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Forecasting Inflation Using Phillips Curve

Master's thesis

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I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

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Abstract

This paper studies the forecasting ability of various Phillips curve specifications. Pseudo out-of-sample exercises are performed to forecast the Swedish inflation over the period 1980-2014. Three measures of inflation are considered (headline inflation, underlying inflation, GDP deflator inflation), in addition to different activity variables, various econometric specifications and different sample periods. Although, the results indicate heterogeneity in individual model performance and evidence for model instability, yet, in general, the Phillips curve models improve across the random walk benchmark for both headline inflation and underlying inflation, and fail to beat the random walk benchmark for GDP deflator inflation. Phillips curve forecasts beat the random walk benchmark especially for period 2004-2013. I also take into account the monetary regime change in 1993, from exchange rate targeting to inflation targeting. The results suggest that the performance of Phillips curve depends to whether the data used for making the predicitons was under the inflation targeting regime or not.

Keywords: Forecasting, Inflation, Phillips curve, Sweden

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Table of Contents

1. Introduction

Inflation is one of the key variables in making consumption and investment decisions and understanding macroeconomic dynamics. Modelling inflation is a core task for inflation-targeting central banks, it is hard to over emphasize the prominence of inflation forecasting in monetary policy making as monetary policy is considered to be more effective when it is forward looking, see Faust and Wright (2013) and Svensson (2005). Phillips curve is an important concept in economics that originally related the unemployment rate with the inflation rate (Phillips (1958)). Later is has been extended to describe the relationship of past, present and future inflation with economic aggregates It remains one of the major cornerstone in macroeconomic forecasting.

Sweden is an interesting case to study the behaviour of the Phillips curve in inflation forecasting because it has had different monetary regimes. It had a fixed exchange from 1973 until 1992. During this period the krona adhered to various fixed exchange rate arrangements, including the unilateral peg to ECU from May 1991 till the collapse of fixed exchange rate system (Berg (1999)). On 15 January 1993, the Sveriges Riksbank (Central Bank of Sweden) announced that monetary policy would be conducted with a view to achieving price stability. The inflation target was set at 2 per cent, meaning the annual rise in the CPI should be close to 2 per cent. As it was one of the first countries to introduce inflation targeting, time-series to study the usefulness of the Phillips curve in inflation forecasting is one of the longest and it is possible to analyze whether the inflation process has changed since the introduction of the inflation target.

This thesis investigates the forecasting ability of various Phillips curve models for three different inflation measures for Sweden: headline inflation (CPI-all), underlying inflation (KPIX[1]) and GDP deflator inflation. Economic activity is measured with several variables including unemployment, GDP, capacity utilization rate, index of industrial production and various measures of gap. To evaluate the usefulness of the Phillips curves, the accuracy of the inflation forecasts by every model at a one-year (or four quarters) forecast horizon is compared to that of a naïve benchmark model proposed by Atkenson and Ohanian (2001). I examine the pseudo out-of-sample performance of 114 forecasting procedures: this includes 40 distinct models, among which 4 prototype models. Econometric study is undertaken by analysing the quarterly inflation data for three decades from 1984 until 2014. This allows to shed light on

[1] KPIX is the measure of the underlying inflation, which is calculated by excluding households' expenditure on mortgage interests from the headline inflation, as well as the direct effects of changes in indirect taxes and subsidies from the headline inflation

how the performance of Phillips curves change with the adoption of the inflation targeting framework. The performance is examined by focusing on different sample periods and predictor/activity variables. The empirical strategy adopted follows closely the 2009 paper by Stock and Watson, with slight changes to models and variables. For example, Stock and Watson (2009) in addition to headline inflation, the underlying inflation and the GDP deflator, they also apply their prototype models to the personal consumption expenditure deflator (PCE-all), and the personal consumption expenditure deflator excluding food and energy (PCE-core). Another difference with the Stock and Watson (2009) study is that they omit supply-side variables, such as oil prices, from their Phillips curve specifications. Such variables can potentially be important for modelling inflation in a small, open economy like Sweden.

Several interesting findings emerge from the analysis. First of all, there is an evidence of time variation in the inflation dynamics and forecasting ability both in univariate and Phillips curve models. This result is supported by the literature review, in which different authors reach different conclusions about the performance of the Phillips curves depending on the sample period, the inflation measure and the country of study.

Second, Phillips curve models are especially good for forecasting underlying inflation, followed by headline inflation, while the worst are for the GDP deflator inflation. My findings support the usefulness of headline and underlying inflation measures in predicting the inflation, but find underestimate the usefulness of Phillips curves for GDP deflator forecasting.

Third, the Swedish Phillips curves show different performance during the two regimes. The Phillips curve forecasts based on data under the fixed exchange rate regime perform remarkably poor and are outperformed compared to a naïve benchmark. In contrast, the forecasts from the data under the inflation targeting regime show good results. This holds for most Phillips curve models and suggests that, in addition to contributing to price stability, the inflation targeting regime contributes to better forecasts of inflation with the Phillips curve in an open economy like Sweden.

The main contribution of the paper is the evaluation of forecasting ability of various Phillips curve specifications for Swedish inflation. I look at the forecasting performance of the Phillips curve on three different measures of inflation and show that there are important differences in forecasting inflation series. For instance, the underlying inflation measures have the best forecasting power, followed by headline inflation. This is in line with theory, which suggests that underlying inflation is easier to forecast. On the other hand, the forecasts for GDP deflator have the worst forecasting accuracy, which is surprising, as GDP deflator is usually less volatile then the headline inflation. Banbura and Mirza (2013) results support the theory, since their forecasts for GDP deflator have the lowest RMSFEs and thus are more accurate.

Unlike the previous literature, this paper considers the effects of monetary regime change on the forecasting power of Phillips curves. In this way, the paper adds to previous empirical work on forecasting the inflation using Phillips curve by also considering the change in monetary policy due to the adoption of inflation targeting in Sweden. The results discussed in this paper are also important in a wider context because Sweden is not the only country with policy regime changes in recent history. There are a significant number of (small) open economy countries (e.g. Australia, New Zealand, UK) that experienced policy regime changes in the last thirty years that are well documented.

My results on periodic forecasting ability are similar to those found in the literature using data for other countries. The evidence has been mixed, depending on the country and period (Banbura and Mirza (2013)). Many studies find support for using the Phillips curve in forecasting. For instance, Stock and Watson (1999) use generalized Phillips curve forecasts and find them useful in forecasting the inflation rate one-year ahead. Stock and Watson (2008) compare Phillips curve forecasts to several multivariate specifications of forecasting models and find a good Phillips curve performance for the US. However several papers find that evidence stating that the importance of Phillips curves is overrated and that these curves are not useful for forecasting. For instance, Atkeson and Ohanian (2001) find that Phillips curve based forecasters are regularly outperformed by naïve random walk benchmark. Matheson (2008) gets a better forecasting performance out of a univariate AR(1) forecaster than from Phillips curve forecasting models. Also, Clausen and Clausen (2010) find that the Phillips curve performs badly oftentimes when analysing data from Germany, the UK and the US. Research examining its performance in open economies is scarcer (Matheson (2006)).

Section 2 in this paper gives an overview of the related literature. Section 3 provides describes the models used in the forecast evaluation and the methods. Section 4 describes the data, while the section 5 reports the results. Section 6 provides some robustness results and Section 7 concludes.

2. Literature Review

Extensive literature is available on inflation forecasting using Phillips curve. Many papers, including several seminal papers use US data. There is considerably less work available on the Eurozone countries and open economies. Stock and Watson (2008), Faust and Wright (2012), and Banbura and Mirza (2013) provide extensive literature surveys. I will first give a general overview of the literature available on the topic, then explain papers closest my study. Therefore, I mostly cover the studies that use pseudo out-of-sample forecasting evaluation exercises. Most of the papers focus on forecasting horizons of one year. Of primary interest is forecasting the inflation using the overall CPI, core inflation and the GDP deflator, although some papers also forecast PCE and PCE-core inflations (Stock and Watson (1999)), and sometimes producer prices, though the latter appears only rarely in the literature.

The first studies in the field of forecasting inflation using the Phillips curve were carried out by Gordon (1982, 1990). During the great inflation and the oil shocks of the 1970s, the Phillips relation was amended by incorporating supply shocks and zero long-run trade-offs. A new interpretation of the Phillips curve has emerged and was called the triangle model of inflation by Gordon (1977), referring to the three determinants of the inflation rate, which are inertia, demand and supply. This triangle model was useful in forecasting the decline in inflation in the early 1980s, which was due to sharp increase in the unemployment rate in 1980. The model improved upon univariate benchmarks almost uniformly, with an exception in the mid-1980s that was due to a temporary decline in oil prices. The good performance of the triangle model on US data for the period 1977-1984 was documented by Stockton and Glassman (1987).

One of the important works on the topic is the study by Stock and Watson (1999). The paper examines the stability of the Phillips curve by doing a pseudo out-of-sample forecasting exercise of inflation measures at the one-year ahead horizon. Their findings suggest that Phillips curve models outperform univariate benchmark models in predicting four quarter ahead inflation using recursive forecasts for the period 1970-1996. They use various activity variables and find that combination forecasts in general perform better than the forecasts from single models. The general conclusion is that although Phillips curves based on the unemployment rate are useful for forecasting unemployment, they are not sufficient. Forecasting based on other measures, or a combination of forecasts can improve results.

A number of papers from the 1990s questioned the usefulness of activity-based inflation forecasts relative to an AR benchmark (Stock and Watson (2008)). These results in the literature of 1990s were summarized by study by Atkenson and Ohanian (AO) (2001). The study critically evaluates the belief that NAIRU (non-accelerating inflation rate of unemployment) Phillips curve-based models are a useful tool for forecasting inflation. They introduce a simple, "no change" benchmark: the random walk model, which states that inflation over the next four quarters is equal to the present inflation. Atkenson and Ohanian (2001) show that this random walk forecast improved substantially upon the AR over 1984-1999. That is to say, the Phillips curve based on NAIRU (using either the unemployment gap or an activity index) could not improve upon their proposed naive model. This was evaluated by Fisher et al (2002), who used rolling regressions with a 15-year rolling window to confirm that Phillips curve models outperformed the RW benchmark in 1977-1984 and for some periods after that. Therefore they argue that the forecasting ability of the Phillips curve models is episodic and depends on the parameters of the exercise: sample period, forecasting horizon, inflation measure chosen.

Later studies by Stock and Watson (2003) and Brave and Fisher (2004) extends the analysis to additional activity predictors and confirmed the dominance of the RW model for the period post 1985. More recent studies (Stock and Watson (2007), Canova (2007), Ang, Bekaert and Wei (2007)) confirm the AO findings through their works, where they extend the analysis with qualifications. On the other hand other more recent papers such as Stock and Watson (2009) and (2010) support the Fisher et al (2002) findings.

Dotsey and Stark (2005) find that the decreases in capacity utilisation fail to add any forecasting power to combination forecasts. However, Stock and Watson (2008) argue that large deviations of the unemployment gap are associated with good performance of Phillips curve-based forecasts.

The Stock and Watson (2009) study, which is used as a base for my study, uses quarterly US data from 1953 to 2008 to carry out a pseudo out-of-sample exercise. The total of 192 forecasting procedures include 157 district models and 35 combination forecasts, as well as six prototype models proposed by Stock and Watson. These models are applied to forecast the CPI-all, CPI-core, PCE-all, PCE-core, and the GDP deflator. Despite some results not being robust, the main idea in the literature is confirmed. The conclusion is that the results are strongly dependent on the sample period and phase of the business cycle. Therefore the performance of Phillip's curve forecasts is episodic.

Most studies on the data from Eurozone countries focus on in-sample evaluation of Phillips curves. Some papers studying out-of-sample forecasting are those by Runstler (2002), Hubrich (2005), Canova (2007), Marcellino and Musso (2010), Buelens (2012), and Banbura and Mirza

(2013). Although the studies have a common goal, the results differ across the papers. Several of them document various forms of time variation in the coefficients of the Phillips curves (e.g. the mean and the slope of the euro area Phillips curve). On the contrary, O'Reilly and Whelan (2005) find the reduced form Phillips curve coefficients to be stable, particularly those related to inflation persistence.

Musso et al (2009) suggest that the dynamics of inflation have changed substantially, especially in the last forty years. Their paper provides a comprehensive analysis of euro area inflation dynamics by focusing on the functional form of the Phillips Curve and analysing the stability of the relationship between inflation and economic activity, while also examining the possibility of structural change in the statistical properties of mean, persistence and volatility. The general conclusion is that the Phillip's curve, at least for the euro area, is a "line", and thus the central bank cannot stimulate economic activity without creating inflationary pressures. Further analysis is still necessary to check for heterogeneity in the stability and functional form of the Phillips curve.

Canova (2007) compares the performance of leading models of inflation (including the Phillips curve) for G-7 countries (Canada, France, Germany, Italy, the UK, the USA and Japan) using quarterly data from 1980 to 2000. He shows that the multivariate models that are suggested by the economic theory generally do not outperform the univariate benchmark, though some of them still improve upon the univariate models. The forecasting performance of the standard or modified Phillips curve models and of other small-scale fixed coefficients specifications that exploit only domestic interdependencies is far from convincing in the majority of the G-7 countries. On the other hand, multivariate models with time-varying coefficients improve upon univariate ones, both with fixed and time-varying coefficients. Clausen and Clausen (2010) find that the Phillips curve performs badly oftentimes when analyzing data from Germany, the UK and the US.

Banbura and Mirza (2013) examine the predictive ability of various Phillips curve specifications for euro area inflation by comparing their performances with the popular benchmark models. The models used in the study include Phillips curve models (Autoregressive Distributed Lag (ADL) and Vector Auto-Regression (VAR)), Phillips curve models with detrended inflation, univariate models, and forecast combinations. The benchmark is the random walk (RW) model of Atkenson-Ohanian (2001). They use the quarterly euro area data from 1980 to 2011 and perform out-of-sample exercises. The results suggest heterogeneity in the models' performance and the range of the resulting point forecasts is very wide. None of the models based on forecast performance improves upon some version of forecast combination. Moreover, even though some Phillips curve model forecasts outperform the forecasts from univariate benchmark model, yet, these improvements are typically not large.

To sum up, most results confirm that there is model heterogeneity and the forecast accuracy is dependent on period and sensitivity to the sample used.

3. Method

This section defines the models used for forecasting inflation and the estimation methods. The models follow closely Stock and Watson (2009) and are grouped into univariate models' group and Phillips curve models' group. The first group contains forecasts based on past inflation, such as univariate models like autoregressive (AR), moving average (MA) and random walk (RW). The second group contains single-predictor based Phillips curve models (those produced using an activity variable, such as unemployment or another activity variable) and triangle models with and without supply shock variable.

The first group contains ARIMA models and the Atkenson-Ohanian (2001) random walk model. The first of these prototype univariate models is the *autoregressive model (AR),* which is computed using the following direct autoregressive model. It models inflation in terms of the lags of itself (together with a constant):

$$\pi^h_{t+h} - \pi_t = \mu^h + \alpha^h(L) \times \Delta\pi_t + v^h_{t+h}, \tag{1}$$

where μ^h is a constant, $\alpha^h(L)$ is a polynomial in the lag operator. The number of lags is chosen according to the Akaike Information Criterion over the range of 1 to 6 six lags. The unit root is imposed on π_t. The h-quarter ahead error term is denoted by v^h_{t+h}.

The second model, that is chose as the naïve "no change" benchmark is the Atkenson-Ohanian *random walk model*. Here the forecast of the next four-quarter inflation π^4_{t+4} is equal to the average rate of inflation over the previous four quarters (π^4_t). v^4_{t+4} is again the four-step ahead error term. The model is defined by:

$$\pi^4_{t+4|4} = \pi^4_t + v^4_{t+4} \quad \text{or} \quad \pi^4_{t+4|4} - \pi^4_t = v^4_{t+4}, \tag{2}$$

where, for simplicity, $\pi_t = \pi^1_t$ and $\pi^4_t = \frac{1}{4} \times (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})$.

As argued by Atkenson and Ohanian (2001), the reason for choosing random walk model as a benchmark is not because that it provides the best forecasts of inflation available, but rather because any inflation forecasting model based on some hypothesized economic relationship cannot be considered a useful guide for policy if its forecast are no more accurate than a simple atheoretical forecast.

The multivariate model based forecasts family includes two types of Phillips curve models: single-predictor ADL forecasts including an activity variable and two triangle models. I use wide array of Phillips curve models that employ different measures of real economic activity in order to test for their predictive power. This procedure is primarily aimed at finding technically appropriate and significant predictors. Therefore in these models, I regress the inflation – expressed as the first difference of the inflation measure – on own lagged values to take into account the "stickiness" of the inflation process, and the activity variables.

The ADL models use unemployment rate, output, capacity utilisation rate, index of industrial production index, as well as their corresponding gaps as activity variable to forecast the inflation, while the triangle model uses oil prices as supply shock variable. The Phillips curve forecasts are computed by adding a predictor to (1) to form the *Autoregressive Distributed Lag* (ADL) specification defined by:

$$\pi^h_{t+h} - \pi_t = \mu^h + \alpha^h(L) \times \Delta\pi_t + \beta^h(L) \times x_t + v^h_{t+h}. \qquad (3)$$

The degrees of lag polynomials $\alpha^h(L)$ and $\beta^h(L)$ are chosen separately using both Akaike Information Criterion (AIC) and Bayes information criterion (BIC) over the range of one to four lags. Unit root restriction is imposed on π_t. Here x_t is an activity variable, which can be unemployment rate or any of the variable (or its gap) given in Appendix 1. For unemployment rate, two separate models are estimated, one of them using the level of unemployment, and the other, the first difference.

In *Gordon's (1990) "triangle" model*, the inflation depends on inertia, demand and supply. Thus the inflation in this version of Phillips curve model is determined by lagged inflation, the unemployment rate, and the supply shock variables z_t:

$$\pi_{t+1} = \mu + \alpha(L) * \pi_t + \beta(L) \times u_{t+1} + \gamma(L) \times z_t + v_{t+1}, \qquad (4)$$

where u_t is the activity variable, while z_t captures supply side shocks such (e.g. oil prices). The contemporaneous values of unemployment rate and inflation rate, as well as their lags one through four are included in the equation. For oil prices only lags one through four for are included. A version of the triangle model without supply shock variable z_t is also considered. Following Gordon (1998), I construct the multistep forecasts of (4) by using the forecasted values of predictors, that are computed using univariate AR (8) models of u_t andz_t.

This study focuses on one-year horizon forecasts, or in other words four-period ahead forecasts (*h = 4). h*-period inflation is denoted by $\pi_t^h = h^{-1} \times \sum_{i=0}^{h-1} \pi_{t-i}$, where π_t is the quarterly rate of inflation at the annual rate, that is $\pi_t = 400 \times ln(P_t/P_{t-1})$, with P_t being the price index in given quarter t. From here, the four-quarter inflation at date t is $\pi_t^4 = 100 \times \ln(P_t/P_{t-4})$. Consistent with the Stock and Watson (2008) study in this thesis as well direct forecasts are considered, that is the forecasts that are made using a horizon-specific estimated model, where the dependent variable is the multi-period ahead value being forecasted.

Pseudo out-of-sample forecasts are when the sample is divided into an evaluation sample and a forecasting sample, then the evaluation sample is used to estimate the model in order to forecast “out-of-sample”. Typical strategies include recursive (expanding window) estimations and rolling window estimations. The recursive or expanding window strategy is to estimate the model on a sample running through periods *1, 2 ... t*, always starting with the same observation and using it to produce forecasts of variables at date $t + h$, $h > 0$, where h is the forecasting horizon. In contrast the rolling window strategy is to estimate the model on a sample running from $t - s$, $t - s + 1 \ldots t$ and then use it to produce forecasts of variables at date $t + h$, $h > 0$. Parameters (coefficients) of each model are re-estimated with one more observation added to the estimation data and each time the target variable is forecast *h* periods ahead. Therefore, a sequence of pseudo out-of-sample forecasts is produced here for the out-of-sample period using a fixed amount of the most recent data at each point of time. The number of recent observations used in the estimation is referred to as the window size.

In this study the period 1984-1994 was used for initial parameter estimation. The forecast period 1984-2014 was split into the four periods. Pseudo out-of-sample exercise is performed using a rolling window scheme, with the window size equal to 10 years, and an expanding window approach with the observations always starting from 1993. In case of rolling estimation, the window size is essential for reliable estimation, in that it covers sufficient observations. For parameters that are stable over the entire sample, the estimates over the rolling windows will also be stable. However, if the parameters are time varying then the rolling estimates should capture these changes.

The technique used is as follows: the data is initially split into an estimation sample (10-year long series), to which the model is fitted. Next step, the four-step ahead forecasts are made and the four-step ahead forecast errors can be calculated using equation 5. The estimation sample is then rolled forwards one quarter. The difference in calculations among the rolling window and recursive techniques is the start period of the estimation: in case of rolling window the start date moves one quarter ahead with every step, while in the recursive estimation method the start date always stays the same. It may be noted that the sample for calculating the forecast errors is 20 quarters (5 years, 4 quarters each), so in case there are fewer than 20 observations left in the calculation, these periods are omitted from the evaluation. Likewise, the latest period (2014Q1-Q4) was not included in the rolling window estimations, since it was used for forecast accuracy evaluation.

This exercise is repeated for the subsequent five-year long forecast evaluation samples. Stock and Watson (2009) choose eight-year long evaluation samples for the US data, but due to shorter time series available for Sweden and also because of different business cycles for Sweden the five-year periods capture them better. Therefore, chosen forecast estimation periods correspond to different business cycles and are different in terms of their inflation dynamics. For instance, the period from 1979Q1-1983Q4 witnessed an economic boom followed by low rates of inflation. Later on, the period 1994Q1–1998Q4 corresponds to the introduction of the inflation targeting-regime, while the subsequent period portrays relatively stable inflation dynamics. In contrast, the period from 2004Q1-2008Q4 is characterised by volatile inflation rates, which are in due to the financial crisis of 2007-2008. The last sub-period 2009Q1-2013Q4 portrays less volatile inflation rates.

After the predictions have been made for the evaluation samples, the RMSE (Root Mean Squared Error) is calculated for the given period and compared to the Random Walk benchmark so the adequacy of the statistical model can be evaluated. The Root mean squared error (RMSE) for any forecast is the square root of the arithmetic average of the squared differences between the actual inflation rate and the predicted inflation rate over the time period for which simulated forecasts are constructed. The RMSE is given by

$$RMSE_{t1,t2} = \sqrt{\frac{1}{t_2 - t_1 + 1} * \sum_{t=t_1}^{t_2} \left(\pi_{t+h}^{h} - \pi_{t+h\,|\,t}^{h}\right)^2}, \qquad (5)$$

where $\pi_{t+h\,|\,t}^{h}$ is the forecasted value of π_{t+h}^{h} made using data through date t.

This is a common practice in applied econometrics literature to compare the forecasting performance of different forecasting models relative to some benchmark model. To make the forecast results easily comparable to the random walk benchmark the root mean square errors of all forecast models are also computed relative to it. Therefore, the RMSE of the RW model is 1.00 (same as 100%). Models with relative RMSE values below 1.00 perform better than the RW benchmark, while the models with a relative RMSE above 1.00 perform worse.

In Stock and Watson (2008), the lag lengths are chosen using the AIC and BIC. Following their methodology with the univariate autoregressive (AR) models, the lag length is chosen over a range from one to six, while in multivariate models up to four lags are allowed. Model versions with a given fixed (rather than by choice of AIC) number of lags are also considered. For Swedish data the models were fitted with different lags, and the forecasts from models estimated with only one lag were found to on average yield smaller RMSEs.

To summarize the models, the univariate models consist of rolling estimated versions of AR(AIC), AR(BIC), RW, AR(4), MA(1), and MA(1) with coefficients fixed at 0.25 and 0.65. The MA(1) was the suggested as the best ARIMA model according to the AIC, using a function that conducts a search over a possible model within the order constraints provided. Also, for the MA(1) model with fixed coefficients, the above mentioned values are proposed by Stock and Watson (2007). The Phillips curve models include two triangle models (specification (4) with and without supply shock variables) and ADL Phillips curve models (with all the activity variables from Appendix 1 and their corresponding gaps). In the Phillips curve triangle model oil prices are taken as a supply shock indicator (given in SEK, which were converted from USD using the corresponding USDSEK exchange rates).

Therefore, in total there are 12 univariate and 28 Phillips curve distinct models applied to three measures of inflation. This makes a total of 114 forecasting procedures.

4. Data

Sweden is a good example of a small open economy that went through a monetary policy regime change. Inflation targeting is a monetary policy in which a central bank has an explicit target inflation rate for the medium term. Prior to the this regime being introduced in Sweden, in the last decades of fixed exchange rate regime, high inflation was created by rising wages, which were accompanied by accommodative macroeconomic and exchange rate policies. Inflation between the 1970s and 1980s was uncomfortably high compared to the main trading partners (Berg (1999)). This lead to devaluation of the Krona to compensate for the high inflation, and also to increased asset prices and aggregate demand. Then the economic boom of the late 1980s was followed by a depression in the early 1990s. The resulting falling asset prices and cancelled investment allowances led to a deep recession. Inflation jumped as high as 10 per cent in 1990 and then dropped as low as 2 per cent in 1992. This resulted in higher after-tax real interest rates and an increased budget deficit. The Swedish banking system was experiencing a deep crisis. On 15 January 1993, the Sveriges Riksbank announced that monetary policy would be conducted with a view to achieving price stability. The abandonment of a fixed exchange rate led to a sharp depreciation in the value of the krona against other currencies, and to a number of changes to indirect taxes. This led to inflationary impulses and so Riksbank stated that the target for monetary policy would not begin to apply until 1995. The inflation target was set at 2 per cent, meaning the annual rise in the CPI should be 2 per cent.

Although inflation targeting in Sweden was announced in January 1993, yet as Svensson (2014) notes the credibility of the inflation target was quite low in the first few years, with inflation averaging to about 4 percent before the first half of 1995. Few years were needed for Risksbank to learn how to conduct monetary policy under inflation targeting (Svensson (2014)). By 1997, the regime started working bringing the average inflation close to the 2 percent target, though in the period 1997 – 2013 the average CPI inflation has been by around 0.6 less than the target (around 1.4%).

In this study seasonally adjusted quarterly data for Sweden are used. Monthly data are converted to quarterly data by taking the average of the previous three months'. Consequently, inflation can be understood as the percentage growth at an annual rate of the quarterly data. Forecasts of three measures of inflation are examined: headline inflation (CPI-all), underlying or core inflation (KPIX, previously CPIX[2]), and the GDP deflator. The sample covers 1980Q1 to 2014Q4 for CPI Inflation and KPIX, 1981Q2 to 2014Q4 for GDP deflator. The inflation series of these three measures are plotted in Figure 1. As can be seen, inflation has declined in recent years, developing more or less closely aligned to the Riksbank's stability promise.

[2] Statistics Sweden ceased the calculation and publication of the CPIX indicator starting from January 2016. The new measure that corresponds to the underlying inflation is the KPIX.

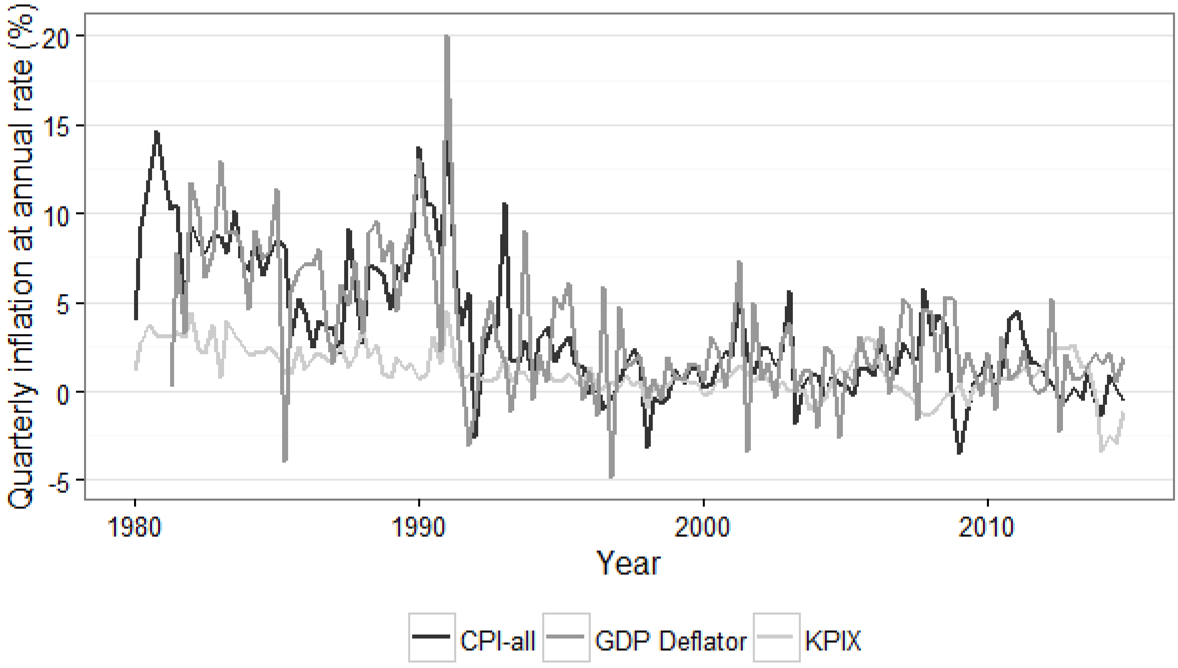

Figure 1: Inflation Series 1980 - 2014

GDP deflator is a price index that measures inflation or deflation in an economy and is calculated by dividing the GDP in current local currency by GDP in constant local currency. GDP deflator inflation is calculated by the annual growth rate of the GDP implicit deflator.

Besides three inflation measures, the prototype models described in section 3 use predictor variables to forecast the inflation. One can think of these activity indicators as different ways to measure underlying economic activity. Groen et al. (2010) consider 10 predictors. Stock and Watson (1999) consider measures of real activity including the unemployment rate. Finally, authors such as Ang et al. (2007) find surveys of inflation expectations to be useful predictors. Economic theory suggests various other predictors, e.g., cost variables, the growth of the money supply, the slope of term structure, etc. This set of variables is a wide one, reflecting the major theoretical explanations of inflation, as well as variables that have been found to be useful in forecasting inflation in other studies (Koop and Korobilis (2012)). Considering this, for this paper I have chosen unemployment rate (UR), capacity utilization rate (CU), real GDP (rGDP) and index of industrial production (IP). The details on these activity variables are given in Appendix 1.

Depending on the series, some data are given in levels, while some in growth rates or first differences. The first differences are taken because not all the variables are expected to be integrated of order 1, but rather there is going to be a mixture of stationary and non-stationary variables. In case of stationary series, the variable is given in its level, while in the non-stationary case the first difference is taken. This holds for example for unemployment rate and capacity utilization rate. Real GDP and index of industrial Production are given in growth rates.

Besides the variables presented in the data appendix, their gaps are also used to evaluate usefulness of Philips curves. Gaps are important in macroeconomic discussions. For example, the output gap (the deviation of output from its trend, or potential value) and the unemployment gap (the deviation of the unemployment rate from its trend) are standard business cycle indicators and key ingredients for Phillips curve forecasts of inflation They are a major concern of central banks, as they are indicators of the degree inflation pressure in the economy.

The variable gaps used in the forecasting models are all one-sided and are constructed using both band-pass (BP) and Hedrick Prescott (HP) filters. HP filter has end-point problems and is a problematic gap measure. It might fail to correctly measure the current state of the economy relative to the potential, resulting in wrong policy decisions. Yet it is an easy method and is widely used. The band pass filters, on the other hand, are designed to eliminate the high and low frequency movements in the data and are more appealing and economically plausible because they depending on the parameters they may suggest smaller number of cycles compared to HP filter. As both statistical filters do not present a totally robust gap measure, both filters are used in this study. The details on how the one-sided output gaps are constructed using these filters and more detailed discussion why the gaps are important for Phillips curves ideology are given in Appendix 2.

5. Results

In this section results regarding the forecasting performance of both univariate and Phillips curves models, as well as the effect of inflation targeting on the performance of Swedish Phillips curve are discussed. The forecasting performance of the models is compared by focusing on the forecast horizon of one year (h = 4). This four-quarter ahead forecasts from RW benchmark, the best ADL model (for given series) and the triangle model with oil prices against the realised inflation series are plotted in Figure A1 of Appendix 3.

The pseudo out-of-sample of forecasting performance procedure is summarized in tabular form in Appendix 4 for absolute values, and in Tables 1-3 below for relative RMSE. First rows of Tables 1-3 contains number of observations for the given sub-period. Blank cells indicate insufficient data for computations in the given forecast period. For example, capacity utilization is only calculated for the sub-period 2009-2013. Second row illustrates the absolute root mean square errors for random walk benchmark model for each evaluation period. Starting from the fourth row, the numbers show root mean square errors (RMSE) relative the ‘best’ benchmark model. The RMSE in each model is computed using (5). When relative RMSE is unity, it means the performance of inflation forecast model being compared is as good as that of RW model. In case it is greater than unity, it means RW model performs better than the model being compared and a value below one means RW model performs worse. In each table the relative RMSE that is shown as a number in bold font highlights the models that beat the naïve benchmark and are best for forecasting inflation in Sweden at four quarter horizon.

To choose the best benchmark model, or in other words, to confirm the random walk model as the benchmark, I initially compare it to eleven other univariate forecasts ranging from AR to MA(1). Out of all these approaches the best inflation forecasts for Sweden for the full sample are generated by RW model and the other univariate models on average are not able to beat random walk approach. There is not a single model that has uniformly better performance than the RW model. In some cases, AR models, where lag lengths are determined using AIC, perform better than the RW. For instance in the periods 1994-1998, 2004-2008, 2009-2013, the AR forecasts of CPI-all and KPIX have very small relative RMSEs, that does not exceed 0.79. In general, the performance of these univariate models is specific to particular series and period. Therefore the performance of the Phillips curve models is going to be evaluated against the random walk model.

Table 1 presents the relative RSMEs for CPI-all for the four sub-periods. It can be seen that in the first two sub-periods none of the Phillips curve models beats the benchmark. The first period corresponds to the data under the fixed exchange rate regime: the data that was used to make the one-year ahead forecasts included series before 1994. The next period uses a combination of data from both regimes. The RMSEs range from 1.09 to 1.62, meaning that the forecasts are 9 to 62 percent worse. This can be explained by the introduction of inflation targeting regime, since the headline inflation started to go towards 2 percent inflation target only around 1997. In the third evaluation period (2004Q1-2008Q4), most of the ADL models beat the random walk benchmark. The existing variability can be explained volatile inflation rates caused by recent financial crisis. During the last sub-period majority of models beat the RW. Those that fail to beat (not marked in bold) have relative RMSEs very close to unity, meaning that even though they did not succeed in beating the random walk model, yet they did almost as good. This success in predicting the inflation rate in the last period is expected, since this is a period of relatively stable inflation rates (see Figure 1).

For an open economy like Sweden, inflation is not only determined by domestic economic conditions but also by developments amongst the economy's trading partners, which influence the competitiveness of the tradable sector. Yet, the triangle model with oil prices as supply shock variable perform quite poorly. It shows very poor forecasting accuracy, with RMSEs being far from realized values (see Appendix 4, Table A1), especially when compared to the model without the oil prices. The conclusion can be made that oil prices are not at all helpful in forecasting the Swedish inflation.

This can be due to high energy efficiency of the Swedish economy. Moreover, this is in line with Stock and Watson (1999) findings. The authors state that "although the supply shock variables are statistically significant in full-sample specifications with unemployment, in a simulated out-of-sample setting their coefficients are poorly estimated for much of the sample and this produces poor out of sample forecasts." Their preliminary results indicated that the forecasting ability of the models that included supply shock variables is worse, on a simulated out-of-sample basis, than the corresponding models in which these variables are excluded.

Table 1: Relative RMSEs by Sub-Periods for CPI-all

Forecast Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
No. of Observations	20	20	20	20
RMSE of AO forecast	1.44	1.16	2.06	1.64
Univariate models forecasts				
AO	1.00	1.00	1.00	1.00
AR(AIC)_roll	**0.74**	1.07	**0.79**	**0.74**
AR(1)_roll	1.22	1.76	1.05	**0.88**
AR(4)_roll	1.40	1.91	1.06	**0.94**
AR(BIC)_roll	1.25	1.85	1.08	**0.89**
AR(AIC)_rec	**0.74**	1.07	**0.79**	**0.74**
AR(1)_rec	1.19	1.65	1.03	**0.89**
AR(4)_rec	1.38	1.80	1.09	**0.88**
AR(BIC)_rec	1.19	1.75	1.06	**0.90**
MA(1)_roll	1.19	1.51	1.03	1.02
MA(1) coeff=.25	1.21	1.51	1.03	1.01
MA(1) coeff=.65	1.29	1.61	1.10	1.05
Single-predictor ADL forecasts				
UR(level)_roll	1.15	1.64	**0.95**	**0.95**
UR(diff)_roll	1.20	1.48	1.10	**0.94**
CU_roll	-	-	-	**0.78**
IP_roll	1.22	1.48	**0.96**	**0.91**
rGDP_roll	1.19	1.56	1.08	**0.88**
UR(level)_HP_roll	1.20	1.57	1.01	**0.86**
CU_HP_roll	-	-	-	**0.88**
IP__HP_roll	1.22	1.43	**0.96**	**0.89**
rGDP_HP_roll	1.20	1.45	**0.86**	**0.97**
UR(level)_BP_roll	1.15	1.53	**0.83**	**0.81**
CU_BP_roll	-	-	-	**0.82**
IP_BP_roll	1.40	1.38	1.01	**0.92**
rGDP__BP_roll	1.22	1.50	**0.92**	**0.96**
UR(level)_rec	1.14	1.48	1.00	1.00
UR(diff)_rec	1.18	1.43	1.05	1.04
CU_rec	-	-	-	**0.82**
IP_rec	1.18	1.48	**0.99**	1.00
rGDP_rec	1.17	1.49	1.01	1.01
UR(level)_HP_rec	1.19	1.52	**0.99**	**0.95**
CU_HP_rec	-	-	-	**0.89**
IP__HP_rec	1.18	1.49	1.00	**0.99**
rGDP__HP_rec	1.19	1.46	**0.97**	1.03
UR(level)_BP_rec	1.13	1.47	**0.93**	**0.93**
CU_BP_rec	-	-	-	**0.89**
IP_BP_rec	1.27	1.38	1.01	1.03
rGDP__BP_rec	1.19	1.48	**0.99**	1.02
Triangle models forecasts				
Triangle	4.43	6.02	3.66	3.90
Triangle (no z)	1.28	1.59	1.15	1.19

In case of KPIX, the ADL models outperform the RW benchmark for the last two sub-periods: all models perform better than the naïve benchmark (see Table 2). Even the triangle models perform well: although they fail to beat RW, the relative RMSEs range from 1.01 to 1.09, which shows that the models still do good job at predicting the inflation.

All of the Phillip's curve forecasts (except triangle models that exclude oil prices) appear to be rather good. The relative RMSEs are less than that of RW, and sometimes even by around 0.31 relative unit points, which shows that these models have 30% better forecasting power than the RW benchmark. This highlights the good predicting ability of these models for forecasting the Swedish underlying inflation at a one-year ahead horizon. This is not surprising given relatively stable and less volatile inflation rates for underlying inflation: the price index KPIX differs from the CPI in that the effects of changes in mortgage costs and the direct effects of changes.

Like in case of headline inflation, here again, when using the data under fixed exchange rate regime to make the one-year ahead forecasts, the Phillips curves perform poorly and almost never beat the benchmark model. On the other hand, when the data used for predictions is after the introduction of inflation targeting regime, then the Phillips curve based models outperform the naïve benchmark.

In the first two periods, not a single Phillips curve forecast outperformed the benchmark. The results are positive for the last two sub-periods, where the best Phillips curve forecast (assessed by the lowest RMSEs) for underlying inflation in Sweden uses GDP growth, unemployment and capacity utilization gaps.

As emphasized in Svensson (1994), the main advantage of a target zone, compared to a fixed peg, is that it gives the monetary authority the ability to stabilize the exchange rate without losing all of its ability to react to domestic shocks. However, supply shocks hit the economy harder during the fixed exchange rate period than during the inflation targeting regime because the exchange rate's role as a shock absorber is more restricted. My results confirm this view: the contribution of oil prices as supply shocks to the forecasting performance of the triangle models is very low. The RMSEs of the triangle models that include the oil prices is much higher than the model that does not include the supply shock variable in the model for predicting the one year ahead inflation.

Table 2: Relative RMSEs by Sub-Periods for KPIX

Forecast Period	1994Q1-1998Q4	1999Q1-2003Q4	2004Q1-2008Q4	2009Q1-2013Q4
No. of Observations	20	20	20	20
RMSE of RW forecast	0.30	0.53	1.43	1.69
Univariate models forecasts				
RW	1.00	1.00	1.00	1.00
AR(AIC)_roll	3.65	2.50	1.11	**0.95**
AR(1)_roll	2.18	1.13	**0.79**	**0.83**
AR(4)_roll	2.38	1.26	**0.80**	**0.81**
AR(BIC)_roll	2.27	1.22	**0.79**	**0.82**
AR(AIC)_rec	**0.91**	1.03	**0.80**	**0.78**
AR(1)_rec	2.23	1.13	**0.80**	**0.89**
AR(4)_rec	2.45	1.24	**0.83**	**0.88**
AR(BIC)_rec	2.40	1.21	**0.83**	**0.90**
MA(1)_roll	1.73	1.08	**0.80**	**0.84**
MA(1) coeff=.25	1.93	1.25	**0.80**	**0.88**
MA(1) coeff=.65	2.78	1.77	**0.90**	**1.00**
Single-predictor ADL forecasts				
UR(level)_roll	1.65	1.15	**0.76**	**0.75**
UR(diff)_roll	1.67	1.13	**0.79**	**0.83**
CU_roll	-	-	-	**0.78**
IP_roll	1.66	1.04	**0.77**	**0.79**
rGDP_roll	1.61	1.06	**0.73**	**0.79**
UR(level)_HP_roll	1.66	1.12	**0.77**	**0.79**
CU_HP_roll	-	-	-	**0.79**
IP__HP_roll	1.67	1.06	**0.77**	**0.79**
rGDP_HP_roll	1.72	1.09	**0.76**	**0.79**
UR(level)_BP_roll	1.62	1.09	**0.73**	**0.72**
CU_BP_roll	-	-	-	**0.72**
IP_BP_roll	1.76	**0.95**	**0.79**	**0.79**
rGDP__BP_roll	1.58	1.14	**0.76**	**0.79**
UR(level)_rec	1.65	1.05	**0.78**	**0.81**
UR(diff)_rec	1.72	1.06	**0.78**	**0.81**
CU_rec	-	-	-	**0.77**
IP_rec	1.72	1.05	**0.78**	**0.80**
rGDP_rec	1.64	1.01	**0.76**	**0.81**
UR(level)_HP_rec	1.71	1.04	**0.77**	**0.81**
CU_HP_rec	-	-	-	**0.79**
IP__HP_rec	1.72	1.06	**0.78**	**0.80**
rGDP__HP_rec	1.81	1.02	**0.78**	**0.81**
UR(level)_BP_rec	1.65	1.05	**0.77**	**0.79**
CU_BP_rec	-	-	-	**0.78**
IP_BP_rec	1.74	**0.93**	**0.79**	**0.80**
rGDP__BP_rec	1.70	1.06	**0.78**	**0.81**
Triangle models forecasts				
Triangle	7.31	3.86	3.16	2.69
Triangle (no z)	1.69	1.09	1.01	1.01

For GDP deflator inflation the results are illustrated in Table 3. Most forecasts are far from the realized value and none of the models beats the random walk model. Univariate models have very poor accuracy, though Phillips curves as well have very high RMSE indicating poor forecasting ability.

The results are especially bad for periods 1999-2003 and 2004-2008. The RMSEs of forecasts of GDP inflation increased from first period (1994-1998) to the second periods (1999-2003) and the magnitude of this increase is striking. For instance, for the GDP growth it is as high as 50%. In this sense inflation has become harder to forecast. The relative performance of the Phillips curve forecasts improves slightly from the second sub-period to the third. This improvement of Phillips curve forecasts is found for almost all the activity predictors.

Triangle models with oil prices do not perform well and show the worst results across all three inflation measures. For example, the relative RMSE for triangle model for the period 2009-2013 is 7.03, while for KPIX it is 2.69 and 3.90 for CPI-all. This surprising, given that one of the differences between CPI and GDP deflator is that GDP deflator reflects the prices of all goods and services produced domestically, whereas CPI reflect the prices of all goods and services bought by consumers. This difference is particularly important when the oil prices change: although Sweden does produce some oil, a lot is imported. As a results, the oil prices are much larger share of consumer spending than of GDP. Therefore, the GDP deflator is expected to be affected less by these price changes.

For Sweden, the GDP deflator shows higher inflation than the CPI or KPIX measures, although generally GDP deflator is usually less volatile then for example the headline inflation. Therefore, the results in Table 3 can be explained with this unexpected volatile GDP deflator inflation rates. What this implies, that Phillips curves in either of the monetary regimes (fixed exchange rate and inflation targeting) are not useful for predicting Swedish GDP deflator inflation.

These findings make the performance of GDP deflator forecasts using the Phillips curves disappointing, relative even to simple alternatives such random walk benchmark, thus giving little evidence on the usefulness of Phillips curves for GDP deflator forecasting and leading to negative assessment of my empirical models for purpose of forecasting the GDP deflator inflation for Sweden.

Table 3: Relative RMSEs by Sub-Periods for GDP Deflator

Forecast Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
No. of Observations	20	20	20	20
RMSE of RW forecast	1.66	1.07	1.25	0.99
Univariate models forecasts				
RW	1.00	1.00	1.00	1.00
AR(AIC)_roll	2.65	3.67	3.22	3.29
AR(1)_roll	2.71	3.56	2.45	2.88
AR(4)_roll	3.04	3.82	3.30	3.34
AR(BIC)_roll	2.85	3.74	3.30	3.33
AR(AIC)_rec	2.64	3.32	2.59	2.90
AR(1)_rec	2.73	3.26	2.30	2.80
AR(4)_rec	2.95	3.44	2.62	3.00
AR(BIC)_rec	2.74	3.35	2.52	2.84
MA(1)_roll	1.84	2.25	2.03	1.77
MA(1) coeff=.25	1.84	2.26	2.02	1.77
MA(1) coeff=.65	1.88	2.34	2.06	1.86
Single-predictor ADL forecasts				
UR(level)_roll	1.76	2.20	2.04	1.66
UR(diff)_roll	1.89	2.11	2.34	1.91
CU_roll	-	-	-	1.85
IP_roll	1.86	2.14	2.00	1.68
rGDP_roll	1.80	2.09	2.16	1.67
UR(level)_HP_roll	1.78	2.19	2.05	1.68
CU_HP_roll	-	-	-	1.86
IP__HP_roll	1.84	2.14	2.00	1.69
rGDP_HP_roll	1.90	2.39	1.98	1.67
UR(level)_BP_roll	1.76	2.13	1.95	1.68
CU_BP_roll	-	-	-	1.75
IP_BP_roll	1.81	2.16	1.85	1.84
rGDP__BP_roll	1.76	2.18	2.02	1.71
UR(level)_rec	1.89	2.19	2.11	1.78
UR(diff)_rec	-	-	-	1.83
CU_rec	1.86	2.14	2.03	1.80
IP_rec	1.78	2.21	2.02	1.76
rGDP_rec	1.78	2.26	2.02	1.72
UR(level)_HP_rec	-	-	-	1.89
CU_HP_rec	1.85	2.14	2.02	1.85
IP__HP_rec	1.87	2.29	2.05	1.75
rGDP__HP_rec	1.77	2.17	1.97	1.72
UR(level)_BP_rec	-	-	-	1.61
CU_BP_rec	1.82	2.17	1.93	1.80
IP_BP_rec	1.86	2.20	2.02	1.74
rGDP__BP_rec	1.84	2.15	1.99	1.68
Triangle models forecasts				
Triangle	7.16	8.08	7.29	7.03
Triangle (no z)	1.89	2.12	1.93	1.80

Several findings emerge from empirical results. First of all, it’s clear that there is a great time variation in the inflation process and predictive ability both in univariate and multivariate Phillips curve models. The variability in performances sometimes is quite large. Across a range of Phillips curves models and of different activity variables, the Swedish Phillips curve generally produces poor forecasting performance relative to a random walk benchmark over the full sample. This episodic performance is in line with the Atkenson-Ohanian (2001) and Stock and Watson (2009) findings and the general literature, in which different authors reach different conclusions about the performance of the Phillips curves depending on the sample period.

Comparing the forecast accuracy across evaluation samples, the RSME are the lowest for underlying inflation (KPIX), for sub-periods 2004-2008 and 2009-2013. Second best are results for headline inflation (CPI-all). In examining the performance of the Phillips curve models with unemployment and other predictors, it stands out that models almost uniformly outperform the benchmark for the latest two sub-periods for headline and underlying inflation. The models with gap variables show a small advantage relative to the models without the gaps, although the best models often contain unemployment gap, output gap or index of industrial production gap. When the gaps are calculated using bandpass filter method, results show better accuracy for KPIX and worse for CPI-all and GDP deflator. This, however, doesn’t necessarily hold for the full sample and there is slight variability in the findings across sub-periods. Concerning the supply shocks, the oil prices do not seem to be the best variables and they never feature in the best model.

6. Robustness Results

In Stock and Watson (2008), the lag lengths are chosen using the AIC and BIC. In case of Swedish data both the AIC and BIC selects too many lags for Phillips curve models which result in overfitting. Although AIC beats BIC yielding smaller RMSEs on average, yet both information criteria fail to choose the best model. For Swedish data the models were fitted with different lags, and the forecasts from models estimated with only one lag were found to on average yield smaller RMSEs. Appendix 5 presents the results from ADL models using various lags both for inflation rate and unemployment rate.

To check the robustness of the results from my forecasts, I estimate all the models both with rolling window approach and expanding window approach. The results in the tables suggest that models estimated using expanding window approach give better results in case of KPIX, while in case of CPI-all and GDP deflator the rolling estimation method shows to be better for forecasting the one year ahead inflation rate for Sweden. However, the pattern remains the same: the Phillips curve models have the lowest forecast accuracy relative to the random walk benchmark in the first two sub-periods and they work best in the last two sub-periods.

Next, Swedish Phillips curves estimated based on data after the introduction of inflation targeting regime improve the accuracy of inflation forecasts compared to those based on the data before the monetary policy change. In other words, for both headline and underlying inflations the Phillips curve models work best for forecasting inflation in Sweden in the inflation targeting regime. This applies to majority of the models ranging from the traditional Phillips curve with unemployment rate to Phillips curves using other activity variables to triangle models (with the exception of triangle model with oil prices as supply shock variable.) This brings the hypothesis that maybe, in addition to contributing to price stability, the inflation targeting regime contributes to better forecasts of inflation with the Phillips curve in an open economy like Sweden.

7. Conclusions

In this thesis I have evaluated forecasting performance of various Swedish Phillips curve models over the period 1980 to 2014. I estimate ADL models on Swedish data using activity variables and their corresponding gaps, as well as two triangle models, one using oil prics as supply shock variable, the other without supply shock variable. The main results suggest model heterogeneity and varying results across sample periods and models. The relative performance of the models varies over time, across models and inflation measures. In general, the Phillips curve models typically improve across the random walk benchmark for both CPI-all and KPIX for the last two evaluation samples, while in the first two periods the Phillips curve models almost uniformly fail to beat the naïve benchmark. The forecast accuracy is somewhat poor in case of the GDP deflator measure over the full sample. My findings support the usefulness of headline and underlying inflation measures in predicting the inflation, but find little evidence on the usefulness of Phillips curves for forecasting GDP deflator inflation forecasting. Similar results about episodic performance of the Phillips curve for these inflation measures and activity variables is reported in the literature. The accuracy of my forecasts provides an alternative metric by which the usefulness of Phillips curves for policy analysis and forecasting can be assessed.

Also, in this study I take into account well documented monetary policy regime shift that occurred after the speculative attack against the Swedish krona in 1992 and the consequent switch from a target zone regime to explicit inflation targeting. The results suggest that the performance of Phillips curve depends to whether the data used for making the predicitons was under the inflation targeting regime or not. According to this findings, one may conclude that in the fixed exchange rate regime its better to use univariate forecasting models rather than making multivariate forecasts, but if the central bank is explicitly targeting the inflation, the Phillips curve can be useful for forecasting the inflation.

The patterns, however, cannot yet be used to make definite conclusions. At the same time, this study may be useful for in a wider context because Sweden is not the only country with policy regime changes in recent history. There are a significant number of small open economy countries (e.g. Australia, New Zealand, UK) that experienced policy regime changes in the last thirty years that are well documented.

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Appendices

Appendix 1. Overview of Data

Data

Name	Description	Transformation	Source
Inflation Series			
CPI-all	CPI, all items	SA, (1-L)ln	Statistics Sweden
KPIX	Underlying inflation	SA, (1-L)ln	Statistics Sweden
GDP deflator	GDP deflator	SA, (1-L)ln	Statistics Sweden
Predictors			
UR	Unemployment rate, total (% of total labor)	SA, level and difference	OECD database
IP	Index of Industrial Production (total)	growth rate	St. Louis Fed
CU	Capacity Utilization rate	SA, level	St. Louis Fed
RGDP	Real GDP	growth rate	St. Louis Fed
Supply shock variables			
OIL	Oil Prices	-	IMF, Reuters

Appendix 2: Importance and Construction of One-sided Gaps

Gaps play major role in macroeconomic discussions. They are of a central concern for central banks and key ingredients for Phillips curve forecasts of inflation. The output gap, which is the deviation of output from its potential value and the unemployment gap, which is the deviation of the unemployment rate from its trend are standard business cycle indicators. Output gap is a summary indicator of the relative demand and supply components of economy. It measures the degree of inflation pressure in the economy and is an important link between the real sides of the economy and inflation. Like output gap, the unemployment gap is a central concept for monetary and fiscal policies.

Measuring gaps is not an easy task. For example, to measure output gap, potential output needs to be estimated by assuming that that output can be divided into a trend and a cyclical component. The trend is interpreted as a measure of the economy's potential output and the cyclical component as a measure of the output gap. In order to estimate potential output trends need to be estimated. This means removing the cyclical changes. One popular way to measure the potential output is by applying statistical techniques in order to differentiate between short-term ups and downs and the long-term trend. The Hodrick-Prescott and band pass filters are popular techniques for separating the short from the long term.

Gaps are two-sided concepts, which means that the value of the trend at a given point in time, for example, depends on how the observed value at that time compares to its past values and to future values. Because gaps require both past and future data, it is much more difficult to estimate their values at the beginning of the sample (where there is no past data) and at the end of the sample (where there is no future data)

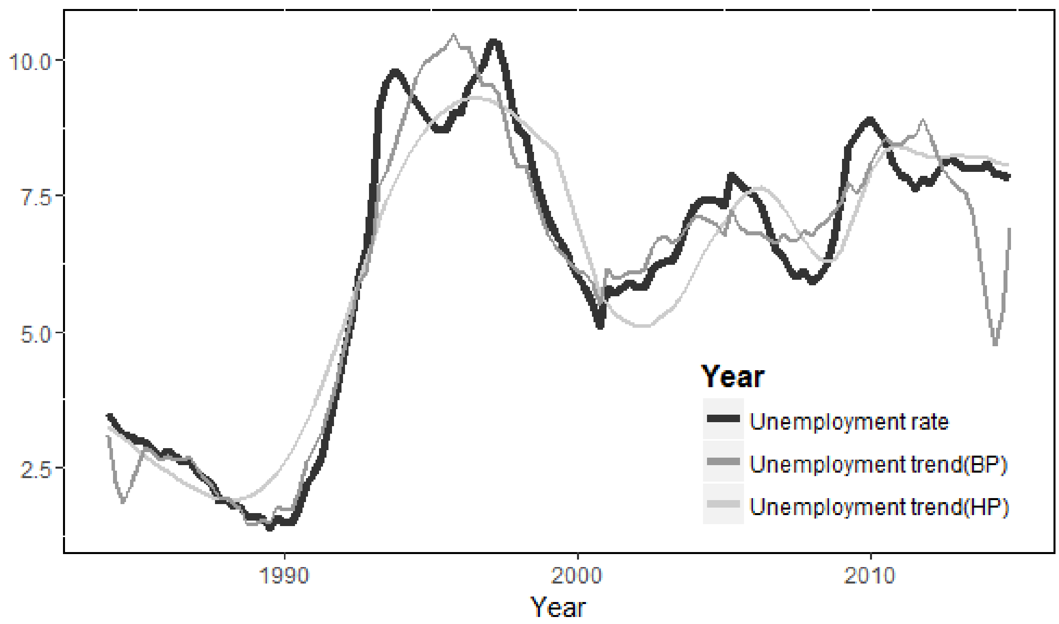
To construct one-sided gaps, that is the trends at any point in time during the observation period the Drehman et al. (2011) and Basel Committee (2010) technique is used (Gerdrup, Kvinlog, Schaning (2013)). The two-sided filter coincides with the one-sided filter at the end of the observation period, which means that the one-sided filter consists of all the endpoints from a two-sided filter. A minimum number of observations (minT) is needed to calculate the trend. In this study this number is taken equal to T/2. Then the HP trend for each column vector is calculated from column T/2 of the original data matrix below. Here the value y_t is the value of the indicator at time t.

$$Y = \begin{bmatrix} y_1 & y_1 & \cdots & y_1 & y_1 & y_1 & \cdots & y_1 \\ & y_2 & \cdots & y_2 & y_2 & y_2 & \cdots & y_2 \\ & & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ & & & y_{minT-1} & \vdots & \vdots & \ddots & \vdots \\ & & & & y_{minT} & \vdots & \ddots & \vdots \\ & & & & & y_{minT+1} & \ddots & \vdots \\ & & & & & & \ddots & \vdots \\ & & & & & & & y_T \end{bmatrix}$$

The constructed two-sided series and the one-sided series (marked in bold symbols) are shown below. The final series, which corresponds to one-sided trends consists of the first column vector and the endpoints of the following columns.

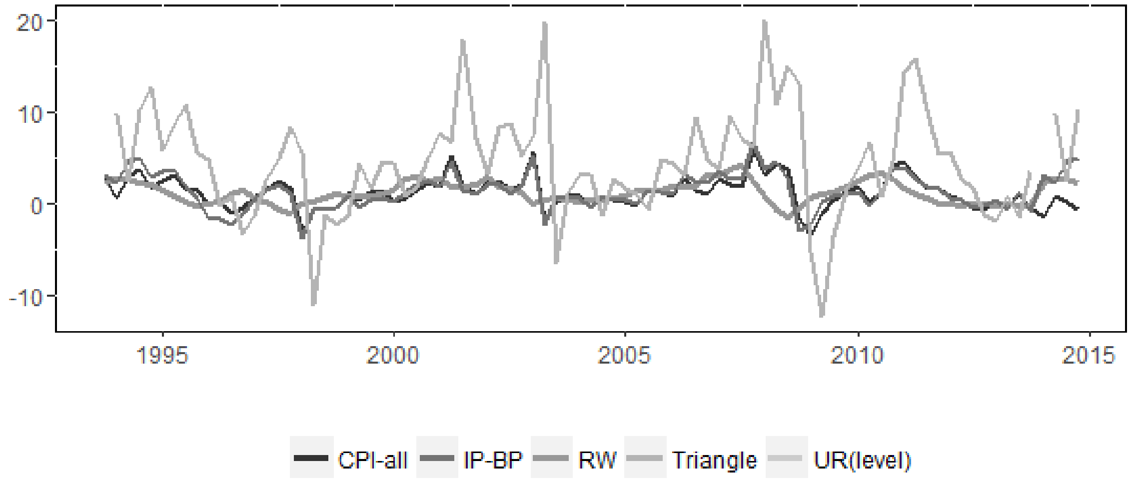
$$TREND = \begin{bmatrix} \boldsymbol{\mu_{1,minT}} & \mu_{1,minT+1} & \cdots & \mu_{1,T} \\ \boldsymbol{\mu_{2,minT}} & \mu_{2,minT+1} & \cdots & \mu_{2,T} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\mu_{minT,minT}} & \vdots & \ddots & \vdots \\ & \boldsymbol{\mu_{minT+1,minT+1}} & \ddots & \vdots \\ & & \ddots & \vdots \\ & & & \boldsymbol{\mu_{T,T}} \end{bmatrix}$$

As an example the unemployment gap for Swedish data constructed using the above describe technique for HP and band pass filters is illustrated below figure.

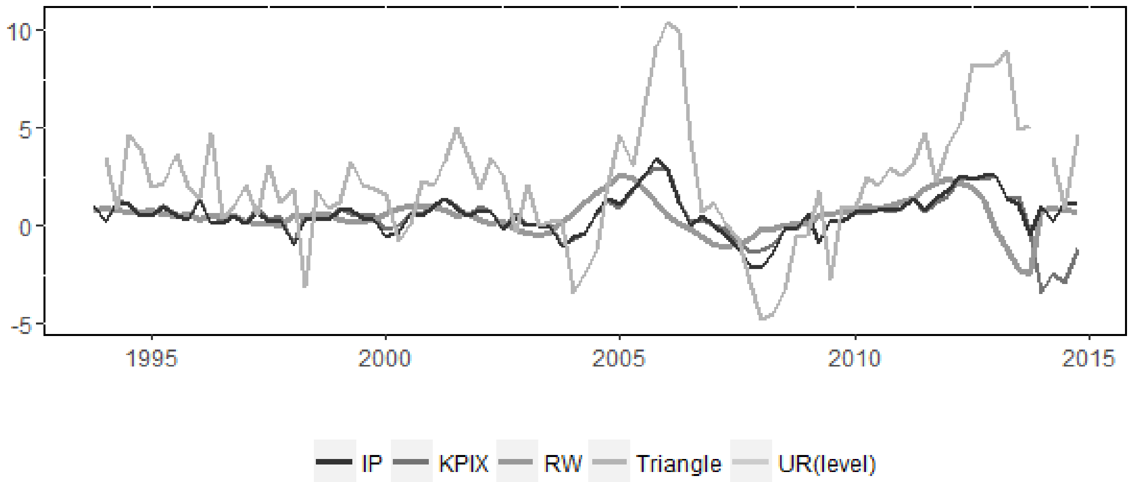


Appendix 3. Inflation Forecasts from Different Models

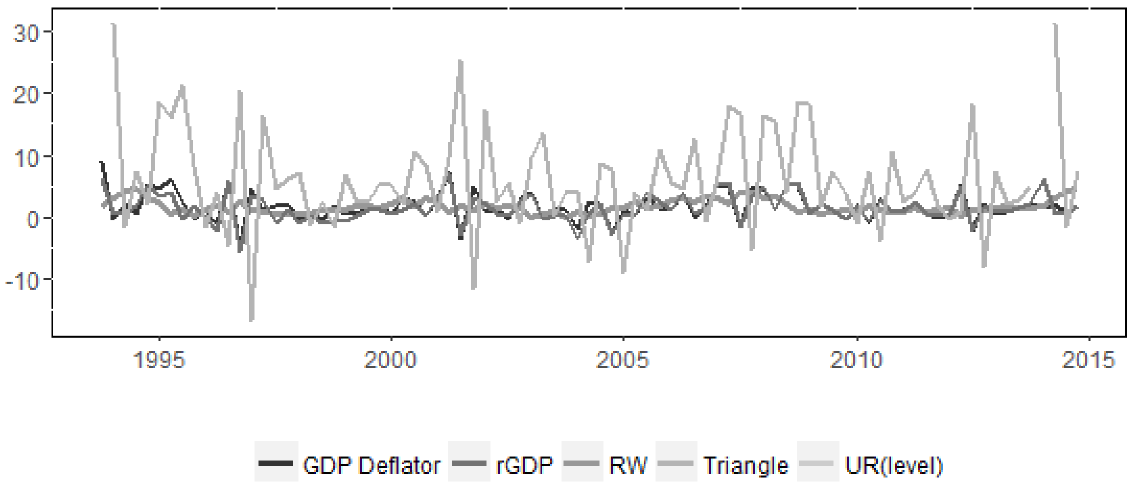
Figure A1: Actual and forecasts of 3 inflation measures



(a) Headline Inflation (CPI-all)



(b) Underlying Inflation (KPIX)



(c) GDP Deflator

Appendix 4. RMSEs for Inflation Forecasting Models

Table A1: RMSEs by Sub-Periods for CPI-all

Forecast Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Univariate models forecasts				
AO	1.44	1.16	2.06	1.64
AR(AIC)_roll	1.07	1.24	1.62	1.21
AR(1)_roll	1.76	2.04	2.16	1.45
AR(4)_roll	2.01	2.21	2.17	1.54
AR(BIC)_roll	1.79	2.14	2.22	1.47
AR(AIC)_rec	1.07	1.24	1.62	1.21
AR(1)_rec	1.71	1.91	2.13	1.47
AR(4)_rec	1.99	2.09	2.23	1.45
AR(BIC)_rec	1.71	2.03	2.17	1.48
MA(1)_roll	1.71	1.75	2.12	1.68
MA(1) coeff=.25	1.73	1.75	2.13	1.66
MA(1) coeff=.65	1.86	1.87	2.25	1.73
Single-predictor ADL forecasts				
UR(level)_roll	1.65	1.89	1.95	1.56
UR(diff)_roll	1.73	1.72	2.26	1.54
CU_roll	-	-	-	1.29
IP_roll	1.75	1.71	1.97	1.50
rGDP_roll	1.71	1.80	2.22	1.44
UR(level)_HP_roll	1.73	1.82	2.07	1.41
CU_HP_roll	-	-	-	1.44
IP__HP_roll	1.75	1.65	1.97	1.47
rGDP_HP_roll	1.72	1.68	1.77	1.60
UR(level)_BP_roll	1.66	1.77	1.71	1.33
CU_BP_roll	-	-	-	1.34
IP_BP_roll	2.01	1.59	2.07	1.50
rGDP__HP_roll	1.76	1.74	1.89	1.57
UR(level)_rec	1.64	1.71	2.05	1.64
UR(diff)_rec	1.69	1.66	2.16	1.71
CU_rec	-	-	-	1.34
IP_rec	1.70	1.71	2.03	1.65
rGDP_rec	1.68	1.72	2.07	1.65
UR(level)_HP_rec	1.71	1.76	2.04	1.56
CU_HP_rec	-	-	-	1.47
IP__HP_rec	1.70	1.73	2.05	1.63
rGDP__HP_rec	1.71	1.69	1.98	1.70
UR(level)_BP_rec	1.62	1.71	1.92	1.53
CU_BP_rec	-	-	-	1.46
IP_BP_rec	1.82	1.60	2.08	1.69
rGDP__BP_rec	1.70	1.71	2.03	1.68
Triangle models forecasts				
Triangle	6.36	6.97	7.52	6.40
Triangle (no z)	1.83	1.84	2.37	1.96

Table A2: RMSEs by Sub-Periods for KPIX

Forecast Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Univariate models forecasts				
RW	0.30	0.53	1.43	1.69
AR(AIC)_roll	1.11	1.33	1.59	1.60
AR(1)_roll	0.66	0.60	1.12	1.40
AR(4)_roll	0.72	0.67	1.14	1.37
AR(BIC)_roll	0.69	0.65	1.13	1.39
AR(AIC)_rec	0.28	0.55	1.14	1.32
AR(1)_rec	0.68	0.60	1.15	1.50
AR(4)_rec	0.74	0.66	1.19	1.50
AR(BIC)_rec	0.73	0.65	1.19	1.52
MA(1)_roll	0.53	0.57	1.14	1.43
MA(1) coeff=.25	0.58	0.66	1.14	1.49
MA(1) coeff=.65	0.84	0.94	1.28	1.70
Single-predictor ADL forecasts				
UR(level)_roll	0.50	0.61	1.09	1.27
UR(diff)_roll	0.51	0.60	1.12	1.41
CU_roll	-	-	-	1.32
IP_roll	0.50	0.55	1.11	1.34
rGDP_roll	0.49	0.56	1.05	1.35
UR(level)_HP_rol	0.50	0.60	1.10	1.33
CU_HP_roll	-	-	-	1.34
IP__HP_roll	0.51	0.56	1.10	1.33
rGDP_HP_roll	0.52	0.58	1.08	1.34
UR(level)_BP_roll	0.49	0.58	1.04	1.23
CU_BP_roll	-	-	-	1.22
IP_BP_roll	0.53	0.51	1.13	1.34
rGDP__HP_roll	0.48	0.60	1.08	1.34
UR(level)_rec	0.50	0.56	1.11	1.37
UR(diff)_rec	0.52	0.56	1.12	1.38
CU_rec	-	-	-	1.30
IP_rec	0.52	0.56	1.12	1.36
rGDP_rec	0.50	0.54	1.09	1.36
UR(level)_HP_rec	0.52	0.56	1.10	1.36
CU_HP_rec	-	-	-	1.34
IP__HP_rec	0.52	0.56	1.12	1.36
rGDP__HP_rec	0.55	0.54	1.12	1.38
UR(level)_BP_rec	0.50	0.56	1.10	1.33
CU_BP_rec	-	-	-	1.32
IP_BP_rec	0.53	0.49	1.12	1.35
rGDP__BP_rec	0.51	0.56	1.12	1.37
Triangle models forecasts				
Triangle	2.21	2.05	4.51	4.56
Triangle (no z)	0.51	0.58	1.44	1.71

Table A3: RMSEs by Sub-Periods for GDP Deflator

Forecast Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Univariate models forecasts				
RW	1.66	1.07	1.25	0.99
AR(AIC)_roll	4.41	3.93	4.02	3.26
AR(1)_roll	4.51	3.81	3.06	2.85
AR(4)_roll	5.06	4.09	4.12	3.30
AR(BIC)_roll	4.75	4.00	4.12	3.30
AR(AIC)_rec	4.39	3.55	3.24	2.87
AR(1)_rec	4.55	3.49	2.87	2.77
AR(4)_rec	4.92	3.68	3.27	2.97
AR(BIC)_rec	4.55	3.59	3.14	2.82
MA(1)_roll	3.07	2.41	2.53	1.75
MA(1) coeff=.25	3.06	2.42	2.52	1.76
MA(1) coeff=.65	3.12	2.51	2.57	1.84
Single-predictor ADL forecasts				
UR(level)_roll	2.93	2.35	2.55	1.64
UR(diff)_roll	3.14	2.26	2.93	1.90
CU_roll	-	-	-	1.83
IP_roll	3.09	2.29	2.49	1.66
rGDP_roll	2.99	2.24	2.69	1.66
UR(level)_HP_roll	2.96	2.35	2.56	1.66
CU_HP_roll	-	-	-	1.84
IP__HP_roll	3.07	2.30	2.50	1.68
rGDP_HP_roll	3.16	2.56	2.47	1.66
UR(level)_BP_roll	2.94	2.28	2.44	1.66
CU_BP_roll	-	-	-	1.74
IP_BP_roll	3.01	2.32	2.31	1.83
rGDP__HP_roll	2.93	2.34	2.52	1.70
UR(level)_rec	3.14	2.34	2.64	1.76
UR(diff)_rec	-	-	-	1.81
CU_rec	3.09	2.29	2.53	1.78
IP_rec	2.96	2.37	2.52	1.74
rGDP_rec	2.96	2.42	2.52	1.70
UR(level)_HP_rec	-	-	-	1.87
CU_HP_rec	3.08	2.29	2.52	1.83
IP__HP_rec	3.11	2.45	2.56	1.74
rGDP__HP_rec	2.94	2.32	2.46	1.70
UR(level)_BP_rec	-	-	-	1.59
CU_BP_rec	3.03	2.33	2.41	1.78
IP_BP_rec	3.09	2.35	2.53	1.73
rGDP__BP_rec	3.07	2.31	2.48	1.66
Triangle models forecasts				
Triangle	11.92	8.65	9.10	6.96
Triangle (no z)	3.15	2.27	2.40	1.78

Appendix 5: Results from ADL forecasts with different lags

The first number in under column lags represents the lag number for inflation, while the second number after the comma is the lag number for the activity variable that varies across models.

UR(level)

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	1.56	1.86	1.91	1.78
1,2	1.57	1.87	1.85	1.83
1,3	1.56	1.81	1.84	1.83
1,4	1.65	1.70	1.86	1.84
2,1	1.57	1.87	1.87	1.75
2,2	1.57	1.88	1.83	1.78
3,1	1.60	1.81	1.84	1.77
3,3	1.58	1.89	1.73	1.82
4,1	1.58	1.79	1.76	1.75
4,4	1.61	1.86	1.65	1.82

UR(diff)

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	1.63	1.68	2.23	1.78
1,2	1.70	1.64	2.24	1.72
1,3	1.72	1.72	1.72	1.72
1,4	1.80	1.66	2.19	2.00
2,1	1.66	1.68	2.20	1.74
2,2	1.70	1.65	2.21	1.69
3,1	1.72	1.67	2.14	1.85
3,3	1.76	1.60	2.09	2.08
4,1	1.70	1.66	2.06	1.88
4,4	1.74	1.64	2.05	2.42

UR-HP

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	1.67	1.79	2.04	1.67
1,2	1.72	1.82	1.89	1.73
1,3	1.77	1.84	1.86	1.75
1,4	1.86	1.66	1.91	1.78
2,1	1.71	1.79	1.98	1.64
2,2	1.73	1.82	1.86	1.70
3,1	1.76	1.72	1.91	1.64
3,3	1.75	1.91	1.76	1.76
4,1	1.78	1.69	1.81	1.63
4,4	1.84	1.81	1.74	1.71

CU

RMSE of RW	**1.64**
Period	**2009Q1-2013Q4**
Lags	
1,1	1.57
1,2	1.61
1,3	1.73
1,4	1.79
2,1	1.55
2,2	1.68
3,1	1.56
3,3	2.13
4,1	1.57
4,4	2.33

CU-HP

RMSE of RW	**1.64**
Period	**2009Q1-2013Q4**
Lags	
1,1	1.69
1,2	1.55
1,3	1.64
1,4	1.51
2,1	1.67
2,2	1.53
3,1	1.73
3,3	1.82
4,1	1.71
4,4	1.67

IP

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	1.59	1.61	1.83	1.68
1,2	1.66	1.55	1.76	1.66
1,3	1.60	1.62	1.81	1.68
1,4	1.86	1.78	1.67	1.63
2,1	1.60	1.62	1.81	1.68
2,2	1.67	1.56	1.73	1.66
3,1	1.61	1.62	1.79	1.69
3,3	1.82	1.82	1.69	1.68
4,1	1.57	1.66	1.72	1.67
4,4	1.87	1.80	1.57	1.62

IP-HP

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	1.54	1.76	1.97	1.54
1,2	1.57	1.60	1.89	1.45
1,3	1.73	1.86	1.84	1.43
1,4	1.98	1.81	1.77	1.39
2,1	1.55	1.72	1.91	1.52
2,2	1.58	1.60	1.85	1.44
3,1	1.60	1.74	1.86	1.57
3,3	1.77	1.86	1.76	1.50
4,1	1.62	1.73	1.78	1.59
4,4	1.93	1.85	1.65	1.46

rGDP

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	2.15	1.88	2.20	1.95
1,2	2.29	1.90	2.34	1.98
1,3	3.11	2.01	2.49	2.11
1,4	3.33	1.82	2.51	2.21
2,1	2.31	1.87	2.13	2.04
2,2	2.29	1.91	2.31	1.97
3,1	2.54	1.89	2.06	2.15
3,3	3.14	2.06	2.40	2.10
4,1	2.67	1.86	1.98	2.34
4,4	3.47	1.95	2.40	2.24

rGDP-HP

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags				
1,1	1.60	1.96	1.95	1.72
1,2	1.61	1.85	1.72	1.75
1,3	2.00	1.69	1.65	1.65
1,4	2.08	1.54	1.60	1.52
2,1	1.62	1.94	1.92	1.71
2,2	1.61	1.86	1.68	1.74
3,1	1.67	1.82	1.88	1.75
3,3	2.03	1.72	1.64	1.65
4,1	1.66	1.78	1.79	1.69
4,4	2.05	1.67	1.60	1.45

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