

IMF Working Paper

Simulating Inflation Forecasting in Real-Time: How Useful Is a Simple Phillips Curve in Germany, the UK, and the US?

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European Department

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Abstract

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This paper simulates out-of-sample inflation forecasting for Germany, the UK, and the US. In contrast to other studies, we use output gaps estimated with unrevised real-time GDP data. This exercise assumes an information set similar to that available to a policymaker at a given point in time since GDP data is subject to sometimes substantial revisions. In addition to using real-time datasets for the UK and the US, we employ a dataset for real-time German GDP data not used before. We find that Phillips curves based on ex post output gaps generally improve the accuracy of inflation forecasts compared to an AR(1) forecast but that real-time output gaps often do not help forecasting inflation. This raises the question how operationally useful certain output gap estimates are for forecasting inflation.

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[#] Development Economics Research Group, The World Bank. The views expressed here do not reflect those of the World Bank, its Executive Directors, or the countries they represent.

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I. INTRODUCTION

The uncertainty related to estimating output gaps is widely acknowledged. However, Phillips curve equations remain a workhorse of many macroeconomic models.¹ Simple Phillips curves employ an estimate of the output gap to project inflation. The intuition behind this equation is straightforward: when the output gap is positive (actual output is above potential output), inflationary pressures should increase; when the output gap is negative (output is below its trend), inflationary pressures should recede. The same logic underlies the Taylor-rule that suggests raising or lowering interest rates depending on where output is with regard to its trend, in addition to where inflation stands relative to its target (Taylor, 1993).

When analyzing whether the output gap can be a useful indicator for inflation in practice, one has to ensure that the estimation process for the output gap uses an information set similar to that available to a policymaker at a given point in time.² To give an example: when questioning today whether the output gap was a useful indicator for inflation in the past, let's say in 1985, one should not use information available only ex post, meaning from today's standpoint. The series of GDP in the 1980s or 1990s, available to researchers today, was, of course, not available to policymakers in 1985. This is particularly important if you use a detrending method to estimate potential output. In addition, the revised GDP data that is downloadable today for the period 1980-85, is not the same GDP data that policymakers looked at in 1985.

This paper sets out to use the GDP series (in constant prices) available to policymakers at a certain point in time. To do that we employ real-time GDP datasets available for the United Kingdom and the United States (see Appendices 1 and 2, respectively) and build a real-time GDP dataset for Germany—which has not been used elsewhere—that enlarges a dataset created by Clausen and Meier (2005) (see Appendix 3). We estimate real-time and ex post output gaps for Germany, the UK, and the US following the spirit of Orphanides and van Norden (2005), who apply this exercise to the US. We apply some simple detrending methods to estimate potential output in all three country datasets and compare results across countries.

After estimating different output gaps series, ex post and in real-time, we simulate inflation forecasting by conducting out-of-sample forecasts. We simulate being at a certain point in time and using only the real GDP series available at that point in time to estimate an output gap series. We then estimate coefficients for the output gap in a simple backward-looking Phillips curve for an initial training period that uses data only available until that point in

¹ See Stock and Watson (2008) for a review of the literature on evaluating inflation forecasts and Taylor (1999a) for a collection of papers that employ models using Phillips curve-like equations. Berger and Stavrev (2008) find for the euro area that Phillips curve-like equations with ex post GDP data outperform other models in forecasting inflation.

² See Orphanides and van Norden (2002 and 2005), who did the pioneer work on this approach.

time. Using these parameter estimates we then forecast inflation for different time periods ahead and compare the forecast errors to the errors produced when projecting inflation using a simple AR(1) process. We define an output gap series to be useful for forecasting inflation if its role in the Phillips curve leads to smaller forecasting errors than those produced by the naive benchmark. We repeat this process from the initial training period by re-estimating the Phillips curves recursively for every additional point in the forecast period, updating the coefficients as we proceed and comparing forecasts to actual inflation.

We find that the ex post output gaps (as estimated by the two methodologies used in this paper) might overstate the practical usefulness of using Phillips curve style frameworks for forecasting inflation. When simulating a real-time perspective close to reality, this analysis suggests that output gaps might not always be as helpful in forecasting inflation in practice as commonly thought—due to the uncertainty and difficulty in estimating potential output in real-time and due to the revisions to the output series itself. This does not preclude output gaps to still be a useful tool in guiding forecast judgments, especially when used in conjunction with other indicators of spare capacity.

The paper is structured as follows: Section II provides an overview of the real-time GDP datasets used in this paper; Section III discusses revisions to GDP data and how potential output and real-time and ex post output gaps are estimated. Section IV describes how we simulate the inflation forecasting procedures and how we evaluate the usefulness of our Phillips curves. Section V presents the results of the inflation forecasting exercise and Section VI concludes.

II. REAL-TIME GDP DATASETS

The real-time GDP datasets consist of seasonally adjusted quarterly real GDP series. The datasets can be thought of as matrices, with each column vector of the matrix representing a new “vintage” of data (see Table 1). The vintage of 1980Q4, as an example, represents the real GDP series available to policymakers in 1980Q4 and has as its last data point a real GDP figure for 1980Q3 since the first estimate of GDP data for a given quarter has usually been available during the next quarter. More generally, at a time $t + n$, policymakers and researchers have a real GDP series available with data from t until $t + n - 1$.

The dataset for the *United Kingdom* as configured for this paper constitutes a 205 x 126 matrix, with 126 different vintages starting in 1976Q1 and ending in 2007Q2. The last and longest vintage contains 205 observations (1956Q1 until 2007Q1). The data is obtained from the Bank of England (see Appendix 1).

The dataset for the *United States* as configured for this paper constitutes a 245 x 171 matrix, with 171 vintages starting in 1965Q4 and ending in 2008Q2. The last and longest vintage contains 245 observations (1947Q1 until 2008Q1). The data is obtained from the Federal Reserve Bank of Philadelphia (see Appendix 2).

The dataset for *Germany* constitutes a 183×140 matrix, with 140 different vintages. The first vintage represents the perspective from 1973Q1 and the last vintage represents the perspective in 2007Q4. This last (and longest) vintage contains 183 observations (1962Q1 until 2007Q3). This series is considered the ex post GDP data available to researchers today. Each vintage reaches back to 1962Q1 but ends in a different time period. All 140 series were manually entered using 140 issues of the Bundesbank's publication *Saisonbereinigte Wirtschaftszahlen*. Clausen and Meier (2005) constructed this dataset for the vintages from 1973 to 1998 and the dataset used in this paper adds 36 vintages until 2007Q4 (see Appendix 3 for more details).

III. ESTIMATING OUTPUT GAPS

To compute an output gap, we need an estimate for potential output. While there are multiple ways of doing that (theoretical and empirical), we focus on separating the non-cyclical component from the cyclical component of real GDP. If y^* is the log of the unobserved underlying trend of real GDP and y is the log of the observed actual output, then the output gap og is $og_t = y_t - y^*_t$.

Table 1. Real GDP Vintages and Output Gap Series ¹

	Time _{t+n}	Time _T
Time _t						c_t
...						$c_{t+...}$
Time _{t+n-1}	a_{t+n-1}					$b_{t+n-1}; c_{t+n-1}$
...		$a_{t+...}$				$b_{t+...}; c_{t+...}$
...			$a_{t+...}$			$b_{t+...}; c_{t+...}$
...				$a_{t+...}$		$b_{t+...}; c_{t+...}$
...					$a_{t+...}$	$b_{t+...}; c_{t+...}$
Time _{T-1}						$a_{T-1} = b_{T-1} = c_{T-1}$

¹ Frequency of the data is quarterly. The series a_t refers to the *real-time* output gap series, while c_t refers to the *ex post* output gap series and the series b_t constitutes the *quasi-real-time* output gap series.

Real-time estimates of the output gap may deviate from ex post estimates for two reasons. First, real GDP figures undergo revisions with the consequence that output y_t observed in $t+1$ is likely to be different than observed in time $t+n$, meaning $y_{t/t+1} \neq y_{t/t+n}$. This also leads to different estimates of y^* and therefore different estimates of og . Second, the information set for real GDP is larger ex post than the information available at a point in time. For example, the outlook for medium-term real GDP in early 1973 (before the oil price shock) was likely different from what real GDP looks like from today's perspective. This end-of-sample problem makes the separation of trend and cycle less reliable than it is ex post

where the complete series is available. Therefore, one would expect the output gap series to differ even if the underlying data would not have been revised at all.³

Table 1 illustrates the different output gap series. The series a_t refers to the *real-time* output gap series, computed as the difference of the log of potential output—estimated recursively for each vintage in time—and the log of actual output as observed at that point in time. The real potential output series are therefore calculated for each column in each of the three datasets (140 times for Germany, 126 times for the UK, and 171 times for the US). In contrast, potential output is estimated only *once* in each dataset for the *ex post* output gap series c_t , used widely, that is the result of estimating log potential output once with revised ex post data and subtracting the log of revised output.

To get a visual sense of the magnitude and sign of data revisions, Figure 1 portrays the real GDP growth rates over the previous year computed from the data available *ex post* (the last column vector or vintage in our matrices, basically the data available to researchers today) as well as from the *real-time* data (meaning the growth rate of the latest available GDP data at a certain point in time over the previous year).⁴ To compute the ex post GDP growth rates, we use only one series (the latest available), while the real-time growth rate series is a collection of growth rates calculated for each vintage in time. We therefore compute how growth was initially reported, for example, in 1995Q2 for 1995Q1. By doing this, we can see how the initial growth report (e.g., for 1995Q1) compares with the growth rate we compute today for 1995Q1. This allows us to get a sense for the sign and magnitude of the revisions.

	Mean of Revision	St. Dev. of Revision	Corr ²
Germany	0.26	0.83	0.92
UK	0.83	1.20	0.79
US	0.41	0.96	0.91

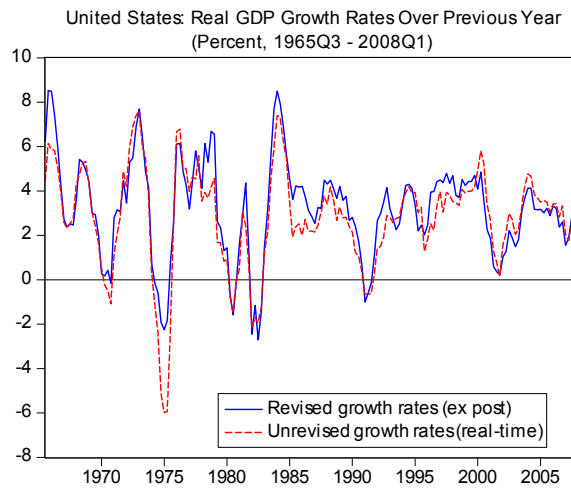
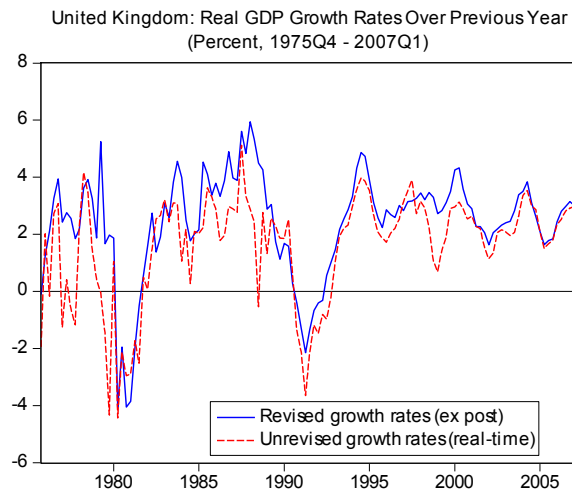
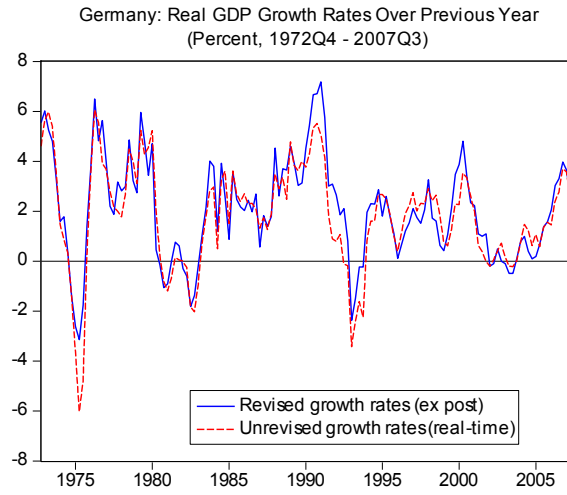
¹ Revisions are calculated in percentage points as the difference between GDP growth rates calculated with ex post data and GDP growth rates reported in real-time.
² Corr: correlation of real-time growth rates and ex post growth rates.

- For *Germany*, two periods stand out: 1975Q1 and 1991Q1 (for West Germany). Output was significantly underestimated in real-time and revised upwards after the initial publication for both periods.
- In the *UK*, revisions are also noticeable, especially in the first half of the sample. The ex post and real-time growth rates deviate substantially with revised growth rates being higher than the ones calculated in real-time. This seems to suggest that real GDP growth was systematically underestimated, especially in the period until 1991.

³ This is what, for example, Berger and Stavrev (2009) find for euro area data. They calculate what we call the series b_t in Table 1, which constitutes the *quasi-real time* output gap series (Orphanides and van Norden, 2002). The log of potential output is estimated recursively but using ex post data and subtracting the log of ex post output.

⁴ It is important to point out that the lag between the end of a quarter and the initial announcement of growth in this report can vary between countries and thereby influence the magnitude of later revisions.

Figure 1. Real GDP Growth Ex Post and Real-Time



- In the *US* data, the two largest revisions were in 1966Q1, when growth was later revised upwards 2½ percentage points, and in 1975Q2, when growth was revised from an initial decline of 6 percent to a decline of only 2 percent, a revision of 4 percentage points. In all three countries, the mean revision to the original data was upwards, meaning that all countries portrayed a bias to initially underreport growth.⁵

While there are numerous methods to detrend a series, we focus only on two simple methods: linear detrending and using the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997), which were used on *ex post* data in Taylor's (1993 and 1999b) seminal publications to compute Taylor rules.⁶ We will show that the choice between the two detrending methods plays only a minor role with regard to producing inflation forecast errors.

The *linear detrending* yields three output gap series. The first is based on a trend on the whole *ex post* sample (*ex post* output gap). For the second series, we recursively estimate a trend on a sample with its beginning date fixed (referred to as *real-time recursively*). This is used for illustrative purposes only. Real GDP can display a stochastic trend which implies that real GDP is subject to shocks that can have a permanent effect on the level of GDP. This renders a constant linear trend unrealistic. The third version takes this into account and runs repeated trend regressions using rolling windows with ten years of data (referred to as *real-time rolling window*). This serves to account for breaks in the trend that occurred in the data.

The *HP-filter* is a commonly used method to estimate the trend component of a time series although it also has been criticized for its end-of-sample problem. To compensate for that the calculation of the filter at the end of the sample is based on data including forecasts over the next 12 quarters. The forecasts are generated from an AR(8) model for the change in real GDP.⁷ The characteristics of the HP-filter allow for stochastic shocks to the trend component of real GDP. Both detrending methods can be reproduced and provide a comparable framework for empirical studies.

The results of using these detrending methods are shown in Appendices 4, 5, and 6. As indicated above, the "real-time series" in these charts are a collection of final values of recursively estimated output gaps. The common "ex post" series represent the values from once detrending the data. Not surprisingly, output gaps estimated *ex post* and in real-time show major and significant differences in all three countries and across time.

⁵ This is also shown by Faust, Rogers, and Wright (2005) for G7 countries.

⁶ Taylor (1993) uses a linear trend to estimate potential output, Taylor (1999b) uses the Hodrick-Prescott filter. While a quadratic trend is sometimes used in the literature (see, e.g. Clarida, Gali, and Gertler, 1998, as a prominent example), this assumes increasing or decreasing growth rates and is not pursued here.

⁷ Clausen and Meier (2005) argue that the benefits of adding a forecast are higher than the costs of not doing so.

IV. SIMULATING INFLATION FORECASTING

After estimating the output gap series, we simulate inflation forecasting by conducting out-of-sample forecasts. We simulate being at a certain point in time and using only the real GDP series available at that point in time to estimate the output gap. While many other studies have conducted out-of-sample inflation forecasts, common practice is to use revised GDP data, which distorts the analysis.⁸ We compute forecasts from a simple backward-looking Phillips curve as expressed in equation (1):

$$\pi_{t+h} = \alpha\pi_{t-1} + \beta og_t + \varepsilon_t \quad (1)$$

with π being annual CPI inflation, og being the output gap series, and h being the forecast horizon.

As the starting training period we use the sample length for which the first real-time output gap is estimated: for Germany the starting training period is 1962Q1 to 1972Q4; for the UK, the first regression is estimated for the period 1956Q1 to 1975Q4; and for the US, the starting training period lasts from 1947Q1 to 1965Q3.

After estimating the Phillips curve using GMM to address the possible endogeneity of the output gap (using lagged values of the output gap as instruments), we forecast inflation one, four, eight, and 12 quarters ahead using the initial parameter estimates. This is repeated for each additional quarter following the initial training period: we re-estimate the Phillips curve with one additional quarter of data, update the coefficients, and forecast inflation again one, four, eight, and 12 quarters ahead. Doing so recursively, we use an increasing data window, but always starting with the same observation.

We also estimate a naive AR(1) process as a benchmark (equation 2), where inflation is dependent on a constant and lagged inflation.

$$\pi_{t+h} = \alpha + \beta\pi_{t-1} + \varepsilon_t \quad (2)$$

We then compare the forecasting errors from equation 1 (the bivariate Phillips curves) and equation 2 (the univariate benchmark). We define an output gap estimate to be useful for forecasting inflation if it leads to smaller forecasting errors than those produced by the naive benchmark as measured by the root mean squared error (RMSE). The RMSE of h -period ahead forecasts made over the period t_1 to t_2 is:

⁸ We are however not using real-time inflation data here. However, inflation data is not subject to the same revision process as is output data. See Appendix 7 for a figure showing “ex post” inflation data for Germany, the UK, and the US.

$$RMSE_{t_1, t_2} = \sqrt{\frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} e_{ht}^2} \text{ with } e_{ht} = \hat{\pi}_{t+h} - \pi_{t+h|t}, \text{ where } \pi_{t+h|t} \text{ is the } h\text{-period ahead}$$

forecast at step t using data through t and $\hat{\pi}_{t+h}$ is the actual inflation value at $t+h$.

V. RESULTS

Table 2 shows the ratio of the RMSE of the bivariate inflation forecast (employing output gap estimates) to the RMSE generated by the AR(1) forecast. Ratios above 1 are marked in **bold** and mean that the output gaps did **not** help reduce forecast errors.

Table 2. Inflation Forecast Errors¹
(Ratio of RMSE out-of-sample forecast errors)

Output Gap Measure	1 Quarter	4 Quarters	8 Quarters	12 Quarters
UK				
Using Ex Post GDP Data and ...				
... Potential Output Estimated with HP-Filter	0.95	0.92	0.91	0.92
... Potential Output Estimated with Linear Trend	0.95	0.91	0.86	0.83
Using Real-Time GDP Data and ...				
... Potential Output Estimated with HP-Filter	1.03	1.01	0.86	0.92
... Potential Output Estimated with Linear Trend (Roll. Wind.)	1.03	1.04	0.88	0.93
US				
Using Ex Post GDP Data and ...				
... Potential Output Estimated with HP-Filter	0.89	0.87	0.90	0.92
... Potential Output Estimated with Linear Trend	0.92	0.89	0.89	0.92
Using Real-Time GDP Data and ...				
... Potential Output Estimated with HP-Filter	0.84	0.86	1.00	1.28
... Potential Output Estimated with Linear Trend (Roll. Wind.)	0.89	1.02	1.34	1.91
Germany				
Using Ex Post GDP Data and ...				
... Potential Output Estimated with HP-Filter	0.98	0.89	0.81	0.78
... Potential Output Estimated with Linear Trend	1.01	1.04	1.10	1.17
Using Real-Time GDP Data and ...				
... Potential Output Estimated with HP-Filter	1.02	1.14	1.55	2.24
... Potential Output Estimated with Linear Trend (Roll. Wind.)	1.01	1.11	1.60	2.41

¹ The figures represent the ratio of the RMSE of the bivariate inflation forecast to the RMSE of the benchmark AR (1) forecast. Bold figures mean that the RMSE of the univariate benchmark is smaller than the RMSE generated by the bivariate inflation forecast employing output gap estimates.

For all three countries, a simple Phillips curve framework—using the *ex post* output gap—seems to be useful for forecasting inflation since inflation errors are consistently below those from forecasts generated by an AR(1) process—independent from which of the two *ex post* output gap series was used (with the exception for Germany, where only the HP-filter generated output gap series helps forecast inflation better than the naive benchmark⁹). However, the more realistic *real-time* output gap series mostly show the opposite result.

For *Germany*, neither the HP-filter real-time output gap nor the linear trend real-time output gap help generate forecast errors that are smaller than the naive benchmark across the forecasting horizon.

Regarding the *US*, for the one-quarter ahead forecast both real-time output gap series proved useful in addition to the HP-filter generated output gap for the four-quarter ahead forecast. We therefore find similar results for the US as Orphanides and van Norden (2005) did, who show that the accuracy of real-time forecasts is almost always lower than that of the forecasts from the benchmark model.

For the *UK*, both real-time output gap series did not prove useful for the one and four-quarter ahead forecasts but improved forecast accuracies for the eight and 12-quarter ahead forecasts. Nelson and Nikolov (2003), in a similar but smaller exercise for the UK, reach similar conclusions with regard to the finding that using *ex post* data helps reduce forecast errors compared to the AR forecasts.¹⁰

VI. CONCLUSION

This paper simulates out-of-sample inflation forecasting for Germany, the UK, and the US. In contrast to many other studies, we use output gaps estimated with unrevised real-time GDP data. This exercise assumes an information set similar to that available to a policymaker at a given point in time since GDP data is subject to sometimes substantial revisions. In addition to using real-time datasets for the UK and the US, we employ a dataset for real-time German GDP data not used before. We find that the simple Phillips curves as specified here and based on *ex post* output gaps generally improve the accuracy of inflation forecasts compared to an AR(1) forecast but that real-time output gaps often do not help forecasting inflation.

⁹ The fact that the output gap generated by linear detrending using *ex post* data does not help forecast inflation in Germany is not necessarily explained by the structural break in the German data after unification. To avoid a jump due to reunification, within the vintages from 1995Q2 onwards, we link the data for West Germany with that of the reunified country by using West Germany's growth rates from 1993Q4 backwards.

¹⁰ In a different exercise, Groen, Kapetanios, and Price (2009) find that the inflation forecasts in the Bank of England's *Inflation Report* dominate those generated by autoregressive processes.

The usefulness of ex post output gap estimates indicates that when looking at ‘historic’ revised GDP, output gaps can measure the extent of slack in the economy and do have an explanatory value for the dynamics of inflation. When simulating a real-time perspective close to reality, this analysis suggests that output gaps (as calculated by the two methodologies used in this paper) might not always be as helpful in forecasting inflation in practice as commonly thought—due to the uncertainty and difficulty in estimating potential output in real-time and due to the revisions to the output series itself. This does not preclude output gaps to still be a useful tool in guiding forecast judgments—especially when used in conjunction with other indicators of spare capacity—and also does not invalidate the theoretical concept of Phillips curves but calls more into question how to measure the slack in the economy in real-time.

There are a number of ways to extend the research presented in this paper. One interesting exercise would be to take a look at sub-samples of the time periods chosen here to see whether the magnitude of revisions has changed over time and what effect this might have on forecast errors. An additional insight could also be gained by applying other methodologies of estimating the output gap in order to assess what these other methods imply for the differences between real-time and ex post estimates. We leave these extensions for further research.

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Appendix 1. United Kingdom: Real-Time GDP Dataset

The quarterly real-time dataset for seasonally adjusted real GDP used in this paper constitutes a 205 x 126 matrix, with 126 vintages starting in 1976Q1 and ending in 2007Q2. The last and longest vintage contains 205 observations (1956Q1 until 2007Q1; see Table below). This series is considered the ex post GDP data in this paper. Each vintage reaches back to 1956Q1 but ends in a different time period (the first vintage, for example, ends in 1975Q4). The data is obtained from the Bank of England's website (see <http://www.bankofengland.co.uk/statistics/gdpdatabase/>) and uses the GDP(E) series. Castle and Ellis (2002) provide details on the construction of this dataset. There are datasets available for variables other than real GDP.

Real-time data for the UK is also available from <http://www.econ.cam.ac.uk/dae/keepitreal/> (see Egginton, Pick, and Vahey, 2002). Garrat and Vahey (2006) provide a comparison of these sources and an overview of real-time data availability for the UK.

Appendix Table 1. United Kingdom: Real-Time GDP and Output Gap Dataset ¹

	1976Q1	2007Q2
1956Q1						c_{1956Q1}
...						c_t
1975Q4	a_{1975Q4}					$b_{1975Q1}; c_{1975Q1}$
...		a_t				$b_t; c_t$
...			a_t			$b_t; c_t$
...				a_t		$b_t; c_t$
...					a_t	$b_t; c_t$
2007Q1						$a_{2007Q1} = b_{2007Q1} = c_{2007Q1}$

Source for real-time real GDP data: Bank of England, <http://www.bankofengland.co.uk/statistics/gdpdatabase/>

¹ The series a_t refers to the *real-time* output gap series, while c_t refers to the *ex post* output gap series and the series b_t constitutes the *quasi-real-time* output gap series. These series are estimated by the authors using the Bank of England's real-time GDP dataset.

The CPI data for the UK is taken from the IMF's *International Financial Statistics* database and the descriptor refers to CPI (ALL ITEMS).

Appendix 2. United States: Real-Time GDP Dataset

The quarterly real-time dataset for seasonally adjusted real GDP used in this paper constitutes a 245 x 171 matrix, with 171 vintages starting in 1965Q4 and ending in 2008Q2. The last and longest vintage contains 245 observations (1947Q1 until 2008Q1; see Table below). This series is considered the ex post GDP data in this paper. Each vintage reaches back to 1947Q1 but ends in a different time period (the first vintage, for example, ends in 1965Q3). The data is obtained from the Federal Reserve Bank of Philadelphia (see <http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/>) and uses the *ROUTPUT* series. Croushore and Stark (2001) provide details on the construction of this series. There are datasets available for variables other than real GDP.

Appendix Table 2. United States: Real-Time GDP and Output Gap Dataset ¹

	1965Q4	2008Q2
1947Q1						c_{1947Q1}
...						c_t
1965Q3	a_{1965Q3}					$b_{1965Q3}; c_{1965Q3}$
...		a_t				$b_t; c_t$
...			a_t			$b_t; c_t$
...				a_t		$b_t; c_t$
...					a_t	$b_t; c_t$
2008Q1						$a_{2008Q1} = b_{2008Q1} = c_{2008Q1}$

Source for real-time GDP data: Federal Reserve Bank of Philadelphia,
<http://www.philadelphiafed.org/econ/forecast/real-time-data/index.cfm>

¹ The series a_t refers to the *real-time* output gap series, while c_t refers to the *ex post* output gap series and the series b_t constitutes the *quasi-real-time* output gap series. These series are estimated by the authors using the Federal Reserve Bank of Philadelphia's real-time GDP dataset.

Appendix 3. Germany: Real-Time GDP Dataset

The quarterly real-time dataset for seasonally and working day adjusted real GNP/GDP used in this paper constitutes a 183 x 140 matrix, with 140 vintages starting in 1973Q1 and ending in 2007Q4. The last and longest vintage contains 183 observations (1962Q1 until 2007Q3; see Table below). This series is considered the ex post GDP data in this paper. Each vintage reaches back to 1962Q1 but ends in a different time period (the first vintage, for example, ends in 1972Q4). All 140 series were manually entered, with each series originating from a different issue of the Bundesbank's publication *Saisonbereinigte Wirtschaftszahlen*. Clausen and Meier (2005) constructed this dataset for the vintages from 1973 to 1998¹² and the dataset used in this paper adds 36 vintages until 2007Q4.

The Deutsche Bundesbank also provides a real-time dataset for multiple variables in addition to real GDP (see http://www.bundesbank.de/vfz/vfz_echtzeitdaten.en.php and Gerberding, Seitz, and Worms, 2005).

Appendix Table 3. Germany: Real-Time GDP and Output Gap Dataset ¹

	1973Q1	2007Q4
1962Q1						c_{1962Q1}
...						c_t
1972Q4	a_{1972Q4}					$b_{1972Q4}; c_{1972Q4}$
...		a_t				$b_t; c_t$
...			a_t			$b_t; c_t$
...				a_t		$b_t; c_t$
...					a_t	$b_t; c_t$
2007Q3						$a_{2007Q3} = b_{2007Q3} = c_{2007Q3}$

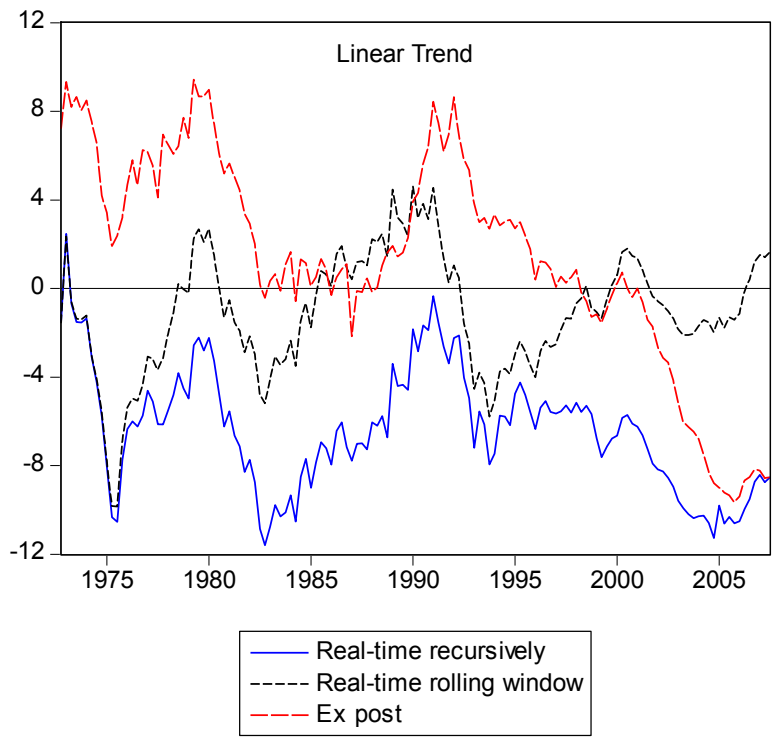
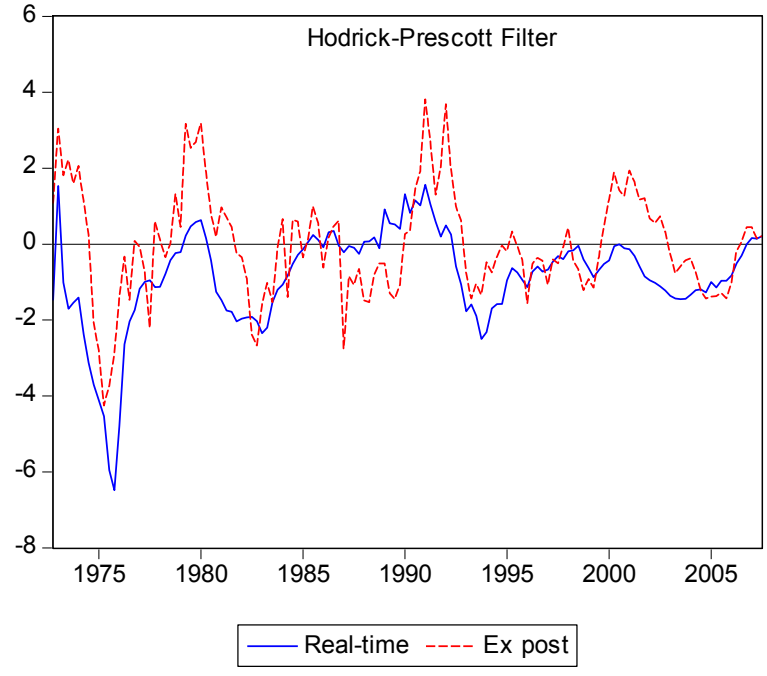
Source: This dataset for real GNP/GDP has been put together by the authors, while drawing from Clausen and Meier (2005) for the vintages from 1973Q1 to 1998Q4. The data for the respective vintages are from different issues from the Bundesbank's publication *Saisonbereinigte Wirtschaftszahlen*.

¹ The series a_t refers to the *real-time* output gap series, while c_t refers to the *ex post* output gap series and the series b_t constitutes the *quasi-real-time* output gap series. These series are estimated by the authors using the real-time GDP dataset.

¹² See Clausen and Meier (2005) for details on how reunification and other technical issues were dealt with.

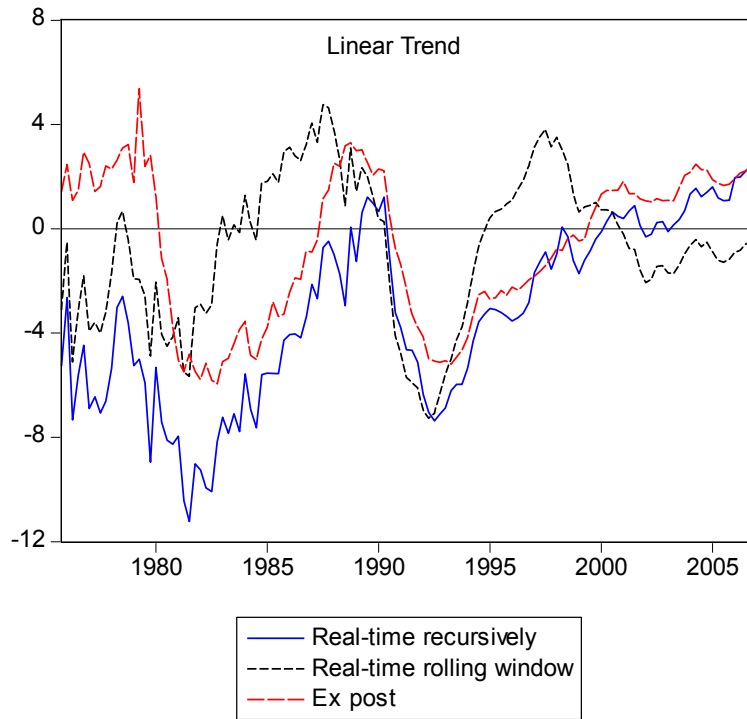
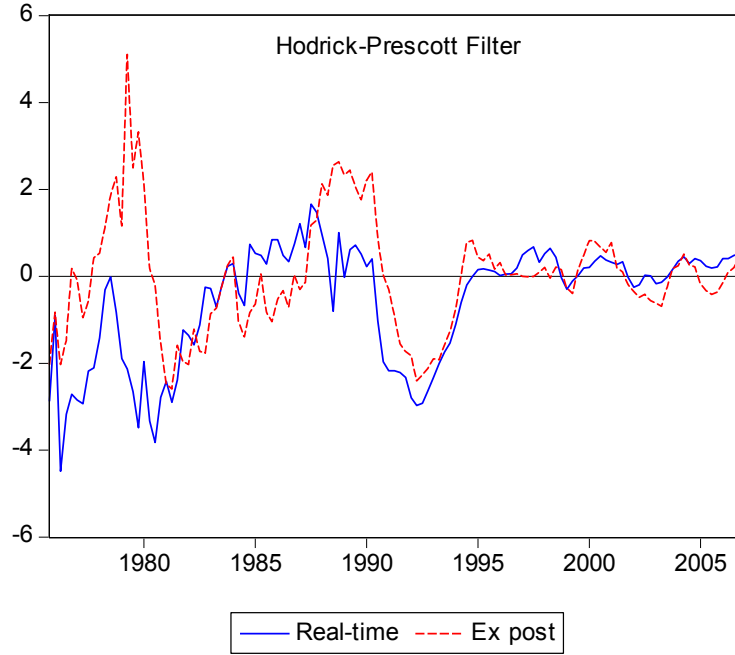
Appendix 4. Germany: Output Gap Estimates

Real-Time vs. Ex Post Output Gaps (Percent)



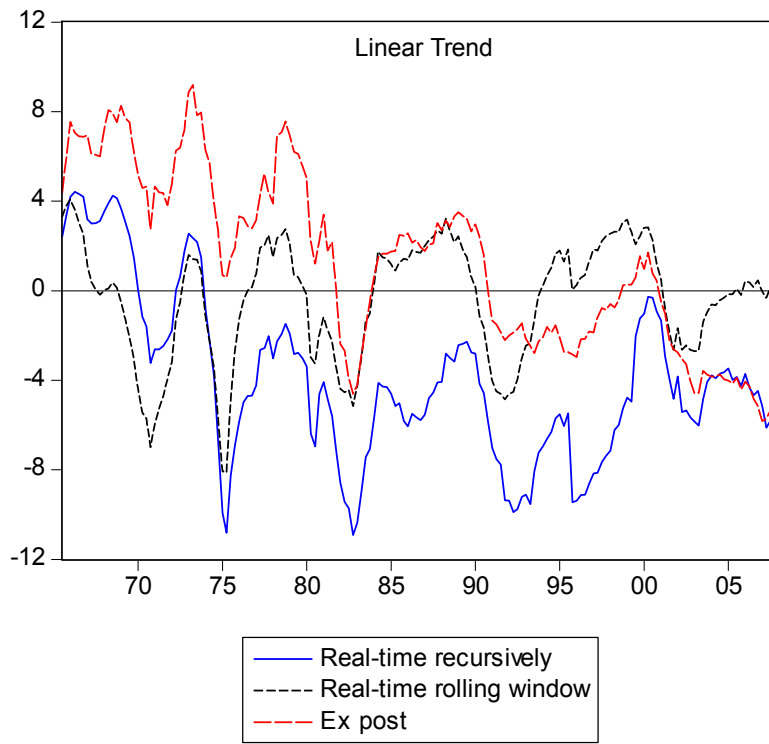
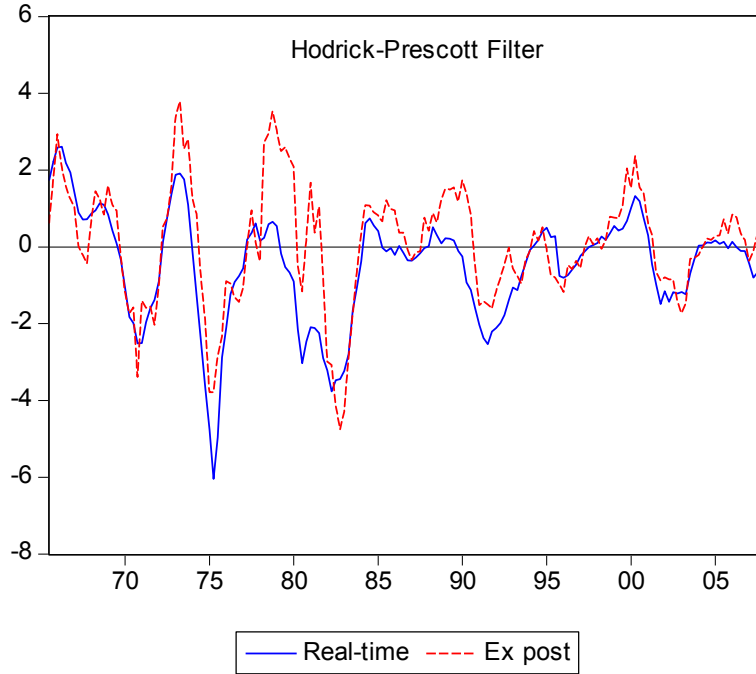
Appendix 5. United Kingdom: Output Gap Estimates

Real-Time vs. Ex Post Output Gaps (Percent)



Appendix 6. United States: Output Gap Estimates

Real-Time vs. Ex Post Output Gaps (Percent)



Appendix 7. Inflation in Germany, the UK, and the US**Year-on-year CPI Inflation in Germany, the UK, and the US, 1962 - 2007
(Percent, quarterly averages)**