Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Department Socioeconomics

Has Macroeconomic Forecasting changed after the Great Recession? – Panel-based Evidence on Accuracy and Forecaster Behaviour from Germany

Jörg Döpke

Ulrich Fritsche

Karsten Müller

DEP (Socioeconomics) Discussion Papers
Macroeconomics and Finance Series
3/2018

Hamburg, 2018

Has Macroeconomic Forecasting changed after the *Great Recession*? – Panel-based Evidence on Accuracy and Forecaster Behaviour from Germany

Jörg Döpke*, Ulrich Fritsche†, Karsten Müller ‡

May 2, 2018

Abstract

Based on a panel of annual data for 17 growth and inflation forecasts from 14 institutions for Germany, we analyse forecast accuracy for the periods before and after the *Great Recession*, including measures of directional change accuracy based on Receiver Operating Curves (ROC). We find only small differences on forecast accuracy between both time periods. We test whether the conditions for forecast rationality hold in both time periods. We document an increased cross-section variance of forecasts and a changed correlation between inflation and growth forecast errors after the crisis, which might hint to a changed forecaster behaviour. This is also supported by estimated loss functions before and after the crisis, which suggest a stronger incentive to avoid overestimations (growth) and underestimations (inflation) after the crisis. Estimating loss functions for a 10—year rolling window also reveal shifts in the level and direction of loss asymmetry and strengthens the impression of a changed forecaster behaviour after the *Great Recession*.

Keywords: Macroeconomic Forecasting, Forecast Error Evaluation, Germany

JEL classification: E32, E37, G11

*University of Applied Sciences Merseburg (Hochschule Merseburg)

†Universität Hamburg.

‡Corresponding author. University of Applied Sciences Merseburg, Eberhard-Leibnitz-Straße 2, D-06217 Merseburg / Germany, Phone: +49 3461 46-2427, Mail: karsten.mueller@hs-merseburg.de

1 Introduction

The stunning magnitude of the forecast error during so-called *Great Recession* and the harsh debates[1] about the usefulness of macroeconomic forecasting has renewed the interest in this topic. Due to the lack of data for the time period after the crisis, evidence on a possible change of both measures of accuracy and efficiency as well as forecaster behaviour is missing. This paper aims at closing this gap.

Before the *Great Recession* there has arguably been a widespread shared view about the quality of business cycle forecasts.[2] This view may include the following points (see Fritsche and Tarassow, 2016, and the literature cited therein):

- First, macroeconomic forecasts in Germany are unbiased, but inefficient. The latter claim depends to some extent on the underlying assumption regarding the forecasters' loss function and on what kind of forecasts are considered: While growth forecasts seem to be best understood under the assumption of a symmetric loss function, for inflation forecasts evidence suggests that this assumption is inadequate (Krüger and Hoss, 2012). Krüger (2014) finds further in a multivariate setting of growth and inflation forecasts some evidence for inefficiency as well as for an asymmetric loss function.

- Second, there is no obvious tendency of forecast errors to in- or decrease over time. Heilemann and Stekler (2013) analyse the long-term development of forecast accuracy of German GDP growth and inflation forecasts from 1967 to 2010 and come to a rather sobering conclusion: Enhancements of in form of small forecast errors in the 1980s and 1990s appeared to be only temporary in nature and are largely driven by a low inflation and growth variance in these periods. The authors summarize that neither technical (e.g. better data availability or a superior performance of computers and programs) nor possible improvements in economic theories and methods led to a significant decline of forecast errors. This claim is further supported by findings that the anticipation of economic recessions failed in almost all cases (Loungani, 2001; Zidong An and Loungani, 2018).

- Third, beside a diverging information base due to different forecasting dates and - consequently - forecasting horizons - no notable differences in accuracy across institutions may be established: Döhrn and Schmidt (2011) based on a long time series of forecasts do not find significant differences in accuracy across institutions. Instead, the forecast horizon and therefore the available information set is more important in explaining accuracy. The authors further argue that the link between forecast errors and horizon is best characterized by a linear relationship.

Against this background we ask whether German forecasters may have learned from the failure to predict the *Great Recession* and whether this learning effect is visible in standard measures of accuracy and efficiency. Furthermore, we wonder whether forecaster behaviour may have changed. For example, forecasters may act more cautiously to avoid another over-estimation of growth after a similar mistake before the recession.

These questions are also important from a perspective of macroeconomic policy, since, first, business cycle forecasts are an important input for fiscal and monetary policy and, second, professional forecasters play a crucial role in forming macroeconomic expectations of a broader public.

[1]The group of critics is even in retrospect impressively wide-ranging and outspoken. Queen Elisabeth II asked: "Why did nobody notice it?“, prompting a response letter from British economists (Besly and Hennessy, 2009). Nienhaus (2009) calls economists "duds" and argues that " economist will also miss the coming crisis ". Scholars from within the profession discuss "the guilt of economists" (Riedel, 2013) or claim: "Most work in macroeconomics in the past 30 years has been useless at best and harmful at worst" (Paul Krugman, quoted after The Economist (2009)).

[2]See, e.g., Fildes and Stekler (2002) and Döpke and Fritsche (2006a) (for German data) and the literature cited therein

The latter aspect is, e.g. emphasized by the model of Carroll (2003) in which households derive their expectation from the media, which reflect of the rational expectations of professional forecasters. Since households in this model update their expectation only in part and occasionally, expectations of the households as an aggregate adjust only slowly to new information, while professional forecasters still have rational forward-looking expectations.

Some papers have already elaborated on related questions: Frenkel et al. (2011) address the question, whether the expectation formation process of professional forecasters may have changed due to the crisis. Based on expectations backed out from the *Survey of Professional Forecasters* provided by the European Central Bank (see Garcia, 2003) the authors conclude that core equations of applied macroeconomics, namely an Okun relation, a Phillips curve, and a Taylor rule have not changed in the eyes of professional forecasters. Pain et al. (2014) argues that international organizations like the OECD learned from crisis and pay now more attention to global economic or financial developments. Heilemann and Schnorr-Bäcker (2017) provide an in-depth *post-mortem* analysis of the failed forecast of the downturn after the financial crisis in Germany and conclude that the forecasters had low priors about the probability of a recession in the first place. Moreover, the authors consider in great detail the information available to the forecasters during the crisis and find considerable evidence that important pieces of information have been ignored. A different perspective is taken by Drechsel and Scheufele (2012) who argue that forecasters had little chances to correctly predict the recession, insofar the forecast relied on leading indicators: While the combination of forecasts provides same gains of accuracy, the forecasts made in the dawning of the recession came pretty close to the best indicator based forecasts. In a survey of related research Castle et al. (2016) find, that not model misspecification by itself causes large forecast errors, but structural breaks in the estimated relationships do.

In the following we use a panel consisting annual data ranging from 1971 to 2016 covering 17 different forecasts stemming from 14 distinct institutions and compare standard measures of forecast accuracy for the time period after the crisis and before. We refer to regression based test of unbiasedness and efficiency and test for parameter stability. Furthermore, we collect evidence regarding the question, whether the behaviour of forecasters might have changed since the crisis by analysing the loss function of the forecasters.

Our results indicate that there are only small differences on forecast accuracy between both time periods. Quantitative measures of forecast accuracy slightly increase after the crisis. As regards growth forecasts, before the crisis the number of over- exceeds the number of underestimations, while for period after the crisis, the opposite is true. An increased cross-section variance of forecasts after the crisis indicate a more divided forecaster community. Qualitative measures of forecast accuracy like Receiver Operating Curves (ROC) suggest less informative power after the crisis. Moreover, contingency analysis support the impression that forecast quality has not changed, but forecaster‘s behaviour.

Tests for (strong) efficiency of the forecasts over the entire sample indicate that growth and inflation forecasts appear to be unbiased, but not (strongly) efficient. Rationality tests for the time period before and after the crisis confirm these findings, first of all for the period after the crisis. A further hint for a change in the behaviour of forecasters is given with the significant change of correlation between inflation and growth forecasts errors. The estimated loss functions give some evidence for a difference between both time periods: For the period after the *Great Recession* the estimated asymmetry parameter points to incentives for underestimations (growth forecasts), respectively overestimations (inflation forecasts), whereas the same parameter estimated with pre-recession data points to symmetric loss functions. 10-year rolling windows loss function estimates show shifts in the level and direction of loss asymmetry and strengthens the impression of a changed forecaster behaviour after the *Great Recession*.

All in all, the quantitative and qualitative measures of forecast error do not imply a change in forecast quality, but the overall results support the thesis of changed forecaster behaviour.

The remainder of the paper is organized as follows: Section 2 briefly describes the data at hand.

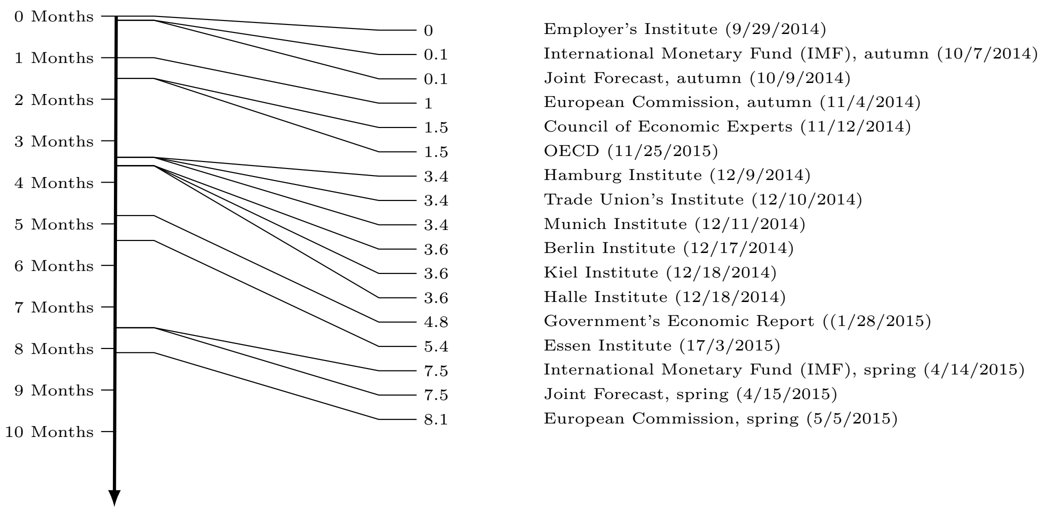
Section 3 discusses whether the accuracy of German business cycle forecasts has changed after the crisis. Section 4 examines based on estimations of implied loss functions whether the forecaster's behaviour has changed. The last section 5 concludes.

2 Data

In the following section we use an updated version of the data-set used by Döpke and Fritsche (2006a) and evaluate forecasts of several institutions delivering forecasts for the German economy. In particular, we take into account the following institutions:

- International organizations, namely: the International Monetary Fund (IMF) and the European Commission (EC), for each the autumn and the spring forecast, as well as the OECD.
- The six largest economic research institutes in Germany, that are formally politically and economically independent: the Berlin Institute (DIW), the Essen institute (RWI), the Halle institute (IWH), the Hamburg institute (HWWI),[3] the Kiel Institute (IfW), and the ifo institute located in Munich.
- Institutes that are financed by interest groups: the trade union's institute (IMK)[4] and the employer's institute (IW).
- Forecasts that have been conducted by institutions within the process of economic policy advice: the joint forecast (GD) of the so-called "leading" research institutes, both in spring and autumn, the German Council of Economic Experts, and the Government's economic report.

Figure 1: Time Line of Business Cycle Forecasts in Germany for 2015



In the following, we refer to forecasts in the Winter semester from September to March/April at the latest to capture the typical forecasting situation of most institutions.[5] It should be noted, however, that the forecasters do not all publish at the same time. Figure 1 shows the timing of

[3] Up to 2005, this institute was named HWWA and mainly funded by public money. From 2006 onwards, the institute has been run as a private funded institute.

[4] Up to 2004 we refer to the forecasts of the WSI institute, which is also an institute funded by the trade unions. While still existing, the WSI institute provides no business cycle forecasts since the IMK came into existence.

[5] This is also the reason, why some institutions shine up twice in our data set, while other do not. In some other cases (e.g. the Kiel institute) the forecasting frequency has also changed during time from twice a year to four times a year.

the forecasts during 2014/15 as an example for the usual timing of the publications. Of course, the varying forecasting dates have direct consequences for the accuracy of the forecasts since a later forecasting date allows the forecaster to take additional information into account.[6] Note, however, that the pattern of forecasting dates as shown above is stable over time: an institution that has forecasted, say, in November, has done so for all years in our sample. Thus, a comparison for time periods before and after the crisis remains meaningful.

For all institutions, we have collected the growth and inflation forecasts. The growth forecast is the predicted rate of change of real GNP (for the time span 1983 to 1989) and of real GDP (for all other years).[7] In the case of interval forecasts the simple average is used. The numbers refer to West Germany up to 1992, and to unified Germany from 1993 to present. As the inflation forecast we use the predicted change of the deflator of private consumption when this figure was available.[8] As regards the actual outcome, it is possible to refer to the last available revised data or to the first published ("real-time") data. As it is more or less common in the analysis of business cycle forecasts, we make use of the latter type of numbers i.e. we compare the forecasts made at the end of a certain year t or at the beginning of the following year $t+1$ with the first published figure for the year $t+1$. The forecast error is defined as $e_t = A_t - P_t$, i.e. the actual value in period t minus the forecast made in period $t-1$. Hence, a negative forecast error corresponds to an overestimation of the growth (inflation) rate, whereas a positive value represents an underestimation.

3 Has the Forecaster Performance changed?

3.1 Forecast Accuracy

Figure 2 shows the distribution of the growth and inflation forecast errors of the institutions under investigation.[9] We use two sub-samples, before (2002-2008) and after (2010-2016) the *Great Recession*. The year with the largest forecast errors, 2009, is not included in either sample. The distributions of errors have means and medians in the neighbourhood of zero, pointing to unbiased forecasts. Before and after the crisis, the interquartile range includes a forecast error of zero. The distribution of growth forecast errors shifts after the crisis to a stronger tendency of underestimation. A similar pattern for inflation forecasts is not visible in the data.

Turning to statistical measures of forecast accuracy (see De Gooijer and Hyndman, 2006, for an overwiew) Table 1 represents a couple of standard measures for pooled data of all institutions under investigation[10]

Some noteworthy differences occur: as regards growth forecasts, the mean error before the crisis is practically zero, whereas the same measure indicates a slight under-estimation of growth for the period after the crisis. This is in line with the assumption that forecasters have become more cautious after the huge over-estimation of growth in 2009. The mean error of the inflation forecasts remains unchanged.

[6]For an extensive discussion of the impact of the forecasting date on forecast accuracy see Döhrn and Schmidt (2011).

[7]This choice is motivated by the "headline figure" of the statistical office for the respective year. Note, however, that frequently the forecasts refer to "growth" rather than explicitly to either GDP or GNP or to one figure only. In these cases we have assumed that the forecasters made no distinction between the concepts and had the same forecast for both figures.

[8]In some cases, however, no explicit reference was given whether a mentioned inflation forecast referred to the consumption deflator or to the CPI. In such cases we assume that no distinction between the figures was intended by the forecaster and used the available inflation forecast.

[9]All computations reported in this paper have been done with *GRETL* (Cottrell and Lucchetti, 2017) and *R* (R Core Team, 2017).

[10]The Mean Absolute Scaled Error has been suggested more recently (Hyndman and Koehler, 2006). It includes, like other scaled error measures, a relation to the naive "no-change"-forecast as a benchmark model but with the benefit of less susceptibility to data. A value under one indicates a more accurate forecast power as the benchmark model.

Table 1: Descriptive Statistics on Forecast Accuracy in Germany - Before and After the *Great Recession*

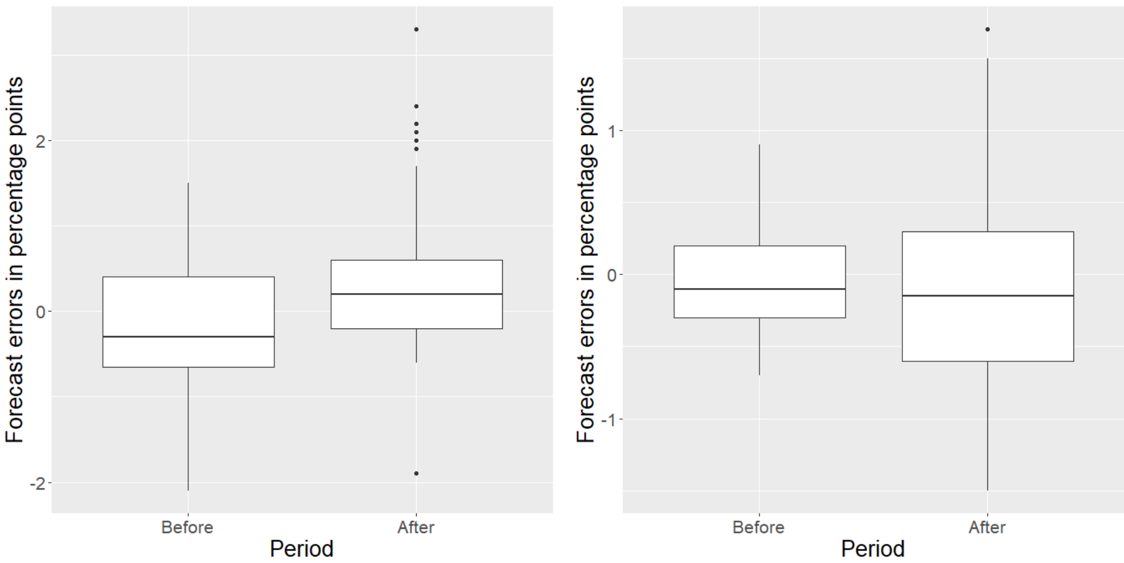
	Before Crisis: 2002 to 2008	After Crisis: 2010 to 2016	p-value[a)]
	Growth Forecasts		
Number of observations	119	119	
Mean Error	-0.151	0.380	(0.000)
Mean Absolute Error	0.662	0.614	(0.148)
Mean Absolute Scaled Error	0.697	0.784	
Root Mean Squared Error	0.796	0.938	
Theil's Inequality Coefficient	0.497	0.443	
Rank Test[b)]	(0.931)	(0.138)	
Wilcoxon Rank Test[b)]	(0.369)	(0.002)	
Number of Overestimations	76	48	
Number of Underestimations	43	71	
Variance of Forecasts	0.244	0.387	(0.006)
	Inflation Forecasts		
Number of observations	119	119	
Mean Error	-0.041	-0.065	(0.249)
Mean Absolute Error	0.279	0.525	(0.000)
Mean Absolute Scaled Error	0.931	1.657	
Root Mean Squared Error	0.352	0.641	
Theil's Inequality Coefficient	0.227	0.447	
Rank Test[b)]	(1.000)	(0.931)	
Wilcoxon Rank Test[b)]	(0.350)	(0.107)	
Number of Overestimations	73	76	
Number of Underestimations	46	43	
Variance of Forecasts	0.142	0.224	(0.007)

Notes: Source: own calculations. The mean error ME $= \frac{1}{T}\sum_{t=1}^{T} e_t$, where e_t is the forecast error in each period, defined as actual A_t (in t) minus predicted P_t (in $t-1$ for period t). Thus, a positive (negative) value of the mean error corresponds to an under (over-) estimation of the growth rate. $t = 1, ..., T$ is the time index. The mean absolute error MAE $= \frac{1}{T}\sum_{t=1}^{T} |e_t|$. The Root Mean Squared Error: RMSE $= \sqrt{\frac{1}{T}\sum_{t=1}^{T} |e_t^2|}$. The mean absolute scaled error MASE $= \frac{\frac{1}{T}\sum_{t=1}^{T}|e_t|}{\frac{1}{T-1}\sum_{t=1}^{T}|A_t-P_t|}$. [a)] p-values (in brackets) refer to a t-test for equal means and an F-test for equal variances, respectively. [b)]refers to the test of Campbell and Ghysels (1997).

Figure 2: Box-Plots of Forecasts Errors in Germany

(a) Growth Forecast Errors

(b) Inflation Forecast Errors



Notes: Own calculation

Both the Mean Absolute Error and the Root Mean Squared Error increase after the crisis. The lion's share of these increases stems from the forecast error in 2010, in which most forecasts missed the magnitude of the recovery. This confirm a wide-spread believe among practitioners according to which — as a rule — beginning upswings are likely to be underestimated. Dovern and Jannsen (2017) also report that growth forecasts errors depend on the stance of the business cycle. A similar albeit less pronounced picture is visible in the inflation forecast errors.

The count of the number of under- and overestimations of economic growth reveals a marked change between the two time periods considered. Before the crisis overestimations have been more frequent, afterwards the opposite holds. This points to a changed loss function of the forecasters. We will turn to this question in the remainder of the paper in greater length. Moreover, it is not possible to find a similar picture in the inflation forecast errors.

A hint to a possibly changed forecaster behaviour is also provided by the cross-section variance of the forecasts itself, which points to more divided forecasters after the crisis. An increase of disagreement among forecasters is frequently interpreted as a measure of uncertainty. This interpretation is not undisputed (see Döpke and Fritsche, 2006b, an the literature cited therein). Still, the figure may reflect some doubts about theories and forecasting models that had been considered as reliable before the crisis, but did not help to foresee it.

Even if one considers the magnitude of forecast from the perspective of a macroeconomic policy-maker as large, the forecasts can still be useful, if they give some information about the tendency of the underlying business cycle. Hence, the analysis of the accuracy of the directional change implied by the forecasts is of relevance.

Table 2 shows the result of a contingency analysis of the forecast errors before and after the crisis. The results of a test for independence indicate, at least at a 10 percent significance level, that the forecast errors have information content for directional changes of both growth and inflation before and after the crisis.

We also apply an analysis based on a Receiver Operating Characteristic (ROC) curve. A deceleration of growth (inflation) that has been forecasted may happen or not. Consequently, false positive and false negative errors have to be evaluated. The goals of minimizing both types of errors contradict each other: Predicting a downturn very often reduces the risk of missing a downturn, but increases the number of false alarms. Predicting a downturn rarely gives likely almost no false

Table 2: Cell Counts for 2 × 2 Contingency Table Before and after the *Great Recession*

	N	$\Delta P > 0$, $\Delta A > 0$	$\Delta P > 0$ $\Delta A < 0$	$\Delta P < 0$ $\Delta A > 0$	$\Delta P < 0$ $\Delta A < 0$	p-value
				Growth Forecasts		
Before crisis	119	36	37	15	31	0.07
After Crisis	119	54	10	14	41	$< 0,01$
				Inflation Forecasts		
Before crisis	119	60	16	8	35	$< 0,01$
After Crisis	119	36	37	15	31	0.07

Notes: P denots the predicted value, A the actual outcome. $\Delta P > 0$ therefore denotes a forecasted acceleration of the growth (inflation) rate, while $\Delta A > 0$ denotes a respective acceleration that ha actually happened.

alarms, but increases the proportion of false negatives. An apparent solution would be, to introduce a cutoff value. In our case this would mean, that below a certain predicted growth (inflation) rate a deceleration of the forecasted value would be assumed. The problem is, that this cutoff is arbitrary. Therefore, the so-called Receiver operating characteristic (ROC) curves consider all possible cutoff values. They have been frequently used in economic recently (see, e.g. Berge and Jordà, 2011; Pierdzioch and Rülke, 2015; Liu and Moench, 2016).

A ROC analysis starts from calculating the *sensitivity* and *specificity*. The former is proportion of true positives relative to all decelerations (including zero rates of change), the latter the proportion of true negatives relative to all accelerations. Sensitivity and specificity are both functions of the cutoff-value, c, and are defined as

$$PTP(c) = \frac{1}{n_R} \sum_{t=1}^{N} \mathbf{1}_{A_t = P_t = 1} \tag{1}$$

$$PTN(c) = \frac{1}{n_{NR}} \sum_{t=1}^{N} \mathbf{1}_{A_t = P_t = 0} \tag{2}$$

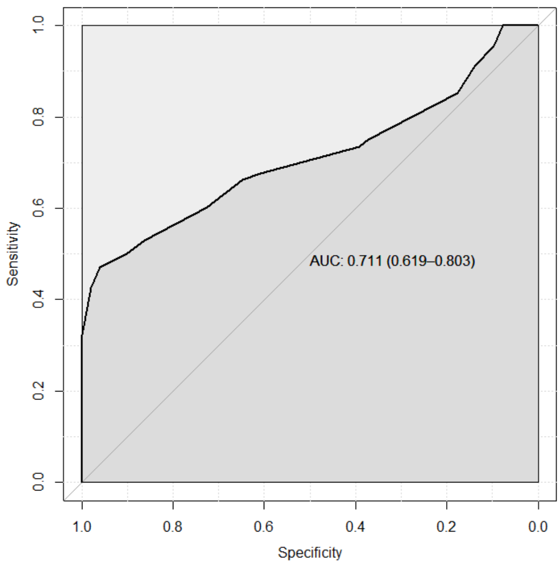
where n_R denotes the number of deceleration periods (true positives plus false negatives) and n_{NR} denotes the number of periods with accelerating rates of change (true negatives plus false positives), where $N = n_R + n_{NR}$.

Within this framework, two extreme cases are possible: on the one hand, if the forecaster never predicts a deceleration PTP assumes a value of zero. On the other hand, if the forecaster always predicts a deceleration, there are no false negatives, but many false positives. In this case, PTP is equal to 1 and PTN is zero. Different combinations of the proportion of true positives and false positives can be plotted by varying the cutoff value resulting in the ROC curve, which depicts combinations of the proportion of false positives on the horizontal axis and the proportion of true positives on the vertical axis.

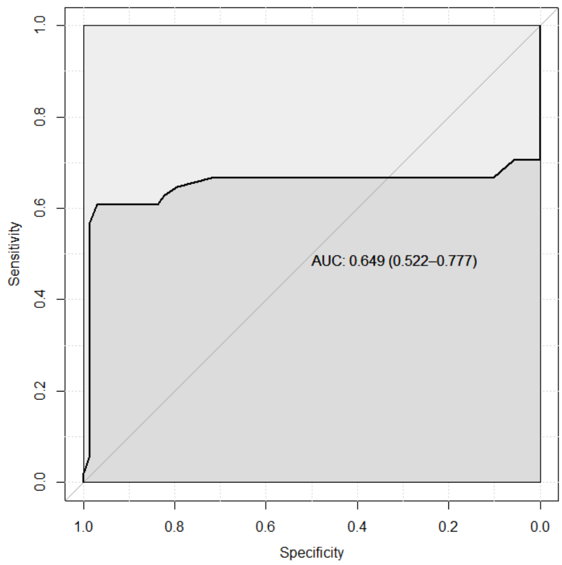
The area under a ROC curve (AUROC) is a useful measure of the quality of directional forecasts. Perfect forecasts result in AUROC = 1 because the corresponding ROC curve hugs to the top left corner, while forecasts that are indistinguishable from a coin-flip result in AUROC = 0.5 because the ROC curve coincides the 45° line. Finally, if the forecasts are even worse than pure coin-flip, then AUROC < 0.5.

The results, depicted in Figure 3, show that both inflation and growth forecasts have AUROC values significantly larger than the coin-flip benchmark before the crisis. But for both predictions the value decreases after the crisis, indicating that the prediction have become less informative at least for the directional change of growth and inflation rates.

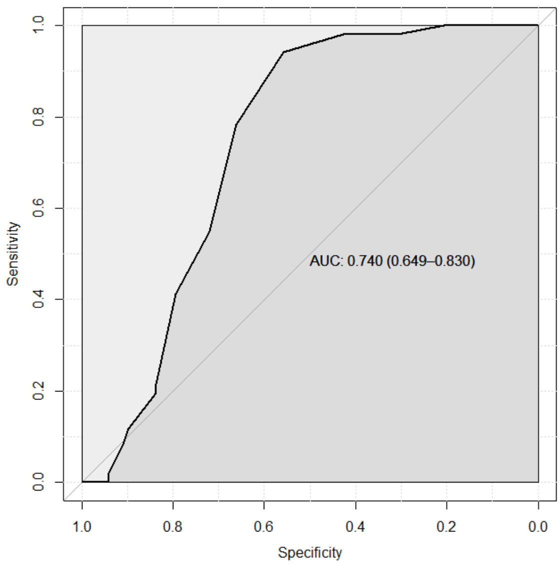
Figure 3: Reciever Operating Curves before and after the *Great Recession*



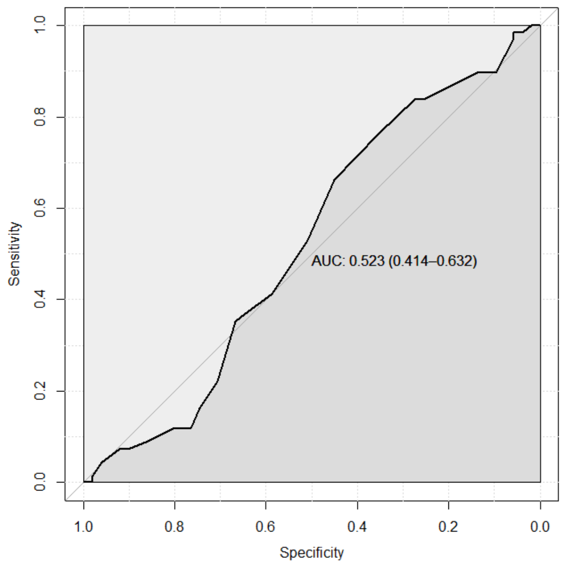
(a) Growth Forecasts before crisis



(b) Growth Forecasts after crisis



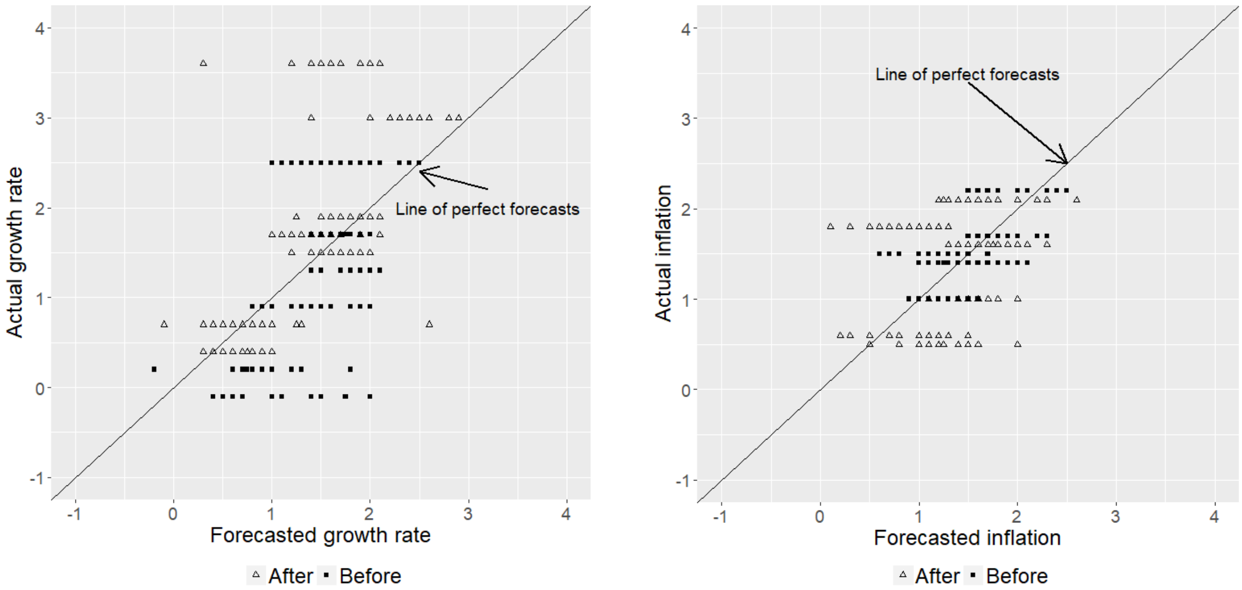
(c) Inflation Forecasts before crisis



(d) Inflation Forecasts after crisis

Source: Own calculations, using the package of Robin et al. (2011)

Figure 4: Correlation of Forecasts and Actuals



(a) Growth Forecasts

(b) Inflation Forecasts

Notes: Own calculation

3.2 Tests for Forecasts Rationality

Figure 4 shows the relation between the forecasted and actual rates of change before and after the crisis. Furthermore, the line of perfect forecasts is included. This line represents the ideal of a rational - i.e. unbiased and efficient - forecast.

This benchmark for the quality of business cycle forecasts implies that an optimal forecast has to be unbiased (at least, as long as a symmetric loss function is assumed) and efficient, i.e. it makes use of all information available at forecasting date. To test the hypothesis, we use the following three approaches:

- First, we test for the unbiasedness of the forecasts. To this end we use the Mincer and Zarnowitz (1969)-regression: $A_t = \beta_0 + \beta_1 P_t + u_t$, where P_t is the forecast made in period $t-1$ for period t and A_t is the actual outcome in period t. We then test the hypothesis $H_0 : \beta_0 = 0 \wedge \beta_1 = 1$ with a F-test. The respective column in the tables reports the marginal significance level of this test based on robust standard errors.

- As a test for (weak) efficiency of the forecasts, we refer to a test for autocorrelation of forecast errors. For an optimal forecast one should be unable to find any variable, which helps to forecast the error, including its own lagged values. Again, we report the marginal significance level of the tests based on robust standard errors.

- Furthermore, we provide tests for (strong) efficiency for the full sample using the approach of Holden and Peel (1990). In particular, the following equation has been estimated for the efficiency tests:

$$e_{i,t} = \beta_{0,i} + \beta_1 e_{i,t-1} + \beta_2 x_{t-1} + u_{i,t} \qquad (3)$$

For equation 3 we report the p-value for the test of the hypothesis

$$H_0 = \begin{cases} \beta_{0,i} = 0 \\ \beta_1 = 0 \\ \beta_2 = 0 \end{cases}$$

In equation 3, x_{t-1} denotes an exogenous variable, which is known by the forecasters at the forecasting date. We use the following variables as potentially relevant for business cycle forecasters in Germany:

- Lagged U.S. industrial production growth. A significant coefficient in this case would imply that forecasters have not been fully aware of the stance of the business cycle in one of Germany's most important trading partners.
- The lagged rate of change of money supply M1[11], and
- the lagged short-term interest rate to capture a possible impact of monetary policy on the business cycle that might have not fully taken into the account by the forecasters.
- The lagged real exchange rate, which reflects the price competitiveness on the German economy.

All panel regressions are calculated based on fixed-effects (within-) estimator to allow for forecaster heterogeneity across time as well as robust and cross-section SUR (PCSE) standard errors and covariances (d.f. corrected) following the method of Beck and Katz (1995). A further advantage of the fixed effect model is that stable but different forecasting dates should be (partly) considered. The results shown in Table 3 broadly confirm results of previous studies (see, e.g., Döpke and Fritsche, 2006a) that growth and inflation forecasts appear to be unbiased but not (strongly) efficient. Inflation forecasts do not clear the hurdle of weak efficiency over the full sample.

We also test for the possibility of a structural break in full sample environment. Exemplary, we use the specification with the interest rate as exogenous variable and a Dummy variable interaction term to test for structural break in the equation:

$$e_{i,t} = \beta_{0,i} + \beta_1 e_{i,t-1} + \beta_2 x_{t-1} + \beta_3 D_t + \beta_4 (D_t \cdot x_{t-1}) + u_{i,t} \tag{4}$$

with D_t equals 1 after the crisis and 0 before. It turns out, however, that we cannot find a hint to structural break based on the simple method: neither the coefficient in front of the Dummy (β_3) nor in front of the interaction term (β_4) turns out to be significantly different from zero.[12]

3.3 Forecast Consistency

Sinclair et al. (2010) have argued that evaluating growth and inflation forecasts separately might be misleading from the perspective of policy-makers. Hence, it is useful to have a look on the relation between the two forecast errors before and after the crisis. Rather, they should be judged together. A first information in this regard is given by Figure 5. Apparently, the correlation between the variables has changed: before the crisis it has been negative, albeit small and only marginally significant in a statistical sense, whereas after the crisis it is significantly positive and large.

We also address the question, whether the assessment on rationality has been altered by the large forecast errors due to the financial crisis. Table 4 reports rationality tests for the periods before and after the *Great Recession.* After crisis sub-sample results indicate that forecasts appear to be unbiased, but inefficient, in the sense that exogenous information is not taken into account sufficiently. In contrast, before crisis sub-sample tests show unbiased and (strongly) efficient forecasts.

[11]From 2001 onwards we refer to the German contribution to the money supply of the Euro-zone.

[12]For the sake of brevity, we report only this results. Similar ones have been obtained for the other endogenous variables. They are available upon request from the authors.

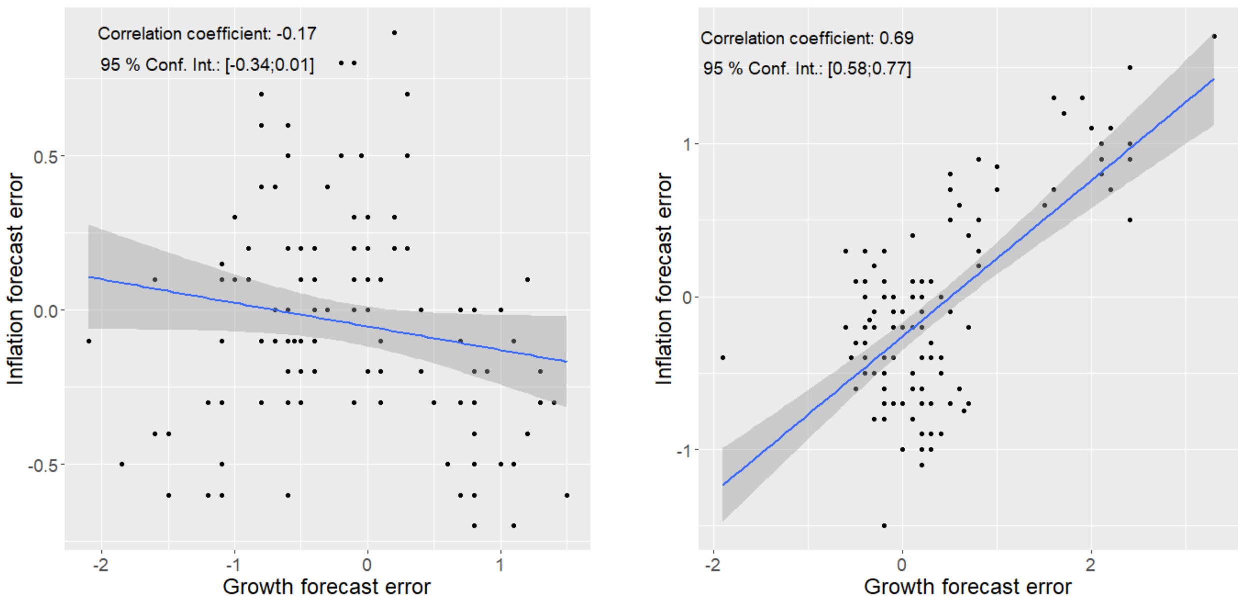
Table 3: Tests for Forecasts Rationality - Full Sample

Growth Forecast					
	Dependent Variable: Growth Forecast Errors				
Constant	−0.221	−0.197	−0.211	−0.220	−0.210
	(−1.131)	(−0.991)	(−1.126)	(−1.137)	(−1.184)
Lagged Forecast error	−0.054	0.008	−0.020	−0.077	−0.028
	(−0.416)	(0.051)	(−0.163)	(−0.597)	(−0.241)
Lagged U.S. production		−0.152			
		(−0.681)			
Lagged short term interest rate			-0.391^{*}		
			(−2.045)		
Lagged real exchange rate				−0.194	
				(−0.981)	
Lagged money supply M1					0.538^{**}
					(3.095)
n	753	740	753	753	753
$\bar{R}^2$	0.003	0.010	0.073	0.020	0.148
Wald-Test (p-value)	0.523	0.663	0.170	0.518	0.034

Inflation Forecast					
	Dependent Variable: Inflation Forecast Errors				
Constant	−0.035	−0.060	−0.035	−0.040	−0.033
	(−0.363)	(−0.634)	(−0.364)	(−0.438)	(−0.362)
Lagged Forecast error	0.366^{***}	0.416^{***}	0.335^{***}	0.357^{**}	0.416^{***}
	(3.449)	(3.141)	(3.004)	(3.512)	(4.159)
Lagged U.S. production		−0.078			
		(−0.834)			
Lagged short term interest rate			0.072		
			(0.684)		
Lagged real exchange rate				0.192^{*}	
				(2.037)	
Lagged money supply M1					0.228^{**}
					(2.535)
n	749	737	749	749	749
$\bar{R}^2$	0.138	0.124	0.144	0.189	0.213
Wald-Test (p-value)	0.012	0.038	0.025	0.007	0.003

Notes: Source: own calculations. t-values in brackets, calculated based on within-estimator, robust and cross-section SUR (PCSE) standard errors and covariances (d.f. corrected). p-values: 0.1 < * < 0.05; 0.05 < ** < 0.01; *** < 0.01.

Figure 5: Correlation of Growth an Inflation Forecast Errors before and after the *Great Recession*



(a) Before *Great Recession* (b) After *Great Recession*

Table 4: Consistency Tests for Unbiasedness and Efficiency - Before and After the *Great Recession*

	Before Crisis: 2002 to 2008	After Crisis: 2010 to 2016
	Growth Forecasts	
Number of observations	119	119
Test for unbiasedness	0.785	0.458
Test for weak efficiency	0.637	0.064*
U.S. production (-1)	0.325	0.000***
Short term interest rate (-1)	0.499	0.045**
Real exchange rate (-1)	0.569	0.000***
Money supply M1 (-1)	0.129	0.006***
	Inflation Forecasts	
Number of observations	119	119
Test for unbiasedness	0.059*	0.138
Test for weak efficiency	0.684	0.954
U.S. production (-1)	0.841	0.009***
Short term interest rate (-1)	0.775	0.097*
Real exchange rate (-1)	0.501	0.001**
Money supply M1 (-1)	0.241	0.166

Notes: Source: own calculations. F-test, respectively Wald-test p-values for H0, see Methods. Regression tests calculated based on within-estimator, robust and cross-section SUR (PCSE) standard errors and covariances (d.f. corrected). p-values: 0.1 < * < 0.05; 0.05 < ** < 0.01; *** < 0.01.

Table 5: Cell Counts for 4×4 Contingency Table Before and after the *Great Recession*

	Actual Outcome			
	Before crisis: 2002 to 2008			
Predicted value	Δ Growth > 0, Δ Inflation > 0	Δ Growth > 0, Δ Inflation ≤ 0	Δ Growth ≤ 0, Δ Inflation > 0	Δ Growth ≤ 0, Δ Inflation ≤ 0
Δ Growth > 0,Δ Inflation > 0	11	13	0	7
Δ Growth > 0,Δ Inflation ≤ 0	6	4	0	27
Δ Growth ≤ 0,Δ Inflation > 0	0	0	28	4
Δ Growth ≤ 0,Δ Inflation ≤ 0	0	0	6	13
Pearson χ^2-test	120.29 [p-value: < 0.01]			
	After crisis: 2009 to 2016			
Δ Growth > 0,Δ Inflation > 0	16	12	0	5
Δ Growth > 0,Δ Inflation ≤ 0	1	16	0	3
Δ Growth ≤ 0,Δ Inflation > 0	0	19	5	6
Δ Growth ≤ 0,Δ Inflation ≤ 0	0	4	12	20
Pearson χ^2-test	85.97 [p-value: < 0.01]			
	Difference: Before minus After			
Δ Growth > 0,Δ Inflation > 0	-5	1	0	2
Δ Growth > 0,Δ Inflation ≤ 0	5	-12	0	24
Δ Growth ≤ 0,Δ Inflation > 0	0	-19	23	6
Δ Growth ≤ 0,Δ Inflation ≤ 0	0	-4	-6	-7

Regarding the question, whether the informational content of forecasts has changed after the crisis in more detail, Table 5 shows the result of the test suggested by Sinclair et al. (2010). In both sub-periods, inflation and growth forecasts still appear to be valuable information about the situation the economy is heading to, i.e. the null hypothesis of no information content has to be rejected. Beyond this, the differences between the two sub-periods show almost identical numbers of correct assessments (on the diagonal of the table), namely 56 (= 47 %) before and 57 (= 48 %) after the crisis. Nevertheless, the table highlights that some combinations of forecast errors occur more frequently or more rarely than before: Consider the situation, when a deceleration of growth and an acceleration of inflation has been expected and the opposite combination (acceleration of growth and deceleration of inflation) occurs. This combination does not occur at all before, but nineteen times after the crisis. Also, the forecast of accelerating growth and decelerating inflation results much more often in realized decelerating growth and inflation rates before than after the crisis. So, there are some hints towards a changed forecaster behaviour, even their accuracy to predict directional changes still remains.

4 The loss function of the forecasters before and after the crisis

In Figure 6, we present the loss function of German business cycle forecasters estimated by the method proposed by Elliott et al. (2008). The approach uses the following general loss function of forecasters:

$$L(p, \alpha, \theta) = [\alpha(1 + 2\alpha) \cdot \mathbf{1}(A_t - P_t < 0) \, |A_t - P_t|^p] \,. \tag{5}$$

In equation 5, α denotes the degree of asymmetry of the loss function: $\alpha > 0.5$ implies incentives for forecasters to deliver optimistic forecasts, while $\alpha < 0.5$ represents the opposite case. p shows, whether the loss function is linear ($p = 1$) or quadratic ($p = 2$). The coefficient α can be estimated by an instrumental (GMM) estimator also suggested by Elliott et al. (2008). Following the original contribution we use a constant and lagged forecast errors as instruments.[13] Additionally, we report the results of the tests also suggested by Elliott et al. (2008). The first tests the null hypothesis of a symmetric loss function (i.e. $\alpha = 0.5$), the second tests for rationality of the forecasts and allows for an asymmetric loss function.

[13]The main results do not depend on the chosen instruments. 5 shows estimations with similar results based on the lagged forecast error as instrument.

Table 6: Tests for Asymmetry of Forecasters Loss Functions Before and After the Crisis

	$\hat{\alpha}$	Test for symmetry	p-value	Test for rationality	p-value
		Lin-Lin Loss Functions			
		Before Crisis - 2002 to 2008			
Growth forecasts	0.530	0.598	0.550	0.274	0.601
	[0.433; 0.626]				
Inflation forecasts	0.490	-0.200	0.841	0.543	0.461
	[0.393; 0.587]				
		After Crisis - 2010 to 2016			
Growth forecasts	0.349	-3.208	0.001	17.968	0.000
	[0.256; 0.441]				
Inflation Forecasts	0.785	7.015	0.000	21.201	0.000
	[0.706; 0.865]				
		Quad-Quad Loss Functions			
		Before Crisis - 2002 to 2008			
Growth forecasts	0.542	0.710	0.478	2.015	0.156
	[0.426; 0.659]				
Inflation forecasts	0.597	1.614	0.107	3.422	0.064
	[0.479; 0.714]				
		After Crisis - 2010 to 2016			
Growth forecasts	0.408	-1.470	0.141	15.874	0.000
	[0.286; 0.531]				
Inflation Forecasts	0.928	18.065	0.000	12.194	0.000
	[0.882; 0.974]				

Notes: Source: Own calculations, based on Tarassow and Schreiber (2017). The instrument for the GMM estimator is the lagged forecast error. In brackets: 95% confidence interval.

Figure 6 plots the implied loss functions before and after the crisis together with a 95 % confidence interval. Beside the question of a significant difference of the loss function before and after the crisis in a statistical sense, the exhibit suggest a possible change of the loss function that may be relevant in economic terms. Concerning the growth forecasts, the results for both, the Lin-Lin- and the Quad-Quad-loss function point to a substantial higher cost of too optimistic forecasts after the crisis, whereas forecaster‘s loss before the crisis seems to be nearly symmetric. As regards inflation forecasts forecaster‘s seems to have an incentive to avoid underestimations because of a higher loss after the crisis, but not before. Table 6 gives the respective estimates of the asymmetry parameters. For the time before the crisis and under the assumption of a linear loss function, the null hypothesis of $\alpha = 0.5$, i.e. a symmetric loss function cannot be rejected for the growth and inflation forecasts. After the crisis a similar test results in a rejection of the null in case of both forecasts. The latter difference does not imply, however, that the loss function has changed significantly (Gelman and Stern, 2006). In case of a quadratic loss function, the null of a symmetric loss has to be rejected for inflation forecasts after the crisis. Tests for rationality indicate in the same direction and support findings of Table 4. Before crisis, rationality cannot be rejected for growth and inflation under linear as well quadratic loss at a 5 % significance level whereas the null hypothesis of rationality has to be rejected for both loss functions and both variables after the crisis.

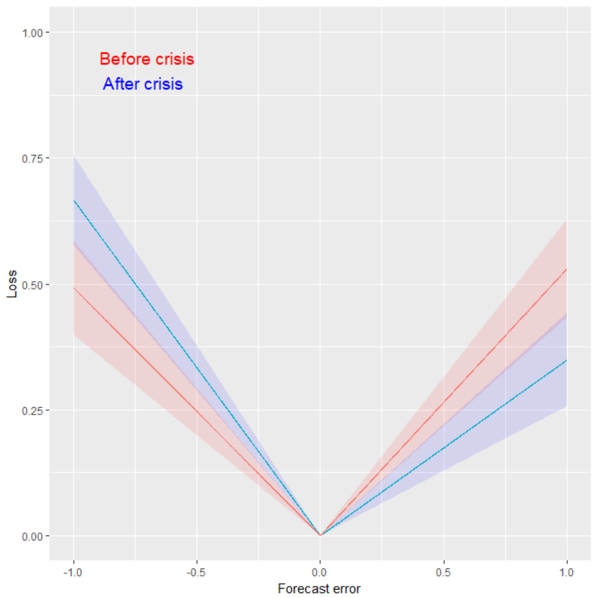
Figure 7 extends the analyses so far by employing the approach of Wang and Lee (2014) and plots the Rolling Window Loss Functions for a window of 10 years. The figure on the left report estimates of the respective asymmetric loss parameter α together with a 95 % confidence interval for each loss function specification. The p-values for the test of loss symmetry (red line) and forecast rationality under asymmetric loss (cyan line) over the time are given on the right-hand side in figure 7. The horizontal axis represents on the left-hand side as well as on the right-hand side the end (date) of each 10-year rolling window estimation. The estimates start in 1974 because of the sample includes then all forecasters.[14] Hence, we obtain a total of $T - N$ estimations for the asymmetric loss parameter α and the test statistics with $\sum_{t=1}^{N}(\frac{1}{N} * f_t)$ observations per estimate, where $T = 43$ denotes the sample size, $N = 10$ is the size of the rolling window and f_t the number of forecaster in year t.

Considering, first of all, the linear loss function for growth forecasts, it turns out that the asymmetric parameter α is time-varying in both degree and direction. Starting with α below 0.5 (dashed line) in the 1980s and 1990s, α rise until the upper peak and turning point in the mid 2000s, where α changed the direction again and goes down but stays until the end 2000s above 0.5. This suggests that the incentive for under-prediction in the 1990s changed until the end 2000s towards a more optimistic behaviour which punish under-prediciton more than over-prediction. In both phases, α is significantly below (1990s), respectively above (2000s) 0.5. The pattern changed anew after the *Great Recession* to a decreasing asymmetric parameter α. Symmetry test reflects similar pattern and give further hints for this interpretation. With exception of a stronger degree of severity of α, estimates of quadratic loss function are generally in line with linear specification results. But periods in the 1980s and in the 2010s differs from linear setting, the latter case even differs from the picture gives by the loss function specification above (see Table 6).

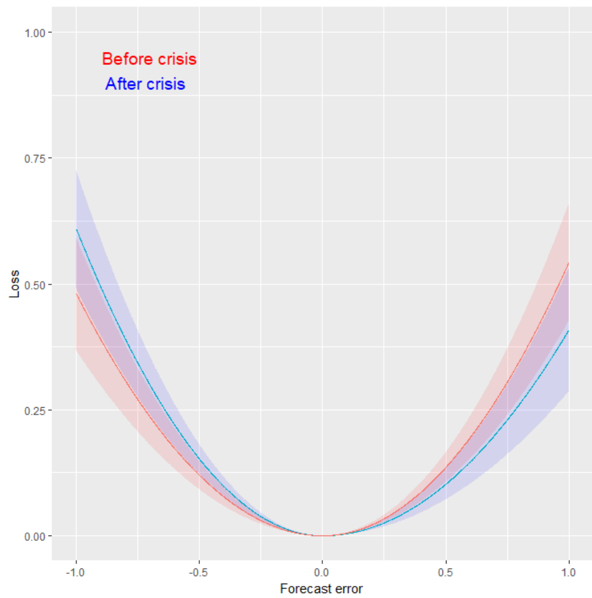
Estimates of linear loss function for inflation forecasts give a wave-like oscillation picture, starting with an α below 0.5, it reaches the global upper turning point in the end of the 1980s and oscillate with shrinking amplitudes between the symmetry degree of 0.5 and above. The level of loss asymmetry is significantly above 0.5 for nearly all periods from the end-1980s until the mid-2000s. This indicates an asymmetric loss function which punishes under-prediction more than over-prediction and gives some incentives to overrate the inflationary development. Afterwards, the asymmetric loss parameter α oscillate insignificantly around 0.5 and ends with a rising tendency from 2012 onwards. Test statistics on the right-hand side confirm for the most part the picture. Symmetry of loss is mostly rejected at a 5 % significance level (dashed line) until the beginning

[14] With the exception of Halle institute (IWH) which starts in 1991.

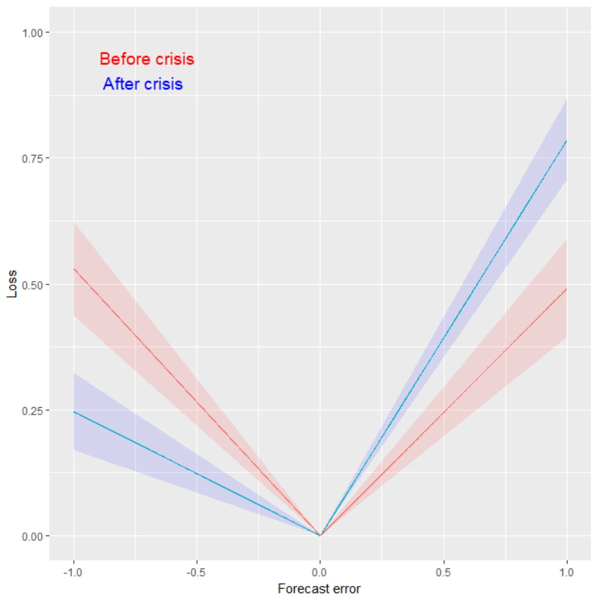
Figure 6: Loss Functions of German Forecasters before and after the *Great Recession*



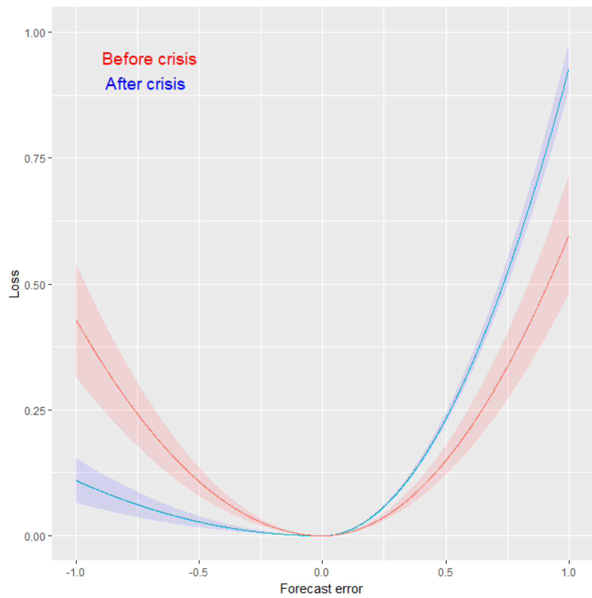
(a) Lin-Lin Loss Function, Growth Forecasts



(b) Quad-Quad Loss Function, Growth Forecasts



(c) Lin-Lin Loss Function, Inflation Forecasts



(d) Quad-Quad Loss Function, Inflation Forecasts

Source: Own calculations, based on Tarassow and Schreiber (2017). Shaded areas: 95 % confidence area.

of the 2000s. Test for forecast rationality follows similar pattern as symmetry test in the whole. Forecast rationality under asymmetric loss has to be rejected until the beginning of the 2000s.

Considering the quadratic framework, except the year 1997, the estimates of the asymmetric parameter α are even higher and consistently significant above 0.5 from the end-1980s until the end-2000s. The hypothesis of symmetric loss is rejected more frequently as in linear setting whereas forecast rationality remain unchanged.

All in all, rolling window loss functions support single estimation findings of forecasters loss before and after the *Great Recession* in regard to asymmetry and direction of the parameter α , although the level of loss asymmetry is generally more phlegmatic in the longer rolling window size than the shorter single comparison. The strong decreasing (growth in linear setting) and increasing (inflation) tendency of α after the crisis give hints for a changed or changing behaviour of forecasters.

5 Conclusions

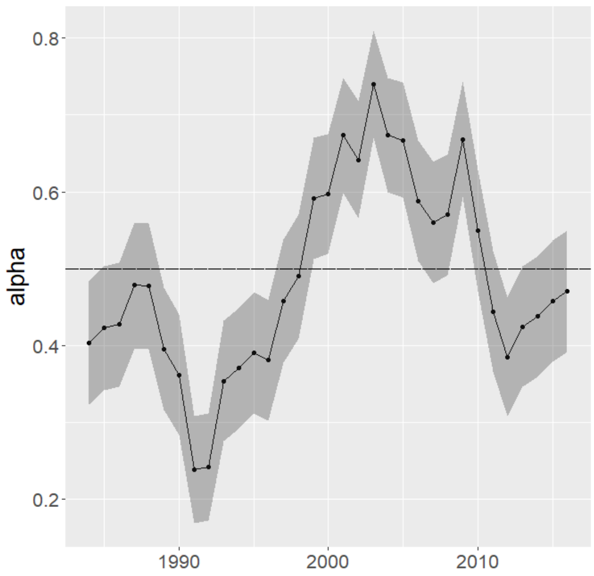
Based on a panel consisting annual data ranging from 1971 to 2016 we empirically analyse 17 different forecasts for growth and inflation stemming from 14 different institutions. We address the question, whether forecaster‘s performance or forecaster‘s behaviour has changed due to the experience of the large forecasting error related to the *Great Recession*.

There are some, albeit small differences ín forecast accuracy between both time periods. The respective quantitative error measures (slightly) increase after the crisis. As regards growth forecasts, we document that before the crisis the number of overestimations exceeded the number of underestimations considerably, while for the time after the crisis the opposite is true. This could be a hint to a changed forecaster behaviour. Moreover, an increased variance of forecasts after the crisis may indicate a more divided forecaster community. Qualitative measures of forecast accuracy like Receiver Operating Curves suggest less informative power after the crisis, whereas contingency analysis support the impression that the quality does not changed, but forecaster‘s behaviour. Tests for (strong) efficiency of the forecasts over the entire sample indicate that growth and inflation forecasts appear to be unbiased, but not (strong) efficient. Rationality tests for the time period before and after the crisis strengthen these findings, first of all for the period after the crisis. Further hints are the increased cross-section variance of the forecasts and the changed correlation between inflation and growth forecasts errors point to some changes in the behaviour of forecasters.

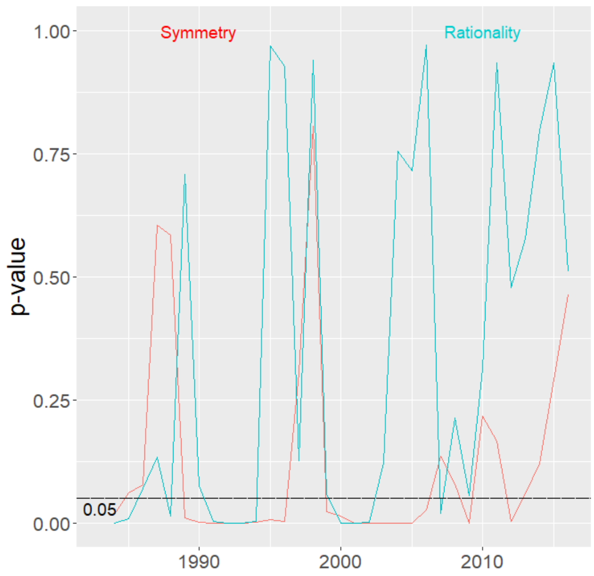
Also the estimated loss functions for growth and inflation forecasts give some evidence for a change of forecasters loss before and after the *Great Recession* in regard to symmetry and direction of the asymmetric parameter α as well as the level of loss asymmetry. For the period after the *Great Recession* the estimated asymmetry parameter points to incentives for underestimations (growth), respectively overestimations (inflation), whereas the same parameter estimated with pre-recession data shows symmetric loss functions. 10-year rolling windows loss estimates are time-varying in both degree and direction. Nevertheless, rolling window loss functions development and overall results support findings from the single period loss function estimates and give some hints for changed behaviour of forecasters.

All in all, the quantitative and qualitative measures of forecast error do not imply a change in forecaster quality, but indicate, as well as the estimated loss functions, to a change of forecaster‘s behaviour.

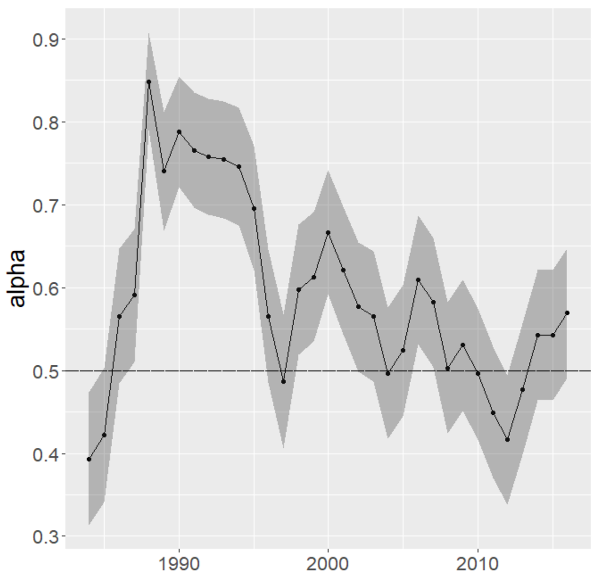
Figure 7: Rolling Window Loss Functions of German Forecasters



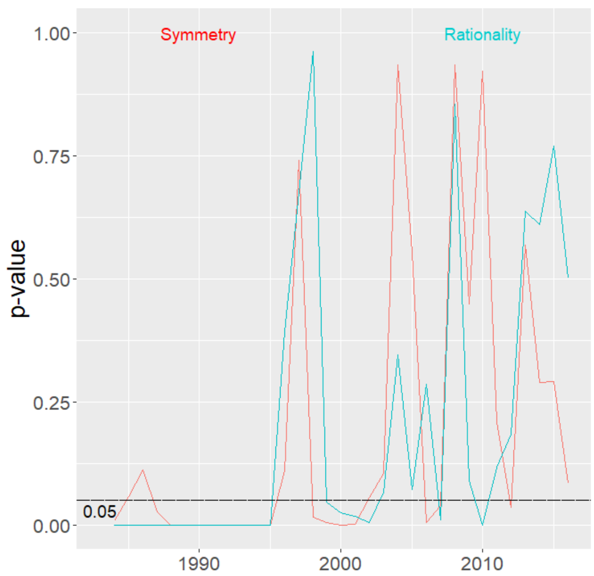
(a) Estimates Lin-Lin, Growth



(b) Tests Lin-Lin, Growth

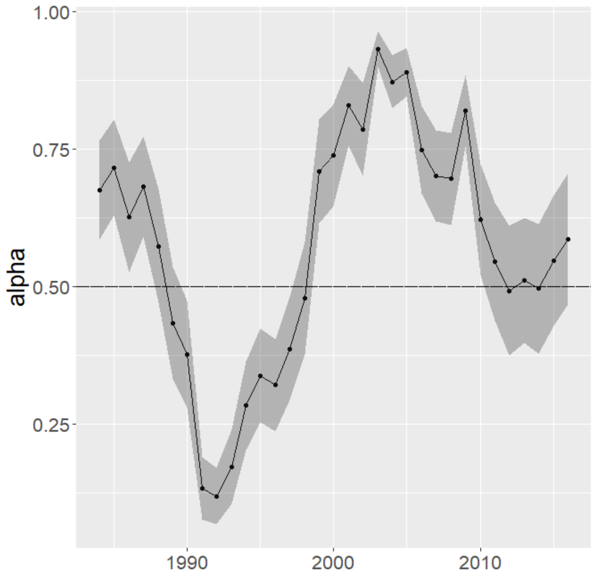


(c) Estimates Lin-Lin, Inflation

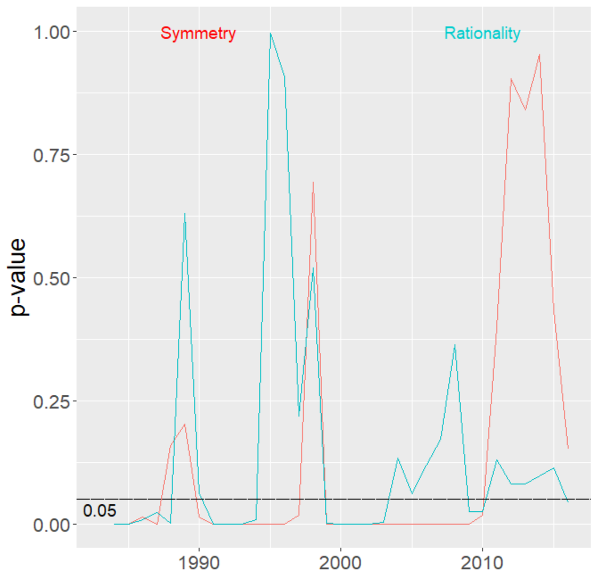


(d) Tests Lin-Lin, Inflation

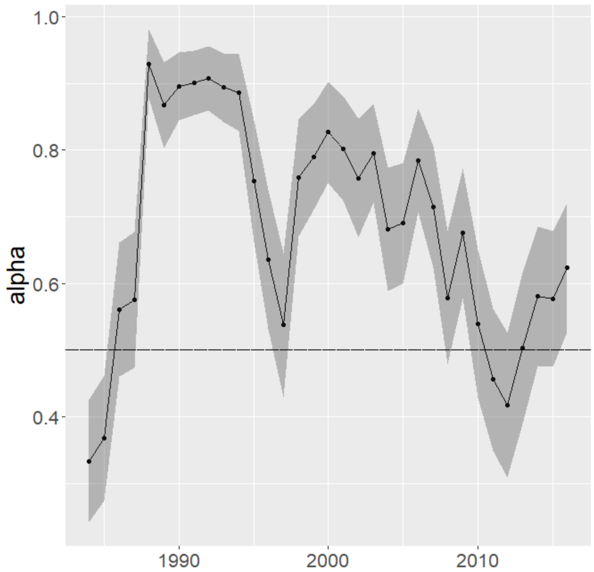
Figure 7, cont.



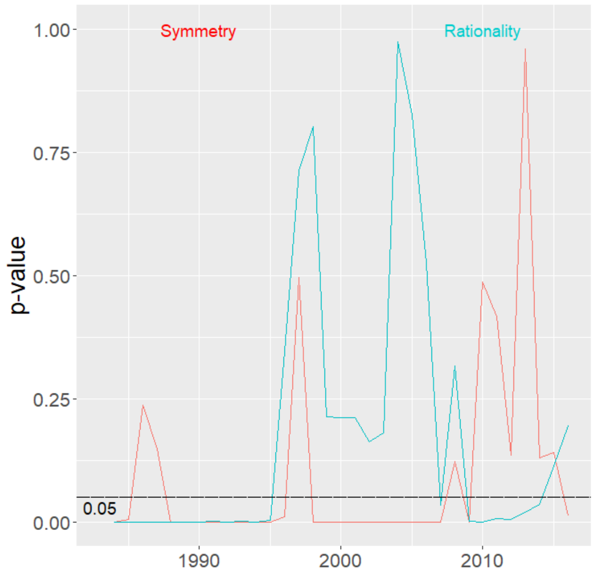
(a) Estimates Quad-Quad, Growth



(b) Tests Quad-Quad, Growth



(c) Estimates Quad-Quad, Inflation



(d) Tests Quad-Quad, Inflation

Source: Own calculations. Shaded areas: 95 % confidence area.

References

Beck, N., Katz, J. N., 1995. What to do (and not to do) with time-series cross-section data. American Political Science Review 89 (03), 634–647.

Berge, T. J., Jordà, Ò., 2011. Evaluating the classification of economic activity into recessions and expansions. American Economic Journal: Macroeconomics 3 (2), 246–277.

Besly, T., Hennessy, P., 2009. Letter to the queen.
URL https://www.euroresidentes.com/empresa_empresas/carta-reina.pdf

Campbell, B., Ghysels, E., 1997. An empirical analysis of the canadian budget process. The Canadian Journal of Economics 30 (3), 553–576.

Carroll, C. D., 2003. Macroeconomic expectations of households and professional forecasters. the Quarterly Journal of economics 118 (1), 269–298.

Castle, J. L., Clements, M. P., Hendry, D. F., 2016. An overview of forecasting facing breaks. Journal of Business Cycle Research 12 (1), 3–23.

Cottrell, A., Lucchetti, R., 2017. Gretl User's Guide.
URL http://ricardo.ecn.wfu.edu/pub//gretl/manual/en/gretl-guide.pdf

De Gooijer, J. G., Hyndman, R. J., 2006. 25 years of time series forecasting. International journal of forecasting 22 (3), 443–473.

Döhrn, R., Schmidt, C., 2011. Information or institution? on the determinants of forecast accuracy. Journal of Economics and Statistics (Jahrbuecher fuer Nationaloekonomie und Statistik) 231 (1), 9–27.

Döpke, J., Fritsche, U., 2006a. Growth and inflation forecasts for germany: A panel-based assessment of accuracy and efficiency. Empirical Economics 31 (3), 777–798.

Döpke, J., Fritsche, U., 2006b. When do forecasters disagree? an assessment of german growth and inflation forecast dispersion. International Journal of Forecasting 22 (1), 125–135.

Dovern, J., Jannsen, N., 2017. Systematic errors in growth expectations over the business cycle. International Journal of Forecasting 33 (4), 760–769.

Drechsel, K., Scheufele, R., 2012. The financial crisis from a forecaster's perspective. Kredit und Kapital 45 (1), 1–26.

Elliott, G., Komunjer, I., Timmermann, A., 2008. Biases in macroeconomic forecasts: irrationality or asymmetric loss? Journal of the European Economic Association 6 (1), 122–157.

Fildes, R., Stekler, H., 2002. The state of macroeconomic forecasting. Journal of macroeconomics 24 (4), 435–468.

Frenkel, M., Lis, E. M., Rülke, J.-C., 2011. Has the economic crisis of 2007-2009 changed the expectation formation process in the euro area? Economic Modelling 28 (4), 1808–1814.

Fritsche, U., Tarassow, A., December 2016. Vergleichende evaluation der konjunkturprognosen des instituts für makroökonomie und konjunkturforschung an der hans-böckler-stiftung für den zeitraum 2005-2014.

Garcia, J. A., 2003. An introduction to the ecb's survey of professional forecasters. ECB Occasional Paper (8).

Gelman, A., Stern, H., 2006. The difference between "significant" and "not significant" is not itself statistically significant. The American Statistician 60 (4), 328–331.

Heilemann, U., Schnorr-Bäcker, S., 2017. Could the start of the german recession 2008–2009 have been foreseen? evidence from real-time data. Jahrbücher für Nationalökonomie und Statistik 237 (1), 29–62.

Heilemann, U., Stekler, H. O., 2013. Has the accuracy of macroeconomic forecasts for germany improved? German Economic Review 14 (2), 235–253.

Holden, K., Peel, D. A., 1990. On testing for unbiasedness and efficiency of forecasts. The Manchester School 58 (2), 120–127.

Hyndman, R. J., Koehler, A. B., 2006. Another look at measures of forecast accuracy. International Journal of Forecasting 22 (4), 679–688.

Krüger, J., 2014. A multivariate evaluation of german output growth and inflation forecasts. Economics Bulletin 34 (3), 1410–1418.

Krüger, J. J., Hoss, J., 2012. German business cycle forecasts, asymmetric loss and financial variables. Economics Letters 114 (3), 284–287.

Liu, W., Moench, E., 2016. What predicts us recessions? International Journal of Forecasting 32 (4), 1138–1150.

Loungani, P., 2001. How accurate are private sector forecasts? cross-country evidence from consensus forecasts of output growth. International journal of forecasting 17 (3), 419–432.

Mincer, J. A., Zarnowitz, V., 1969. The evaluation of economic forecasts. In: Mincer, J. A., Zarnowitz, V. (Eds.), Economic Forecasts and Expectations: Analysis of Forecasting Behavior and Performance. NBER, pp. 3–46.

Nienhaus, L., 2009. Die Blindgänger: Warum die Ökonomen auch künftige Krisen nicht erkennen werden. Campus Verlag.

Pain, N., Lewis, C., Dang, T.-T., Jin, Y., Richardson, P., 2014. Oecd forecasts during and after the financial crisis.

Pierdzioch, C., Rülke, J.-C., 2015. On the directional accuracy of forecasts of emerging market exchange rates. International Review of Economics & Finance 38, 369–376.

R Core Team, 2017. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
URL `https://www.R-project.org/`

Riedel, F., 2013. Die Schuld der Ökonomen. Berlin.

Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J.-C., Müller, M., 2011. proc: an open-source package for r and s+ to analyze and compare roc curves. BMC Bioinformatics 12, 77.

Sinclair, T. M., Stekler, H., Kitzinger, L., 2010. Directional forecasts of gdp and inflation: a joint evaluation with an application to federal reserve predictions. Applied Economics 42 (18), 2289–2297.

Tarassow, A., Schreiber, S., 2017. F e p 1.3. – forecast evaluation package (gretl package).
URL `https://sites.google.com/site/arturtarassow/code/test-2`

The Economist, 2009. Dismal sciencehttp://www.economist.com/node/13832580.

Wang, Y., Lee, T.-H., 2014. Asymmetric loss in the greenbook and the survey of professional forecasters. International Journal of Forecasting 30 (2), 235–245.

Zidong An, J. J., Loungani, P., Feb. 2018. How well do economists forecast recessions? https://drive.google.com/file/d/1PUe6immJ5VYiwDjgGucTQsQutm9Hphev/view, last checked: 2/13/2018.

Appendix: Tests for Asymmetry of Forecasters Loss Functions Before and After the Crisis - Alternative Instrument

	$\hat{\alpha}$	Test for symmetry	p-value	Test for rationality	p-value
		Lin-Lin Loss Functions			
		Before Crisis - 2002 to 2008			
Growth forecasts	0.592	2.035	0.042	2.240	0.134
	[0.502; 0.682]				
Inflation forecasts	0.504	0.095	0.925	1.843	0.175
	[0.413; 0.596]				
		After Crisis - 2010 to 2016			
Growth forecasts	0.341	-3.672	0.000	1.505	0.212
	[0.254; 0.427]				
Inflation Forecasts	0.573	1.615	0.106	1.466	0.226
	[0.483; 0.664]				
		Quad-Quad Loss Functions			
		Before Crisis - 2002 to 2008			
Growth forecasts	0.617	2.188	0.029	6.607	0.010
	[0.510; 0.724]				
Inflation forecasts	0.589	1.568	0.117	1.625	0.202
	[0.478; 0.700]				
		After Crisis - 2010 to 2016			
Growth forecasts	0.064	-22.718	0.000	15.491	0.000
	[0.027; 0.102]				
Inflation Forecasts	0.626	2.425	0.015	6.490	0.011
	[0.524; 0.729]				

Notes: Source: Own calculations, based on Tarassow and Schreiber (2017). The instrument for the GMM estimator is the lagged actual value. In brackets: 95% confidence interval.