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Kontakt/Contact
ZBW – Leibniz-Informationszentrum Wirtschaft/Leibniz Information Centre for Economics
Düsternbrooker Weg 120
24105 Kiel (Germany)
E-Mail: *rights[at]zbw.eu*
https://www.zbw.eu/econis-archiv/

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FORECASTING INFLATION USING THE PHILLIPS CURVE: EVIDENCE FROM SWEDISH DATA

Diana Gabrielyan

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FORECASTING INFLATION USING THE PHILLIPS CURVE: EVIDENCE FROM SWEDISH DATA

Diana Gabrielyan[1]

Abstract

This paper studies the forecasting ability of various Phillips curve specifications in a pseudo out-of-sample exercise for 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 of model instability, in general, the Phillips curve models improve inflation forecasts against 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 2004–2013. The monetary regime change in 1993 from exchange rate targeting to inflation targeting is also taken into account. The results suggest that for all Phillips curve models and all three inflation measures, the performance of the Phillips curve depends on whether the data used for making the predictions was under the inflation targeting regime or not. Univariate forecasting models perform well for the fixed exchange rate regime period, but the Phillips curve models are useful under the inflation targeting regime.

JEL Classification: E31, E37, C53, E58

Keywords: forecasting, inflation, Phillips curve, Sweden

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[1], PhD student, University of Tartu, Faculty of Social Sciences, School of Economics and Business Administration. Email: gabrielyandiana@yahoo.com.
The paper is based on my master thesis. I would first like to thank my supervisors Lenno Uusküla and Jaan Masso for their direction and relentless support during the process of writing this master thesis. They consistently allowed this paper to be my own work, but steered me in the right direction whenever I needed it. Furthermore, I would like to thank, Sulev Pert, Nicolas Reigl, Jaanika Meriküll, Lucie Tomanova and Robin Hazlehurst, for useful comments on earlier versions. The doors to their offices were always open whenever I ran into trouble or had a question about my research or writing. The paper has also benefited from comments received at a presentation at the Bank of Estonia. Still, I take the whole responsibility for all remaining errors and omissions.

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; Svensson, 2005). The Phillips curve is an important concept in economics that originally related the unemployment rate with the inflation rate (Phillips, 1958). Later, it has been extended to describe the relationship of past, present and future inflation with economic aggregates. It remains one of the major cornerstones in macroeconomic analysis. The implications of Phillips curve based inflation forecasting models for the use of policy analysis and macroeconomic modelling have always been of great interest.

Sweden is an interesting case for studying the behaviour of the Phillips curve in inflation forecasting because it has had different monetary regimes. Sweden had a fixed exchange from 1973 until 1992: during this period the krona adhered to various fixed exchange rate arrangements, including the unilateral ECU peg from May 1991 till the collapse of the fixed exchange rate system (Berg, 1999). On 15 January 1993, the Sveriges Riksbank 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, the time-series for studying the usefulness of the Phillips curve in inflation forecasting is one of the longest and it is possible to analyse whether the inflation process has changed since the introduction of the inflation target. Therefore, this paper focuses on the quarterly Swedish inflation rate for three decades from 1984 until 2014. This makes it possible to contribute to the discussion on how the performance of Phillips curves change with the adoption of inflation targeting. The performance is examined by focusing on different sample periods and predictor/activity variables. Existing research on open economy offers very little in the way of studies of the changes that monetary policy changes can bring. This paper discusses the effects of monetary regime change on the forecasting power of Phillips curves, in this way, adding to previous empirical work on forecasting inflation when considering a change in monetary policy due to the adoption of inflation targeting. 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 (Cúrdia and Finnocchiaro, 2010).

This paper investigates the forecasting ability of the Phillips curve for three different inflation measures in Sweden: headline inflation (CPI-all), underlying inflation (KPIX[2]) and GDP deflator inflation, contributing to the literature analysing which inflation measure the Phillips curve can help forecast the best. For instance, when forecasting underlying inflation measures the models have the best forecasting power compared to headline inflation and GDP deflator inflation. This is in line with the theory, which suggests that underlying inflation is easier to forecast. Contrary to much of the previous literature, I find that the forecasts for GDP deflator have the worst forecasting accuracy. For example, the results from Banbura and Mirza (2013) support the theory, since their forecasts for GDP deflator have the lowest RMSFEs, and therefore, are more accurate.

Moreover the paper employs a wide set of economic activity measures including unemployment, GDP, capacity utilization rate, index of industrial production and various measures of gap. To evaluate the usefulness of the Phillips curve, the accuracy of the inflation forecasts for every model at a one-year (or four-quarter) forecast horizon is compared to that of the naïve benchmark model proposed by Atkenson and Ohanian (2001). Altogether the paper examines the performance of 114 pseudo out-of-sample forecasting procedures. The empirical strategy adopted follows closely the 2009 paper by Stock and Watson, with slight changes to models and variables. For example, in addition to headline inflation, underlying inflation and GDP deflator, Stock and Watson (2009) 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.

Although in general the performance is not overwhelming, Phillips curve based forecasts do still contain some useful information about inflation, especially compared to other forecasting approaches. This improvement, although small, is still valuable for improving inflation

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

predictions. 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 challenge that with evidence stating that the importance of Phillips curves is overrated and that these curves are not useful for forecasting. For instance, Atkenson and Ohanian (2001) find that Phillips curve based forecasters are regularly outperformed by a naïve random walk benchmark. Matheson (2008) gets 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).

The paper proceeds as follows. Section 2 provides an overview of the related literature. Section 3 describes the models used in the forecast evaluation and the methods. Section 4 describes the data, while 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 the Phillips curve. Many papers, including several seminal papers use US data. There is considerably less work available on the euro area countries and small open economies. Stock and Watson (2008), Faust and Wright (2012), and Banbura and Mirza (2013) provide extensive literature surveys. This paper reviews the most important strands within the topic.

The first strand focuses on the studies of forecasting inflation and evaluating a wide range of model specifications. Gordon (1982, 1990) was one of the first researchers to study Phillips curves. His new interpretation of the curve, the triangle model (Gordon, 1977), referred to the three determinants of the inflation rate, which are inertia, demand and supply. The triangle model was useful in forecasting the decline in inflation during the business slump of the early 1980s. The good performance of the triangle model using US data was also documented by

Stockton and Glassman (1987). The study of inflation forecasting using the Phillips curve by Stock and Watson (1999) is one of the best-known papers on the topic. They find that Phillips curve models outperform univariate benchmark models in predicting US inflation four quarters ahead using recursive forecasts. Still, a number of papers from the 1990s questioned the usefulness of activity-based inflation forecasts relative to univariate benchmarks (Stock and Watson 2008). Atkenson and Ohanian (AO) (2001) summarize the results in the literature of the 1990s. Their study critically evaluates the belief that Phillips curve based models are a useful tool for forecasting inflation and find that the Phillips curve could not improve on the forecasts by their proposed random walk model. On the other hand, findings by Fisher et al. (2002) suggest that the performance of the Phillips curve is sensitive to the sample period, forecasting horizon, as well as the inflation measure chosen. More recent works by Stock and Watson (2009 and 2010) support the conclusion by Fisher et al. (2002) for the US.

The second strand of the literature review focuses on papers that account for the potential instability in the Phillips curve relationship (Canova, 2007; Musso, Stracca, and van Dijk, 2009). These papers document various forms of variation in the coefficients of the Phillips curve, such as the mean and the slope of the euro area Phillips curve. They therefore focus on inflation forecasting using different policy regimes, inflation levels and volatilities. Musso et al. (2009) observe a time variation in the coefficients of the euro area Phillips curve and find that for the euro area the Phillips curve is a "line". The authors propose employing a smooth transition model. By contrast, O'Reilly and Whelan (2005) find the reduced form Phillips curve coefficients to be stable, particularly those related to inflation persistence. Blix (1999) proposes VAR with Markov switching for the Swedish inflation process considering both high and low inflation regimes. This allows for downward shift in inflation, which causes a mean-reversion. This mean reversion is the reason behind the model's failure in giving accurate forecasts. By taking into account the credibility factor; that is, the probability of remaining in the low inflation regime, it becomes possible to observe how the credibility factor affects the inflation forecast. Consequently, the inflation forecasts become model-consistent and produce plausible forecasts one or two years ahead.

Highly relevant for the current paper is the part of the literature that evaluates the three measures of inflation and compares forecasts of different inflation measures. These measures are headline inflation or CPI-all, underlying inflation or CPI-core and GDP Deflator inflation. Stock and Watson (2009) use quarterly US data on 157 distinct models and 35 combination forecasts and apply them to forecast the CPI-all, CPI-core, personal consumption expenditure (PCE-all), PCE-core, and GDP deflator. Their results indicate that for some periods and inflation measures, the Phillips curve models perform quite well, while for others they do not. Banbura and Mirza (2013) evaluate the forecasts for the harmonized index of consumer prices (HICP), GDP deflator and long-run inflation expectations for HICP. They find that the forecasts are best for headline inflation and GDP deflator for one sample period, while they are better for the HICP excluding food and energy in another period.

As already mentioned, the strand of literature on euro data and on small open economies is considerably thinner. Runstler (2002), Hubrich (2005), Canova (2007), Marcellino and Musso (2010), Buelens (2012), and Banbura and Mirza (2013) study out-of-sample forecasting performance for the euro area. 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) and shows that the multivariate models that are suggested by 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 coefficient 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 analysing data from Germany, the UK and the US. Matheson (2006) assesses whether the good findings by Stock and Watson (1999) extends to open economies like Australia and New Zealand, and find that the open economy Phillips curve performs poorly relative to the naïve autoregressive benchmark. However, when the forecasts from Phillips curves for both non-tradable and tradable sectors are combined, this highly increases the forecasting power of the Phillips curve.

Finally, this paper also relates to the literature that studies the different activity variables used for measuring the Phillips curve. Stock and Watson (1999) use various activity variables and find that a combination of forecasts in general perform better than 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. Later studies by Stock and Watson (2003) and Brave and Fisher (2004) extend the analysis to additional activity predictors and confirm the dominance of the benchmark model. Dotsey and Stark (2005) find that the decreases in capacity utilisation fail to add any forecasting power to combination forecasts. Stock and Watson (2008) argue that Phillips curve forecasts using an activity variable are better than other multivariate forecasts, but their performance is episodic. They find that large deviations of the unemployment gap are associated with good performance of Phillips curve-based forecasts. Matheson (2006) finds that for Australia and New Zealand, the diffusion index, combining a large number of indicators of real economic activity, has better forecasting performance than more conventional measures of real demand; therefore, supporting the findings by Stock and Watson (1999). Stock and Watson (2009) also show that relevant activity variables seem to change over time, and therefore, the forecast combinations from different models tend to give better forecasts than the individual model predictions.

3. METHOD

This section presents the models used for forecasting inflation and the estimation methods. The paper concentrates on studying the ability of single-predictor based Phillips curve models and triangle models with a supply shock variable to forecast inflation. I compare the Phillips curve forecasting results with various univariate models based on past inflation, such as autoregressive (AR), moving average (MA) and random walk (RW) models. The selection of models follows the paper by Stock and Watson (2009).

For a benchmark, I use various ARIMA models and the random walk model of Atkenson and Ohanian (2001). The first of these 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):

$$\pi_{t+h}^{h} - \pi_t = \mu^h + \alpha^h(L) \times \Delta\pi_t + v_{t+h}^{h}, \quad (1)$$

where μ^h is a constant, $\alpha^h(L)$ is a polynomial in the lag operator, and v_{t+h}^{h} denotes the h-quarter ahead forecasting error term. The number of lags is chosen according to the Akaike information criterion (AIC) over the range of 1 to 6 six quarters.

The second model, as the naïve no change benchmark, is the Atkenson and Ohanian *random walk model*. Here the forecast of inflation for the next four quarters π_{t+4}^4 is equal to the average rate of inflation over the previous four quarters (π_t^4). The model is defined by:

$$\pi_{t+4|4}^4 = \pi_t^4 + v_{t+4}^4 \quad \text{or} \quad \pi_{t+4|4}^4 - \pi_t^4 = v_{t+4}^4, \qquad (2)$$

where, v_{t+4}^4 is again the four-step ahead error term, for simplicity, $\pi_t = \pi_t^1$ and $\pi_t^4 = \frac{1}{4} \times (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})$.

As argued by Atkenson and Ohanian (2001), the random walk model is a good benchmark not because 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 forecasts are no more accurate than a simple atheoretical no change forecast.

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

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 as:

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

Where x_t is an activity variable such as the unemployment rate, output, capacity utilisation rate, index of industrial production index, as well as their corresponding gaps (see Appendix 1). The degrees of lag polynomials $\alpha^h(L)$ and $\beta^h(L)$ are chosen separately using both the

Akaike information criterion and the Bayes information criterion (BIC) over the range of one to four lags.

In the triangle model from Gordon (1990), in addition to the Phillips curve relationship, inflation also depends on supply side controls. Therefore, the inflation in this version of Phillips curve model is determined by lagged inflation, the unemployment rate, and the supply shock variables z_t:

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

where z_t captures supply side shocks (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 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) using the forecasted values of predictors that are computed using univariate AR (8) models of x_t and z_t.

This study focuses on one-year horizon forecasts, or in other words four-period ahead forecasts (*h = 4)*. Inflation for *h*-period 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, where $\pi_t = 400 \times ln(P_t/P_{t-1})$, with P_t being the price index in the 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 paper direct forecasts are also considered; that is, the forecasts are made using a horizon-specific estimated model, where the dependent variable is the multi-period ahead value being forecasted.

For the pseudo out-of-sample forecasts, the sample is divided into an evaluation sample and a forecasting sample. The evaluation sample is used to estimate the model and the fit of the forecast is evaluated using the forecasting sample. For benchmark results, I use the rolling window strategy 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 are re-estimated with one more observation added to the end and one subtracted from the beginning of the estimation sample, 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 in time. The number of recent observations used in the estimation is referred to as the window size. This approach stands in contrast to the recursive or expanding window strategy, which is used in robustness analysis. In the case of the recursive model, the sample always starts with the same observation and observations are added at the end of the sample.

In this study, the period 1984–1994 was used for the initial parameter estimation. The forecast period 1984–2014 was split into the four periods. The 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 the case of the rolling estimation, the window size is essential for reliable estimations, 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, 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 between the rolling window and the recursive techniques is the start period for the estimation: in the case of the 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 when there are fewer than 20 observations left in the calculation, these periods are omitted from the evaluation. Likewise, the latest year (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 the shorter time series available for Sweden, and also because of the different business cycles for Sweden, the five-year periods capture them better. Therefore, the chosen forecast estimation periods correspond to different business cycles and are different in terms of their inflation dynamics. For instance, the period 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.

The Root Mean Squared Error (RMSE) 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 period for which forecasts are constructed. The RMSE is given using:

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

where $\pi_{t+h\,|\,t}^{h}$ is the forecasted value of π_{t+h}^{h} 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 RMSE for 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 quarters, 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 on average to 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 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 abovementioned 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).

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. Inflation between the 1970s and 1980s was high compared to the main trading partners (Berg, 1999). This led to a devaluation of the krona to compensate for the high inflation. 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 to 2 per cent by 1992. The Swedish banking system experienced 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 inflation target was set at 2 per cent, meaning the annual rise in the CPI should be 2 per cent. The abandonment of a fixed exchange rate led to a sharp depreciation in the value of the krona against other currencies, and a number of changes to indirect taxes. This led to inflationary impulses, and therefore, the Riksbank stated that the target for monetary policy would not begin to apply until 1995.

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

Forecasts of three measures of inflation are examined: headline inflation (CPI-all), underlying or core inflation (KPIX, previously CPIX[3]), and the GDP deflator. The sample covers 1980Q1 to 2014Q4 for CPI Inflation and KPIX, 1981Q2 to 2014Q4 for the GDP deflator. The GDP deflator is a price index that measures inflation or deflation in an economy and is calculated by dividing the GDP in the current local currency by the GDP in the constant local currency. GDP deflator inflation is calculated using the annual growth rate of the GDP implicit deflator. The inflation series of these three measures are plotted in Figure 1. As can be seen, inflation has

[3] 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.

declined in recent years, becoming more or less closely aligned to the Riksbank's stability promise. In this study seasonally adjusted quarterly data for Sweden are used. Monthly data are converted to quarterly data by taking the average of the three months.

Measures of the economic activity are unemployment rate (UR), capacity utilization rate (CU), real GDP (rGDP) and index of industrial production (IP). The details for these activity variables are given in Appendix 1.

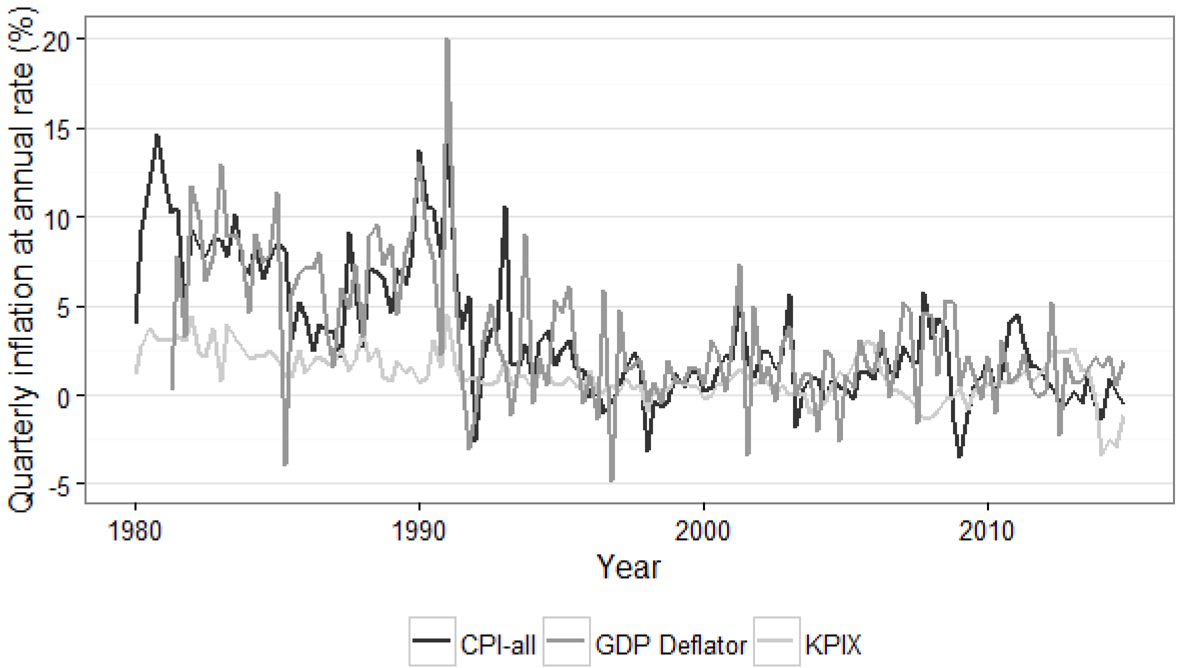

Figure 1: Inflation Series 1980 – 2014

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 by order 1, but rather there is going to be a mixture of stationary and non-stationary variables. In the case of the stationary series, the level of the variable is used, while in the non-stationary case the first difference is taken. This holds, for example, for the 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 the usefulness of Philips curves. 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 for central banks, as they are indicators of the degree inflation pressure in the economy.

The gaps used in the forecasting models are all one-sided and are constructed using both band-pass (BP) and Hedrick Prescott (HP) filters. The 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 potential, resulting in incorrect 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 depending on the parameters, they may suggest a smaller number of cycles compared to the HP filter. As neither of the statistical filters presents a totally robust gap measure, both filters are used in this study.

The set of variables is similar to other papers. 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; for example, 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).

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).

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

5. RESULTS

In this section 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). The pseudo out-of-sample for forecasting the performance of CPI-all inflation is summarized in Table 1 below for relative RMSE. The first rows in tables 1–3 contain a 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. The second row illustrates the absolute root mean square errors for the random walk benchmark model for each evaluation period. Starting from the fourth row, the numbers show root mean square errors (RMSE) relative to the 'best' benchmark model. The RMSE in each model is computed using equation (5). When relative RMSE is equal to unity, it means the performance of the inflation forecast model being compared is as good as that of the RW model. When it is greater than unity, it means the RW model performs better than the model being compared, and a value below one means the RW model performs worse. In each table the relative RMSE shown in bold font highlights the models that beat the naïve benchmark and are best for forecasting inflation in Sweden for a four-quarter horizon.

To demonstrate the forecasting ability of simple models, I initially compare it to eleven other univariate forecasts ranging from AR to MA(1). Out of all of these approaches the best inflation forecasts for Sweden for the full sample are generated by the RW model, and the other univariate models on average are not able to beat the random walk approach. There is not a single model that has unambiguously 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 do not exceed 0.79. In general, the performance of these univariate models is specific to particular series and periods. Therefore, the performance of the Phillips curve models will 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 per cent worse. This can be explained by the introduction of the inflation targeting regime, since the headline inflation only started to go towards the 2 per cent inflation target 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 by volatile inflation rates caused by the recent financial crisis. During the last sub-period, the majority of the models beat the RW. Those that fail to beat it (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, they functioned almost as well. 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).

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

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 the supply side variable, performs quite poorly, showing very poor forecasting accuracy, with high RMSEs and predicted values being far from the realized values, especially when compared to the model without oil prices. The conclusion here is that oil prices are not at all helpful in forecasting Swedish inflation. This can be due to the high energy efficiency of the Swedish economy. Moreover, this is in line with the findings of Stock and Watson (1999). They 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." (Stock and Watson, 1999 p.3) 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.

In the 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 the RW, the relative RMSEs range from 1.01 to 1.09, which shows that the models still do a good job of predicting inflation. All of the Phillip's curve forecasts (except triangle models that include oil prices) appear to be rather good. The relative RMSEs are less than that of the 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 in indirect taxes and subsidies are excluded.

As in the case of headline inflation, here again, when using the data under a 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 is used for the predictions after the introduction of inflation targeting regime, then the Phillips curve based models outperform the naïve benchmark. In contrast to the first two periods, the results for the last two sub-periods are positive, where the best Phillips curve forecast (assessed by the lowest RMSEs) for underlying inflation in Sweden uses GDP growth, unemployment and capacity utilization gaps.

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 the 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 also have very high RMSE indicating poor forecasting ability. The results are especially bad for the periods 1999–2003 and 2004–2008. The RMSEs for forecasts of GDP inflation increased from the first period (1994–1998) to the second period (1999–2003) and the magnitude of this increase is striking. For instance, for 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 the Phillips curve forecasts is found for almost all the activity predictors.

The 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 the triangle model for the period 2009–2013 is 7.03, while for KPIX it is 2.69 and for CPI-all 3.90. This is surprising, given that one of the differences between the CPI and GDP deflator is that the GDP deflator reflects the prices of all goods and services produced domestically, whereas the CPI reflects 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 result, oil prices form a 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 the GDP deflator is usually less volatile than, for example, the headline inflation. Therefore, the results in Table 3 can be explained by the unexpectedly volatile GDP deflator inflation rates. What this implies is 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 Phillips curves disappointing, relative even to simple alternatives such the random walk benchmark; therefore, providing little evidence of the usefulness of Phillips curves for GDP deflator forecasting and leading to a negative assessment of my empirical models for the 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 the empirical results. First of all, it is clear that there is a great time variation in the inflation process and the predictive ability using both univariate and multivariate Phillips curve models. The variability in performance is sometimes quite large. Across a range of Phillips curve models and using 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 findings from Atkenson and Ohanian (2001) and Stock and Watson (2009) and the literature in general, in which different authors reach different conclusions about the performance of the Phillips curve depending on the sample period.

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

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 in the former case. 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 oil prices is much higher than the model that does not include the supply shock variable in the model for predicting one year ahead inflation.

6. ROBUSTNESS RESULTS

In Stock and Watson (2008), the lag lengths are chosen using the AIC and BIC. In the case of Swedish data, both the AIC and BIC selects too many lags for the Phillips curve models, which results in over-fitting. Although AIC beats BIC yielding smaller RMSEs on average, both information criteria fail to choose the best model. For Swedish data, the models were fitted with different lags, and the forecasts from the models estimated with only one lag were found on average to yield smaller RMSEs. Appendix 4 presents the results from the 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 using a rolling window approach and expanding window approach. The results in the tables suggest that models estimated using the expanding window approach give better results in the case of KPIX, while in the case of CPI-all and GDP deflator, the rolling estimation method turns out 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 the 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 the 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 the triangle model with oil prices as a supply shock variable.) This brings the hypothesis that maybe, in addition to contributing to price stability, one additional benefit of the inflation targeting regime is better forecasts of inflation using the Phillips curve in an open economy like Sweden, which itself indirectly contributes to a better performing monetary policy.

7. CONCLUSIONS

In this paper I have evaluated the 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 prices as a supply shock variable, the other without a supply shock variable. The main results suggest model heterogeneity and varying results across sample periods and models. 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 the case of the GDP deflator measure over the full sample. My findings support the usefulness of headline and underlying inflation measures in predicting inflation, but find little evidence on the usefulness of Phillips curves for GDP deflator inflation forecasting. Similar results reflecting the episodic performance of the Phillips curve for these inflation measures and activity variables are 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.

Furthermore, in this study I take into account the 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 the Phillips curve depends on whether the data used for making the predictions was under the inflation targeting regime or not. According to these findings, one may conclude that in a fixed exchange rate regime it is better to use univariate forecasting models than making multivariate forecasts, but if the central bank is explicitly targeting inflation, the Phillips curve can be useful for inflation forecasting.

The patterns, however, cannot yet be used to make definite conclusions. At the same time, this study may be useful 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 have experienced policy regime changes in the last thirty years that are well documented.

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APPENDICES

Appendix 1. Overview of 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: 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.

Table A4.1. UR(level)

RMSE of RW	**1.43**	**1.15**	**2.05**	**1.64**
Period	**1994Q1-1998Q4**	**1999Q1-2003Q4**	**2004Q1-2008Q4**	**2009Q1-2013Q4**
Lags of AR, lags of activity				
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

Table A4.2. 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

Table A4.3. 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

Table A4.4. 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

Table A4.5. 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

Table A4.6. 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

Table A4.7. 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

Table A4.8. 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

Table A4.9. 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

KOKKUVÕTE

Inflatsiooni ennustamine Philipsi kõveraga

Käesoleva artikli teemaks on erinevate Philipsi kõvera spetsifikatsioonide võime prognoosida inflatsiooni. Inflatsioon on üks olulisemaid makromajanduslikke näitajaid, niisiis on enamiku majandusotsuste tegemiseks nii riigi kui ka majapidamiste ja ettevõtete tasemele tarvilik omada hinnangut tulevase inflatsiooni kohta. Philipsi kõver iseloomustab ajaloolist vastassuunalist seost inflatsiooni ja tööpuuduse tasemete vahel, nt madal tööpuudus tingib kõrgemat inflatsiooni läbi töötajate palkade, ning Philipsi kõvera võimet tuleviku inflatsiooni prognoosida on kirjanduses laialt käsitletud. Töös kasutatakse antud eesmärgil Rootsi inflatsiooni andmeid perioodist 1980-2014. Rootsi on valitud analüüsitavaks riigiks, kuna analüüsitaval perioodil vaheldusid seal erinevad rahapoliitilised režiimid: kui kuni 1992 aastani kasutas Rootsi fikseeritud vahetuskurssi, siis peale seda lasti vahetuskurss vabaks ja rahapoliitikas on eesmärgiks olnud hinnastabiilsus läbi inflatsiooni eesmärgistamise (mõõduka suurusega positiivne inflatsioonimäär), Rootsi oli seejuures üks esimesi riike maailmas antud lähenemise kasutuselevõtmisel. Seeläbi on võimalik hinnata mudelite prognoosivõimet erinevate rahapoliitiliste režiimide tingimustes, mis on ka antud töö suurim uudsus võrreldes varasema kirjandusega. Mudelite prognoosivõimet hinnatakse pseudo valimiväliste prognooside täpsusega, s.t. osa andmete ajaperioodi kasutatakse mudelite hindamiseks ja neile järgnevat perioodi mudelite prognoosivõime testimiseks. Analüüsis kasutatakse kolme inflatsiooni mõõdikut – laiapõhjalist hinnaindeksi inflatsiooni (*headline inflation*), alusinflatsiooni (kus laiapõhjalisest inflatsioonist on välja jäetud majapidamiste kulutused eluasemelaenud intressimaksetele, samuti maksude ja toetuste muutuste mõju) ja SKP deflaatori inflatsiooni. Lisaks viimastele uuritakse tulemuste tundlikkust kaasates erinevaid majandusaktiivsuse taseme mõõdikuid, erinevaid ökonomeetrilisi spetsifikatsioone ja analüüsides erinevaid valimi alamperioode. Nii kasutatakse ka erinevaid nö kolmnurga mudeleid (*triangle models*), kus inflatsiooni mõjutavad tegurid on grupeeritud kolme gruppi, need on inerts, nõudluspoolsed tegurid ja pakkumispoolsed tegurid.

Töö tulemused näitavad üldiselt erinevate mudelite prognoosivõime heterogeensust ja parim mudel varieerub üle ajaperioodide ja inflatsiooni näitajate. Siiski saab üldistada, et võrreldes võrdlusbaasiks oleva juhusliku ekslemise mudeliga ennustavad Philipsi kõveral põhinevad mudelid inflatsiooni paremini laiapõhjalise hinnaindeksi inflatsiooni ja alusinflatsiooni korral, kuid mitte SKP deflaatori inflatsiooni korral. Viimane tulemus on mõnevõrra üllatav, sest tavaliselt on SKP deflaator vähem muutlikum võrreldes laiapõhjalise hinnaindeksi inflatsiooniga. Sellised tulemused Philipsi kõvera kasulikkuse teatud episoodilisuse kohta on leitavad ka mujal teaduskirjanduses. Philipsi kõveral põhinevad ennustused on oluliselt täpsemad hilisemal 2004-2013 perioodil.

Uuringus vaadatakse ka, kuidas erinevate mudelite võime inflatsiooni prognoosida muutus seoses rahapoliitika režiimi vahetumisega 1993 aastal vahetuskursi eesmärgistamiselt inflatsiooni eesmärgistamisele. Tulemused näitasid, et just inflatsiooni eesmärgistamise režiimi korral võib Philipsi kõver olla kasulik inflatsiooni prognoosimiseks, samas kui fikseeritud vahetuskursi kasutamise korral on mõistlikum inflatsiooni prognoosimiseks kasutada ühedimensioonilisi mudelid võrreldes mitmedimensiooniliste mudelitega, s.t. inflatsiooni on eelistatum prognoosida inflatsiooni enda mineviku dünaamika alusel. Antud tulemused on olulised laiemas riikide kontekstis, kuna lisaks Rootsile ka paljud teised väikese avatud majandusega riigid (nt Austraalia, Uus-Meremaa, Ühendkuningriik) on viimase 30 aasta jooksul kogenud rahapoliitilise režiimi muutust.