
DMA200	25.41	18.03	0.00	25.41	18.03	0.00
Output gap						
Variables	ACD	AIC	BIC	ACD	AIC	BIC
GAP	0.82	0.00	0.00	3.28	0.00	0.00
INF	26.23	15.57	1.64	27.87	16.39	0.82
RTB	61.48	43.44	9.84	63.93	41.80	9.02
VDAX	98.36	98.36	96.72	98.36	97.54	96.72
TSP	19.67	0.00	0.00	18.03	0.00	0.00
JAN	67.21	14.75	0.00	72.95	14.75	0.00
IFO	28.69	3.28	0.00	35.25	3.28	0.00
DMA100	31.15	16.39	1.64	33.61	9.84	0.82
DMA200	25.41	18.0328	0.00	25.41	18.03	0.00

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.

By contrast, the investor's choice of the other regressors would have been highly dependent on the model selection criteria applied to select a forecasting model. As concerns the macroeconomic data, the investor would have selected the inflation rate more often as a regressor than either industrial production, orders inflow, or the output gap. Finally, there is no general tendency that an investor would have included real-time macroeconomic data more often in the optimal forecasting model than revised macroeconomic data, and vice versa.

In order to analyze the accuracy of forecasts of stock market volatility based on real-time and revised macroeconomic data, we report in Panel A of Table 3 for each model the RMSE. In Panel B, we document results for the U statistic. A comparison of the RMSEs shows that no clear ranking of models is apparent. In fact, the results for the U statistic reveal that forecasting models based on real-time macroeconomic data work as well as forecasting models based on revised macroeconomic data. This suggests that preliminary real-time macroeconomic data are as (un-)informative with regard to stock market volatility as are revised macroeconomic data. In other words, an investor who must rely on real-time macroeconomic data to forecast stock market volatility would have done not worse than an investor who had access to revised macroeconomic data to forecast stock market volatility. Given the large attention that financial market participants and the mass media often pay to data revisions this result is somewhat surprising.

Table 3 — RMSE and U Statistic

PANEL A: Root mean squared error statistics

	Revised data	Real-time data
	Industrial production (month-to-month changes)	
ACD	5.8922	5.9163
AIC	5.7650	5.7772
BIC	5.6066	5.5197
	Orders inflow (month-to-month changes)	
ACD	5.9558	5.9109
AIC	5.7650	5.7569
BIC	5.6066	5.6061
	Output gap	
ACD	5.8926	5.9087
AIC	5.7650	5.7569
BIC	5.6066	5.6061

PANEL B: U statistic

	Industrial production
ACD	1.0041
AIC	1.0021
BIC	0.9845
	Orders inflow
ACD	0.9925
AIC	0.9986
BIC	0.9999
	Output gap
ACD	1.0027
AIC	0.9986
BIC	0.9999

Note: ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

Because statistical measures of forecasting ability may not be closely related to forecasts' profits (Leitch and Tanner 1991), we analyzed a utility-based criterion to study the implications of using real-time and revised macroeconomic data for forecasting stock market volatility. In Table 4, we report in Panel A for each model average utility as defined in (7). In Panel B, we report the wealth-sacrifice ratios one obtains by comparing average utility of forecasting models based on real-time (revised) macroeconomic data with average utility of the other forecasting models based on real-time (revised) macroeconomic data. In Panel C, we report the wealth-sacrifice ratios one obtains by comparing average utility of forecasting models based on real-time macroeconomic data with average utility of forecasting models based on revised macroeconomic data. The better forecasting model has a wealth-sacrifice ratio of zero. In order to assess the robustness of our results, we report results for coefficients of relative risk aversion of $\delta = 1$ and $\delta = 10$.

Table 4 — Utility-Based Criterion

PANEL A: Average utility

	Revised data		Real-time data	
Industrial production (month-to-month changes)				
Criteria	δ = 1	δ = 10	δ = 1	δ = 10
ACD	113.03	107.21	110.26	105.68
AIC	113.64	107.54	114.61	108.07
BIC	114.91	108.24	115.02	108.30
Orders inflow (month-to-month changes)				
Criteria	δ = 1	δ = 10	δ = 1	δ = 10
ACD	113.39	107.41	111.08	106.13
AIC	113.65	107.54	114.43	107.97
BIC	114.91	108.24	114.89	108.23
Output gap				
Criteria	δ = 1	δ = 10	δ = 1	δ = 10
ACD	113.05	107.22	110.44	105.78
AIC	113.65	107.54	114.43	107.97
BIC	114.91	108.24	114.89	108.23

Table 4, continued.

PANEL B: Wealth-sacrifice ratio
(revised data vs. revised data; real-time data vs. real-time data)

	Revised data		Real-time data	
Industrial production (month-to-month changes)				
Criteria	δ = 1	δ = 10	δ = 1	δ = 10
ACD	1.96	1.14	4.96	2.90
AIC	1.32	0.77	0.43	0.25
BIC	0.00	0.00	0.00	0.00
Orders inflow (month-to-month changes)				
Criteria	δ = 1	δ = 10	δ = 1	δ = 10
ACD	1.58	925.25	3.99	2.33
AIC	1.320	770.86	0.49	0.28
BIC	0.00	0.00	0.00	0.00
Output gap				
Criteria	δ = 1	δ = 10	δ = 1	δ = 10
ACD	1.94	1.13	4.65	2.72
AIC	1.32	0.77	0.49	0.28
BIC	0.00	0.00	0.00	0.00

PANEL C: Wealth-sacrifice ratio
(revised data vs. real-time data)

	Revised	Real-time	Revised	Real-time
Industrial production (month-to-month changes)				
Criteria	δ = 1		δ = 10	
ACD	0.00	2944.34	0.00	1707.42
AIC	1007.37	0.00	587.60	0.00
BIC	112.67	0.00	65.82	0.00
Orders inflow (month-to-month changes)				
Criteria	δ = 1		δ = 10	
ACD	0.00	2451.60	0.00	1423.51
AIC	818.52	0.00	477.12	0.00
BIC	17.44	0.00	0.00	76.68
Output gap				
Criteria	δ = 1		δ = 10	
ACD	0.00	2776.24	0.00	1609.99
AIC	818.52	0.00	477.17	0.00
BIC	0.00	17.44	0.00	10.20

Note: δ denotes the coefficient of risk aversion. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

As regards the optimal model selection criterion, the results summarized in Table 4 show that an investor who had used the BIC model selection criterion would have reaped the highest average utility. In contrast, an investor who had used the ACD model selection criterion would have reaped the lowest average utility. This ranking of model selection criteria is indifferent to the calibration of the coefficient of relative risk aversion. As regards forecasting models based on real-time and revised macroeconomic data, no clear-cut ranking is possible. Under the ACD and the AIC model selection criteria, forecasting models based on revised macroeconomic data outperform models based on real-time macroeconomic data. In contrast, under the BIC model selection criterion, in terms of the wealth-sacrifice ratios, the forecasting models based on real-time macroeconomic data are better than the forecasting models based on revised macroeconomic data. However, the differences between models are small because, under the BIC criterion, macroeconomic variables are included only occasionally in the optimal forecasting model. All in all, we conclude that an investor who uses our utility-based criterion to evaluate the accuracy of forecasts of stock market volatility should use the BIC criterion to select a forecasting model for two reasons. First, choosing the BIC criterion maximizes average utility. Second, the BIC criterion helps the investor to minimize the negative impact on average utility that results from the fact that the investor must use preliminary real-time rather than reliable revised macroeconomic data for forecasting stock market volatility in real time.

Finally, we report results for our options-based criterion of the accuracy of forecasts of stock market volatility. In Table 5, we report cumulative profits, the standard deviation of cumulative profits, and standardized profits that an investor would have realized who had traded straddles in our synthetic options-market. We computed standardized profits as the ratio of cumulative profits and their standard deviation. Profits do not add up to zero because both traders are short in straddles if their forecasts of stock market volatility are identical. Columns 2-4 summarize results for revised macroeconomic data, and Columns 5-7 summarize results for real-time macroeconomic data.

Corroborating the results for the statistical and utility-based criteria, the options-based criterion does not clearly favor forecasting models based on real-time over forecasting models based on revised macroeconomic data. Thus, in terms of our options-based criterion, the accuracy of an investor's volatility forecasts does not change much when reliable revised rather than noisy real-time macroeconomic data are available for forecasting stock market volatility. Interestingly, however, the standard deviation of cumulative profits is always relatively small when forecasts of stock market volatility are based on revised macroeconomic data. Thus, when trading options based on volatility forecasts derived from revised macroeconomic data, an investor runs the danger of underestimating the standard deviation of profits. If only forecasting models based on real-time data are considered, it is clear from the results given in Table 5 that, as was the case with the utility-based criterion, the BIC model selection criterion performs very well.

Table 5 — Options-Based Criterion

	Revised data			Real-time data		
Industrial production (month-to-month changes)						
	Profits	SD	Profits/SD	Profits	SD	Profits/SD
ACD	0.13	0.04	3.45	0.25	0.04	6.83
AIC	0.45	0.04	12.08	0.30	0.04	8.05
BIC	0.42	0.04	11.32	0.28	0.04	7.58
Orders inflow (month-to-month changes)						
	Profits	SD	Profits/SD	Profits	SD	Profits/SD
ACD	0.15	0.04	3.95	-0.01	0.04	-0.22
AIC	0.45	0.04	12.01	0.44	0.04	11.99
BIC	0.41	0.04	11.16	0.46	0.04	12.57
Output gap						
	Profits	SD	Profits/SD	Profits	SD	Profits/SD
ACD	0.13	0.04	3.45	0.44	0.04	11.91
AIC	0.45	0.04	12.01	0.44	0.04	11.99
BIC	0.41	0.04	11.16	0.46	0.04	12.57

Note: ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

5. Conclusion

In real time, an investor faces the problem that only preliminary real-time macroeconomic data are available for forecasting stock market volatility. The result of our empirical research using German real-time macroeconomic data may provide some guidelines for investors for how to deal with this problem. Our main result is that the statistical and economic value of forecasts of stock market volatility based on real-time data is comparable to the value of forecasts based on revised macroeconomic data. This result has two implications. For investors who act in real time, our result implies that they can safely use real-time macroeconomic data to forecast stock market volatility. For researchers who ex post analyze macroeconomic and financial data, our result implies that they can employ revised macroeconomic data to study the equilibrium relations between macroeconomic variables and stock market volatility. Of course, before our result can be generalized, much more research has to be done. For example, it would be interesting to use data for other countries and periods of time to study further the macroeconomic determinants of stock market volatility in real time.

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