

# Does the ECB Rely on a Taylor Rule During the Financial Crisis? Comparing Ex-post and Real Time Data with Real Time Forecasts

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**Abstract:** We assess the differences that emerge in Taylor rule estimations for the ECB when using ex-post data instead of real time forecasts and vice versa. We argue that previous comparative studies in this field risk mixing up two separate effects. First, the differences resulting from the use of ex-post and real time data per se and, second, the differences emerging from the use of non-modified real time data instead of real-time data based forecasted values (and vice versa). Since both effects can influence the ECB reaction to inflation and the output gap either way, we use a more clear-cut approach to disentangle the partial effects. However, “good” forecasts have to be as close as possible to the forecasts the ECB governing council had at hand when taking its interest rate decision. Therefore we use two approaches to generate the forecasts: First, forecasts generated relying on a pure AR process and, second, explicit ECB staff projections which are available only at a quarterly frequency. So we found it indispensable to estimate all variants of the reaction function using also quarterly data. Our estimation results indicate that using real time instead of ex post data leads to higher estimated inflation and output gap coefficients. If real time forecasts are used (since actual data become available with a lag), the output response is reduced while the inflation response depends crucially on the inclusion of an interest rate smoothing term, the data frequency and forecast type.

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## I. INTRODUCTION

Ever since the founding of the European Central Bank (ECB) in 1999 the question was raised whether it follows or should follow the by now famous Taylor rule (Taylor (1993)). In fact many economists so far have investigated this issue with respect to the euro area using either data of a “fictitious” ECB prior to its establishment (see e.g. Peersman and Smets (1999), Gerlach and Schnabel (2000), Clausen and Hayo (2002), Altavilla and Landolfo (2005)) or the limited data thereafter (see e.g. Surico (2003), Fourçans and Vranceanu (2003), Gerdesmeier and Roffia (2004), Garcia-Iglesias (2007), Belke and Polleit (2007) and Fendel and Frenkel (2009)).<sup>2</sup> By now we have seen more than ten years of ECB monetary policy and are now able to derive new estimates from a sufficiently broad euro area-specific database. This becomes even more important since the financial crisis started in 2007 because it might be argued that Taylor reaction functions can no longer be used in such an environment since the policy rate should be negative which is impossible in the Taylor rule framework as nominal rates are constraint to be positive. However, Gorter *et al.* (2009), Belke and Klose (2010), Jensen and Aastrup (2010), Gerlach (2011) and Klose (2011) showed that Taylor rules can still be estimated within the financial crisis but the coefficients need to be adjusted.

The whole array of Taylor rule estimations enumerated above essentially rely on ex-post data. This comes as a surprise as the use of ex-post data “is based on unrealistic assumptions about the timeliness of data availability and ignores difficulties associated with the accuracy of initial data and subsequent revisions” (Orphanides (2001), p. 964). Therefore, the analysis should be carried out using real time data instead of ex-post data simply because the latter were not available to the central bank decision making body at the time the interest rate decision was made. That is exactly why we focus on the extent of quantitative differences between the estimates occurring from using ex-post instead of real time data.

To be more specific, these quantitative differences potentially stem from four sources. First, inflation and output gap data are available only with a lag. Second, data sets are revised as time goes by (‘data uncertainty’). Third, the central bank governing council can construct the variables needed based only on past data and not with reference to the whole relevant sample period as is the case with ex-post data, since when the council constructs these variables it cannot “look back” at the whole sample (‘statistical uncertainty’), and, fourth (and less specific for the problem investigated here), the empirical model used to derive the estimates is not unique (‘model uncertainty’).

However, in our paper we do not only focus on the changes in numerical values of estimation results arising from the use of ex-post instead of real time data but also on those stemming from the use of forecasted variables instead of contemporaneous ones since central banks would react systematically too late when applying only contemporaneous variables because monetary impulses become effective with a lag (see, for instance, Svensson (2003), p. 449). In principle, there are two ways in which this comparison can be enacted: either by using ex-post data or by applying real time data. However, we prefer to follow the latter approach because

<sup>2</sup> In fact, also combinations of these two types can be found, mostly to expand the sample in order to generate more reliable estimates (see e.g. Gerlach-Kirsten (2003), Siklos and Bohl (2009)). For a comparison between these two types of data at the early stage see Ullrich (2003).

it appears to us more realistic that the ECB builds its forecast upon real time data than on the (not available) ex-post data. Another advantage of this approach is that we are able to use a transparent procedure by comparing estimates based on ex-post with those employing real time data and, later on, comparing real time data estimates with estimates based on variable forecasts based on real time data.

So far, estimations of ECB Taylor rules using real time data are still quite scarce. In fact, there is only a couple of papers available dealing with this topic. Most of these papers focus on estimates on a monthly basis which is the natural frequency to choose because the ECB decides about its interest rate every month and not every quarter. However, we present estimations based on monthly and quarterly data which both rely exclusively on the EMU sample period.

We add quarterly data estimates because we want to distinguish the effects of using ex-post versus real time data from the use of real time forecasts instead of real time data. This is because both effects can influence the monetary policy reaction coefficients either way. For the second above-mentioned comparison we need forecasts that correspond as close as possible to the unknown forecasts on which the ECB governing council bases its interest rate decisions. To find a database or derive forecasts that are as close to those of the ECB is the crucial task when assessing ECB policy.

We follow two approaches to cope with these requirements: First, we incorporate forecasts based on autoregressive (AR) processes because these forecasts are based on the available real time data and, in principle, should also be easily available to the governing council when taking its interest rate decisions. Second, we make explicit use of the ECB staff projections which appear to be highly appropriate to exploit in our case because these data are generated by the ECB itself. Unfortunately, they are available only at a quarterly frequency. Consequently, we do have to add quarterly estimates in order to be able to detect potential differences in performance between these forecasts and real time data.

The paper proceeds as follows. In section II, the Taylor rule and its extensions are described before we turn to the pattern of results gained in this field so far in section III. In section IV, we explain our data choice and variable selection. In section V we display our estimation results. Section VI finally concludes.

## II. THE TAYLOR RULE

It is well over a decade since John B. Taylor set out what has become part of the current orthodoxy of monetary economics by now. In 1993 he proposed a new and simple monetary policy rule which suggests that the central bank should set interest rates according to deviations of the inflation rate from its target and the percentage deviations of the output from its potential (the so called output gap). So the rule can be derived in the following way:

$$i_t = r_t^* + \pi_t + \alpha_\pi (\pi_t - \pi^*) + \alpha_y (y_t - y_t^*), \quad (1)$$

where  $i_t$  is the interest rate set by the central bank,  $r_t^*$  stands for the equilibrium real interest rate,  $\pi_t$  is the inflation rate over the previous four quarters,  $\pi^*$  represents the constant inflation target,  $(y_t - y_t^*)$  stands for the output gap and  $\alpha_\pi, \alpha_y$ , are coefficients measuring the strength of

the reaction to the inflation and output gap. Both coefficients are expected to be larger than zero. In fact, Taylor (1993) himself proposed that each coefficient should be equal to 0.5.<sup>3</sup> All variables with the exception of the inflation target are allowed to vary over time and are therefore indexed by  $t$ . However, in the literature this is the exception rather than the rule with respect to  $r_t^*$  when it comes to Taylor rule estimations.<sup>4</sup> For this purpose, we use the Fisher equation with adaptive expectations ( $r_t = i_t - \pi_t$ ) and apply the Hodrick-Prescott filter (HP-filter) (see Hodrick and Prescott (1997)) to the resulting real interest rate variable. In order to construct our variable measuring potential output  $y_t^*$ ,<sup>5</sup> we also apply the HP-filter. However, we check for the robustness of our estimation results by constructing this variable with the help of a linear and a quadratic trend because mis-measurement of the potential output has the potential to cause serious problems in Taylor rule estimations especially when the underlying output time series is based on real time data.<sup>6</sup>

For estimation purposes equation (1) can be rearranged as follows:

$$i_t = r_t^* + (1 - \alpha_\pi)\pi_t^* + \alpha_\pi\pi_t + \alpha_y(y_t - y_t^*), \quad (2)$$

with  $\alpha_\pi = 1 + \alpha_\pi$ . In the notation of equation (2), the Taylor principle implies that the coefficient  $\alpha_\pi$  needs to be larger than unity in order to raise the nominal interest rate by more than the inflation rate and, by this, to increase the real interest rate which is the decisive variable for investment or consumption decisions. If  $\alpha_\pi < 1$ , the real interest rate would decrease if inflation is rising, leading to even more inflationary pressure in the future. Since Taylor proposed  $\alpha_\pi = 0.5$  it immediately follows that  $\alpha_\pi = 1.5$ .

The first commonly used extension of the Taylor rule is the inclusion of an interest rate smoothing term to account for the fact that central banks typically adjust the key interest rate in rather small steps without hardly ever revising the direction thereafter. In this case, equation (2) turns into:

$$i_t = \rho \cdot i_{t-1} + (1 - \rho) \cdot [r_t^* + (1 - \alpha_\pi)\pi_t^* + \alpha_\pi\pi_t + \alpha_y(y_t - y_t^*)], \quad (3)$$

where  $\rho$  represents the smoothing parameter. If  $\rho = 1$  the interest rate is solely influenced by the past interest rate and for  $\rho = 0$  equation (2) reduces to equation (1). However, as experience shows, reasonable results should lie somewhere in between ( $0 < \rho < 1$ ).

A second extension is the forward-looking perspective. Clarida and Gertler (1996), for instance, argued in favor of using a forward-looking specification of the Taylor rule because any other specifications would imply that the central bank would respond systematically too

<sup>3</sup> However, Ball (1999) argues that the coefficients need to be adjusted in order to display an optimal policy reaction. Accordingly, also Belke and Polleit (2009), pp. 714ff. and 765ff., conclude that central bank's orientation and the structure of the economy have to be taken into consideration when determining the coefficients.

<sup>4</sup> Our results clearly indicate that using a time varying equilibrium real interest rate improves the fit of Taylor rule signaled by the adjusted  $R^2$  as compared to reaction functions assuming a constant rate. The results for the latter are available from the authors upon request.

<sup>5</sup> The choice of the correct potential output measure is of course one possible source of measurement problems of the Taylor rule.

<sup>6</sup> See Orphanides and van Norden (2002) for a detailed discussion on the unreliability of output gap estimates in real time. See Gros, Mayer and Ubide (2005), p. 10, for the same discussion in the context of EMU as a special case.

late as monetary impulses become effective only with a lag. Therefore, they proposed to use expected future values of the inflation rate based on the information available at the point in time where the decision is made. Later on this concept was expanded to the use of forecasts for the output gap as well. Hence, a forward-looking Taylor reaction function would look like:

$$i_t = \bar{r}_t^* + (1 - a_\pi)\pi^* + a_\pi \cdot E(\pi_{(t+j|t)}) + a_y \cdot [E(y_{(t+k|t)}) - \bar{y}_t^*], \quad (4)$$

where  $E$  is the expectations operator and  $j, k$  are some positive values indicating the forecast horizon. Note that  $j$  and  $k$  need not be equal so that different forecasts horizons for the inflation rate and the output are possible. With forecasts used in the Taylor rule also the variables  $\bar{r}_t^*$  and  $\bar{y}_t^*$  are adjusted because in the former case the expected inflation measure alters and in the latter case the trend changes because of more data.

It is of course possible to complement forward-looking Taylor rules with an interest rate smoothing term and this is in fact done in most of the cases. However, imposing forward-looking elements onto the Taylor reaction function only makes sense in the context of real time data because these were the data the central bank has based its forecasts on. In contrast, extracting forecasts from ex-post data means forming forward-looking expectations based on data which were de facto not available at the time of decision making which is quite unrealistic.

Therefore, the approach carried out here is a three-step one. First, we estimate Taylor reaction functions with ex-post data. Second, we compare the resulting estimates with those gained for estimates of the Taylor rule based on unmodified pure real time (which are available to the decision making body “contemporarily”) data. Third, we assess the differences between real time data based estimated Taylor rules and the ones which rely on forecasted variables based on real time data.

### III. SURVEY OF THE LITERATURE

As mentioned above, up to now the available empirical work providing Taylor rule estimates in real time for the euro area is by far not exhaustive. Nevertheless, their findings are worth mentioning here because they are natural candidates for comparisons to the results derived from the analysis carried out in our paper. We pick up five of them in the following.

In Adema (2004), Taylor rule estimates using ex-post and “quasi” real time data are compared. The difference between real time and “quasi” real time data is simply that data revisions are supposed to be fairly small and can thus be neglected. Making this assumption, Adema ends up with coefficients  $\rho = 0.75$ ,  $\alpha_\pi = 1.80$ ,  $a_y = 1.72$  for ex-post and  $\rho = 0.64$ ,  $\alpha_\pi = 1.89$ ,  $a_y = 0.46$  for “quasi” real time data covering the sample period 1994Q1 to 2000Q4 thus mostly the pre-ECB era.

In the same vein as Adema is the paper by Carstensen and Colavecchio (2004). The authors limit themselves to an estimation of Taylor rules with “quasi” real time data but do not compare their results to Taylor rules using ex-post estimates. Thus, they do not only neglect the data revisions but also abstract from any time lag problem. This is exactly why their results are, in the quantitative dimension, somewhere in between Taylor rules estimated with ex-post and those based on real time data. For the sample period 1999M1 – 2004M2 they come up with coefficients  $\rho = 0.95$ ,  $\alpha_\pi = 1.01$  and  $a_y = 1.36$ .

Gerdemeier and Roffia (2005) are among the first authors using real time data instead of quasi real time data. They estimate Taylor rule coefficients for the period 1999M1 – 2003M6. For ex-post data they find  $\rho = 0.84$ ,  $\alpha_\pi = 1.08$ , and  $a_y = 0.70$ . When using contemporaneous realizations of real time data, the picture changes as in this case the estimated output gap coefficient increases (2.05) while the estimated inflation parameter falls far below unity (0.39). The degree of interest rate smoothing decreases to 0.63. However, conducting their analysis with twelve month *forecasts* of the independent macro variables based on *survey* data collected in real time, they arrive at much higher values for the estimated coefficient of inflation (1.31) while  $\rho$  and  $a_y$  remain more or less unchanged ( $\rho = 0.71$  and  $a_y = 1.95$ ). The already rather high estimated inflation coefficient gets even larger when applying a two year instead of a one year forecast based on real time survey data ( $\alpha_\pi = 2.9$ ,  $\rho = 0.67$ , and  $a_y = 2.02$ ).

Working with *ex-post* data, Sauer and Sturm (2007) come up with estimated coefficients  $\rho = 0.94$ ,  $\alpha_\pi = -0.84$ ,  $a_y = 1.45$  for the period ranging from January 1999 to October 2003. Employing *real time* data instead, the estimated coefficients turn out to be  $\rho = 0.98$ ,  $\alpha_\pi = -0.27$ ,  $a_y = 3.01$ . When they implement forecasts of the independent macro variables based on real time data, the estimated inflation coefficient becomes positive and larger than unity (6.62) and the estimated interest rate smoothing parameter and the estimated coefficient of the output gap become  $\rho = 0.98$  and  $a_y = 9.24$ , respectively. However, in all cases, the Taylor rule coefficients are insignificant which is probably due to the overly large estimated interest smoothing parameter.

Finally, Gorter, Jacobs and de Haan (2008) compare estimates of the ECB Taylor rule using ex-post data with estimates based on independent macro variables which are forecasted based on real time data.<sup>7</sup> For the period 1997M1 – 2006M12, they find estimated coefficients for the former equal to  $\rho = 0.95$ ,  $\alpha_\pi = 0.09$  and  $a_y = 0.37$  and  $\rho = 0.86$ ,  $\alpha_\pi = 1.39$ ,  $a_y = 1.52$  for the latter. However, we would like to argue that the next issue for further research beyond this study is to really distinguish between the effect of using real time instead of ex-post data and the one induced by the use of forecasts.

Our analysis contributes to this literature by adding two additional aspects: First we estimate the Taylor reaction functions using the three-step approach, namely comparing ex-post data with real time data with the latter being compared to real time forecasts. Second, we are the first who compare ex-post and real time data within the recent financial crisis which is supposed to have altered the reaction coefficients in Taylor rule estimations.

#### IV. THE DATA ISSUE

Our Taylor rule estimations for the EMU period are based both on quarterly and monthly data. All data are taken from the ECB real time database (see Giannone *et al.* (2010)). The output variable is captured as usual by real GDP (for quarterly data) and industrial production (for monthly data).

The price level is proxied by the harmonized index of consumer prices (HICP) and the interest rate variable by the three-month Euribor. Unfortunately, these data are only available

<sup>7</sup> This study relies on survey data of real time forecasts made by major banks in the EMU.



from 2001 onwards in the ECB real time database so that the data before (1999 and 2000) have been collected from the ECB monthly bulletins.

All data are seasonally adjusted and cover the sample period 1999Q1 (1999M1) to 2010Q2 (2010M6). We choose the specific end of the sample period with an eye on the fact that the data provided by the ECB real time database are cut off in March 2011. To account for ex post data adjustments even at the end of the sample period which have the potential to lead to differences of estimation results, dependent on the use of ex-post versus real time data, we decided to leave ample room of three quarters for revisions. With this, we are in line with the findings and recommendations by Coenen, Levin and Wieland (2005). Hence, in our case the ex-post variables are those available in 2011M3 for the whole estimation period (1999M1 to 2010M6). In the case of the interest rate this is also the (forecasted) real time series because the interest rate is not subject to the real time critique. In contrast to that, the other real time data are known by the ECB governing council at the time the decision was made and, hence, represent exactly the information that could explain interest rate rises/ cuts. Unfortunately, the last values known to the ECB are never the contemporaneous ones as information about them becomes available only with a lag. Therefore, when using real time data, the ECB would react systematically too late in the sense that it reacts to values which are not up to date.

That is why *forecasts* of the variables included in the Taylor reaction function need to be implemented. It appears straightforward to construct forecasts covering exactly that “time lag deficit” because in this case a comparison between ex-post and real time data would rely exactly on the same time periods. So this type of forecast is applied by us as a first strategy.

But as the ECB monetary strategy is medium term oriented it also appears reasonable to incorporate a really forward-looking forecast. We use this as our second empirical strategy. Here, we strictly follow Sauer and Sturm (2007) who implement forecasts of 6 months for inflation and 3 months for the output gap. Using these forecast horizons, we address the ECB’s medium term orientation. What is more, we take into account that the primary goal of the ECB is to maintain price stability since the smaller forecast horizon of the output gap takes the future inflationary pressures associated with this variable into account. So we explicitly model with this choice of the forecast horizon the leading indicator properties of output to inflation.

A second problem which emerges along with forecasts is the choice of the forecasting method/database to mimic forward-looking behavior of the monetary authority since there are no reliable monthly ECB internal data available to the researcher. So the resulting Taylor rule estimates using calculated forecasts or survey data are just as good to the extent to which they coincide with the ECB forecasts.<sup>8</sup> So what forecast technique is the most preferable in our context? As our first strategy, we decided to strictly follow Sauer and Sturm (2007) by employing an AR(3) process to model monthly forecasts. For the purpose of quarterly forecasting we decided to use an AR(2) process.<sup>9</sup> These forecasts are based on the real time data which

<sup>8</sup> Obviously, the respective forecasts have to be as close as possible to the (unknown) ECB predictions to be good forecasts in the sense of modeling the Taylor rule correctly and not close to the true values emerging several periods thereafter. If the ECB does not make any forecast errors at all (perfect foresight) then the ECB forecasts and “true” values would be the same. However, this is quite unrealistic as especially the period of the recent financial crisis shows.

<sup>9</sup> We also experimented with different AR processes but the results did not change significantly. The results are available on request.

are in principle also available to the governing council when making its interest rate decision.

In addition, we estimate the forward looking equations using the ECB staff projections. These projections are supposed to be the best proxy for the forecasts of the ECB governing council when making its interest rate decision. From December 2000 onwards these projections were published bi-annually (in June and December) as “Eurosystem staff economic projections”. Since September 2004 the latter are complemented by “ECB staff projections” which are included in the respective March and September issue of the ECB Monthly Bulletin. Thus we are capable of generating a time series on a quarterly basis for which in the third month of each quarter a new projection becomes available. In order to take these forecasts into account, our sample has to start in 2000Q4 and is adjusted for the absence of any projections in the first and third quarter before 2004Q3 by taking the respective values of the prior projections. Since both projections come up with a corridor for the inflation rate and real GDP growth we decided to simply use the mean of it as our empirical realization of the projection variable.

Coming back to the Taylor rule, there are in fact five variables that are needed. First, the interest rate ( $i_t$ ), second, the equilibrium real interest rate ( $r_t^*$ ), third, the inflation target ( $\pi_t^*$ ), fourth, the inflation rate ( $\pi_t$ ) and fifth, the output gap ( $y_t - y_t^*$ ) which consists of an output measure and the potential output.

Turning from the least to the most complex variable, we start with the inflation target which is simply set equal to two percent in line with the ECB announcement to define price stability with a increase of HICP of close to but less than two percent over the medium term. The interest rate can be taken directly from the database without any adjustment. As a measure of the inflation rate, the year-on-year increase in the HICP is taken. Hence, the formula constructing the inflation rate looks like this:

$$\pi_t = 100[\log(HICP_t) - \log(HICP_{t-12})] \quad (\text{for monthly data}) \quad (5)$$

$$\pi_t = 100[\log(HICP_t) - \log(HICP_{t-4})] \quad (\text{for quarterly data}) \quad (5a)$$

Applying these transformations to ex-post data is a trivial task but when it comes to real time data it gets slightly more complicated because in every period the last available value has to be diminished by its value one year ago. However, due to the existence of the time lag, the last value available is never the actual value. For monthly data, the lag is normally two months and thus for quarterly data one quarter.<sup>10</sup> When employing forecasts, we simply use the forecasted HICP value at the corresponding point in time and subtract its value one year before from it.

To get a clearer picture of how we constructed our data, consider the scenario prevailing in January 1999. The last empirical realization of the HICP available to the ECB is the one relating to 1998M11. The HICP variable lagged by one year (1997M11) is subtracted from this value using equation (5). This difference yields the data point of the inflation rate in real time in January 1999. For the forecasts the procedure is the same. Let us again consider as an example the construction of the data point for January 1999. Since we have decided to

<sup>10</sup> In fact the ECB publishes since November 2001 a flash estimate of the HICP which would reduce the time lag to one month. We did not use those estimates for our analysis because it is not available for the whole sample period. However, we checked for robustness of our results by adding the flash estimates and the interpretation is not altered by this.



use the monthly frequency we construct forecasts up to July 1999 (six month forecast) using an AR(3) process for the original series available in January 1999. This means that we have generated eight additional data points to the original series (1998M12-1999M7). From this expanded series we take the value of 1999M1 and subtract it by the value of 1998M1 again using equation (5) for our contemporaneous forecasts and the values 1999M7 subtracted by its 1998M7 counterpart for the forward looking forecasts. The results of the calculations are taken as the data points for January 1999 in the contemporaneous forecast series and the forward looking forecast series, respectively. In case of quarterly data generated with an AR(2) process our procedure is the same except for the fact that the forecast horizon changes from six months to two quarters and we use equation (5a) to calculate the inflation rate.

When using ECB staff projections we always used the projections to expand the forecasted HICP series since the ECB publishes forecasts for each year. So for 2000Q4 the mean projection of the inflation rate of the year 2000 is taken as the contemporaneous forecast and for the forward looking forecast the mean inflation rate of the year 2001 available in 2000Q4 is chosen. Since the forecast horizon amounts to two quarters, thus, the forecasted inflation rate is that for 2001Q2. Again, both results are considered as the data points for 2000Q4 in the respective series.

To construct the output gap variable, a measure of the potential output is needed. In the literature the HP-filter is commonly used. However, the HP-filter is as a de-trending method not necessarily displaying the correct path of the output potential.<sup>11</sup> Therefore, we also use potential output measures based on a linear and, alternatively, a quadratic trend.<sup>12</sup> When the HP-filter is employed the smoothing parameter is set to 14.400 for monthly and 1.600 for quarterly data. With these potential output measures it becomes possible to calculate the output gap which is done using the following transformation:

$$Y_t = 100[\log(y_t) - \log(y_t^*)] \quad (6)$$

In case of ex-post data it is again straightforward to calculate the output gap because here the potential output can be built over the whole sample period (1999M1-2010M6). To get the output gap in real time is, however, much harder because initially after the start of EMU there were only data of the pre-ECB era available to construct the potential output. The question is now how far this data set needs to reach into the past to generate reliable estimates of the potential. In the following, we use the data of the ten preceding years, thus, the output gap in 1999M1 was built on the data going back to 1989M1. However, it is clearly at odds with the experience of any observer that the ECB is deriving its potential output estimates still today from data of 1989. Hence, every real time estimate relies on the preceding ten years of data. For instance, in order to construct the output gap in real time for every month/ quarter, the output gap is calculated with the data of the preceding ten years and the last value of this 10-year period is taken as the data point of the respective period in real time.

<sup>11</sup> See for an extensive comparison between various types of potential output gap measures and their relevance for output gap estimates Chagny and Döpke (2001).

<sup>12</sup> The linear de-trended potential output is generated by the expression  $Y_t^* \text{ lin} = Y_0^* \text{ lin} + \alpha * t$ , while the potential output computed imposing a quadratic trend is derived from the transformation  $Y_t^* \text{ qua} = Y_0^* \text{ qua} + \beta * t^2$ , with  $\alpha$  and  $\beta$ , respectively, being the slope coefficients.

As an example, in 1999M1 the output gap is estimated based on the data ranging from 1989M1 to 1999M1 and value of the time series in the last month is taken as the data point of the output gap for 1999M1 in real time.<sup>13</sup> We apply the same procedure for all other periods as well in order to generate the output gap in real time.<sup>14</sup> In order to generate the AR forecasted estimates we simply add the values using the same AR-processes as for the inflation rate construction explained above, assuming a forecast horizon of three months/ one quarter. For each output time series we then construct the realization of potential output which is used to construct the output gap. As a next step, we take the respective values of each time series and include them in the two forecasted output gap time series.

For the ECB staff projection forecasts we first take the output growth factor for every year and multiply it by its value lagged one year to get a measure of real GDP for the respective quarter. The following procedure corresponds to the forecasts generated with AR-processes. Consider again the period 2000Q4 as an example. So in the original GDP series we have data up to 2000Q2 and need to add data up to 2001Q1. For the periods 2000Q3 and Q4, we use the mean growth factor of the year 2000 as it was available in 2000Q4 and multiply it by the values of GDP as of 1999Q3 and Q4. We adopted the same procedure to our forecast of 2001Q1 where we take the mean growth factor of 2001 as it was available in 2000Q4 and multiply it by the value of GDP in 2000Q1. With this expanded series we again calculate the realization of potential output which is used to construct our output gap variable for 2000Q4. The respective data points are then included in the forecasted output gap series.

The last independent macro variable that needs to be specified is the equilibrium real interest rate. In fact, the equilibrium real interest rate has in the context of Taylor rules almost never played the role it should have because it was mainly just held constant over time by making it a part of the constant in econometric analysis.<sup>15</sup>

However, there is considerable uncertainty about how to calculate the non-observable equilibrium real interest rate. It may be approximated by a multi-year average of the difference between the actual nominal interest rate and inflation. However, such a measure would depend on the period used for forming the average. Alternatively, assuming a constant equilibrium real interest rate over long periods may not be appropriate either. Besides the expected rate of return on tangible fixed assets and the general propensity to save, the equilibrium real interest rate may also depend on the general assessment of the uncertainty in the economy and the degree of credibility of the central bank. If these aspects are not taken into account, the resulting Taylor rate may be of questionable informative value.

Seen on the whole, thus, it is widely agreed upon by economists that the equilibrium real interest rate is by no mean constant over time<sup>16</sup> and should be allowed to fluctuate just like other variables. Hence, we insert an explicit measure of the equilibrium real interest rate

<sup>13</sup> In this example, we neglect the time lag problem for reasons of simplicity but we account for the lag of 3 months and 2 quarters respectively when constructing the time series.

<sup>14</sup> In order to account for the well-known end-of-sample bias induced by the HP-Filter, we also used forecasts of the output series to expand the sample and avoid this problem. Therefore we used corresponding values of the forecasts generated by the AR processes explained above.

<sup>15</sup> A notable exception from this rule is Plantier and Scrimgeour (2002).

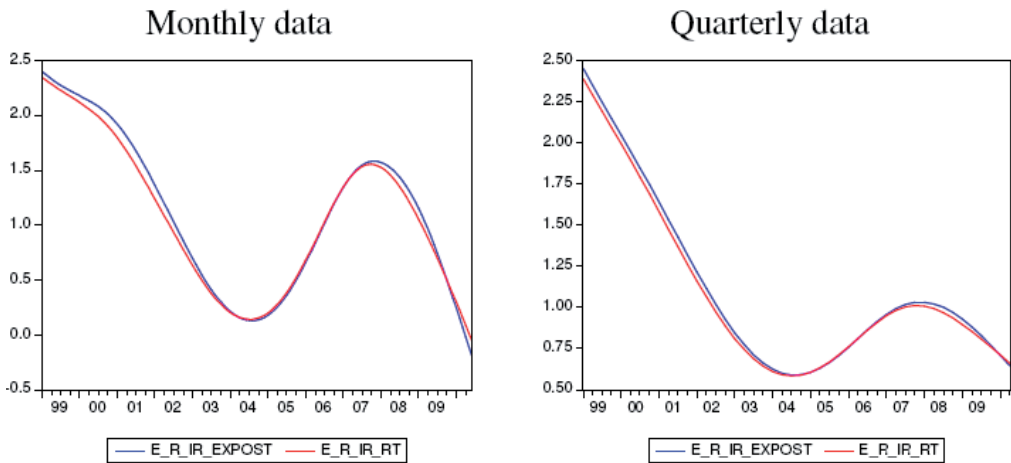
<sup>16</sup> For the case of the euro area see Cuaresma, Gnan and Ritzberger-Gruenwald (2004), Mésonnier and Renne (2007), Garnier and Wilhelmssen (2009).

into the Taylor rule specification by using the Fisher equation with adaptive expectations to construct the real interest rate as

$$r_t = i_t - \pi_t \tag{7}$$

and finally employ the HP-filter to the resulting time series. Applying de-trending methods is probably the easiest and less precise way to calculate a time-varying equilibrium level, however it should be more suitable than assuming a constant equilibrium real rate especially within the recent financial crisis (McCulley and Toloui (2008)). This leads to the time series of the equilibrium rate as shown in *Figure 1*.

*Figure 1: Equilibrium Real Interest Rates*



Source: ECB real time database and own calculations. The blue lines E\_R\_IR\_EXPOST show the equilibrium real interest rate calculated with ex-post data while the red line (E\_R\_IR\_RT) covers the same variable if real time data are used.

In this figure, the calculated paths of the equilibrium real interest rate for monthly and quarterly, ex-post and real time data are displayed. It is obvious that the rate is by no means constant over time. In fact, its absolute deviation over time amounts to about 2.5 percent. For an “equilibrium” interest rate, the gyrations appear to be rather strong. However, the scale of our calculations is in line with the real equilibrium interest rates calculated by other authors such as, for instance, Cuaresma, Gnan and Ritzberger-Gruenwald (2004), p. 194, Mésonnier and Renne (2007), p. 1776, Garnier and Wilhelmsen (2009), p. 310, who all come up with a similar variance. A striking observation is that the shapes of the curves turn out to be rather similar – independent on whether they are based on ex-post or on real time data. Hence, differences in the Taylor rule coefficients cannot be explained by differences in this measure.

## V. ESTIMATION RESULTS

We now estimate Taylor reaction functions using GMM. As instruments we employ only lagged values of the right hand side variables. In the case of monthly data, our set of instruments comprises up to the last six months of inflation and the output gap and whenever implemented six lags of the interest rate. When we use quarterly data, the maximum number of lags is reduced from six to four.<sup>17</sup> Whenever it is necessary according to the usual diagnostics, up to six lags of the equilibrium real interest rate are included. We test for the appropriateness of our instrument choice by calculating the J-statistic. The results reveal that the set of instruments is chosen properly in the sense of being orthogonal with the error term. As the relevant weighting matrix we choose the heteroskedasticity and autocorrelation consistent HAC matrix by Newey and West (1987).

Our regression equations are directly derived from equations (2) to (4) which were explained in section 2. For estimation purposes they can be written as follows when taking an inflation target of 2 % into account:

$$i_t = a_0 + r_t^* + (1 - a_\pi) \cdot 2 + a_\pi \pi_t + a_y Y_t + \varepsilon_t \quad (2a)$$

$$i_t = \rho \cdot i_{t-1} + (1 - \rho) \cdot [a_0 + r_t^* + (1 - a_\pi) \cdot 2 + a_\pi \pi_t + a_y Y_t] + \varepsilon_t \quad (3a)$$

$$i_t = a_0 + \bar{r}_t^* + (1 - a_\pi) \cdot 2 + a_\pi \cdot E(\pi_{(t+j|t)}) + a_y \cdot [E(y_{(t+k|t)}) - \bar{y}_t^*] + \varepsilon_t \quad (4a)$$

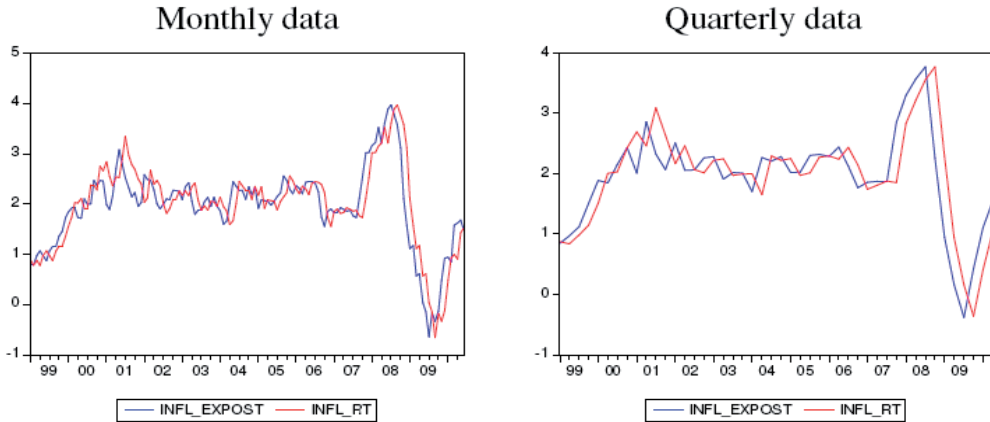
Here, the constant  $a_0$  is expected to be equal to zero because all variables typically included in the constant (namely the equilibrium real interest rate and the inflation target) are now explicitly appearing in the Taylor rule specification. In fact, we even go beyond these three specifications by adding forecasts to the interest rate-smoothed Taylor rule and, by this, in a way merging equations (3a) and (4a). We display first eyeball evidence of potential numerical differences in the realization of ex-post and real time data based variables in *Figures 2* and *3*.

*Figure 2* gives an overview of the respective inflation rates. It becomes obvious that the differences do mainly occur because of the imposed time lag of two months and one quarter respectively (see *section 4*). This does not come as a surprise as inflation data are not affected by statistical uncertainty (inflation rates get calculated instead of estimated) and are typically hardly ever revised later on.

In contrast to that, the output gap time series displayed in *Figure 3* differ quite considerably in many cases. Especially at the start of our sample period the empirical realizations of the output gap deviate significantly from each other, indicating large statistical uncertainty and data revisions. From 2001 to 2005 both time series moved mainly in tandem except for the output gap on a quarterly basis constructed by a quadratic trend, which signals less statistical

<sup>17</sup> The choice of the instruments was made in line with the empirical literature in this field so far. For monthly data this is Sauer and Sturm (2007) and for quarterly data Belke and Polleit (2007). Although using GMM is strictly speaking not needed when estimating real-time and forward-looking Taylor rules, we decided to use it also in these specifications because otherwise we would induce model uncertainty within our estimates which we want to avoid. We also considered using information criteria in order to extract the “best” specification but this would mean employing a different set of instruments to each estimate. As this different choice of instruments is an additional source of differences between the estimates, we feel legitimized to rely on a constant set of instruments.

Figure 2: Inflation Rates Ex-Post and in Real Time



Source: ECB real time database and own calculations. The blue line (INFL\_EXPOST) shows the inflation rate calculated with ex-post data and the red line (INFL\_RT) covers the inflation rate variable available to policy decision makers in real time.

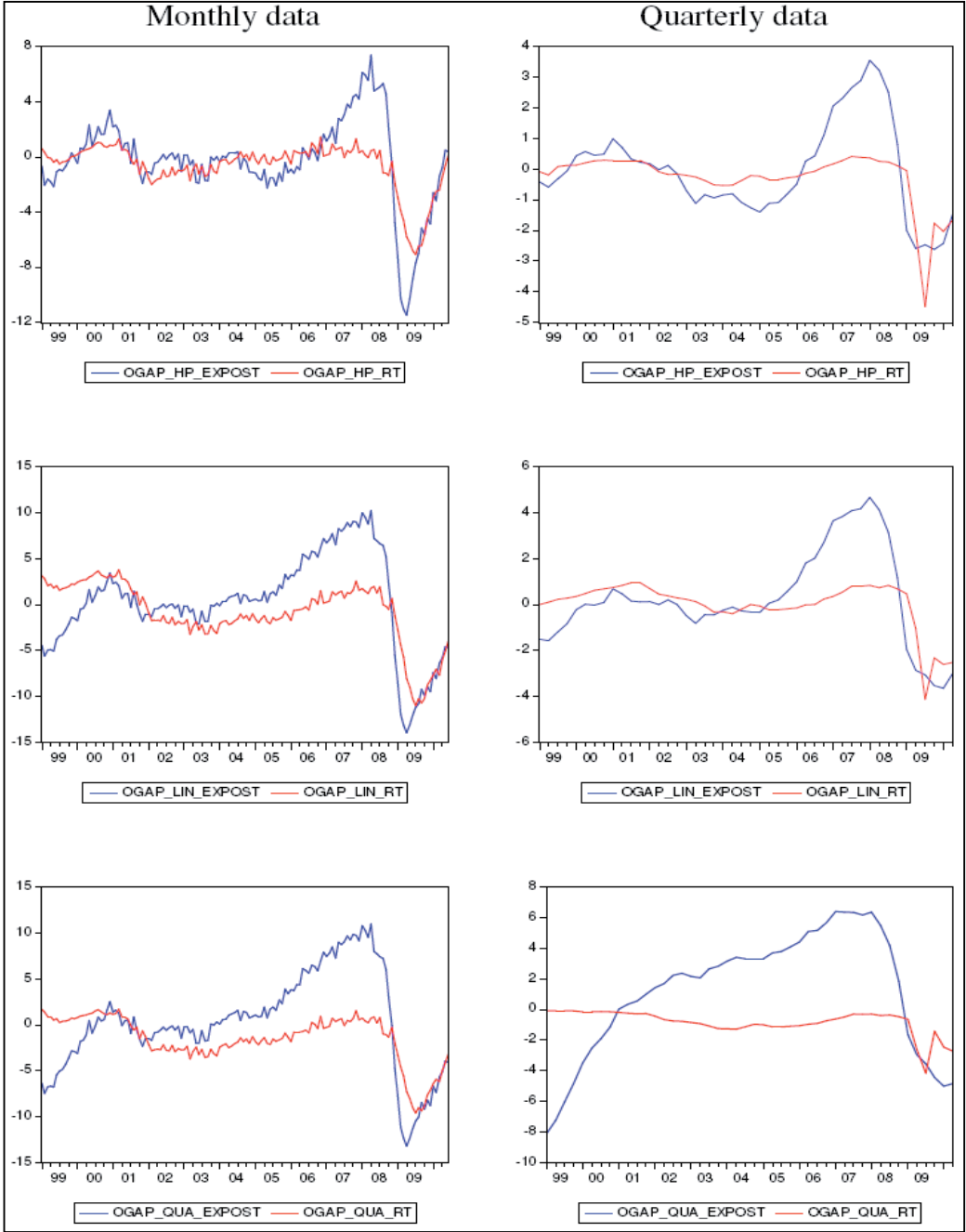
uncertainty and data revisions. However, even before the financial crisis started we observe that from 2006 onwards the output gap estimated with ex-post data is steadily increasing while the real time measures remain more or less constant. This trend holds until the end of 2008 where all time series irrespectively of the frequency, trend-method or set of data exhibit a large decline which has to be traced back to the financial crisis especially after Lehman got bankrupt. However, it is observed that the output gap tends to be lower when using ex-post data instead of real time data. There are only two exceptions namely the second quarter of 2009 when applying the HP-filter or a linear trend. So we verified that the ECB governing council could not observe the true drop in economic activity when they had to make their decision in the financial crisis period. But we have also shown that there are substantial differences between ex-post and real time data which could lead to different reaction coefficients in Taylor rule estimations. Whether this is true will be evaluated in the next section.

### 5.1 Estimations of Original Taylor Rules – Ex-Post Versus Real Time Data

We now make use of this array of variables to estimate the coefficients of differently specified Taylor reaction functions. *Table 1* displays the respective estimations of the *original* Taylor rule without any interest rate smoothing and any forward-looking components.

Looking at the results displayed in *Table 1*, the first stylized fact is that ex-post and in real time the coefficients of the inflation rate and the output gap are almost always significantly different from zero while this is hardly ever the case for the constant term ( $\alpha_0$ ). This clear empirical pattern provides evidence in favor of the hypothesis that the inflation target and the equilibrium real interest rate are indeed the only terms influencing the constant and by modeling them explicitly, the constant becomes zero.

Figure 3: Output Gaps Ex-Post and in Real Time



Source: ECB real time database and own calculations. The blue lines cover the output gaps estimated using ex-post data while the red lines show those if real time data are used, the abbreviations HP, LIN, QUA signal that potential output for this output gap is estimated using the HP-filter, linear trend or quadratic trend.



Table 1: Original Taylor Rule Estimates (eq. (2a))

	Ex-post data								Real time data													
	(1.1)	(1.2)	(1.3)	(1.4)	(1.5)	(1.6)	(1.7)	(1.8)	(1.9)	(1.10)	(1.11)	(1.12)	(1.13)	(1.14)	(1.15)	(1.16)	(1.17)	(1.18)	(1.19)	(1.20)		
$\alpha_0$	0.09* (0.05)	-0.04 (0.06)	-0.03 (0.05)	0.04 (0.04)	-0.19** (0.08)	-0.58*** (0.18)	0.10 (0.08)	0.13 (0.08)	0.19* (0.10)	0.08 (0.09)	-0.42*** (0.05)	0.54*** (0.10)	0.43*** (0.11)	0.46*** (0.09)	0.52*** (0.08)	0.49* (0.29)	0.73*** (0.07)	0.66*** (0.10)	0.69*** (0.09)	0.85*** (0.17)	0.88*** (0.07)	0.68*** (0.06)
$\alpha_\pi$	0.11*** (0.03)	0.08*** (0.01)	0.06*** (0.01)	0.49*** (0.03)	0.34*** (0.03)	0.16*** (0.05)	0.12*** (0.03)	0.09*** (0.03)	0.10*** (0.03)	1.58*** (0.25)	0.33*** (0.05)	0.70*** (0.05)	0.11*** (0.03)	0.08*** (0.01)	0.06*** (0.01)	0.16*** (0.05)	0.12*** (0.03)	0.09*** (0.03)	0.10*** (0.03)	1.58*** (0.25)	0.33*** (0.05)	0.70*** (0.05)
$\alpha_\gamma$	0.85	0.88	0.88	0.85	0.84	0.57	0.86	0.85	0.86	0.80	0.61	0.70	0.85	0.88	0.88	0.57	0.86	0.85	0.86	0.80	0.61	0.70
$adj R^2$	0.06 (0.48)	0.05 (0.65)	0.05 (0.70)	0.11 (0.41)	0.06 (0.71)	0.13 (0.32)	0.03 (0.89)	0.04 (0.73)	0.04 (0.80)	0.12 (0.54)	0.16 (0.62)	0.06 (0.74)	0.06 (0.48)	0.05 (0.65)	0.05 (0.70)	0.13 (0.32)	0.03 (0.89)	0.04 (0.73)	0.04 (0.80)	0.12 (0.54)	0.16 (0.62)	0.06 (0.74)

Notes: GMM estimates, \*/ \*\*/ \*\*\* denote significance at the 10%/ 5%/ 1% level, standard errors in parenthesis, for J-statistic p-value in parenthesis; M=monthly estimate, Q=quarterly estimate, HP=HP-filter, LIN=linear trend, QUA=quadratic trend used.

Table 2: Taylor Rule Estimates with Interest Rate Smoothing (eq. (3a))

	Ex-post data								Real time data													
	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)	(2.6)	(2.7)	(2.8)	(2.9)	(2.10)	(2.11)	(2.12)	(2.13)	(2.14)	(2.15)	(2.16)	(2.17)	(2.18)	(2.19)	(2.20)		
$\rho$	0.95*** (0.02)	0.89*** (0.01)	0.90*** (0.02)	0.43*** (0.08)	0.47*** (0.05)	0.84*** (0.04)	0.97*** (0.02)	0.91*** (0.03)	0.94*** (0.02)	0.83*** (0.02)	0.44*** (0.16)	0.72*** (0.04)	0.02 (0.19)	-0.17*** (0.05)	-0.24*** (0.06)	-0.37* (0.22)	1.48 (1.29)	0.74*** (0.24)	1.66*** (0.64)	-0.59*** (0.24)	-0.22* (0.11)	0.16 (0.23)
$\alpha_0$	0.47 (0.35)	0.06 (0.14)	0.12 (0.15)	0.57*** (0.06)	0.44*** (0.13)	1.39*** (0.34)	-6.13 (6.29)	-0.24 (0.25)	-0.55 (0.46)	0.60*** (0.18)	1.32*** (0.32)	0.83*** (0.11)	0.47 (0.35)	0.06 (0.14)	0.12 (0.15)	0.57*** (0.06)	-6.13 (6.29)	-0.24 (0.25)	-0.55 (0.46)	0.60*** (0.18)	1.32*** (0.32)	0.83*** (0.11)
$\alpha_\pi$	0.39* (0.21)	0.20*** (0.03)	0.21*** (0.03)	0.44*** (0.04)	0.45*** (0.03)	0.10 (0.10)	3.68 (3.31)	0.39*** (0.10)	0.71*** (0.25)	0.43*** (0.18)	1.33*** (0.28)	0.50*** (0.08)	0.39* (0.21)	0.20*** (0.03)	0.21*** (0.03)	0.44*** (0.04)	3.68 (3.31)	0.39*** (0.10)	0.71*** (0.25)	0.43*** (0.18)	1.33*** (0.28)	0.50*** (0.08)
$\alpha_\gamma$	0.98	0.98	0.98	0.94	0.93	0.89	0.97	0.97	0.97	0.85	0.48	0.86	0.98	0.98	0.98	0.89	0.97	0.97	0.97	0.85	0.48	0.86
$adj R^2$	0.12 (0.71)	0.09 (0.55)	0.09 (0.87)	0.18 (0.78)	0.12 (0.71)	0.16 (0.49)	0.10 (0.81)	0.05 (0.93)	0.05 (0.95)	0.18 (0.78)	0.13 (0.66)	0.15 (0.55)	0.12 (0.71)	0.09 (0.55)	0.09 (0.87)	0.18 (0.49)	0.10 (0.81)	0.05 (0.93)	0.05 (0.95)	0.18 (0.78)	0.13 (0.66)	0.15 (0.55)

Notes: GMM estimates, \*/ \*\*/ \*\*\* denote significance at the 10%/ 5%/ 1% level, standard errors in parenthesis, for J-statistic p-value in parenthesis; M=monthly estimate, Q=quarterly estimate, HP=HP-filter, LIN=linear trend, QUA=quadratic trend used.

If we base our estimations on ex-post data (columns 1.1 to 1.6), the Taylor principle ( $\alpha_\pi > 1$ ) is always violated. The coefficients approach empirical realizations of about 0.5 which means that the ECB is not even close to fulfill the Taylor principle. However, finding coefficients of below unity is a common feature when estimating Taylor reaction functions including the financial crisis (see Klose (2011)).<sup>18</sup> Turning to the inflation coefficients using real time data (columns 1.7 to 1.12) we observe that the estimates remain below unity thus the Taylor principle is also not satisfied in this case. But the order of the estimates is consistently above that based on ex-post data. Hence, we feel legitimized to conclude that using ex-post instead of real time data understates the underlying “true” reaction of the ECB to inflation.

With respect to the output reaction we observe that when using ex-post data the coefficients are quite low, especially in case of monthly data (columns 1.1 to 1.3). This pattern does not change significantly when the analysis is employed with real time data (columns 1.7 to 1.9). However, for quarterly data the estimated coefficients are larger than for monthly data. Moreover, we find a stronger reaction if real time instead of ex-post data are used and the HP-filter or a quadratic trend is employed (comparing 1.4 to 1.10 and 1.6 to 1.12). When constructing the output gap with a linear trend there is almost no difference in the reaction coefficient. So we conclude that the reaction to the output gap is – if anything – stronger in real time.

Note that our findings support partly the main findings of the studies of Gerdesmeier and Roffia (2005) and Sauer and Sturm (2007). While Gerdesmeier and Roffia find a stronger reaction to output and a weaker reaction to inflation in real time, the opposite is true for the results of Sauer and Sturm (2007) if no interest rate smoothing term is included. However, our results reveal that both reactions tend to be stronger in real time. Reasons for this result might be the longer sample period we choose which includes the financial crisis where reaction coefficients are supposed to have changed and the different set of instruments Gerdesmeier and Roffia (2005) use in their study. The latter reason seems to be the driving force behind the differences between our results and those generated by Gerdesmeier and Roffia (2005) since when shortening our sample period to their sample up to mid 2003 we still find a higher reaction coefficient also for inflation. Nevertheless, the choice of our instruments is appropriate as the J-statistic reveals.

It is worthwhile to note that our empirical findings are independent of the frequency used. In both cases – monthly and quarterly data – we are able to identify a stronger reaction of ECB monetary policy to inflation and a slightly stronger reaction to the output gap in real time.

### *5.2 Taylor Rule Estimations with Interest Rate Smoothing – Ex-Post Versus Real Time Data*

Summarizing, for the Taylor rule without interest rate smoothing the differences of results are quite substantial at least with respect to the inflation reaction. Whether this remains true for Taylor rules including interest smoothing can be judged based on the entries in *Table 2*.

When including an interest rate smoothing term ( $\rho$ ) we always find estimated values of this reaction coefficient of about 0.9 when conducting the analysis with monthly data, but

<sup>18</sup> Gerlach (2011) finds even insignificant estimates for the inflation rate. Thus, he drops this variable from the estimation. However, this is not the case in our estimation.

irrespective of the use of ex-post or real time data. So it seems that the interest rate is mainly driven by its past value and less by fundamentals for monthly data. But for quarterly data we find consistently lower smoothing parameters. However, there is no clear pattern whether the smoothing parameter is larger or lower in real time since for the HP-filter it increases (columns 2.4 and 2.10) while it decreases for the quadratic trend (columns 2.6 and 2.12) and stays almost equal for the linear trend (columns 2.5 and 2.11).

Due to the high estimated smoothing coefficient we do not arrive at significant estimates of the inflation coefficient in any of our specifications using monthly data. So our comparisons concerning the inflation reaction have to rely on quarterly data. Here we observe that ex-post the Taylor principle is again empirically violated for the HP-filtered estimate and the linear trend case (columns 2.4 and 2.5). However, for the estimate using a quadratic trend (column 2.6) the Taylor principle is satisfied which might be due to the relatively high smoothing parameter compared to the other ex-post estimates. Accordingly, we find a stronger reaction to inflation in real time for the HP-filtered and linear-de-trended estimates (comparing columns 2.4 to 2.10 and 2.5 to 2.11) while in the latter even the Taylor principle is satisfied. However, for the quadratic trend estimate the reaction is weaker in real time. But this is in our opinion due to the relatively high interest rate smoothing coefficient for ex-post data. Thus, we find overall the same pattern as for the inflation reaction without an interest rate smoothing term, namely that the reaction is stronger in real time.

Even though the smoothing coefficients are high for monthly data we arrive at significant estimates of the output coefficients in five of six estimates. Only for the HP-filtered estimate in real time (column 2.7) the estimate is not statistically significant. However, this pattern does not come as a surprise since the smoothing coefficient amounting to 0.97 is the highest of all. Thus, the fundamentals like the output gap appear to explain almost nothing. Since the HP-filtered estimate in real time is insignificant, our comparisons between ex-post and real time data have to rely on the two remaining specifications, namely the linear and quadratic de-trended output gap. Here we observe – quite consistently with our findings of the reaction functions without interest rate smoothing – a stronger reaction in real time (comparing columns 2.2 to 2.8 and 2.3 to 2.9). When using quarterly instead of monthly data we can actually draw the same conclusion. For the linear and quadratic trend specification (columns 2.5/ 2.6 and 2.11/ 2.12) the estimated reaction coefficients of output in real time exceed those of ex-post data, while for the HP-filtered estimate there is almost no difference (columns 2.4 and 2.5).

Thus, we can conclude from this section that the results that we obtained for the specifications without interest rate smoothing are even reinforced when a smoothing term is included in the reaction function. We observe in both cases that the reaction to inflation and the output gap is stronger when real time data are used instead of ex-post data.

### *5.3 Estimations of Taylor Rules Based on Real Time Data – Current Period Forecasts and “True” Forecasts Generated by AR Processes Versus Rriginal Real Time Data*

So far, we have compared the relative performance of Taylor rule estimations dependent on the use of ex-post data or real time data, the data set available to the ECB at the time it has to make its decision. So we have made the first two steps in our three-step approach. As a final step, we now check whether our estimations based on real time data change numerically

if we implement real time forecasts. If we find significant numerical estimation differences between both types of Taylor rules we are able to distinguish the effects which the use of real time data has from the ones that are essentially induced by the application of a forecast which is based on real time data.

We thus strive to go beyond those comparative studies which consider those two effects simultaneously and, hence, risk mixing up both effects. What is more, we feel legitimized to argue that we are – as an innovation to the literature – able to identify whether both effects played a role or (even more important) whether the results are driven by only one source whereas the other actually does not have any influence. In order to clarify issues, we display our Taylor rule estimations based on forecasted macro variables without interest rate smoothing and two different forecasts in *Table 3*.

Concerning the inflation response for forecast of the current period (which becomes necessary as monetary policy operates with a lag) the results depend on the frequency chosen. For monthly data we observe that using forecast reduces the inflation response (comparing 1.7 to 1.9 with 3.1 to 3.3) while the reverse is true for the comparisons between real time data and real time forecasts if quarterly data are used (1.10 to 1.12 and 3.4 to 3.6). For real time forecasts using quarterly data we find the Taylor principle satisfied even in two of the three cases.

With respect to the output response for current period forecasts when using monthly data we can again not find any difference to real time data as it was also the case when comparing ex-post and real time data. However, when using quarterly data the response coefficient is clearly lower for current period forecasts than for real time data. This result holds independent of the method used to calculate the output gap.

If we use “true” forecasts the interpretation remains the same for monthly data (columns 3.7-3.9) as it was for the current forecasts, namely that the inflation response is reduced while the output gap response is not altered. For quarterly data (columns 3.10-3.12) we observe that the output response of the forecasts is again lower compared to the simple use of original real time data as it was also the case for current period forecasts. However, we now observe that using “true” forecasts substantially lowers the response to inflation in contrast to the current period forecasts where the response coefficients even increase. Yet, this is the only difference between the use of current period forecasts or “true” forecasts.

#### *5.4 Estimations of Taylor Rules with Interest Rate Smoothing Based on Real Time Data – Current Period Forecasts and “True” Forecasts Generated By AR Processes Versus Original Real Time Variables*

In this part of our comparative investigation exercise, we check for the relative performances of Taylor reaction functions including an interest rate smoothing term based on time series of macro variables generated by current period forecasts and “true” forecasts. Our estimation results are shown in *Table 4*.

The high degree of interest rate smoothing at a monthly frequency (columns 4.1 to 4.3 and 4.7 to 4.9) already identified by us in section 5.2 can also be supported by both forecasts. This leads again to no significant estimates of the inflation coefficients using a monthly frequency. Hence, our comparisons of the inflation coefficients have to rely on quarterly data where

Table 3: Taylor rule Estimates Based on AR Forecasted Macro Variables – Real Time Data (Eq. (4a))

	Forecast for current period						Forecast inflation 6M / output gap 3M					
	(3.1) $Y_{HP}^M$	(3.2) $Y_{LIN}^M$	(3.3) $Y_{QUA}^M$	(3.4) $Y_{HP}^Q$	(3.5) $Y_{LIN}^Q$	(3.6) $Y_{QUA}^Q$	(3.7) $Y_{HP}^M$	(3.8) $Y_{LIN}^M$	(3.9) $Y_{QUA}^M$	(3.10) $Y_{HP}^Q$	(3.11) $Y_{LIN}^Q$	(3.12) $Y_{QUA}^Q$
$\alpha_0$	-0.11* (0.06)	0.22*** (0.07)	0.36*** (0.09)	-0.06 (0.07)	0.01 (0.08)	0.03 (0.15)	0.15 (0.09)	0.20*** (0.07)	0.34*** (0.10)	-0.31*** (0.10)	-0.49*** (0.06)	0.75*** (0.18)
$\alpha_{\pi}$	0.45*** (0.11)	0.20* (0.10)	0.28*** (0.09)	1.33*** (0.12)	0.98*** (0.15)	1.14*** (0.10)	0.03 (0.09)	0.04 (0.07)	0.04 (0.08)	0.40** (0.16)	0.41*** (0.13)	0.53** (0.21)
$\alpha_{\gamma}$	0.08* (0.05)	0.13*** (0.02)	0.14*** (0.03)	0.80*** (0.14)	0.05 (0.05)	0.00 (0.05)	0.33*** (0.05)	0.13*** (0.01)	0.14*** (0.02)	0.78*** (0.08)	0.25*** (0.02)	0.15*** (0.03)
$adj R^2$	0.76	0.77	0.77	0.31	0.70	0.69	0.74	0.82	0.80	0.03	0.12	0.48
J-stat	0.11 (0.43)	0.06 (0.46)	0.07 (0.44)	0.13 (0.56)	0.22 (0.35)	0.22 (0.35)	0.06 (0.55)	0.05 (0.58)	0.06 (0.48)	0.15 (0.56)	0.17 (0.54)	0.18 (0.41)

Notes: GMM estimates, \*/ \*\*/ \*\*\* denote significance at the 10%/ 5%/ 1% level, standard errors in parenthesis, for J-statistic p-value in parenthesis; M=monthly estimate, Q=quarterly estimate, HP=HP-filter, LIN=linear trend, QUA=quadratic trend used.

Table 4: Taylor Rule Estimates with Interest Rate Smoothing Based on AR Forecasted Variables (eqs. (3a) and 4a))

	Forecast for current period						Forecast inflation 6M / output gap 3M					
	(4.1) $Y_{HP}^M$	(4.2) $Y_{LIN}^M$	(4.3) $Y_{QUA}^M$	(4.4) $Y_{HP}^Q$	(4.5) $Y_{LIN}^Q$	(4.6) $Y_{QUA}^Q$	(4.7) $Y_{HP}^M$	(4.8) $Y_{LIN}^M$	(4.9) $Y_{QUA}^M$	(4.10) $Y_{HP}^Q$	(4.11) $Y_{LIN}^Q$	(4.12) $Y_{QUA}^Q$
$\rho$	0.98*** (0.02)	0.94*** (0.03)	0.96*** (0.02)	0.53*** (0.09)	0.73*** (0.07)	0.89*** (0.04)	0.97*** (0.02)	0.90*** (0.03)	0.94*** (0.02)	0.93*** (0.02)	0.89*** (0.03)	0.90*** (0.03)
$\alpha_0$	0.10 (0.69)	1.07** (0.51)	2.32* (1.36)	-0.29** (0.13)	-0.33* (0.19)	-2.23** (0.88)	-0.49 (0.33)	0.68*** (0.19)	1.46*** (0.48)	-1.10*** (0.32)	-1.31*** (0.13)	-1.15*** (0.35)
$\alpha_{\pi}$	0.17 (0.95)	-0.34 (0.45)	-0.50 (0.69)	1.48*** (0.21)	1.56*** (0.43)	2.98*** (0.80)	0.14 (0.51)	-0.20 (0.22)	-0.28 (0.35)	1.54** (0.62)	1.27*** (0.46)	2.01*** (0.55)
$\alpha_{\gamma}$	1.42 (1.70)	0.47** (0.19)	0.84* (0.47)	0.54*** (0.12)	0.40** (0.16)	-0.55 (0.34)	1.28** (0.56)	0.24*** (0.04)	0.42*** (0.11)	0.89** (0.40)	0.18** (0.07)	0.16** (0.07)
$adj R^2$	0.98	0.97	0.98	0.82	0.83	0.85	0.98	0.98	0.98	0.87	0.87	0.88
J-stat	0.12 (0.66)	0.06 (0.89)	0.05 (0.93)	0.16 (0.48)	0.14 (0.58)	0.17 (0.79)	0.10 (0.51)	0.12 (0.30)	0.11 (0.74)	0.20 (0.67)	0.19 (0.72)	0.16 (0.48)

Notes: GMM estimates, \*/ \*\*/ \*\*\* denote significance at the 10%/ 5%/ 1% level, standard errors in parenthesis, for J-statistic p-value in parenthesis; M=monthly estimate, Q=quarterly estimate, HP=HP-filter, LIN=linear trend, QUA=quadratic trend used.

the interest rate smoothing term is again found to be considerably lower. For current period forecasts (columns 5.4 to 5.7) we find as in section 5.3 even higher reaction coefficients to inflation than for the real time estimates (2.10 to 2.12). Moreover, now all three estimates clearly indicate that the Taylor principle is fulfilled. This holds also if we look at the inflation response for “true” forecasts (columns 4.10 to 4.12). So whether the reaction to inflation is stronger or weaker for “true” forecasts depends crucially on the inclusion of an interest rate smoothing term.

In line with our findings in section 5.3 including an interest rate smoothing term does lower the response to the output gap for quarterly data irrespectively whether current (columns 4.4 to 4.6) or “true” forecasts (columns 4.10 to 4.12) are used. However, this result applies only to the linear or quadratic de-trended output gap for the HP-filtered specification the reverse is true. But it is by no means granted that the HP-filtered is superior to the others. However, for monthly data we are unable to compare the HP-filtered forecast output estimates (columns 4.1 and 4.7) with the real time specification since the latter was found to be insignificant. But for the remaining linear and quadratic de-trended estimates we do now find an increase for current period forecasts (columns 4.2 and 4.3) and a decrease in “true” forecasts (columns 4.8 and 4.9) in contrast to section 5.3 where there was no difference.

#### *5.5 Estimations of Taylor Rules Based on Real Time Data – Current Period Forecasts and “True” Forecasts Estimated Using Staff Projections Versus Original Real Time Variables*

The final part of our analysis uses staff projections to generate the forecasts. As argued above, these forecasts should be quite close to those the ECB governing council had at hand when making its interest rate decision. Since these projections are only available at a quarterly frequency we just rely on quarterly estimates of Taylor rules, with and without interest rate smoothing. We display our Taylor rule estimates with and without interest rate smoothing based on staff projections forecasted variables in *Table 5*.

For current period and “true” forecasts without interest rate smoothing (columns 5.1 to 5.3 and 5.7 to 5.9) we again find a decrease in the reaction to inflation compared to the original real time data (columns 1.10 to 1.12) as it was also the case for our AR-forecasts. In this case we find also for the output gap coefficient the same pattern as for the forecasts generated by an AR-process, namely that it decreases if forecasts are introduced.

When adding an interest rate smoothing term (columns 5.4 to 5.6 and 5.10 to 5.12) it turns out that the output gap coefficient is again significantly reduced irrespectively of the forecast horizon used which is again consistent with our findings without an interest rate smoothing term or when AR-forecasts are employed. We also find that for “true” forecasts the inflation coefficients increase and thus fulfill the Taylor principle as it was also the case for the AR-forecasts. The only difference we observe when employing ECB staff-projections instead of AR-forecasts is that for current period forecasts de-trended by a linear or quadratic trend the inflation response tends to decrease. However, for the HP-filtered estimate the reverse is true. Hence, this specification is again consistent with the AR-forecast estimates.



Table 5: Taylor Rule Estimates With and Without Interest Rate Smoothing Based on Staff Projections  
Forecasted Variables (eqs. (3a) and 4a))

	Forecast for current period						Forecast inflation 6M / output gap 3M					
	(5.1)	(5.2)	(5.3)	(5.4)	(5.5)	(5.6)	(5.7)	(5.8)	(5.9)	(5.10)	(5.11)	(5.12)
$\rho$	$Y_{HP}^Q$	$Y_{LIN}^Q$	$Y_{QUA}^Q$	$Y_{HP}^Q$	$Y_{LIN}^Q$	$Y_{QUA}^Q$	$Y_{HP}^Q$	$Y_{LIN}^Q$	$Y_{QUA}^Q$	$Y_{HP}^Q$	$Y_{LIN}^Q$	$Y_{QUA}^Q$
$\alpha_0$	-0.07** (0.03)	-0.01 (0.03)	-0.06** (0.02)	-0.33** (0.16)	-0.15** (0.06)	-0.67*** (0.16)	0.03 (0.02)	0.11*** (0.02)	0.08* (0.04)	-0.18*** (0.06)	0.03 (0.05)	-0.28*** (0.07)
$\alpha_\pi$	0.58*** (0.03)	0.55*** (0.04)	0.65*** (0.03)	0.99*** (0.18)	0.55*** (0.09)	0.57** (0.26)	0.78*** (0.06)	0.78*** (0.06)	0.79*** (0.12)	1.83*** (0.20)	1.36*** (0.14)	2.11*** (0.23)
$\alpha_\gamma$	0.36*** (0.03)	0.25*** (0.01)	0.26*** (0.01)	0.09 (0.12)	0.22*** (0.04)	0.15*** (0.04)	0.47*** (0.01)	0.38*** (0.01)	0.21*** (0.02)	0.25*** (0.05)	0.35*** (0.03)	0.09*** (0.03)
$adj R^2$	0.89	0.76	0.90	0.87	0.90	0.87	0.91	0.91	0.68	0.95	0.96	0.95
J-stat	0.17 (0.74)	0.20 (0.72)	0.18 (0.63)	0.11 (0.86)	0.16 (0.93)	0.19 (0.88)	0.22 (0.57)	0.23 (0.54)	0.22 (0.58)	0.12 (0.85)	0.12 (0.83)	0.12 (0.82)

Notes: GMM estimates, \*/ \*\*/ \*\*\* denote significance at the 10%/ 5%/ 1% level, standard errors in parenthesis, for J-statistic p-value in parenthesis; Q=quarterly estimate, HP=HP-filter, LIN=linear trend, QUA=quadratic trend used; Sample period adjusted to 2000Q4-2010Q2.

Seen on the whole, thus, the following empirical picture emerges based on our partial results summarized in Tables 1 to 5 (*sections 5.1 to 5.5*). When estimating Taylor rules for the euro area with ex-post data, the estimated coefficient of inflation and the estimated output gap coefficient turn out to be biased downwards (section 5.1) when compared to estimates using real time data. When we add an interest rate smoothing term to our empirical Taylor rule specification, our previous results are to a large extent reinforced, even though the inflation comparison has to rely on quarterly data since monthly estimates become insignificant.

When it comes to the implementation of forward looking elements into the Taylor rules using real time data (*sections 5.3 and 5.4*), we are unable to verify an additional increase in the output coefficient. Moreover in most of the specifications even the reverse is true. Thus, the use of real time instead of ex-post data and real time forecasts instead of actually available real time data tend to move in opposing directions which might result in the false conclusion that the use of ex-post or real time data has no influence on the ECB's response to the output gap which is not true as we have shown with our three-step approach.

Concerning the inflation response when real time forecasts are employed instead of pure real time data the evidence is mixed. While there seems to be a lower response when no interest rate smoothing term is included the reverse is true if this variable is added to the estimation equation. Thus, we cannot finally judge whether the use of ex-post versus real time data and real time data versus real time forecasts is complementary or substitutive with respect to the inflation coefficient.

## VI. CONCLUSIONS

In this contribution we have shown that, in the case of the ECB, considerable *differences* of the estimated parameter values between Taylor rules emerge *when ex post data are used instead of real-time data and vice versa*. Accordingly, we are able to reproduce a pattern of results which has quite frequently been identified in the literature for other central banks as well.<sup>19</sup>

While our comparisons of ex-post and real time data reveal that the Taylor principle is not fulfilled which is a frequently found pattern if the recent financial crisis is included in the sample period, our empirical results nevertheless reveal that in real time *the inflation rate and the output gap are of greater importance than they have been ex-post*.

When it comes to the discussion of using forecasted variables in Taylor rule estimation equations the overall evidence is mixed especially with respect to the inflation reaction. However, when preparing its interest rate decisions, the ECB governing council is well known to react not only to currently available data but also to (medium-term) forecasts concerning future key variables as, above all, the inflation rate and the output gap. When using forecasts in Taylor rule estimations, the problem is that these forecasts need to be as close as possible to the unknown forecasts the ECB governing council actually bases its decision on. Using staff projections as we did in this paper might be one opportunity to come close to these, but as full coincidence can never be guaranteed, using forecasts always tends to introduce an additional but unavoidable source of differences of estimation results which is not at all related to the

<sup>19</sup> See, for instance, Orphanides *et al.* (2000) for a Fed evaluation, Nelson and Nikolov (2003) for the Bank of England, Sterken (2003) for the Bundesbank and Horvath (2009) for the Czech National Bank.

difference between ex-post and real time data.

In our analysis, we separated the two effects – the first induced by the use of ex-post instead of real time data and the second caused by the use of forecasts based on real time data instead of the original real time data – to show whether the use of forecasts promotes or distorts the results given by a mere comparison between ex-post and real time data. We find that any sound judgment on this question depends crucially on the choice of the forecast horizon, the forecast technique/survey used and the data frequency. That is why we feel legitimized to recommend comparing Taylor rule coefficients with ex-post data and forecasts based on real time data within the three-step approach used here in order to single out the driver of the differences between these two estimates.

#### REFERENCES

- Adema, Y. (2004). A Taylor Rule for the Euro Area Based on Quasi-Real Time Data, DNB Staff Reports. 114/2004, De Nederlandse Bank, Amsterdam.
- Altavilla, C. and L. Landolfo (2005). Do Central Banks Act Asymmetrically? Empirical Evidence from the ECB and the Bank of England, *Applied Economics*. 37: 507-519.
- Ball, L. (1999). Efficient Rules for Monetary Policy, *International Finance*. 2: 63-83.
- Belke, A. and J. Klose (2010). (How) Do the ECB and the Fed React to Financial Market Uncertainty? The Taylor Rule in Times of Crisis, DIW Discussion Paper No. 972, Deutsches Institut für Wirtschaftsforschung, Berlin.
- Belke, A. and T. Polleit (2007). How the ECB and the US Fed Set Interest Rates, *Applied Economics*. 39: 2197-2209.
- Belke, A. and T. Polleit (2009). Monetary Economics in Globalized Financial Markets. Berlin: Springer Verlag.
- Carstensen, K. and R. Colavecchio (2004). Did the Revision of the ECB Monetary Policy Strategy Affect the Reaction Function?, Kiel Working Paper 1221, Institute for the World Economy, Kiel.
- Chagny, O. and J. Döpke (2001). Measures of the Output Gap in the Euro-Zone: A Empirical Assessment of Selected Methods, DIW Vierteljahreshefte zur Wirtschaftsforschung 70, 310-330.
- Clarida, R. and M. Gertler (1996). How the Bundesbank Conducts Monetary Policy, NBER Working Paper 5581, National Bureau of Economic Research, Cambridge/MA.
- Clausen, V. and B. Hayo, B. (2005). Monetary Policy in the Euro Area – Lessons from the First Years, *International Economics and Economic Policy*. 1: 349-364.
- Coenen, G., A. Levin, and V. Wieland (2005). Data Uncertainty and the Role of Money as an Information Variable for Monetary Policy, *European Economic Review*. 49: 975-1006.
- Cuaresma, J., E. Gnan, and D. Ritzberger-Gruenwald (2004). Searching for the Natural Rate of Interest: A Euro Area Perspective, *Empirica*. 31: 185-204.
- Fendel, R. and M. Frenkel (2009). Inflation Differentials in the Euro Area: Did the ECB Care?, *Applied Economics*. 41: 1293-1302.
- Fourçans, A. and R. Vranceanu (2003). ECB Monetary Policy Rule: Some Theory and Empirical Evidence, ESSEC Working Paper 02008, Chergy.
- Garcia-Iglesias, J. (2007). How the European Central Bank Decided Its Early Monetary Policy?, *Applied Economics*. 39: 927-936.
- Garnier, J. and B. Wilhelmssen (2009). The Natural Real Interest Rate and the Output Gap in the Euro Area: A Joint Estimation, *Empirical Economics*. 36: 297-319.
- Gerdesmeier, D. and B. Roffia (2004). Empirical Estimates of Reaction Functions for the Euro Area, *Swiss Journal of Economics and Statistics*. 140: 37-66.
- Gerdesmeier, D. and B. Roffia (2005). The Relevance of Real-Time Data in Estimating Reaction Functions for the Euro Area, *North American Journal of Economics and Finance*. 16: 293-307.

- Gerlach, S. and G. Schnabel (2000). The Taylor Rule and Interest Rates in the EMU Area, *Economics Letters*. 67: 165-171.
- Gerlach, S. (2011). ECB Repo Rate Setting During the Financial Crisis, *Economics Letters*. 112: 186-188.
- Gerlach-Kirsten, P. (2003). Interest Rate Reaction Functions and the Taylor Rule in the Euro Area, ECB Working Paper 258, European Central Bank, Frankfurt/Main.
- Giannone, D., J. Henry, M. Lalik, and M. Mudugno (2010). An Area-Wide Real-Time Database for the Euro Area, ECB Working Paper No. 1145, Frankfurt/Main.
- Gorter, J., J. Jacobs and J. de Haan (2008). Taylor Rules for the ECB Using Expectations Data, *Scandinavian Journal of Economics*. 110: 473-488.
- Gorter, J., J. Jacobs, and J. de Haan (2009). Negative Rates for the Euro Area?, *Central Banking* 20: 61-66.
- Gros, D., T. Mayer and A. Ubide (2005). EMU at Risk, 7th Annual Report of the CEPS Macroeconomic Policy Group, Centre for European Policy Studies (CEPS), Brussels, June.
- Hodrick, R. and E. Prescott (1997). Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money Credit and Banking*. 29: 1-16.
- Horváth, R. (2009). The Time-varying Policy Neutral Rate in Real-time: A Predictor for Future Inflation?, *Economic Modelling*. 26: 71-81.
- Jensen, H. and M. Aastrup (2010). What Drives the European Central Bank's Interest-Rate Changes?, CEPR Discussion Paper 8160, Centre for Economic Policy Research, London.
- Klose, J. (2011). A Simple Way to Overcome the Zero Lower Bound of Interest Rates for Central Banks – Evidence from the Fed and the ECB within the Financial Crisis, *International Journal of Monetary Economics and Finance*. 4: 279-296.
- McCulley, P. and R. Toloui (2008). Chasing the Neutral Rate Down: Financial Conditions, Monetary Policy and the Taylor Rule, Pacific Investment Management Company (PIMCO) February 2008, Newport Beach (CA).
- Mésonnier, J. and J. Renne (2007). A Time-Varying “Natural” Rate of Interest for the Euro Area, *European Economic Review*. 51: 1768-1784.
- Nelson, E. and K. Nikolov (2003). UK Inflation in the 1970s and 1980s: The Role of Output Gap Mismeasurement, *Journal of Economics and Business*. 55: 353-370.
- Newey, W. and K. West (1987). A Simple, Positive Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*. 55: 703-708.
- Orphanides, A. (2001). Monetary Policy Rules Based on Real-Time-Data, *American Economic Review*. 91: 964-985.
- Orphanides, A. (2003). Monetary Policy Evaluation with Noisy Information, *Journal of Monetary Economics*. 50: 605-631.
- Orphanides, A., R. Porter, D. Reifschneider, R. Tetlow, and F. Finan (2000). Errors in the Measurement of the Output Gap and the Design of Monetary Policy, *Journal of Economics and Business*. 52: 117-141.
- Orphanides, A. and S. van Norden (2002). The Unreliability of Output-Gap Estimates in Real Time, *The Review of Economics and Statistics*. LXXX IV: 569-583.
- Peersman, G. and F. Smets (1999). The Taylor Rule: A Useful Monetary Policy Benchmark for the Euro Area?, *International Finance*. 2: 85-116.
- Plantir, L. and D. Scrimgeour (2002). Estimating a Taylor Rule for New Zealand with a Time-Varying Neutral Interest Rate, Reserve Bank of New Zealand Discussion Paper No. 2002/06, Wellington.
- Sauer, S. and J. Sturm (2007). Using Taylor Rules to Understand European Central Bank Monetary Policy, *German Economic Review*. 8: 375-398.
- Surico, P. (2003). Asymmetric Reaction Functions for the Euro Area, *Oxford Review of Economic Policy*. 19: 44-57.
- Sterken, E. (2003). Real-Time Expectations in the Taylor-Rule, manuscript, Department of Economics, University of Groningen. Ansgar Belke and Jens Klose 171.

- Svensson, L. (2003). What Is Wrong with Taylor Rules? Using Judgment in Monetary Policy Through Targeting Rules, *Journal of Economic Literature*. XLI: 426-477.
- Taylor, J. B. (1993). Discretion versus Policy Rules in Practice, *Carnegie-Rochester Conference on Public Policy*. 39: 195-214.
- Ullrich, K. (2003). A Comparison between the Fed and the ECB, ZEW Discussion Paper 03-19, Center for European Economic Research, Mannheim.
- Woodford, M. (2003). *Interest and Prices – Foundations of a Theory of Monetary Policy*, Princeton University Press, Princeton (NJ).

