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Monetary aggregates to improve early output gap estimates in the euro area -- an empirical assessment

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Abstract:

Output gap estimates at the current edge are subject to severe revisions. This study analyzes whether monetary aggregates can be used to improve the reliability of early output gap estimates as proposed by several theoretical models. A real-time experiment shows that real M1 can improve output gap estimates for euro area data. For many periods the cyclical component of real M1 shows good results, while a forecasting strategy based on projecting GDP series seems to be more robust and provides superior results during the Great Recession. Broader monetary aggregates provide no superior information for output gap estimates.

Keywords: Output gap; real-time data; M1; M3; euro area; money cycle.

JEL classification: E32, E37, E41, E58.

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1 Introduction

The output gap is a key variable for assessing and conducting monetary and fiscal policy. However, measuring the output gap in real-time faces enormous problems. First, output gap estimates depend on data that is subject to revisions (compare Garratt et al., 2008 or Clements and Galvao, 2012 for approaches to deal with this issue). Second and most importantly, many common output gap estimates at the current edge are exposed to partly substantial revisions even if they are based on final data as noted by Orphanides and Norden (2002) for the US. Marcellino and Musso (2011) analyze the reliability of early output gap estimates for the euro area with real-time data and, thus, extend the work of Rünstler (2002). They find that the unreliability of early output gap estimates prevails for many output gap measures applied to euro area data, too. Several authors point out that the unreliability of output gap estimates can have severe consequences for monetary policy (Orphanides, 2003, or Nelson and Nikolov, 2004).

Starting with the observation that data revisions for monetary aggregates are less severe than for output, Coenen et al. (2005) discuss the possibility that M3 can be used to improve the measurement of real output by means of a New Keynesian Model. Beck and Wieland (2007,2008) argue based on a New Keynesian Model that M3 can improve the reliability of early output gap estimates, too. A view that is backed by Scharnagel et al. (2012) in a somewhat different model. This rather theoretic evidence is corroborated by several empirical works that find predictive power of monetary aggregates for real activity, however, mainly focussing on narrow money aggregates like M0 or M1 instead of M3. E.g. Sauer and Scheide (1995) analyze the predictive ability of real M1 for national accounts data in several European countries. Nelson (2002) discuss the predictive ability of narrow money in the US and the UK, and Brand et al. (2003) find that M1 can predict real output in the euro area. More recently, Boysen-Hogrefe (2012) discusses real M1 as a turning point indicator for the euro area.

Somewhat at odds, Reimers (2003) finds that M1 is not a useful tool to predict the output gap in the euro area, however, the study of Reimers works with final data and final output gap estimates. Reimers makes no statements on real-time issues.

In sum, there exists empirical evidence that monetary aggregates include information about real activity that can be used for forecasting at least in the euro area. Further, several theoretical papers claim that the link between monetary aggregates and real activity could be used to improve the reliability of early output gap estimates. The aim of this study is to check whether the aforementioned evidence that monetary aggregates may help improving the reliability of early output gap estimates prevails in real-time. For this purpose, the real-time data set provided by the Euro Area Business Cycle Network (EABCN) and the ECB is assessed. As output gap measures two common filter techniques, the Hodrick-Prescott filter (Hodrick and Prescott, 1997) and the Band-Pass filter as proposed by Christiano and Fitzgerald (2003), are applied.

A major issue in this study is how to extract the information that may be contained in monetary aggregates to improve early output gap estimates. Three different approaches are proposed. The first approach is based on a projection of the GDP series similar to Watson (2007). The second approach regresses final output gap estimates on early output gap estimates and on monetary aggregates. The third approach considers a trend-cycle decomposition of monetary aggregates and includes the cyclical component of monetary aggregates ("money cycle") into the regressions of final output gap estimates.

In a real-time experiment it is analyzed whether and how the aforementioned approaches are suitable to extract information for improving early output gap estimates. Main results are that real M1 contains information about the output gap while real M3 does not seem to provide reasonable improvements. The best strategy to use the information contained in real M1 for output gap estimates of the current quarter is to extrapolate the GDP series by means of forecasting models that contain real M1. The use of the cyclical component of real M1 is particularly successful to improve output gap estimates that correspond to the recent past. However, this finding is not robust with respect to the sample and the output gap measure considered.

The rest of the study is structured as follows. Section 2 presents the data used for this study. Section 3 motivates the three approaches that are used to extract information contained in monetary aggregates for output gap estimates. Section 4 presents the real-time data study. Section 5 presets a short degression on the issue of structural stability and section 6 concludes.

2 Data

M1 and M3 are taken from the OECD database until 1979. Afterwards, they are taken from the real-time database (RTDB) of the EABCN and the ECB. The RTDB comprises the data published in the Monthly Bulletin of the ECB. First vintage is January 2001. For a detailed description of the RTDB see Giannone et al. (2010). The last vintage used in this study is Feb 2013. Data published from this vintage is regarded as final data. The final data series of M1 and the vintage data series that include May 2005 were corrected for an outlier. M1 increased heavily in May 2005 due to a technical change that was made by the Spanish central bank in calculating and reporting the Spanish contribution to M1 (ECB 2009). Some deposits were classified as overnight deposits afterwards and, thus, entered M1. Before, they had been defined as deposits redeemable at notice and had not belonged to M1 before. Therefore, I calculated monthly growth rates, replaced the growth rate from June 2005 by the mean growth rate based on the six former years and recalculated the levels of M1 (compare Boysen-Hogrefe, 2012).

In this study, real money is applied.[1] Two versions of real money are calculated. First, M1 and M3 are divided by the GDP deflator. Second, M1 and M3 are divided by the harmonized consumer prices index. The latter is done, since consumer price indices are reported with a much lower lag than the GDP deflator, namely at the same time as M1 and M3 in the Monthly Bulletin of the ECB, while the GDP deflator is typically reported later. Hence, the second version of real money can be attractive for now- and forecasting exercises. Real GDP, GDP deflator, and consumer prices are taken from the Area Wide Model data set from the ECB until 1994. Afterwards they are taken from RTDB.

Finally, the analysis includes two leading indicators that shall deal as benchmarks for the now- and forecasting performance of monetary aggregates, namely, yield spread and industrial confidence indicator. The yield spread is calculated as difference between the yields of government bills (3 month maturity) and government bonds (10 years maturity). Data is taken from the Area Wide Model data set and Thomsen Reuters Datastream. The Industrial Confidence Indicator was reported in the Monthly Bulletin of the ECB from 2001 to 2011. The Industrial Confidence Indicator is chosen as additional variable instead of other survey based indicators, like the Economic Sentiment Indicator, since it covers the whole 1980ies.

[1] Alternatively, nominal money and price indices could be included. However, some preliminary analysis showed that the application of real money is more appropriate since a smaller number of parameters has to be estimated in all three approaches.

3 Revisions of output gap estimates

Marcellino and Musso (2011) discuss four sources of uncertainty for output gap estimates: Model uncertainty, parameter uncertainty, parameter instability, and data uncertainty. Parameter instability and data uncertainty can lead to revisions of output gap estimates and are of particular interest in this study.[2] Several authors, e.g. Garratt et al. (2008) or Clements and Galvao (2012), have recently proposed to model data revisions of GDP to improve output gap estimates for US and UK data. An obstacle for the application of such models for euro area data is the rather short history of vintage data that makes it hard to estimate meaningful models to forecast data revisions. Further, modelling data revisions is complicated by the circumstance that the composition of the euro area is changing. However, the impact of data uncertainty, i.e. data revisions of GDP figures, plays a minor role as a source for revisions of output gap estimates in the euro area as observed by Marcellino and Musso. Therefore, this study refrains from modelling data revisions. However, the study is done for real-time data anyway to get a valid answer to the question whether the approaches to improve early output gap estimates would have worked in real-time and to capture the real-time data character that monetary aggregates have, too.

Marcellino and Musso (2011) report that revisions of output gap estimates due to parameter instability, i.e. the so called end-point problem for two-sided filters, can be severe. Though they report relative high correlation between the first available HP-filtered output gap and the HP-filtered output gap based on final data for the vintages between 2000 and 2010, they show that for some points in time output gap levels are revised substantially. Results for the vintages between 2000 and 2011, as applied in this study, are quite similar (Figure 1). Correlation between first estimates and final estimates is quite high (above 0.8), but output gap levels are revised substantially as the very high RMSE of early output gap estimates relative to the variation of the output gap shows. This is also true when final data is used (Figure 2). That in the case of final data the correlation is even a bit lower underlines the finding of Marcellino and Musso that data revisions have little impact. Correlation between later output gap estimates and final ones increase from period to period and reach values well above 95 % after 10 quarters.

With respect to the relative high correlation it has to be taken into account that the Great

[2] The issue of model uncertainty is assessed by applying a band-pass filter as an alternative to the maybe most common output gap measure, the Hodrick-Prescott filter.

Recession leads to a huge drop in output gap that is reflected in output gap estimates at almost any time. Correlation between first estimates and final ones are much lower without the period of the Great Recession. For final data correlation in the time period between 1980 and 2006 is roughly $\frac{1}{3}$, only. The rRMSE of the first output gap estimate is even above 1. However, later output gap estimates converge quite fast and reach similar values for correlation and rRMSE after 10 periods as in the period between 2000 and 2011 (Figure 3).

A common tool to improve early output gap estimates from statistical filters is the extrapolation of the time series that shall be filtered by means of ARIMA models (see e.g. Maravall and Kaiser 2001). Even after applying such an approach to improve early output gap estimates reliability of early output gap estimates is not increased substantially. Figure (1) and Figure (4) illustrate this point. It shows the first available HP-filtered output gap, the first available HP-filtered output gap after extrapolating the GDP series and the HP-filtered output gap based on final data. Early estimates are made with final data (pseudo real-time) and real-time data. Extrapolation of GDP figures by ARIMA models yields some but limited improvement.

4 Design of forecasting approaches

Aim of the study is to find a way to improve early output gap estimates that are derived from common filter methods for the euro area by means of monetary aggregates. However, a meaningful forecasting exercise for output gap estimates faces a specific difficulty. The output gap estimate can change considerably even for past periods. Given common filter techniques, a reliable estimate is reached many years after the first GDP figure has been published for the corresponding time period. Therefore, final output gap estimates are not suitable for autoregressive forecasting methods and estimation samples of forecasting models have to end in sufficient distance to the current edge. Therefore, typical forecasting techniques for time-series can only be applied with some modifications. Three alternative approaches to obtain forecasts for final output gap estimates are proposed and evaluated in this study:

First, monetary aggregates are used to extrapolate the GDP series in ADL models. Extrapolation of GDP series, e.g. via ARIMA-models (Kaiser and Maravall 2001) or via additional indicators (Watson 2007), is a common approach to deal with the end-point-problem.

Second, final output gap estimates are regressed on early output gap estimates and monetary aggregates to obtain forecasts for final output gap estimates. This approach is related to Reimers (2003) who conducted regressions for final output gap estimates. Since this study performs a real-time analysis the approach has to be modified accordingly.

Third, final output gap estimates are regressed on early output gap estimates and on lagged cyclical components of real money. The motivation of this third approach is based on the eyeball inspection of the cyclical component of GDP and of the cyclical component of real M1 (Figure 2). Technical details for all three approaches are discussed in the following in more depth:

Approach I

The main idea of the first approach is to extrapolate the GDP series by h periods via a linear forecasting model. Approach I is conducted as follows

1. Construct a ADL-model containing lagged GDP and the lagged predictor. The predictor can enter contemporaneously, too, if data is available.

2. Select the number of lags for GDP and the predictor in each forecast step (direct-multi-step and general-to-specific are applied).

3. Make h GDP forecasts and expand the GDP series accordingly.

4. Apply statistical filters on the expanded GDP series.

Approach II

Approach II is conducted as follows

1. Calculate a sufficient number of early estimates for the output gap.[3] For this purpose the current GDP time series is split in two parts. A "core" that shall guarantee a sensible application of the statistical filter and a "learning sample", which is needed to fit the forecasting model.

2. Run regression with early output gap estimates and additional (lagged) predictors as regressors and the final output gap estimate as dependent variable. Model selection can be applied to reach a parsimonious model.

[3]For the exercise below early estimates are obtained from via AR-models extrapolated GDP series.

3. Use the best model for forecasts of the final output gap estimate.

Approach III

Approach III is conducted as follows

1. Do step 1 as in the second approach.

2. Do the same for real money instead of GDP.

3. Regress final output gap estimates on the early output gap estimate and on the forth lag of "money cycle" estimates.

4. Use this regression for forecasts of the final output gap estimate.

Given the proposal to use the "money cycle" as a predictor for the outcome of statistical filters the issue of multivariate filters arises as e.g. applied in Planas and Rossi (2004). However, multivariate filtering affects the output gap measure. This study aims to analyze the informational content of monetary aggregates for common output gap measures, namely the HP-filter and the bandpass-filter, and does not aim to propose a further alternative output gap measure.

5 Real-time out-of-sample analysis

In a real-time out-of-sample analysis that evaluates 40 observations all three approaches are applied. As predictors real M1, real M3 and two benchmark indicators namely the industrial confidence indicator and the yield spread are considered. Price adjustment to obtain real values of M1 and M3 is done in two ways, first, via the GDP deflator, since it is the most comprehensive price index, and second, via the consumer price index. The latter indicator is additionally considered since it has much lower publication lag than the GDP deflator. This may be a serious advantage in a forecasting exercise.

The exercise is done for the current output gap, i.e. the output gap that related to the most recent GDP figure, for the output gap of the past four quarters, and also for the output gap of up to four quarters ahead. As results the RMSE relative to output gap estimates based on via autoregressive models extrapolated GDP series.[4] RMSE are are reported for the whole sample,

[4]The extrapolation allows that output gap estimates beyond the last available GDP figure can be assessed.

i.e. a sample of 40 real time forecasts (Table 1 and 3). The first forecast is made with the vintage from Feb 2001. The GDP of the 3 quarter 2000 is the most recent published in the Monthly Bulletin at that time. The last vintage that is considered is from Feb 2011. Since this sample includes the Great Recession results may be driven by this special dynamics. Therefore, results for the first 25 vintages, only, are presented, too (Table 2 and 4).

Table 1 and 2 present results for the HP-filter as output gap measure. For real M1 approach I is quite successful in the full sample. All past and the current output gap estimates can be improved. Output gap estimates for the following one or two quarters can be improved, too. For the first approach and the full sample the yield spread provides some good results, too. However, estimates beyond two quarters cannot be substantially improved by any model. For the smaller sample improvements are much smaller, but real M1 and to a lesser degree the yield spread lead to better early output gap estimates around the current quarter. The second approach yields almost no improvement at all. The third approach provides some improvements for early output gaps estimates of past periods when the cycle of real M1 is considered. For a smaller sub-sample improvements are very strong. Thus, the cycle of real M1 seems to contain useful information, but the extraction of this information may suffer from structural instability. In contrast, the informational content of real M3 seems to be much lower. Only for output gap estimates in the third and in the forth quarter ahead and for the smaller sub-sample extrapolation of GDP series by real M3 beats extrapolation of GDP series by real M1.

Table 3 and 4 present results for the bandpass-filter as output gap measure. Results that are based on the HP-filter are by and large confirmed. Real M1, when applied to extrapolate the GDP series, improves early output gap estimates. However, improvements are smaller, especially when the cycle of real M1 is considered.

Combining results for both types of output gap measure, results of approach I suggest that real M1 contains some information about the output gap that can be extracted for output gap estimates of the current period and for those of the recent past and the close future. The same is true for the yields spread, but improvements are smaller. Whether price adjustment of real M1 should be done by the GDP deflator or consumer prices is almost irrelevant. However, there seems to be a tendency that price adjustment via consumer prices works better for future output gaps. This is reasonable since most recent movement in M1 can only be included by price adjustment via consumer prices. Instead real M3 generally does not improve output gap estimates of the current period. However, for output gap estimates three or four quarters ahead real M3 provides smaller rRMSE than 1, but improvements are small and given the large volatility of such forecasts should not be stressed too much.

Approach II generally provides no substantial improvement. Extracting information from regressions of final output gap measures on other time series does not seem to be very successful. Possible reasons are that the number of observations to select and estimate the forecasting models is too small, given that selected models contain up to 7 parameters, and that the time gap between estimation sample and the time periods that are to be forecasted is too large. Interestingly, the results are somewhat in line with Reimers (2003) who finds little predictive power of monetary aggregates for the output gap.

Results for approach III are mixed. On the one hand, the best performing models for output gap estimates of past and current periods in terms of rRMSE often follow this approach, but results are sensitive with respect to the sample and the output gap measure. The cycle of real M1 seems to include information about the output gap but the structural instability makes it hard to extract it in real time. The following section shall shed some light on the issue of structural stability of the relation between the cycle of real M1 and the output gap estimates obtained by a HP-filter.

6 Degression: Structural stability

The forecasting exercise shows that while the money cycle seems to be a potentially quite efficient method to extract information about the output gap from real M1 structural instabilities in the relation between output gap and money cycle makes it maybe unreliable. To illustrate the issue of structural stability, I estimate a simple time varying coefficient model (with final data), where the output gap (measured via the Hodrick-Prescott-filter) is the dependent variable y_t and the forth lag of the money cycle is the regressor x_t. The money cycle is measured via the Hodrick-Prescott filter and price adjustment is obtained via the GDP deflator. The model takes the form:

$$\begin{aligned} y_t &= \alpha + \beta_t x_t + e_t, \quad e_t \sim N(0, \sigma_y^2), \\ \beta_t &= \beta_{t-1} + u_t, \quad u_t \sim N(0, \sigma_\beta^2). \end{aligned} \tag{1}$$

Figure 6 depicts the smoothed path of β_t. The parameter quite volatile from the very beginning, however, it mainly stays in a band between 0.3 and 0.6 until the 1990ies. After a spike in 1990 it drops quite fast shortly after the ECS-crisis in 1992/1993 and reaches its all time low in the the second half of the 90ies. Afterwards the coefficient increases again. During the Great Recession it reaches an extreme spike and falls to a low value about 0.2 afterwards.

This degressions shows that the relation between the output gap and the lagged "money cycle" is always positive, but that its intensity is volatile especially in big crisis like the ECS-crisis and the Great Recession. However, results show also that in more normal times the "money cycle" can contain valuable and exploitable information about the output gap.

7 Conclusion

This study evaluates the ability of monetary aggregates to improve early output gap estimates. This is done in a real-time analysis based on the RTDB. Results suggest that extrapolation of the GDP series by real M1 can improve early output gap measures obtained via statistical filters like the HP-filter and bandpass-filters. Approaches that regress the final output gap measures on covariates seem to be less successful. Under some circumstances regressions on the "money cycle" lead to substantial gains, but the relation seems to be unstable over time.

While the findings are in line with the forecasting literature that finds good forecasting properties of narrow money for real activity they do not support the view that M3 contains useful information about the output gap. Accordingly, the two pillar strategy of the ECB would not be rectified by the reference to output gap uncertainty. However, it may be the case that the approaches applied here are not well suited to extract the information contained in M3. Otherwise theoretical models that claim a relation between monetary aggregates and the output gap should focus M1 instead of M3.

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Figures and Tables

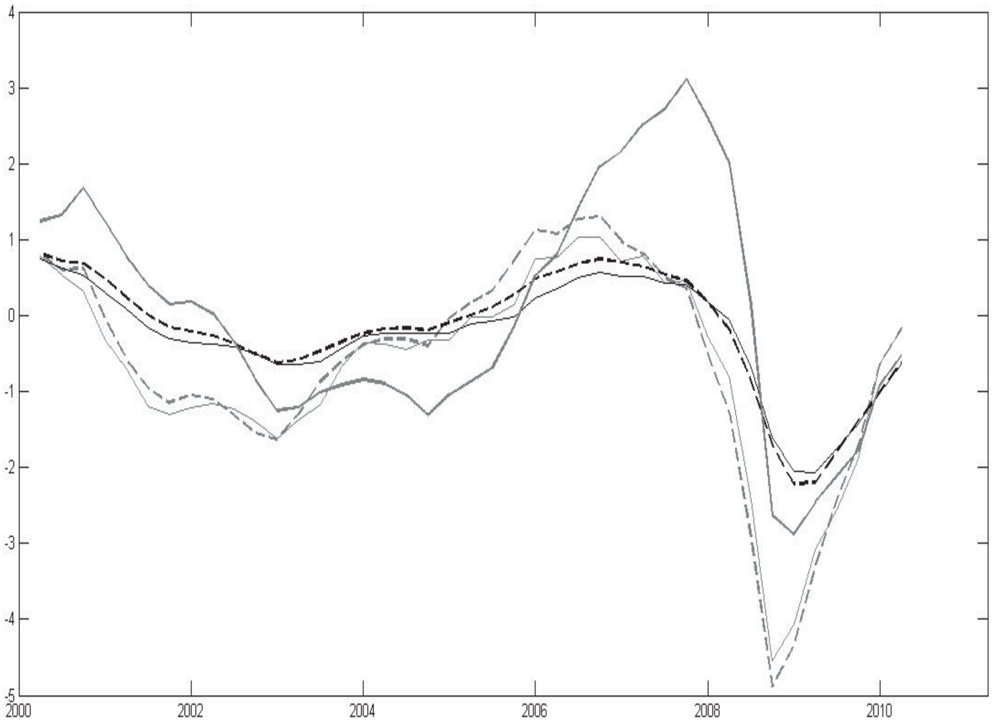

Figure 1: Early output gap estimates from the HP-filter. Grey bold line: final estimates. Black dashed line: Early estimates based on final data (extrapolated GDP series). Black solid line: Early estimates based on real-time data (extrapolated GDP series). Grey dashed line: Early estimates based on final data. Grey solid line: Early estimates based on real-time data.

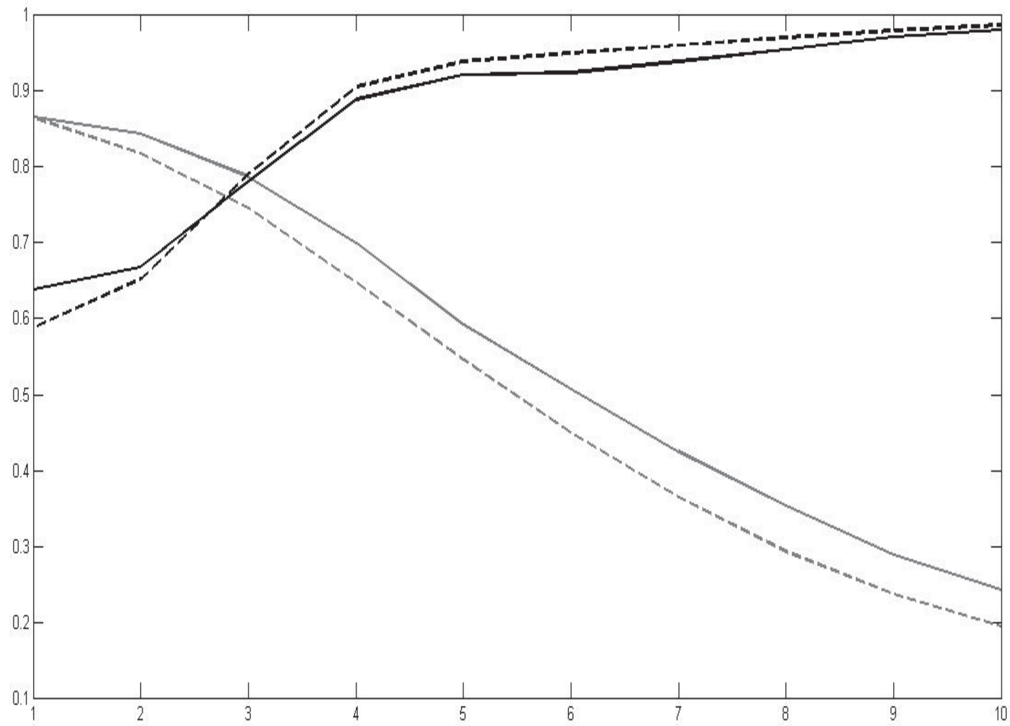

Figure 2: Reliability of early output gap estimates from the HP-filter. Sample ranges from 2000 to 2011. Black solid line: Correlation between early estimates and final estimates based on final data. Black dashed line: Correlation between early estimates and final estimates based on real-time data. Grey solid line: rRMSE of early estimates based on final data. Grey dashed line: rRMSE of early estimates based on real-time data.

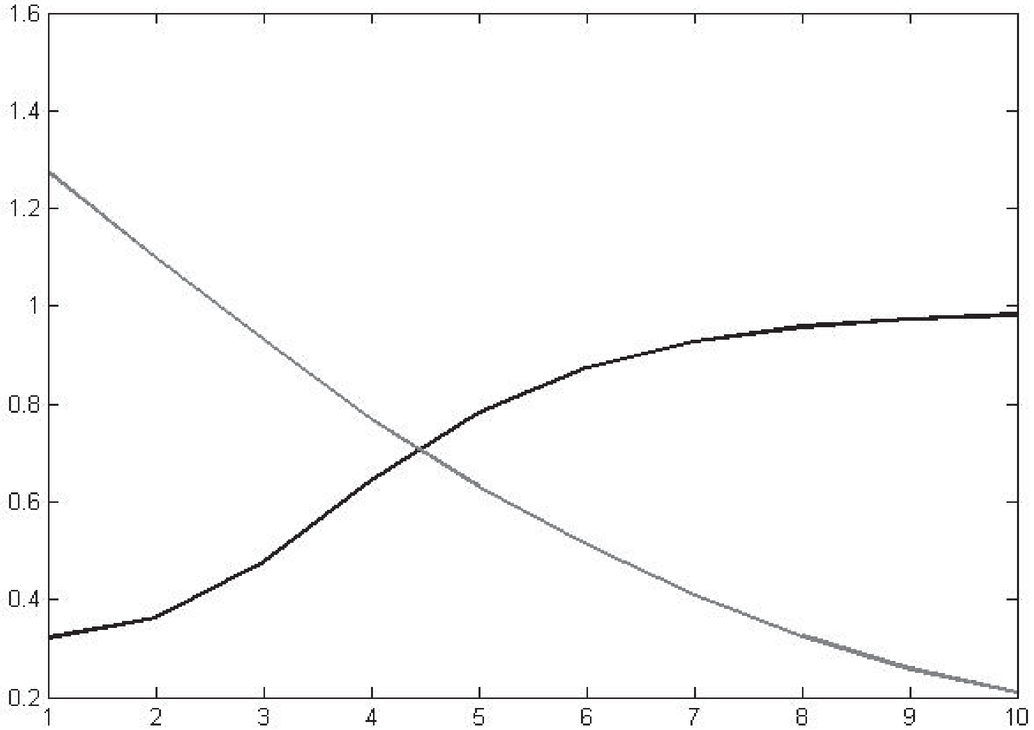

Figure 3: Reliability of early output gap estimates from the HP-filter including. Sample ranges from 1980 to 2011 (final data only). Black solid line: Correlation between early estimates and final estimates based on final data. Grey solid line: rRMSE of early estimates based on final data.

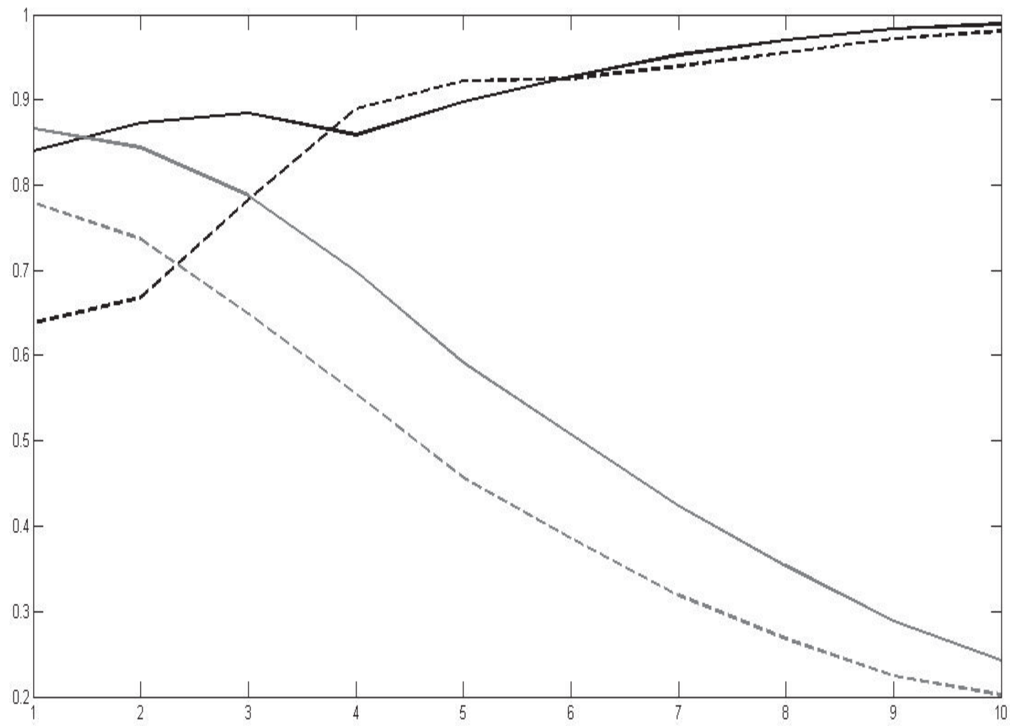

Figure 4: Reliability of early output gap estimates from the HP-filter. Sample ranges from 2000 to 2011 (real-time data). Black solid line: Correlation between early estimates and final estimates (extrapolated GDP series). Black dashed line: Correlation between early estimates and final estimates. Grey solid line: rRMSE of early estimates based on final data (extrapolated GDP series). Grey dashed line: rRMSE of early estimates.

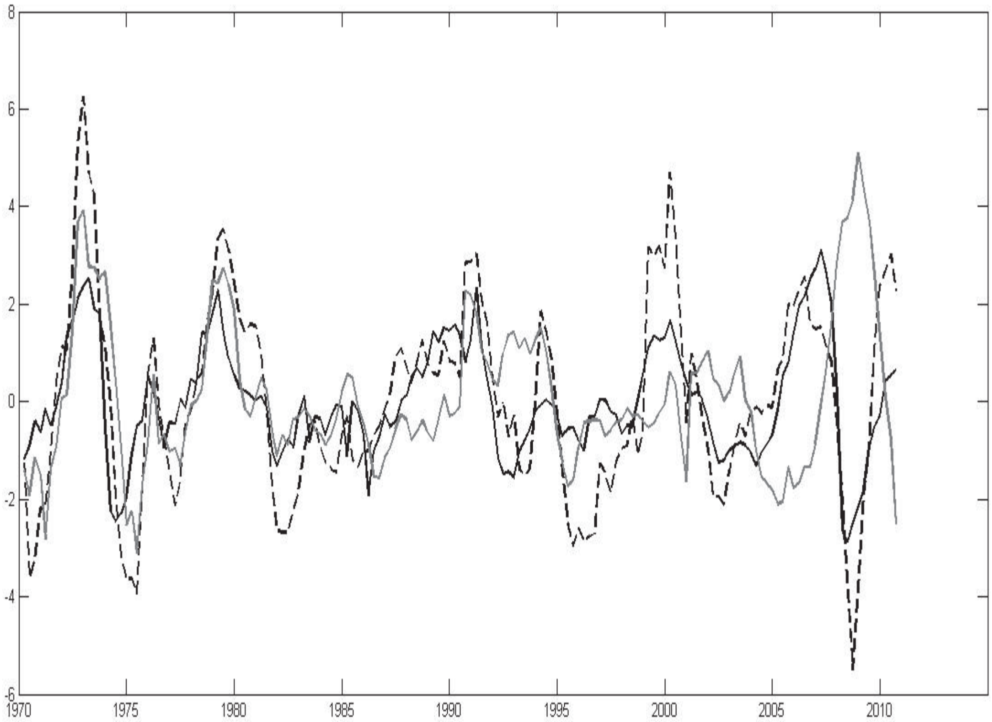

Figure 5: Output gap and "money cycle". Black solid line: output gap estimate (final data; Hodrick-Prescott filter). Black dashed line: cyclical component of real M1 based on Hordrick-Preccott filter; price adjustment via GDP deflator; time-shift of four quarters. Grey solid line: cyclical component of real M3 based on Hordrick-Preccott filter; price adjustment via GDP deflator; time-shift of four quarters.

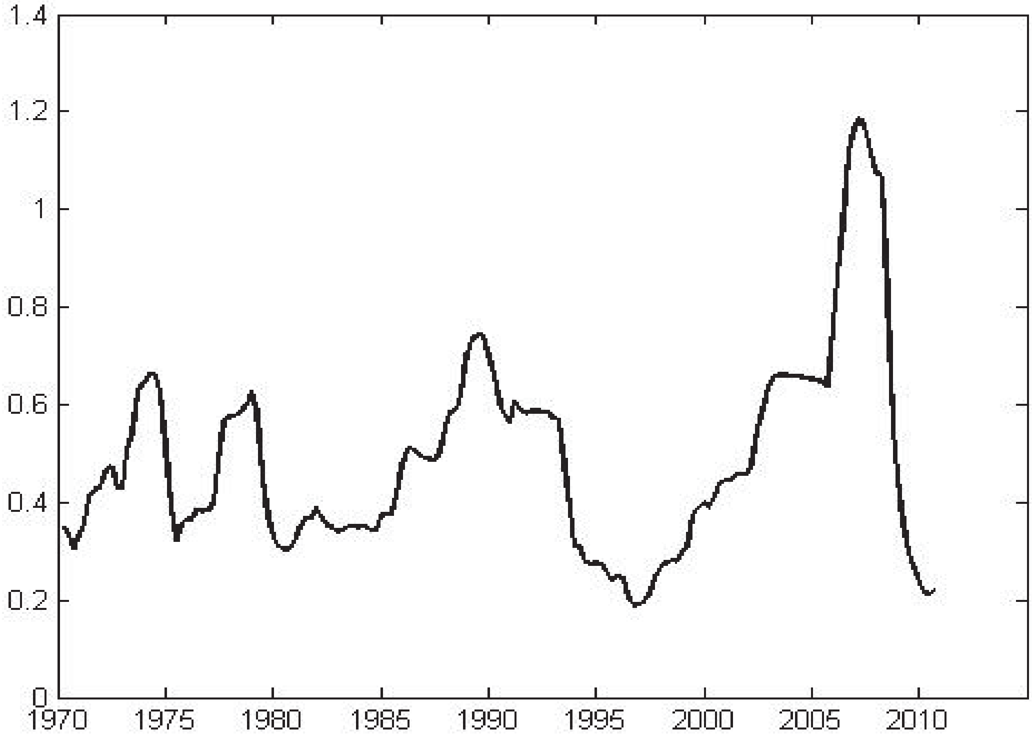

Figure 6: Time-varying coefficient β_t. Results from the Kalman smoother. Compare model in equation 1.

	Forecast horizon								
	-4	-3	-2	-1	0	1	2	3	4
				Approach I					
M1	**0.846**	**0.801**	**0.764**	**0.730**	**0.693**	**0.782**	0.946	1.034	1.054
M3	1.249	1.277	1.301	1.326	1.351	1.159	0.994	0.979	1.080
M1(HICP)	0.894	0.850	0.816	0.787	0.764	0.776	**0.906**	**0.973**	1.052
M3(HICP)	1.228	1.266	1.296	1.330	1.364	1.229	1.052	0.987	1.005
ZS	0.906	0.885	0.871	0.861	0.852	0.898	0.967	1.009	1.053
IC	1.034	1.060	1.087	1.118	1.151	1.083	0.979	1.002	**0.978**
				Approach II					
M1	1.419	1.336	1.449	1.570	1.695	1.344	1.054	1.454	1.394
M3	1.334	1.267	0.998	1.092	1.224	1.288	1.372	1.292	1.436
M1(HICP)	1.216	1.132	1.207	1.343	1.556	1.207	0.953	1.199	1.308
M3(HICP)	1.226	1.171	1.225	1.000	1.426	1.549	1.372	1.403	1.380
ZS	1.057	1.101	1.041	0.926	0.954	1.072	1.202	1.247	1.209
IC	1.089	1.038	1.031	1.070	1.075	1.202	1.258	1.268	1.330
				Approach III					
M1	0.889	0.898	0.906	0.921	0.929	1.038	1.103	1.112	1.219
M3	1.225	1.283	1.341	1.350	1.346	1.290	1.203	1.158	1.119
M1(HICP)	0.908	0.921	0.917	0.911	0.907	0.975	1.013	1.026	1.051
M3(HICP)	1.274	1.312	1.336	1.328	1.312	1.265	1.184	1.135	1.109

Table 1: Forecasts for hp-filtered output gaps (full sample). Bold: best performing approach.

	Forecast horizon								
	-4	-3	-2	-1	0	1	2	3	4
Approach I									
M1	1.026	0.994	0.965	0.922	0.858	0.850	0.947	1.069	1.115
M3	1.130	1.187	1.232	1.279	1.338	1.107	1.004	**0.930**	0.941
M1(HICP)	1.004	0.967	0.933	0.910	0.881	**0.842**	**0.927**	1.013	1.130
M3(HICP)	1.042	1.110	1.156	1.225	1.303	1.193	1.037	0.973	**0.928**
ZS	0.975	0.973	0.964	0.955	0.937	0.928	0.977	1.061	1.121
IC	0.998	1.029	1.055	1.077	1.111	1.098	0.958	0.971	0.979
Approach II									
M1	2.333	2.370	2.753	3.043	3.180	1.946	0.950	1.583	1.640
M3	1.197	1.184	1.519	1.557	1.412	1.494	1.605	1.450	1.433
M1(HICP)	1.983	2.047	2.307	2.681	3.166	2.087	0.988	1.296	1.505
M3(HICP)	0.952	0.852	1.246	1.223	1.251	1.677	1.786	1.724	1.551
ZS	0.954	1.158	1.149	1.186	1.117	1.042	0.999	0.999	0.987
IC	0.884	1.033	1.189	1.202	1.170	1.192	1.204	1.245	1.353
Approach III									
M1	**0.743**	**0.722**	**0.671**	**0.697**	**0.703**	0.843	0.940	1.064	1.315
M3	1.144	1.283	1.360	1.346	1.352	1.294	1.204	1.181	1.117
M1(HICP)	0.766	0.777	0.767	0.807	0.855	0.940	0.987	1.032	1.079
M3(HICP)	1.204	1.343	1.413	1.404	1.401	1.343	1.234	1.185	1.147

Table 2: Forecasts for hp-filtered output gaps (first 25 forecasts). Bold: best performing approach.

	Forecast horizon								
	-4	-3	-2	-1	0	1	2	3	4
					Approach I				
M1	0.974	0.913	**0.843**	**0.786**	**0.768**	0.815	0.904	0.976	1.019
M3	1.146	1.224	1.293	1.339	1.333	1.229	1.049	0.969	1.027
M1(HICP)	0.987	0.939	0.886	0.832	0.787	**0.785**	**0.855**	**0.941**	0.993
M3(HICP)	1.105	1.184	1.258	1.317	1.342	1.286	1.134	1.006	0.997
ZS	0.984	0.949	0.918	0.896	0.888	0.904	0.947	0.992	1.023
IC	0.993	1.030	1.074	1.108	1.121	1.093	1.031	0.988	**0.983**
					Approach II				
M1	1.043	0.989	1.016	1.083	1.207	1.274	1.229	1.175	1.187
M3	1.188	1.193	1.222	1.312	1.282	1.311	1.338	1.327	1.295
M1(HICP)	**0.967**	**0.909**	0.923	1.047	1.162	1.168	1.104	1.136	1.111
M3(HICP)	1.115	1.175	1.209	1.256	1.264	1.372	1.432	1.413	1.329
ZS	1.139	1.104	1.033	1.032	1.061	1.088	1.088	1.110	1.077
IC	1.207	1.194	1.181	1.160	1.218	1.283	1.245	1.200	1.253
					Approach III				
M1	1.026	1.017	0.990	0.980	1.038	1.150	1.199	1.140	1.085
M3	1.107	1.211	1.299	1.332	1.327	1.296	1.218	1.123	1.058
M1(HICP)	1.049	1.040	1.034	1.047	1.112	1.209	1.224	1.132	1.072
M3(HICP)	1.078	1.165	1.220	1.239	1.252	1.256	1.206	1.110	1.052

Table 3: Forecasts for band pass-filtered output gaps (full sample). Bold: best performing approach.

	Forecast horizon								
	-4	-3	-2	-1	0	1	2	3	4
				Approach I					
M1	1.043	1.035	1.007	0.970	0.938	0.924	0.940	1.006	1.096
M3	1.063	1.107	1.153	1.191	1.201	1.155	1.047	**0.939**	**0.920**
M1(HICP)	1.036	1.026	1.008	0.977	0.935	**0.894**	**0.888**	0.964	1.076
M3(HICP)	1.012	1.047	1.091	1.135	1.160	1.146	1.086	1.001	0.944
ZS	1.026	1.018	1.009	0.997	0.977	0.956	0.963	1.027	1.101
IC	**0.987**	0.995	1.015	1.039	1.053	1.047	1.026	1.004	0.980
				Approach II					
M1	1.142	1.185	1.297	1.407	1.617	1.556	1.307	1.231	1.280
M3	1.173	1.173	1.250	1.428	1.259	1.336	1.510	1.586	1.567
M1(HICP)	1.074	1.092	1.190	1.413	1.569	1.514	1.323	1.282	1.229
M3(HICP)	1.073	1.171	1.168	1.250	1.103	1.321	1.548	1.739	1.724
ZS	1.075	1.034	0.996	1.022	1.065	1.098	1.114	1.118	1.117
IC	1.129	1.197	1.122	1.113	1.184	1.132	1.175	1.215	1.301
				Approach III					
M1	0.997	**0.955**	**0.887**	**0.835**	**0.843**	0.915	1.024	1.124	1.139
M3	1.036	1.060	1.060	1.039	1.027	1.038	1.067	1.089	1.062
M1(HICP)	1.032	1.010	0.985	0.962	0.974	1.028	1.091	1.122	1.093
M3(HICP)	1.026	1.063	1.059	1.029	1.020	1.038	1.067	1.080	1.054

Table 4: Forecasts for band pass-filtered output gaps (first 25 forecasts). Bold: best performing approach.