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With or without you: Do financial data help to forecast industrial production?

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Tobias Kitlinski

With or Without You - Do Financial Data Help to Forecast Industrial Production?

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Tobias Kitlinski[1]

With or Without You – Do Financial Data Help to Forecast Industrial Production?

Abstract

This paper analyzes the forecasting performance of financial market data in comparison to other indicator groups to forecast industrial production for Germany and the US. We focus on single-indicator models and various weighting schemes and evaluate the forecasting performance using a significance test. In addition, we investigate the stability of forecasting models before and during the recent financial crisis. This paper shows that financial market indicators are useful for short-term forecasting, especially for the US and longer forecast horizons. Nevertheless, the results indicate that the Great Recession was not foreseeable even if financial market indicators were taking into account. Furthermore, the reliability of pooled forecasts is higher than most of the forecasts obtained from single-indicator models.

JEL Classification: C53, E37

Keywords: Forecasting; financial market data; single-indicator model; pooling of forecasts

May 2015

1 Tobias Kitlinski, RWI. – *I thank Michael Roos and Christoph M. Schmidt for helpful comments and suggestions. -* *All correspondence to: Tobias Kitlinski, e-mail: kitlinski.tobias@gmail.com*

1 Introduction

Forecasters and economists faced criticism that they have not foreseen the Great Recession that started in 2007/2008 (see Koll et al. (2009) for a discussion). It has been the deepest worldwide economic crisis since the Great Depression in the late $1920's$. One point of criticism concerned the fact that financial market data was not used in the forecasting models, although it might have helped anticipating the beginning of the crisis. The crisis itself started as a subprime crisis in the US, which led to a loss of confidence in the financial sector and finally hit the real economy.

In this paper, we analyze if financial market data are indeed able to improve the short-term forecasting performance of single-indicator models for forecasting industrial production (IP) in times of a financial market crisis, such as the phase recently experienced. Furthermore, we explore if financial market data is helpful to improve the general forecasting performance by applying a sample that include the Great Recession as well as periods of stable growth.

Short-term forecasting is needed for a timely evaluation of the current economic situation as well as a correct estimation of the near-term outlook for decision making in private enterprises, governments or central banks since official data of GDP is published with a delay of six weeks or even more. Therefore, it is often called "nowcasting" or "backcasting".[1] Banbura et al. (2011), Banbura et al. (2013) or Camacho et al. (2013) provide some complementary overviews of the existing literature on short-term forecasting.

In general, short-term forecasting uses information of indicators that are related to the target variable (e.g. GDP) and published with a higher frequency. Most of these indicators are available at monthly frequency. One very popular indicator in the short-term forecasting literature is IP. IP shows a very high correlation with GDP in many countries.[2] For example, the growth rate of quarterly IP shows a correlation with the growth rate of GDP of 0.80 in Germany for the period $1995q1 - 20012q4$. For the US, the correlation between the same variables and for the same period of time is 0.73.

[1] Nowcasting refers to the current quarter that a forecaster aims to forecast while backcasting refers to a quarter that has just ended. For example, a forecast for GDP ($q1$) in March in any year is a nowcast while a forecast for the same quarter in April is a backcast. The official data for the first quarter of a year is published in May in Germany.

[2] This is true if IP is aggregated on a quarterly basis.

Hence, a strand of the short-term forecasting literature applies IP instead of GDP as the target variable since providing precise forecasts for IP in a first step is the basis for a good performance in forecasting GDP (Golinelli and Parigi, 2007). A major benefit of this approach is that all variables are at the same level of frequency and no information is lost. In a mixed-frequency approach information contained in the monthly variation is lost if monthly indicators have to be aggregated in a first step.

Regardless of the chosen frequency, a forecaster has to decide how to extract the information that is included in the variety of indicators. Two main approaches emerged in the forecasting literature. First, factor models which pool the indicators to get a few common factors (Pooling of Information). In a next step, these factors are used in a single equation to forecast the target variable. A second way of extracting the information of the indicators is to set up (many) different single equations (Pooling of Forecasts). Each indicator enters at least one equation to forecast the target variable.[3]

Single-indicator models as a forecasting tool are very popular because of their simplicity: Each single forecast can be traced back to the indicator where it originates from. Therefore, it is very easy to analyze the forecasting performance of each indicator. In a second step the forecasts of the single-indicator models have to be pooled using different weighting schemes.

Pooling of forecasts using different weighting schemes (as discussed by Timmermann (2006) or Drechsel and Maurin (2011)) as the second step is widely used in the forecasting literature, based on the seminal work of Bates and Granger (1969). There are also some results for the US and Germany in a multi-country comparison (see e.g. Stock and Watson (2003a) or Stock and Watson (2004)). Concerning the forecasting performance there is no clear advantage for one of these approaches (see e.g. Angelini et al. (2011), Kitchen and Monaco (2003), Schumacher and Dreger (2004), Antipa et al. (2012) and Schumacher (2014)).

For Germany, the empirical evidence for single-indicator models to predict IP (and GDP) is large (see e.g. Breitung and Jagodzinski (2001), Fritsche and Stephan (2002), Kholodilin and Siliverstovs (2006), Kuzin et al. (2009), Schumacher and Breitung (2008) or Drechsel and Scheufele (2012a)). The empirical

[3]The equations to forecast the target variable can include different numbers of indicators, starting with only one indicator per equation. Moreover, different combinations of the indicators are typically included per equation, resulting in a variety of forecasting equations.

work on single-indicator models for the US is rather concentrated on GDP than IP (see e.g. Stock and Watson (2006), Clements and Galvao (2009) or Castle et al. (2013)). For forecasting IP the research is scarce (see e.g.Byers and Peel (1995) or Siliverstovs and Dijk (2003)).

Concerning financial market data, there are several good reasons to take them into account, especially for short-term forecasting. First, they are very timely available. Next, financial market data include market expectations about the future state of the economy. Third, they may play an important role in detecting turning points for the following reasons. First, unrest on the financial markets often leads to tighter financial and credit conditions, which may hamper the investment activity of firms (Bloom, 2009). Second, private consumption of credit-constrained households is restricted (Espinoza et al., 2009).

The use of financial market indicators for short-term forecasting has already aroused academic interest before the financial and economic crisis (for example Stock and Watson (2003b)). Furthermore, Estrella and Hardouvelis (1991), Estrella and Mishkin (1999), Estrella et al. (2003), Kitchen and Monaco (2003), Stock and Watson (2003b), Stock and Watson (2006), Clements and Galvao (2009) or Wheelock and Wohar (2009) show that financial market indicators provide useful information for short-term forecasting.

However, there are still some open questions. First, to the best of our knowledge there is no comparison of the influence of financial market data on short-term forecasts for IP in Germany and the US that include the Great Recession in the evaluation sample. In general, the evidence for the role of financial variables in predicting economic activity for Germany is scarce (Drechsel and Scheufele, 2012b). Next, stability in terms of robust results in different sub-samples is often neglected. Most of the authors concentrate either on the overall forecasting performance of financial market indicators (Stock and Watson (2003b) or Ang et al. (2006)) or if they can predict recessions (Stock and Watson, 2003a). Finally, the majority of the short-term forecasting analyses that consider financial market data were published before the Great Recession and new evidence on this topic is scarce.

This paper analyzes the forecasting performance of financial market data in comparison to other indicator groups to predict IP over the short-term. In performing this task, we divide the available and potentially relevant economic indi-

cators which are available on a monthly basis into different groups: real economic indicators, surveys and composite indicators and financial market data. This is done for the US and Germany to investigate if the forecasting performance of financial market data differs between both countries, since financial market integration in the US is much higher than in Germany or other European countries (Weber, 2006).

For each country, we set up a set of indicators that contain the three different groups of indicators. Next, we set up single-indicator models to forecast IP for the forecast horizon up to six months.[4] The sample of our forecasting exercise consists of the period $1995m1 - 2012m12$. The out-of-sample period starts in $2004m1$ and ends in $2012m12$. Based on the forecasts for the different forecast horizons, we analyze the forecasting performance of each single model and the different weighting schemes which pool the forecasts.

We assess the forecasting performance by the root mean squared forecast error (RMSFE) of each single-indicator model and the respective pooled forecasts relative to the RMSFE of an autoregressive forecasting model for IP. As a significance test, we apply the pairwise test of equal forecast ability introduced by Giacomini and White (2006). Besides the general forecasting performance, we evaluate the forecasting performance of each category before and during the crisis to find out if the previous results are robust.

Our results indicate that to some extent financial market indicators are useful to forecast IP. This holds for both countries, especially for longer forecast horizons and the US. Furthermore, some of the single-indicator models and pooling approaches are significantly better than the benchmark model. Nevertheless, the majority of the financial market indicators show only in one of the defined sub-samples a higher forecasting performance than the benchmark model. By contrast, some of the pooling approaches indicate stability since they show in both sub-samples a smaller RMFSE than the benchmark model. Finally, our results indicate that the Great Recession was not foreseeable even financial market indicators were taken into account.

The remainder of the paper is structured as follows. Section 2 provides an overview of the data and our investigation approach. Section 3 presents and discusses the results of the investigation and section 4 summarizes and concludes.

[4]We concentrate on the first, the third and the sixth month to keep the analysis manageable.

2 Forecasting models and evaluation framework

2.1 Data

We apply three different groups of indicators for each country.[5] The first group contains *real economic indicators* like new orders, labor market variables or the number of sales. Typically, new orders of a certain product category will lead to higher production in the future. Furthermore, labor market indicators are useful for forecasting, since labor demand decisions may indicate the company's belief of the future development of the economy.

The second group of indicators contains *surveys and composite leading indicators*. The advantages of these indicators are that they are timely available and they usually include business expectations. For Germany, most of these indicators origin from the ifo Business Survey. For the US, there are several surveys from the Conference board. Furthermore, we apply surveys that exist for both countries, namely the Purchasing Manager Index (PMI) or the OECD Composite Leading indicator.

Finally, we take *financial market indicators* into account since many papers show that they are helpful to forecast economic activity (Stock and Watson, 2003b). As many professional forecasters were criticized that they did not use financial market data in their forecasting models, we pay special attention to these indicators. For both countries we use several interest rates with different maturities and term spreads for various bonds and swap rates. Furthermore, we employ monetary aggregates since Sims (1972) showed that there is a causal link between money and income.

Thus, it provides information about the future development of output. As well as monetary aggregates, we use different exchange rates and (commodity) prices, which provide useful information about future output growth. For example, in the latest recession, oil prices increased dramatically and in the US, the Case-Shiller home price index reported its largest price drop in its history in December 2008. Furthermore, we take use of some share price indices.

For both countries, we set up a set of indicators that contain all three groups of indicators. Nevertheless, the number and the composition of indicators for

[5]The complete list of the used indicators can be found in the Appendix A.3 for Germany and Appendix A.4 for the US.

each country is different. While we apply for Germany 104 indicators we have 74 indicators for the US. The different size of the indicator set is mainly for reasons of data availability.

Due to differences in publication lags, the indicators are typically incomplete for the same month ("ragged edge problem"). We updated the data on December $20, 2013$ and applied the shape of the ragged edge at this point of time in each forecasting step to get a realistic forecasting setup. More precisely, going back t months in time from December $20, 2013$, we delete the last t observations for each indicator. Hence, in each forecasting step we keep the setting as close as possible to the real forecasting situation.[6]

2.2 Single-indicator models

Our forecasting exercise is executed for the period $1995m1 - 2012m12$. We determine a rolling window of 108 in-sample months between $t - 108$ and $t - 1$ to estimate the relationship between IP and the indicators and to forecast IP up to six months. Hence, the first forecasts for IP refer to 2004m1-2004m6, based on the in-sample period 1995m1-2003m12. The last forecasts are conducted for 2012m7-2012m12, estimated with data from 2003m7-2012m6.

Every forecasting round is carried out for both countries. We set up one equation for each indicator.[7] Let $Y_t = \Delta lnIP_t$, where IP_t is the level of industry production and let X_t be an indicator for IP_t. Y_{t+h}^h is growth of IP over the next h periods in terms of a monthly growth rate. Each forecast is based on an h-step-ahead regression model:

$$Y_{t+h}^h = c + \sum_{i=k}^{p} \beta_i Y_{t-i} + \sum_{j=l}^{q} \gamma_j X_{t-j} + \epsilon_{t+h} \tag{1}$$

Regarding the timely availability of the different indicators, we use the indices l and k. The values for both indices vary between 0 and 3, depending on the publication lag. Each single-indicator model is optimized for its lag length by the Schwarz information criterion (SIC). After every estimation, we forecast IP up

[6]The forecasting design in this paper is pseudo-real time, i.e. we only account for data which were available at the time of the forecast. Nevertheless, we do not consider revisions in the data that can be substantial, especially for IP.

[7]All indicators enter the evaluation process as stationary variables.

to six months. In every forecasting round, we get as many forecasts as indicators. We concentrate on this forecast horizon since most of the information contained in the indicators accounts only for the short-term.

2.3 Pooling of forecasts

Many authors showed that forecast errors can be reduced in comparison to a single forecast by different combination models (see e.g. Stock and Watson (2003a), Stock and Watson (2004) or Timmermann (2006)). We therefore apply different pooling approaches as competitors to the single-indicator models.

Several pooling approaches are used in our forecasting framework. First, we apply simple averaging schemes like the *mean* and the *median*. Next, we use two approaches that take in-sample estimation errors of each indicator model into account. The AIC (Atkinson, 1980) (the lower the AIC value, the higher the weights) and the R^2 (the higher the R^2, the higher the weights) are used for this purpose. The weights given to the forecasts of the single model $i = 1, \ldots, n$ are constructed in the following way:

$$\omega_{i,t}^{IC} = e^{-0.5 \cdot (|IC_{i,t} - IC_{opt,t}|)} \Big/ \sum_{i=1}^{n} e^{-0.5 \cdot (|IC_{i,t} - IC_{opt,t}|)} \; . \tag{2}$$

IC denotes the respective information criteria, AIC or R^2 and $IC_{opt,t}$ either equals the largest R^2 value ($R^2_{max,t}$) or the smallest AIC value ($AIC_{min,t}$) among the in-sample estimations.

Nevertheless, models performing well in-sample may generate poor out-of sample forecasts (Stock and Watson, 2003a). Therefore, we use pooling approaches which account for models' past forecast performance over the same forecast horizon to estimate weights. An often very effective weighting scheme is the trimming approach that gives equal weights to a certain selection of forecasts, while excluding all other forecasts. Therefor, it takes the mean forecast from only the best $1 - x\%$ of models in terms of past squared forecast errors of the corresponding model (Timmermann, 2006). According to the literature we set the threshold x equal to 25, 50 and 75.[8]

[8] As a result, the forecast for a certain month using the trimming 75 approach relies on 26 indicators for Germany and 18 indicators for the US, respectively. For the trimming 25 approach, the number of indicators increases to 78 (Germany) and 54 (US).

Furthermore, we incorporate pooling based on discounted means of models' past squared forecast errors. The current weights assigned to forecasts are inversely proportional to the discounted means of their past squared forecast errors:[9]

$$\omega_{i,t,h}^{j} = \frac{\left(\sum_{l=t_0}^{t-1} \delta^{t-l} \cdot \left(\hat{\epsilon}_{i,l}^{j}\right)^2\right)^{-1}}{\sum_{s=1}^{n}\left(\sum_{l=t_0}^{t-1} \delta^{t-l} \cdot \left(\hat{\epsilon}_{s,l}^{j}\right)^2\right)^{-1}} \,. \tag{3}$$

2.4 Forecast evaluation

We calculate for each single forecast and pooling approach the RMSFE relative to a benchmark model. The latter is a simple univariate autoregressive model, optimized for its lag length by the Schwarz criterion for each forecast horizon for both countries:

$$Y_{t+h}^{h} = c + \sum_{i=k}^{p} \beta_i Y_{t-i} + \epsilon_{t+h} \tag{4}$$

The relative RMSFE is calculated as follows:

$$\textit{relative RMSFE} = \frac{\sqrt{\sum_{t=T_0+h}^{T_1-h}\left(Y_{t+h}^{h} - \hat{Y}_{i,t+h}^{h}\right)^2}}{\sqrt{\sum_{t=T_0+h}^{T_1-h}\left(Y_{t+h}^{h} - \hat{Y}_{t,h}\right)^2}} \tag{5}$$

We denote $\hat{Y}_{t,h}$ in equation 5 as the h-quarter-ahead forecast of Y_t performed by the benchmark AR model. $\hat{Y}_{i,t+h}$ describes the forecast, which was conducted with indicator i. T_0 denotes the first out-of sample forecast and T_1 the last date, where a forecast is executed. If the relative RMSFE is smaller than one, it indicates that the single-indicator model performs relatively better than the benchmark model.

In a first step, we compare the forecasting performance of each model by a ranking for each forecast horizon ($h = 1, ..., 6$). In a simple comparison of the rankings, we can detect the change of the forecasting power of the different indicator groups for the different forecast horizons. Furthermore, we include the different pooling approaches to compare the forecasting performance of single-

[9] In line with the literature, the discount factor δ is set equal to 0.95.

indicators models and the pooling approaches.

Nevertheless, differences in relative RSMFEs are only relevant, if they is statistically significant. For this purpose, the Diebold and Mariano (1995) test of equal predictive ability is very often used. This test is suitable to compare the general predictive ability of two models (Giacomini and White, 2006). However, in a real forecasting situation, the general forecasting performance is of secondary importance. It is more important to execute a forecast at a certain date using a certain model that provides a small forecast error.

For this reason, we choose the Giacomini and White (2006) test of conditional predictive ability. Using the Giacomini-White test, we address the problem of the so called *asymptotic irrelevance*, that occurs when forecasts are made by regression models, since the coefficients as well as estimation specifications in each model may change over time (West, 2006). Moreover, it enables us to compare the forecast accuracy of nested and non-nested models. Since we apply a rolling window, our benchmark model may be nested in one of the indicator models in some cases.[10]

3 Results

In this section we report the results based on the forecasts for IP for Germany and the US. Starting with the first one-step-ahead forecast ($h = 1$) for $2004m1$ and the last one for $2012m7$ we evaluate 103 forecasts. Since some of the pooling approaches (Section 2.3) that consider the past forecasting performance need at least one forecast error for their calculation we finally evaluate 102 forecasts for each forecast horizon ($h = 1, \ldots, 6$).[11] The last forecast for $h = 6$ is executed for $2012m12$. We concentrate on the forecasts for the one, three and six-step-ahead forecasts.[12]

3.1 General forecasting performance

For Germany, we conclude that the indicators with the best forecasting performance for the whole sample are mostly surveys or real economic indicators (e.g.

[10] For a detailed description of the test and the test statistic see Giacomini and White (2006).
[11] Hence, our investigation starts with the forecasts of IP in 2004m2.
[12] The results for the remaining forecast horizons are available upon request.

business expectations for next 6 months (manufacturing), New orders (intermediate goods)) for the forecast horizon $h = 1$ (Table 1). From the 25 best indicators, ranked by the relative RMSFE of the corresponding indicator model, there are only four models which include financial market indicators. Interestingly, some indicator models outperform the pooling approaches.

However, the results change if IP is forecasted for longer forecast horizons. Table 2 and Table 3 show the relative RSMFE for the forecast horizons $h = 3$ and $h = 6$. For $h = 3$ the single-indicator model with the lowest relative RMSFE is a model that includes a spread of interest rates (CLI spread of interest rates). Furthermore, spreads that showed a higher relative RMSFE than other indicators for $h = 1$ improve their forecasting performance for $h = 3$. Again, the different pooling approaches are outperformed by single-indicator models. For $h = 6$ some models that include financial market indicators outperform most of the other indicators and pooling approaches (e.g. spread: Government bonds (maturity 9 up to 10 - maturity 1 up to 2 years), CLI spread of interest rates).

For the US, the results in Table 4 indicate that for the forecast horizon $h = 1$, a spread (Yield spread; Swaps vs. govt; bonds, maturity 2 years) and different indicators based on surveys (e.g. PMI, OECD) perform best. Again, the pooling approaches show a higher relative RMSFE than some of the single-indicator models. For the forecast horizon $h = 3$ (Table 5), the results change. Single-indicator models based on surveys like the PMI do not show a good forecasting performance anymore relative to other models. Instead, financial market indicators (e.g. Dow Jones, Standard & Poors 500 share price index) become relatively more important in terms of a lower relative RMSFE. This holds for $h = 6$ (Table 6) where several survey and financial market indicators work best.

So far, we conclude that some of the financial market indicators perform better than indicators from other groups. In addition, the higher the forecast horizon is, the more important become financial market indicators. This is especially true for the US. For both countries and for the forecast horizons $h = 3$ and $h = 6$, the single-indicator model with the best forecasting performance uses one of the financial market indicators. This holds for the US for the forecast horizon $h = 1$.

However, most of the differences in the RMSFE are not statistically significant. Concerning the single-indicator models, most of them do not display significant differences when compared with the benchmark model. This holds for both coun-

tries and all forecast horizons.[13] But several pooling approaches outperform the benchmark model significantly. For the US, the *mean*, *median*, and the pooling approaches that consider the AIC or R^2 indicate a significant lower RMSFE than the benchmark model for all forecast horizons. This does not apply to the same extent for Germany. Only a few of the different pooling approaches (e.g. *mean*, $dmsfe$, *trimmed* 25) significantly outperform the benchmark model and this only holds for the forecast horizon $h = 3$.

However, the question arises if financial market indicators would have helped to detect the financial crises, that begun in 2007/2008. Therefore, we simply compare the forecast errors for IP of the indicators (Figures $1 - 3$) that worked best for the chosen forecast horizons (red solid line) and the forecast errors of the benchmark model (blue dotted line). Remember that most of the best single-indicator models use a financial market indicator.[14]

Figure 1 shows the root squared forecast error (RSFE) of the best single-indicator model in comparison to the RSFE of the benchmark model for $h = 1$. Obviously, the differences between both models are small before the crisis. The RSFEs start to rise dramatically in 2008 and the benchmark model shows even higher forecast errors than the best single-indicator model. This is particularly true in 2009 and remains until 2011. Afterwards, the differences diminish.

For the forecast horizon $h = 3$, the pattern remains for both countries (Figure 2). Remember that for Germany, the best indicator model changes from $h = 1$ (Business Expectations for next 6 months (ifo); Manufacturing) to $h = 3$ (CLI Spread of interest rates) while for the US it stays the same (Yield spread; Swaps vs. govt; bonds. maturity 2 years). For the forecast horizon $h = 6$, the differences between the benchmark model and the best indicator model (*Germany*: Spread; Government bonds; maturity 9 up to 10 - maturity 1 up to 2 years; *US*: Com-

[13]For Germany, only two single-indicators models show a significant lower RSMFE than the benchmark model using the following indicators: CLI Export order books ($h = 1$), CLI Spread of interest rates ($h = 3$). For the US and forecast horizon $h = 1$ the Yield spread (Swaps vs. govt; bonds. maturity 2 years) and the capacity utilization (Manufacturing) indicate a significant lower RSMFE. For $h = 3$, the capacity utilization (Manufacturing), the PMI (capital expenditure commitments), the Standard & Poors 500 share price index and a Yield (Corporates (Citigroup); AAA to AA. maturity 1-3 years) significantly outperform the benchmark model. For $h = 6$, there are only two OECD Composite Leading indicators, which indicate a significant lower RSMFE.

[14]For Germany and the forecast horizon h=1, the best indicator model uses a survey indicator (Business Expectations for next 6 months (ifo); Manufacturing).

modity price (HWWI); Coal) become smaller for both countries (Figure 3) but the pattern stays the same. Again, the indicator of the best forecasting model changes from forecast horizon $h = 3$ to $h = 6$ for both countries.

Since the best single-indicator model changes for the different forecast horizons in each country, a comparison is not straightforward. However, the results indicate that the best indicator model for each forecast horizon and country, although it is a financial market indicator, failed to forecast the beginning and the sharpness of the recession since the forecasting error increased dramatically. Interestingly, the RSFEs are in general smaller in the US than in Germany.

3.2 Stability of the forecasting performance for Germany

The overall forecasting performance discussed so far ignores the specific performance before and during the crisis. Hence, we want to explore, if the forecasting performance of each indicator and the different pooling approaches is different before and during the crisis.[15]

For Germany, Figures 4 to 6 show the relative RMSFE for both sub-samples for the various groups of indicators and for the different forecast horizons. In the very short-term, $h = 1$, most of the models that apply real economic indicators perform well either before or during the crisis (Figure 4). But none of them perform better than the benchmark model in both sub-samples. Furthermore, some of the real economic indicators show a higher forecast error than the benchmark model in both sub-samples. For the survey indicators, the results differ. We find indicators that perform well in both sub-samples (e.g. business expectations and assessment of business situation of the industry, assessment of different order books (all indicators are obtained from the Ifo-Business survey.)) although there are many indicators that work neither before nor during the crisis (e.g. business expectations; retail sales).

Most of the models that apply financial market indicators show a higher forecasting performance than the benchmark model before the crisis. There is only one financial market indicator (VDAX share volatility index) that performs well in both sub-samples. Finally, most of the different pooling approaches perform

[15]We split the sample into two sub-samples. The "Precrisis-sample" of the out-of-sample forecasts starts in $2004m2$ and ends in $2007m12$. The "Crisis-sample" accounts for the rest of the sample.

well in both sub-samples.

For longer forecast horizons, the results change (Figures 5 to 6). First, the number of real economic indicators that show higher forecast errors than the benchmark model in both sub-sample increases. Second, the forecasting performance of the survey indicators decreases in both sub-samples for $h = 3$ (Figure 5) but increases again for $h = 6$ (Figure 6). The relative RMSFE of the financial market indicators show that many indicators perform well in the precrisis-sample in the short-term ($h = 1$). For the forecast horizon $h = 6$, there are more financial market indicators that perform well in the crisis-sample than before. Nevertheless, there are only a few of them which work in both sub-samples, regardless of the forecast horizon. As for $h = 1$, some of the surveys perform well in both sub-samples. Again, most of them are business expectations or the assessment of the business situation obtained from the Ifo-Business survey. The different pooling approaches perform better than the benchmark model in the crisis but only to some extent before the crisis for $h = 3$ and $h = 6$.

3.3 Stability of the forecasting performance for the U.S.

For the US and the forecast horizon $h = 1$ (Figure 7), there is one real economic indicator (new orders; manufacturing) that shows a higher forecasting performance than the benchmark model in both sub-samples. However, most of the real economic indicators work only in one of the sub-samples. Regarding the survey indicators, most of them work in the crises-sample or in both sub-samples (e.g. PMI manufacturing). For the forecasting performance of the financial market indicators for the US, there is less clear evidence. Some of the indicators have a smaller RMSFE than the benchmark model in the crisis-sample while some of them even perform well in both sub-samples. Nevertheless, some of the financial market data do not work at all (e.g. Standard & Poors 500 share price index). Most of the pooling approaches perform well in both sub-samples and thus indicate stability.

For the forecast horizon $h = 3$ (Figure 8) and $h = 6$ (Figure 9), the results differ for the several indicator groups. First, the forecasting performance for some of the real economic indicators improves in terms that the number of indicators that perform well in both sub-samples increases from one indicator for $h = 1$ to at least four real economic indicators (e.g. employment or the participation

rate) for $h = 3$ and $h = 6$ respectively.[16] The results for the survey and financial market indicators mainly persist for the longer forecast horizons. Most of the survey indicators work well during the crisis but not before.

For the financial market indicators, there are more indicators that perform well in the crisis-sample than in the precrisis-sample. Nevertheless, some of the them work well in both sub-samples (e.g. Standard & Poors 500 share price index or Yield spread: Swaps vs. govt. bonds, maturity 2 years). Regarding the pooling approaches, the results remain. As for the forecast horizon $h = 1$, most of them indicate stability since their RMSFE is smaller than the RMSFE of the benchmark model for both sub-samples.

All in all, we can conclude the following. First, the longer the forecast horizon the better perform financial market indicators. This particularly applies for the US where financial market indicators play a more important role than in Germany. Second, pooling approaches indicate a lower RSMFE than the benchmark model but they are outperformed by some of the single-indicator models. The explanation for this pattern for the simple pooling approaches is obvious since there are many single-indicator models that have higher RMSFE's than the benchmark model.

For the pooling approaches which are based on the past forecasting performance the explanation is different. They have a "memory" since they consider the whole past forecasting performance of an indicator. Hence, if an indicator works well for some years, it is still included even it failed to forecast IP recently. Overall, even if the pooling approaches are not the best choice in terms of lowest relative RMSFE, they are the best choice in terms of achieving a more robust forecasting performance at any time.

Our results show that financial market data help to improve the forecasting performance of short-term forecasts for IP for both countries. However, our results indicate that the Great Recession was not foreseeable even if financial market indicators had been taking into account. This is in line with the existing literature (Drechsel and Scheufele (2012a) or Stock and Watson (2003b)). Furthermore, since there is no financial market indicator which shows the lowest

[16]The forecasting performance of the real economic indicators changes for the different forecast horizons. For example the indicator retail sales works well in both sub-samples for the forecast horizon $h = 3$. But for $h = 6$ the indicator shows a higher RMSFE than the benchmark model in the pre-crisis sample.

relative RMSFE at any time, it is difficult to select one or a group of them a priori.

Hence, concerning the general forecasting performance, the combination of a balanced set of indicators that contains all the needed information to provide a good forecasting performance and a well-working pooling approach seems to be the best solution. Concerning the timely detection of turning points, financial data may help to find them to some extent. But for this task non-linear models seem to be even more important.

4 Conclusion

This paper analyzes the forecasting performance of financial market data in comparison to real economic indicators, surveys and composite indicators to forecast monthly IP up to six months for Germany and the US. We focus on single-indicator models and pooling approaches and evaluate the forecasting performance in comparison to a benchmark model using a significant test. In a first step, we analyze the overall forecasting performance for the sample 2004 to 2012. In a second step we investigate the stability of the different forecasting models before and during the recent financial crisis for both countries.

It turns out that financial market data improve the forecasting performance of short-term forecasts for IP, especially for longer forecast horizons and the US. The different pooling approaches showed consistently a lower RMSFE than the benchmark model but they are outperformed by some of the single-indicator models. Furthermore, some of the single-indicator models and pooling approaches are significantly better than the benchmark model.

The different groups of indicators do not show a stable forecasting performance if the whole sample is divided in a precrisis- and a crisis-sample. Most of them show only in one of the two sub-samples a relatively better forecasting performance than the benchmark model. Only the pooling approaches indicate, to some extent, a stable forecasting performance in both sub-samples. Therefore, including financial market data certainly improve the forecasting performance since new information is provided that was not considered before. Nevertheless, our results indicate that the Great Recession was not foreseeable taking financial market data into account, in particular in its magnitude.

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A Appendix

A.1 A: Graphs

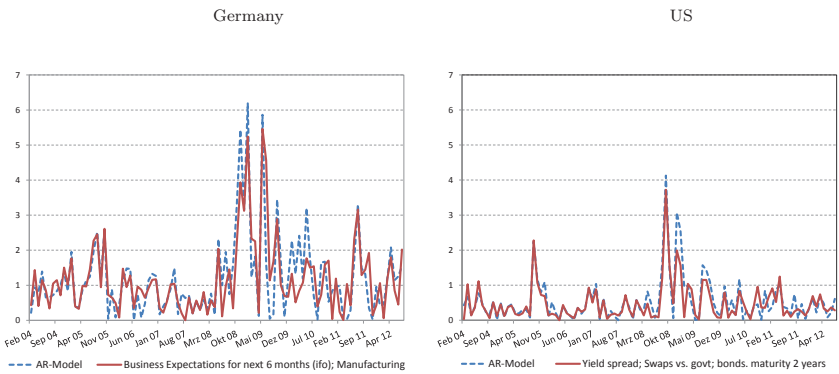

Figure 1: Best Model vs. Benchmark Model $h = 1$

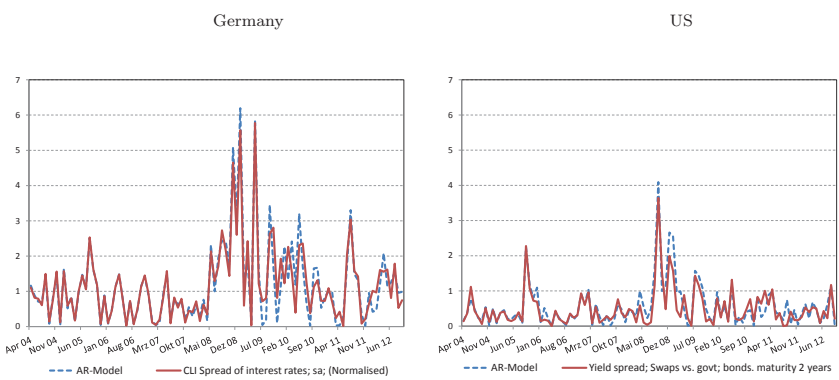

Figure 2: Best Model vs. Benchmark Model $h = 3$

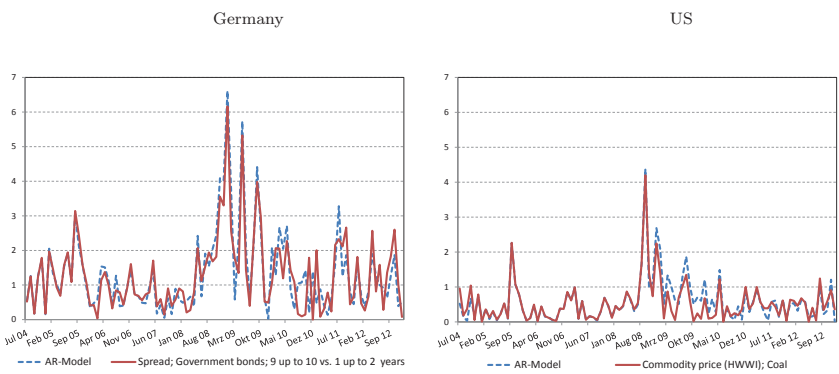

Figure 3: Best Model vs. Benchmark Model $h = 6$

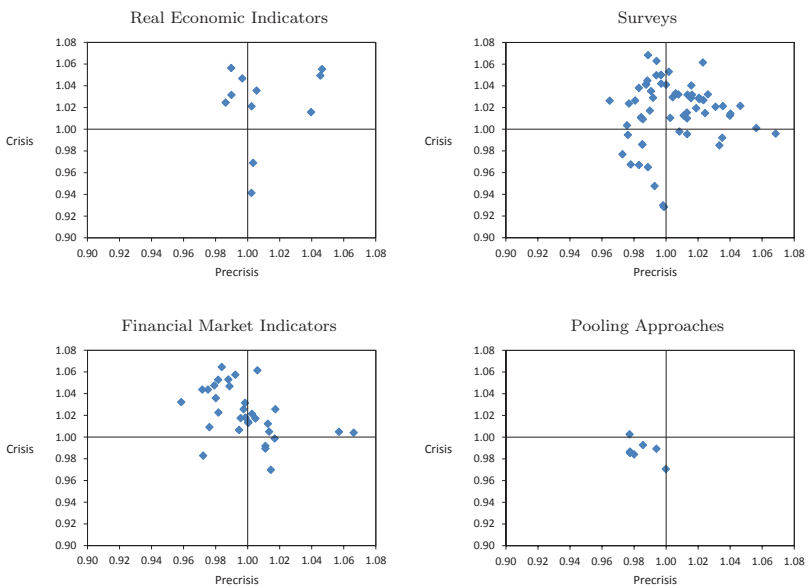

Figure 4: Out-of-Sample stability for IP (Germany $h = 1$)

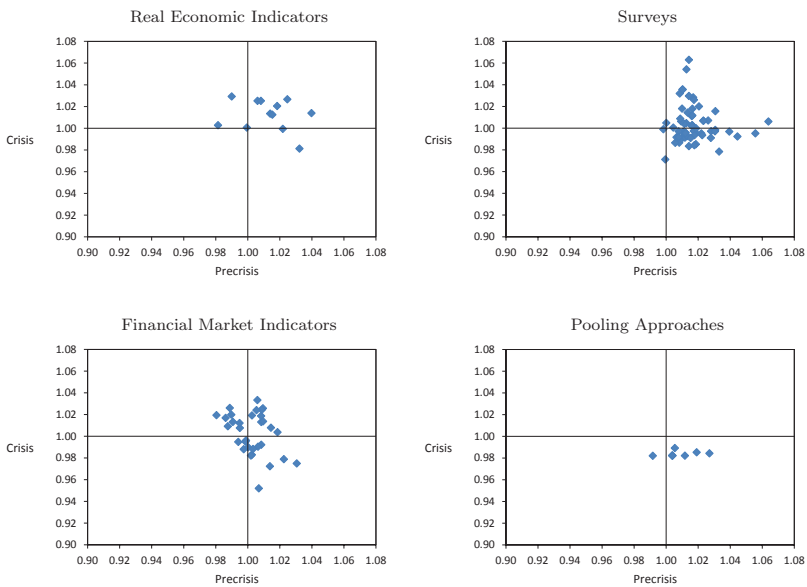

Figure 5: Out-of-Sample stability for IP (Germany $h = 3$)

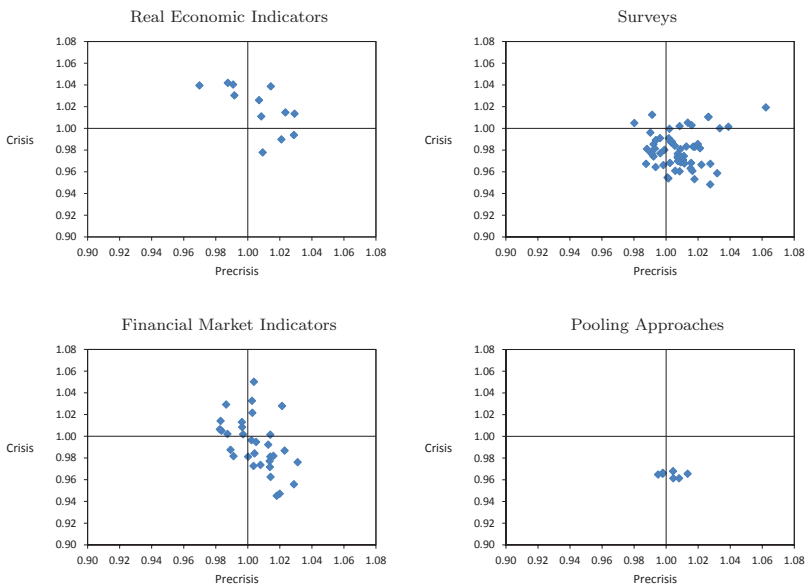

Figure 6: Out-of-Sample stability for IP (Germany $h = 6$)

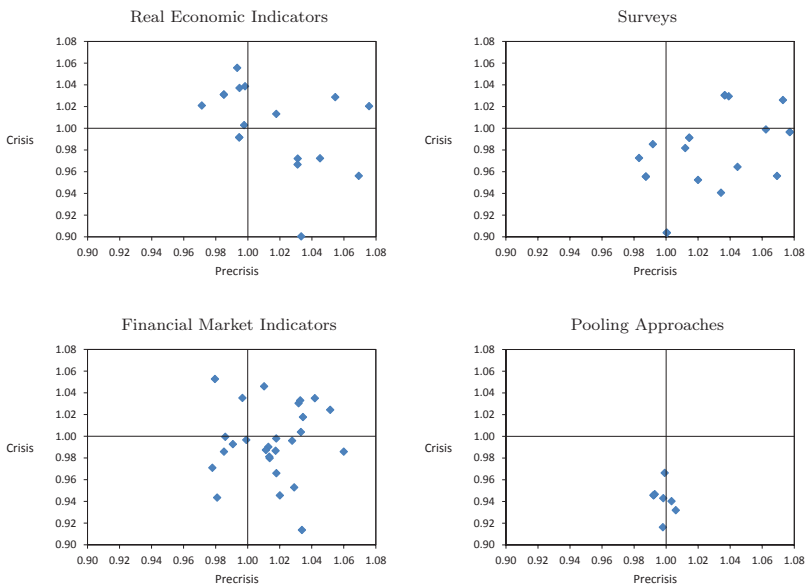

Figure 7: Out-of-Sample stability for IP (US $h = 1$)

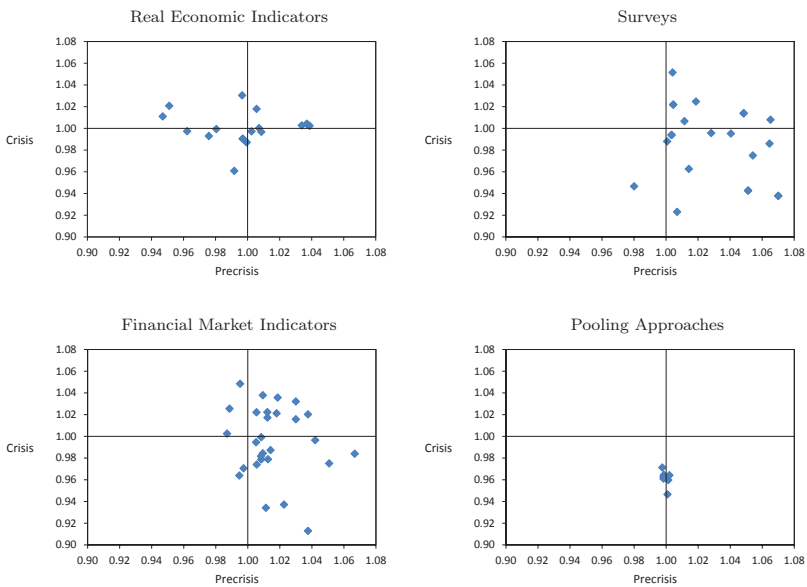

Figure 8: Out-of-Sample stability for IP (US $h = 3$)

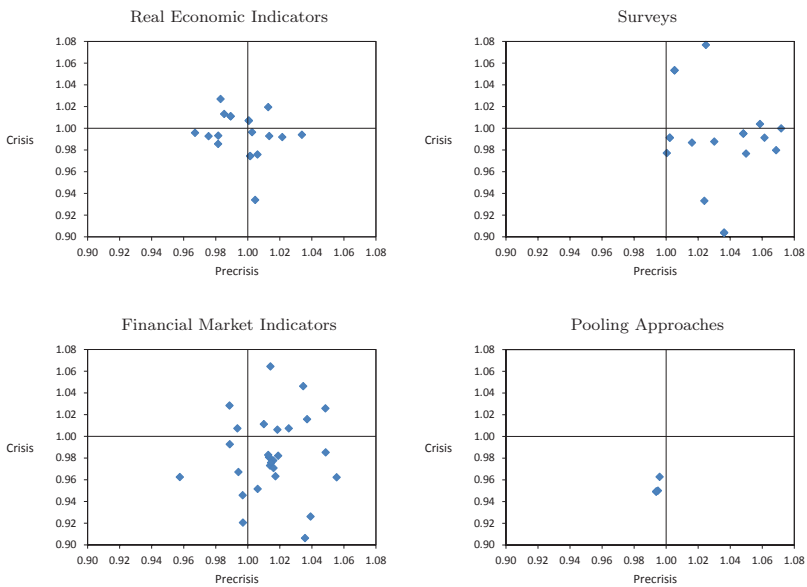

Figure 9: Out-of-Sample stability for IP (US $h = 6$)

A.2 B: Tables

Table 1: Ranking of indicators overall (Germany): Models with best forecast accuracy for forecast horizon $h = 1$

		h=1
1	Business Expectations for next 6 months (ifo); Manufacturing	0.935
2	Business Expectations for next 6 months (ifo); Intermediate goods	0.937
3	New orders. volume. total; Intermediate goods; 2010=100. sa	0.945
4	CLI Orders inflow/demand tendancy; sa (Normalised)	0.949
5	Business Expectations for next 6 months (ifo); Industry	0.965
6	CLI Export order books: level; sa (Normalised)	0.965*
7	Prod. expectations for the months ahead; Manufacturing; sa	0.966
8	CLI Spread of interest rates; sa; (Normalised)	0.971
9	New orders. volume. total; Chemicals; 2010=100; sa	0.973
10	trimmed 75	0.973
11	VDAX share volatility index; % p.a.	0.976
12	OECD Composite Leading indicator (Amplitude adjusted)	0.977
13	OECD Composite Leading indicator (Normalised)	0.981
14	dmsfe	0.981
15	AIC weighted	0.983
16	R2 weighted	0.984
17	Mean	0.984
18	Manufacturing - Production: future tendency; sa	0.985
19	Business Expectations for next 6 months (ifo); Capital goods	0.986
20	Commodity price (HWWI); Energy producing raw mat.	0.986
21	trimmed 50	0.990
22	trimmed 25	0.990
23	Commodity price (HWWI); Crude oil	0.991
24	Assessment of Business situation (ifo); Consumer goods	0.992
25	Stock volume currently hold; Retail trade; sa	0.993

Note: RMSFE of the forecast of each single-indicator model and the different pooling approaches relative to the RSMFE of the benckmark AR forecast. *** : 1%, ** : 5% and * : 10% indicating the significance level of the pairwise test of equal forecast ability as proposed by Giacomini and White (2006).

Table 2: Ranking of indicators overall (Germany): models with best forecast accuracy for forecast horizon $h = 3$

	h=3	
1	CLI Spread of interest rates; sa; (Normalised)	0.962*
2	Business Expectations for next 6 months (ifo); Intermediate goods	0.975
3	Spread; Government bonds. maturity 9 up to 10 - maturity 1 up to 2 years	0.976
4	dmsfe	0.984*
5	Spread; Bank bonds. maturity 9 up to 10 - maturity 1 up to 2 years	0.984
6	Commodity price (HWWI); Energy producing raw mat.	0.985
7	AIC weighted	0.986*
8	R2 weighted	0.986*
9	Spread; Federal bonds. maturity 10 - maturity 1 years	0.986
10	Mean	0.986*
11	FAZ share price index; 1958.12=100	0.986
12	trimmed 25	0.987*
13	Yield; Bank bonds; maturity over 1 up to 2 years	0.987
14	Business expectations over next 3 months; Retail trade; sa	0.989
15	CLI Total new orders manufacturing; sa (Normalised)	0.989
16	New orders; volume; total; Manufacturing; sa	0.990
17	Yield; Federal bonds; maturity 1 year	0.990
18	Commodity price (HWWI); Crude oil	0.990
19	Assessment of Business situation (ifo); Capital goods	0.990
20	trimmed 50	0.991
21	Expected economic situation; sa	0.991
22	trimmed 75	0.991*
23	Median	0.992
24	Assessment of Business situation (ifo); Manufactoring exl. food products; sa	0.992
25	Business expectations over next 3 months; Retail trade incl. Motor verhicle; sa	0.992

Note: RMSFE of the forecast of each single-indicator model and the different pooling approaches relative to the RSMFE of the benckmark AR forecast. *** : 1%, ** : 5% and * : 10% indicating the significance level of the pairwise test of equal forecast ability as proposed by Giacomini and White (2006).

Table 3: Ranking of indicators overall (Germany): models with best forecast accuracy for forecast horizon $h = 6$

	h=6	
1	Spread; Government bonds; maturity 9 up to 10 - maturity 1 up to 2 years	0.958
2	CLI Spread of interest rates; sa; (Normalised)	0.960
3	Business expectations over next 3 months; Retail trade; sa	0.962
4	Total new orders manufacturing; sa (Normalised)	0.963
5	DEU Manufacturing - Order books: level; sa	0.965
6	Order book level assessment; Manufacturing; Balance;sa	0.969
7	Assessment of Business situation (ifo); Capital goods	0.969
8	Business expectations over next 3 months; Retail trade incl. Motor verhicle; sa	0.969
9	Business confidence; Manufacturing; Balance; %. sa;	0.969
10	trimmed 25	0.969
11	Business climate (ifo); Industry; sa	0.970
12	trimmed 50	0.970
13	dmsfe	0.971
14	Assessment of Business situation (ifo); Manufactoring exl. food products; sa	0.971
15	AIC weighted	0.972
16	R2 weighted	0.972
17	Mean	0.972
18	DEU Manufacturing - Export order books: sa; % BALANCE	0.973
19	Commodity price (HWWI); Energy producing raw mat.	0.974
20	DEU Manufacturing - Industrial confidence indicator; sa	0.974
21	Germany Policy Uncertainity Index	0.974
22	trimmed 75	0.975
23	Assessment of Business situation (ifo); Intermediate goods; sa	0.975
24	Median	0.975
25	Employment expectations for the months ahead; Manufacturing; sa	0.976

Note: RMSFE of the forecast of each single-indicator model and the different pooling approaches relative to the RSMFE of the benckmark AR forecast. *** : 1%, ** : 5% and * : 10% indicating the significance level of the pairwise test of equal forecast ability as proposed by Giacomini and White (2006).

Table 4: Ranking of indicators overall (US): models with best forecast accuracy for forecast horizon $h = 1$

	h=1	
1	Yield spread; Swaps vs. govt; bonds. maturity 2 years	0.863*
2	PMI (new orders); Manufacturing	0.883
3	PMI (production); Manufacturing	0.900
4	Employment; Nonfarm private	0.918
5	PMI (ISM); Manufacturing	0.926
6	Business climate (OECD); Manufacturing	0.931
7	PMI (backlog of orders); Manufacturing	0.931
8	trimmed 75	0.934
9	Dow Jones Industrial Average share price index	0.941
10	trimmed 50	0.948
11	Commodity price (HWWI); Energy producing raw mat.	0.952
12	trimmed 25	0.954
13	dmsfe	0.955*
14	AIC weighted	0.956*
15	R2 weighted	0.956*
16	Mean	0.957*
17	PMI (capital expenditure commitments); Manufacturing	0.962*
18	Standard & Poors 500 share price index	0.962
19	OECD Composite Leading indicator (Amplitude adjusted)	0.962
20	OECD Composite Leading indicator (Normalised)	0.962
21	Monetary base	0.967
22	Assets of the banking sector; Commercial & industrial	0.970
23	Commodity price (HWWI); Crude oil	0.972
24	Median	0.973
25	Capacity utilization; Manufacturing	0.975*

Note: RMSFE of the forecast of each single-indicator model and the different pooling approaches relative to the RSMFE of the benckmark AR forecast. *** : 1%, ** : 5% and * : 10% indicating the significance level of the pairwise test of equal forecast ability as proposed by Giacomini and White (2006).

Table 5: Ranking of indicators overall (US): models with best forecast accuracy for forecast horizon $h = 3$

	h=3	
1	Yield spread; Swaps vs. govt. bonds; maturity 2 years	0.881
2	Dow Jones Industrial Average share price index	0.941
3	PMI (capital expenditure commitments); Manufacturing	0.941**
4	Standard & Poors 500 share price index	0.951*
5	PMI (new orders); Manufacturing	0.954
6	Assets of the banking sector; Commercial & industrial	0.956
7	trimmed 75	0.958
8	Commodity price (HWWI); Coal	0.963
9	OECD Composite Leading indicator (Amplitude adjusted)	0.967
10	OECD Composite Leading indicator (Normalised)	0.967
11	Composite Index of 4 Coincident Indicators	0.967
12	Coincident indicator (Conf. Board)	0.967
13	Capacity utilization; Manufacturing	0.967*
14	trimmed 50	0.969
15	dmsfe	0.969**
16	AIC weighted	0.970**
17	R2 weighted	0.970**
18	Commodity price (HWWI); Crude oil	0.970
19	Mean	0.972**
20	trimmed 25	0.972
21	PMI (production); Manufacturing	0.974
22	Commodity price (HWWI); Energy producing raw mat.	0.976
23	Median	0.977**
24	Yield; Corporates (Citigroup); AAA to AA. maturity 1-3 years	0.981**
25	Interbank rate; 1-month offered (US$-LIBOR)	0.985

Note: RMSFE of the forecast of each single-indicator model and the different pooling approaches relative to the RSMFE of the benckmark AR forecast. *** : 1%, ** : 5% and * : 10% indicating the significance level of the pairwise test of equal forecast ability as proposed by Giacomini and White (2006).

Table 6: Ranking of indicators overall (US): models with best forecast accuracy for forecast horizon $h = 6$

	h=6	
1	Commodity price (HWWI); Coal	0.881
2	OECD Composite Leading indicator (Amplitude adjusted)	0.941*
3	OECD Composite Leading indicator (Normalised)	0.941*
4	Dow Jones Industrial Average share price index	0.951
5	Standard & Poors 500 share price index	0.954
6	trimmed 75	0.956*
7	Capacity utilization; Manufacturing	0.958
8	Assets of the banking sector; Commercial & industrial	0.963
9	PMI (capital expenditure commitments); Manufacturing	0.967
10	trimmed 50	0.967
11	trimmed 25	0.967
12	Commodity price (HWWI); Energy producing raw mat.	0.967
13	dmsfe	0.967
14	AIC weighted	0.969**
15	R2 weighted	0.969**
16	Mean	0.970**
17	Monetary base	0.970
18	Yield spread; Swaps vs. govt. Bonds; maturity 2 years	0.970
19	Composite Index of 4 Coincident Indicators	0.972
20	Coincident indicator (Conf. Board)	0.972
21	Median	0.974*
22	Commodity price (HWWI); Crude oil	0.976
23	Interbank rate; 1-month offered (US$-LIBOR)	0.977
24	Spread ; Government bonds (T-Notes); 10 years - 1 year	0.981
25	Spread ; Interbank rate; 12-month - 1-month offered (US$-LIBOR)	0.985

Note: RMSFE of the forecast of each single-indicator model and the different pooling approaches relative to the RSMFE of the benckmark AR forecast. *** : 1%, ** : 5% and * : 10% indicating the significance level of the pairwise test of equal forecast ability as proposed by Giacomini and White (2006).

A.3 C: List of indicators for Germany

Real Economic indicators
Production; Intermediate goods; 2010=100, sa
New orders, volume, total; Manufacturing; 2010=100, sa
New orders, volume, total; Machinery & equipment n.e.c.; 2010=100, sa
New orders, volume, total; Intermediate goods; 2010=100, sa
New orders, volume, total; Consumer goods; 2010=100, sa
New orders, volume, total; Chemicals; 2010=100, sa
New orders, volume, total; Capital goods; 2010=100, sa
New orders, volume, total; Non-durable consumer goods; 2010=100, sa
New orders, volume, total; Electrical & optical equipment; 2010=100, sa
Employment; Mn, sa
Unemployment rate; % of dependent labor force, sa (discontinued)
Unemployment; Registered; Mn, sa

Survey & composite leading indicators
Business climate; Industry, 2005=100, sa
Business expectations; Industry, 2005=100, sa
Assessment of business situation; Industry, 2005=100, sa
Business climate; Manufactoring exl. food, 2005=100, sa
Business expectations; Manufactoring exl. food, 2005=100, sa
Assessment of business situation; Manufactoring exl. food, 2005=100, sa
Business climate; Retail sal incl. cars, 2005=100, sa
Business expectations; Retail sal incl. cars, 2005=100, sa
Assessment of business situation; Retail sal incl. cars, 2005=100, sa
Business climate; Retail sale incl. cars, 2005=100, sa
Business expectations; Retail sale incl. cars, 2005=100, sa
Assessment of business situation; Retail sale incl. cars, 2005=100, sa
Assessment of order books; Manufactoring, 2005=100, sa
Business climate; Investment goods, 2005=100, sa
Business expectations; Investment goods, 2005=100, sa
Assessment of business situation; Investment goods, 2005=100, sa
Business climate; Intermediate goods, 2005=100, sa
Business expectations; Intermediate goods, 2005=100, sa
Assessment of business situation; Intermediate goods, 2005=100, sa
Business climate; Consumer goods, 2005=100, sa
Business expectations; Consumer goods, 2005=100, sa
Assessment of business situation; Consumer goods, 2005=100, sa
CLI Business climate indicator sa / Quantum (non-additive or stock figures), SA; % BALANCE
CLI Export order books: level sa / Quantum (non-additive or stock figures), SA; % BALANCE
CLI Finished goods stocks: level sa / Quantum (non-additive or stock figures), SA; % BALANCE
CLI Orders inflow/demand tendancy sa / Quantum (non-additive or stock figures), SA; % BALANCE
CLI Total new orders manufacturing sa (Normalised) / Quantum (non-additive or stock figures), SA; NORMALISED
CLI Business climate indicator sa (Normalised) / Quantum (non-additive or stock figures), SA; NORMALISED
CLI Export order books: level sa (Normalised) / Quantum (non-additive or stock figures), SA; NORMALISED
CLI Finished goods stocks: level sa (Normalised) / Quantum (non-additive or stock figures), SA; NORMALISED
CLI Orders inflow/demand tendancy sa (Normalised) / Quantum (non-additive or stock figures), SA; NORMALISED
CLI Spread of interest rates (Normalised) / Quantum (non-additive or stock figures), SA; NORMALISED
Consumer confidence indicator sa / Normal = 100, SA; AMP ADJ
Expected economic situation sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Business situation: present sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Employment: future tendency sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Production: tendency sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Export order books: level sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Finished goods stocks: level sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Industrial confidence indicator sa / Normal = 100, SA; AMP ADJ
Manufacturing - Industrial confidence indicator sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Order books: level sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Orders inflow: tendency sa / Quantum (non-additive or stock figures), SA; % BALANCE
Manufacturing - Production: future tendency sa / Quantum (non-additive or stock figures), SA; % BALANCE
Economic sentiment; Business sector & consumers; 2000=100, sa
Business confidence; Manufacturing; Balance, %, sa
Stocks assessment (finished products); Manufacturing; Balance, %, sa
Employment expectations for the months ahead; Manufacturing; Balance, %, sa
Order book level assessment; Manufacturing; Balance, %, sa
Production trend observed in recent months; Manufacturing; Balance, %, sa
Export order book level assessment; Manufacturing; Balance, %, sa
Production expectations for the months ahead; Manufacturing; Balance, %, sa
Business confidence; Retail trade; Balance, %, sa

Business expectations over next 3 months; Retail trade; Balance, %, sa
Business activity (sales) over past 3 months; Retail trade; Balance, %, sa
Employment expectations over next 3 months; Retail trade; Balance, %, sa
Ordering intentions over next 3 months; Retail trade; Balance, %, sa
Stock volume currently hold; Retail trade; Balance, %, sa
Policy Uncertainity Index
OECD Composite Leading indicator (Amplitude adjusted)
OECD Composite Leading indicator (Normalised)
OECD Composite Leading indicator (Trend restored)

Financial market indicators
Money market funds; Level, bn Euro
Citigroup money market performance index; Local currency, 1997.12.31=100
Deposits; Non-MFI; domestic; all maturities; sa
Yield to maturity; bearer bonds; domestic
Money Supply M3
CDAX share performance index; 1987.12.30=100
DAX share performance index; 1987.12.30=1000
FAZ share price index; 1958.12=100
VDAX share volatility index; % p.a.
Yield; Bank bonds, maturity over 1 up to 2 years; Monthly average
Yield; Bank bonds, maturity over 5 up to 6 years; Monthly average
Yield; Bank bonds, maturity over 9 up to 10 years; Monthly average
Yield; Government bonds, maturity over 1 up to 2 years; Monthly average
Yield; Government bonds, maturity over 5 up to 6 years; Monthly average
Yield; Government bonds, maturity over 9 up to 10 years; Fair value; Monthly average
Citigroup bond performance index; Local currency based, 1984.12.31=100
Bund future; Nearest expiration; Month end
Exchange rate; DM/US$; Monthly average
Yield; Government bonds (Eurostat), maturity 10 years; Monthly average
Base rate; Month end
Yield; Federal bonds, maturity 1 year; Estimated; Month end
Yield; Federal bonds, maturity 5 years; Estimated; Month end
Yield; Federal bonds, maturity 10 years; Estimated; Month end
Commodity price (HWWI); Crude oil; US$ based, 2010=100; Monthly average
Commodity price (HWWI); Raw materials, excl. energy; US$ based, 2010=100; Monthly average
Commodity price (HWWI); Energy producing raw mat.; US$ based, 2010=100; Monthly average
Commodity price (HWWI); Energy producing raw mat.; Euro area; €based, 2010=100; Monthly average
Commodity price (HWWI); Raw materials, excl. energy; Euro area; €based, 2010=100; Monthly average
Spread; Bank bonds, maturity over 9 up to 10 years - maturity over 1 up to 2 years; Monthly average
Spread; Government bonds, maturity over 9 up to 10 years - maturity over 1 up to 2 year; Monthly average
Spread; Federal bonds, maturity 10 years - maturity 1 year; Estimated; Month end

A.4 D: List of indicators for the US

Real Economic indicators
New orders, value, total; Durable goods; Bn US$, sa
New orders, value, total; Manufacturing; Bn US$, sa
Employment; Mn, sa
Earnings, per week; Production and non-supervisory employees; US$, sa
Employment; Nonfarm private; Mn, sa
Employed; 000s, sa
Personal income; Bn US$, sa
Retail sales; Excluding cars & food services; Bn US$, sa
Sales; New commercial vehicles: Light trucks (incl. minivans and SUVs), domestic;1000, sa
Sales; New commercial vehicles; 1000, sa
Sales, motor vehicle units; Domestic autos; Thousands, sa
Sales, motor vehicle units; Domestic light trucks; Thousands, sa
Sales, motor vehicle units; Heavy trucks; Thousands, sa
Average hourly earnings; Production and non-supervisory employees, manufacturing; US$, sa
Working hours, weekly; Production and non-supervisory employees, sa
Participation rate; %, sa
Unemployment rate; Based on registrations; % of labor force, sa
Unemployment rate; Total; %, sa

Survey & composite leading indicators
Composite Index of 11 Leading Indicators; 2004=100 ,sa
Composite Index of 4 Coincident Indicators; 2004=100, sa

Composite Index of 7 Lagging Indicators; 2004=100, sa
PMI (backlog of orders); Manufacturing; Diffusion index, %, sa
PMI (employment); Manufacturing; Diffusion index, %, sa
PMI (new export orders); Manufacturing; Diffusion index, %, sa
Business climate (OECD); Manufacturing; Normal = 100, sa
Capacity utilization; Manufacturing; %, sa
Coincident indicator (Conf. Board); 2004=100, sa
Consumer climate (Conference Board); 1985=100, sa
Consumer climate (OECD); Normal = 100, sa
Consumer expectations (Conference Board); 1985=100, sa
Consumer situation (Conference Board); 1985=100, sa
Consumer confidence index; All regions; 1985=100, sa
Expectations; All regions; 1985=100, sa
PMI (ISM); Manufacturing; 50=neutral, sa
PMI (capital expenditure commitments); Manufacturing; Average days
PMI (new orders); Manufacturing; Diffusion index, %, sa
PMI (production); Manufacturing; Diffusion index, %, sa
Leading indicator (Conf. Board); 2004=100, sa
Policy Uncertainity Index
OECD Composite Leading indicator (Amplitude adjusted)
OECD Composite Leading indicator (Normalised)
OECD Composite Leading indicator (Trend restored)

Financial market indicators
Monetary base; Level, bn US$
Money supply M1; Level, bn US$, sa
Money supply M2; Level, bn US$, sa
Assets of the banking sector; Commercial & industrial, all comm. banks; Outstanding amount, bn US$, sa
10-year Treasury future; 2nd expiration; Month end
Citigroup bond performance index; Local currency based, 1984.12.31=100
Money Market Funds: Institutional; BN US$, sa.;
Dow Jones Industrial Average share price index; US$ based
Exchange rate; Ã¯US$; Monthly average
Exchange rate; Euro/US$; Monthly average
Interbank rate; 12-month offered (US$-LIBOR); Monthly average
Interbank rate; 1-month offered (US$-LIBOR); Monthly average
Spread; Interbank rate; 12-month offered - 1-month offered (US$-LIBOR); Monthly average
Standard & Poors 500 share price index; 1941-43=10
Swap rate; US$, 10 years vs. 3-month Libor; Monthly average
Swap rate; US$, 2 years vs. 3-month Libor; Monthly average
Yield spread; Swaps vs. govt. bonds, maturity 10 years; Basis pts; Monthly average
Yield spread; Swaps vs. govt. bonds, maturity 2 years; Basis pts; Monthly average
Spread; Swaps vs. govt. bonds, maturity 10 years - maturity 2 years; Basis pts; Monthly average
Yield; Corporates (Citigroup), AAA to AA, mat. more than 10 y.; Monthly average
Yield; Corporates (Citigroup), AAA to AA, maturity 1-3 years; Monthly average
Spread; Corporates (Citigroup), AAA to AA, mat. more than 10 y. - Corporates (Citigroup), AAA to AA, maturity 1-3 years; Monthly average
Yield; Government bonds (T-Notes), maturity 10 years; Monthly average
Yield; Government bonds (T-Notes), maturity 1 year; Monthly average
Spread; Government bonds (T-Notes), maturity 10 years - Government bonds (T-Notes), maturity 1 year;; Monthly average
Lending rate; Conventional mortgages
Commodity price (HWWI); Crude oil; US$ based, 2010=100; Monthly average
Commodity price (HWWI); Raw materials, excl. energy; US$ based, 2010=100; Monthly average
Commodity price (HWWI); Energy producing raw mat.; US$ based, 2010=100; Monthly average
Commodity price (HWWI); Coal; US$ based, 2010=100; Monthly average
House price; S&P/Case-Shiller Composite-10; 2000.01=100, sa