Can Demographics improve the forecast accuracy of inflation? Evidence from United Kingdom.

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Abstract

This paper seeks to determine whether demographics can increase the forecasting accuracy of United Kingdom's inflation rate. Five forecasting models were employed, namely: the benchmark ARMA model, the SW (2002) model with and without a demographic factor and the FHLR(2003) model with and without a demographic factor. Both the out of sample and the in-sample forecast results indicates that, factor models with a demographic factor have a relatively lower RMSE than the corresponding models without demographic factor. And among the five models considered, the FHLR (2003) model has a lower RMSE relative to both the SW (2002) model and the ARMA model, while the SW (2002) model also has a lower RMSE relative to the ARMA model. The DM-test for equal forecasting accuracy indicates that the SW (2002) model with a demographic factor have a superior forecasting accuracy relative to the corresponding model without a demographic factor. Similar results were found with the FHLR (2003) model with and without a demographic factor. Thus, among the four factor models, the two models with a demographic factor systematically outperform the corresponding two models without a demographic factor.

Key words: Forecasting, Inflation, Demographics, $RMSE$, DM-test, Stock and Watson (2002), Forni et al (2003)

Contents

1 Introduction

Over the previous decades, inflation has been relatively more volatile than it is today. However, what has changed even more is the degree to which economists thought they understood the dynamics of inflation. Since modern monetary policy decisions taken by central banks are reliant on the expected movements of inflation, thus understanding the dynamics of inflation is very important for central banks in their pursuit for price stability. This led the Bank of England's monetary policy committee (MPC) to target annual inflation rate of the CPI at 2% (Bank of England inflation report, 2016). However, the MPC members do not always agree on every assumption on which their projections for inflation are based on as well as the uncertainties surrounding the projections (Bank of England inflation report, 2016). This is due to the fact that, the factors affecting inflation are many and while, requiring the Bank of England to monitor the trend of a large number of variables. However, while all these variables are available, most of the models used for forecasting inflation are univariate models, the Phillip's curve model and the vector autoregression model (VAR). All these models have one thing in common, they use only few of the variables that the central bank use in monitoring inflation. Thus, if the central bank can have one model, which account for all the variables they are monitoring, it could make their projections for inflation more credible and robust. Factor models can accommodate all the variables the Bank of England is monitoring. Factor analysis seeks to summarize a large number of time series variables into few factors without losing too much information from the original variables. This analysis has the ability to capture different shocks that affect the economy without over-parameterizing the model, which makes it superior relative to other approaches. This is evident in the studies done by Schumacher (2005), Cheung and Demers (2007), Lombardi and Maier (2011), Gillitzer and Kearns (2007), Stock and Watson (2006), Eickmeier and Ziegler (200), Faust and Wright (2009) to mention a few, all of whom found that, factor models outperform conventional models use in macroeconomic forecasting. However, despite its superior forecasting accuracy, some authors present evidence of conflicting results about the performance of static and dynamic factor models. For example, Cheung and Demers (2007) evaluated the forecast accuracy of both dynamic and static factor models for GDP growth rate and core inflation of Canada and found that static factor models outperform dynamic factor models for all forecast horizons considered. By contrast, Ginters (2010) and Forni et al (2014) both found that dynamic factor models outperform static factor models in forecasting. And, According to Stock and Watson (2003) dynamic factor models account for the co-movement of a large number of variables into few common factors which captures the evolving common shocks of the observed variables. Therefore, since none of the two models consistently outperform the other, both the Stock and Watson (2002) (SW) model and the Forni et al (2003) ($FHLR$) model are employed in determining the contribution of demographics in forecasting inflation.

The objective of this study is to determine whether demographics can increase the forecasting accuracy of inflation. The following five forecasting models are considered: The $ARMA$ model, the SW (2002) model with and without a demographic factor and the $FHLR$ (2003) model with and without a demographic factor. To determine which of the forecasting models best predicts UK inflation we rely on the Root Mean Square Error ($RMSE$) criterion and the Diebold and Mariano (1995) (DM) test for equal forecast accuracy.

This paper is related to previous works done by Stevenson (2013) and Lindh and Malmberg (2000) who used age structure in forecasting G7 and OECD inflation respectively. They found that a significant part of the variation in inflation is due to demographics. Similar results, were found by Juselius and Takats (2015) who use a panel data of 22 EU countries. According to their results one third of the variation in inflation can be attributed to demographics. However, this paper differs significantly in both substances and technique. In term of substances, this study also used the fertility rate and the gender composition of the UKpopulation. While in term of technique the related papers are based on panel studies and their study does not focus on UK.

The fertility rate in UK has been a major factor in influencing UK inflation for decades. As stated in the social security bulletin (1980), the UK government has increased children's allowances as a way to dampen wage demands and therefore reduce inflation. However, Rutter (2015) found that childcare cost is included in the calculation of CPI of UK and it has a weight of 0.12% as of 2014. This implies that the number of children per family can indirectly affect the inflation rate of the UK through child care expenditures. According to Kyriakopoulou (2014), the cost of raising a child in the UK has risen, and families now spend about 28 percent of their household income on raising their children. Similarly, Ben-Galim (2014) found that child care cost is increasing faster than the inflation rate. However, to the best my knowledge there are no other papers that allow inflation to be affected by the fertility rate. This motivates me to check whether including the fertility rate can increase the forecasting accuracy of the UK inflation rate.

The rest of the paper is set as follows, chapter 2 deals with theoretical and empirical literature. Chapter 3 deals with methodology of the study. Chapter 4 gives an interpretation and analysis of the results and Chapter 5 concludes.

2 Literature review

Several studies have been conducted in modelling macroeconomic variables with large number of variables within the past two decades, notable among them is forecasting the inflation rate. Most of the papers reviewed in this study either use the static factor model developed by SW (2002) or the dynamic factor model advanced by $FHLR$ (2003). In these models the co-movement of a group of variables are assumed to be driven by underlying latent factors. These factors are estimated from a set of variables using principal component analysis. According to Bai and Ng (2006), if the sample size is large enough the factors estimated by principal component analysis can be treated as known as $N \to \infty$.

SW (1989 and 1993) in modelling US inflation with macroeconomic variables extracted one principal component from a set of macroeconomic variables to represent their co-movement. The idea of using a single indicator to represent the co-movements of many macroeconomic variables dates back to Burns and Mitchell (1946). A similar approach was used by Quah and Sargent (1993) in modeling real GDP, the employment rate, industrial production and trade sales of the US real activity. They also extracted only a single factor yet, the R^2 was very large ranging from 73% to 92%. $FHLR$ (2014), Bai and Ng (2002 and 2015), Schumacher (2005), and Lombardi and Maier (2011) use a more elaborate approach and determined the number of principal components using the information criteria developed by Bai and Ng (2002).

A number of studies in modelling macroeconomic variables employed both static and dynamic factor models and have compared their forecasting accuracy to the benchmark univarite $ARMA$ model. Such studies were conducted by Marcellino, Stock and Watson (2000) in forecasting the inflation and real activity of the Euro zone using data from 1982 to 1997. The results indicate that factor models outperform both univariate and VAR models. Similar results were obtained by Cheung and Demers (2007), Zhao (2011), Dreger and Schumacher (2000), Kunovac (2007) and Schumacher (2005) who found that factor models has low forecast error compared to either the VAR or the AR model. Also, Lombardi and Maier (2011), $FHLR$ (2014) found that dynamic factor models outperform the univariate AR model but they are prone to large error variance.

Bai and Ng (2008) noted that dropping variables that have low correlation with the rest of the variables can increase the forecasting accuracy of the factor model. In line with this strategy, Figueiredo (2010) in forecasting Brazilian inflation with a large number of variables, dropped variables that had low correlation with the rest of the variables. This increases the Kaiser-Mayer-Olkin (KMO) value of sampling adequacy for factor analysis and minimizes the number of principal components. A similar strategy was used by Cheung and Demers (2007).

In evaluating the forecasting accuracy of the AR model against the factor augmented regression model, Gillitzer and Kearns (2007) use the ratio of $RMSE$ of each factor model relative to the benchmark AR model. A $RMSE$ ratio of less than one implies that factor models outperform the benchmark. Comparable techniques were used by SW (1998), and Gavin and Kliesen (2006). However, according to Woschnagg and Cipan (2004) one problem associated with the RMSE is that the loss function may vary over time. Thus, Schumacher (2005) and Zhao (2011) test for the equal forecasting accuracy using the DM-test. This test has the ability to compare different models from different time horizons and with different variables used in the forecasting models.

3.0 Methodology

In this chapter, the empirical methodology use in forecasting the inflation rate of UK is presented. As stated above, the objective of this paper is to determine, if demographics can improve the forecasting accuracy of inflation.

3.1 Factor augmented regression model

Inflation rate of a country is affected by many factors in an economy. Thus, modeling inflation with only its lags might not capture all the shocks that affect it. One possible solution is to add more variables in the model. However, this could cause degrees of freedom problems, while most of the variables added are correlated. Factor Augmented regression model can used the information embedded in these variables without running into degrees of freedom problems. The idea is that, large number of variables that can be used to forecast the inflation rate of a country are correlated and there are unobserved factors that capture the co-movement of these variables. These estimated factors capture the co-movement of the observed variables without losing too much information, and they can be used as leading indicators in forecasting inflation. The factors are augmented with the lags of inflation and the model can be estimated by Ordinary Least squares (OLS). The implication is that, the shocks that affect inflation are numerous and the lags of inflation cannot capture all of them. The factors which are generate from a large number of variables are used to capture the additional shocks that affect inflation but not captured by the lags of inflation. Factor augmented model comprise of two equations, the factor model and the forecasting model.

3.2 Factor Model

Factor analysis seeks to use the information in a large number of macroeconomic variables by summarizing them into a smaller number of estimated factors without losing too much information. In factor models, the observed variables are decomposed into two components: a common component and an idiosyncratic error component. The common component is the common variance shared by the observed variables, whiles the idiosyncratic error component is the shocks that are unique to each variable. The common component is what is estimated by principal component analysis to represent the observed variables.

Suppose the observed variables are, X_1,X_2, X_3,…., X_N, the latent factors are F_1, F_2, F_3,….. F_r and unique factors are ξ_1, ξ_2, $\xi_{3,}$…..,ξ_n. The factor model can be written as follows:

$$X_t = \Lambda F_t + \xi_t \tag{1}$$

where X_t is an $Nx1$ vector of observed variables. F_t is an $r\ x1$ vector of unobserved factors, Λ is an $N\ x\ r$ matrix of factor loadings, ΛF_t is the common component and ξ_t is an $Nx1$ vector of idiosyncratic error terms. The square of the factor loadings Λ^2 indicates the proportion of variance of the observed variables captured by the factors. The closer the value approaches 1 the better the factor structure. Thus, factor models reduce the dimension of the N observed variables into r factors, where $r < N$. In factor analysis, there are two types of factors, static factors and dynamic factors.

The above model is an example of a static factor model in which the factors does not evolve over time, by depending on their past shocks or history. It only allow factors to be contemporaneously related to the variables of interest. The factors and the idiosyncratic errors are orthogonal at all time periods. The main advantage of static factor models, is that, they are easy to construct and are favored more on practical grounds Boivin and Ng (2005).

The dynamic version of the static factor model in which factors evolve over time and respond to their previous shocks is given by:

$$X_{it} = \Lambda_i(L)F_t + \zeta_{it} \tag{2}$$

$Where\ X_{it}$, is an $N\ x\ 1$ vector of observed variables, $\Lambda(L)$ is a $q\ x\ M$ matrix of factor loading, F_t is an $M\ x\ q$ matrix of unobserved factors, $\Lambda(L)F$ is the common component, which have a distributive lag structure and ζ_t is a $M\ x\ 1$ vector of idiosyncratic error. It can be inferred that dynamic version of the static factors has a static illustration where, $\Lambda F_t = \lambda_i(L)f_t$. Therefore, a dynamic factor model with q factors should have $r = q(s+1)$ static factors. The estimated factors follow a time series dimension and can be model as time series variables. The dynamic factor models are useful in capturing the primitive shocks related to the observed variables.

3.3 The forecasting equation

The addition of the estimated factors to the otherwise standard regression model is what is called factor augmented regression model (the forecasting model). The factor augmented regression model is given by:

$$Y_{t+h} = \varphi + \theta' F_t + \beta' Y_t + v_{t+h} \tag{3}$$

Where the observed regressors are contained in Y_t and the unobserved regressors F_t are the common factors. One advantages of factor augmented model is that it summarizes and simplify the information in the large number of predictor variables.

The main challenge of factor analysis is the determination of the factors from the observed variables. Most researchers use the principal component method for extracting the components. This is because, after the maximum number of principal components have been extracted the remaining variance to account for is minimized. It is also convenient working with the eigenvalues and eigenvectors to determine the number of factors.

In theory N principal components must account for all the variation in the N variables. However, in practice researchers retain fewer than N principal components, as most of the variables largely loads on the first few common factors. This, is because one is interested in only the most important principal components since they account for the significant variation of the observed variables. The principal component estimator of the factors in F_t is given by:

$$\hat{F}_t = \frac{\hat{\Lambda}' X_t}{N} \tag{4}$$

Where $\hat{\Lambda}$ is a matrix of eigenvectors of the sample variance matrix of X_t. Principal components analysis and factors analysis are different, however, according to Bai and Ng (2006) the estimated factors can be treated as known provided that N and T are large enough.

Forecasting accuracy of factor models largely depends on controlling for the require number of factors. Since using less than required factors can render the model miss-specified, while over fitting the model could lead to increased variance. The benchmark approach used in determining the number of factors is the information criteria advanced by Bai and Ng (2002). The main advantage of this information criteria is that it does not depend on the choice of the number of factors, but through the variance, which is desirable in practice Bai and Ng (2002). The conventional information criteria such as AIC and BIC fails in large dimension data as the penalty terms are a function of both the sample size and the number of variables. It is also inappropriate to use AIC and BIC since the factors are estimated with error and these information criterion as design for variables not measured with error.

3.4 Techniques of Estimation

The inflation rate is modeled with 4 different factor augmented regression models. Since the objective is to determine whether demographics can increase the forecasting accuracy of inflation. First, static principal components are used to construct a factor augmented regression model with and without a demographic factor. Similarly, factor augmented regression models with dynamic principal components were also constructed with and without a demographic factor. This method will make it easy to determine whether demographic variables can increase the forecasting accuracy of inflation. The two factor augmented regression models with a demographic factor are also compared to the benchmark univarite AR model to determine the forecasting accuracy of the models.

3.5 Forecast evaluation

The in-sample and out of sample forecasting accuracy of all the five models were evaluated, using the $RMSE$ and the DM-test for equal forecasting error.

The $RMSE$ is defined as:

$$RMSE = \sqrt{\frac{1}{H}\sum_{i=1}^{H} e_{ti}^2} \qquad (5)$$

Where H is the sample size and e_t is the forecasting error. The $RMSE$ is used to compare the forecasting errors from different models. The lower the $RMSE$ of a model, the better the forecasting accuracy of that models.

3.6 Diebold and Mariano test

This test statistics has the ability to effectively compare the forecasting accuracy of models including different variables or factors. The test statistics is defined as the ratio of the sample mean loss from the forecast error to the standard error. The ratio is normally distributed in large samples. The DM test statistics is specified as follows:

$$DM = \frac{\bar{d}}{\sqrt{Var(\bar{d})}} \qquad (7)$$

$$\bar{d} = \frac{1}{H}\sum_{i=1}^{H}[g(e_{1i}) - g(e_{2i})]$$

Where (e_{ji}) is the loss from forecast error e_{ji} of model j and $j = 1, 2$.

3.7.0 Forecasting model specification

This sub-section explains how demographics enter the forecasting models adopted for this study. The specification will make it easy to isolate the contribution of demographics in the forecasting model.

3.7.1 Factor augmented Regression models

In this study the objective is to determine, if demographics can increase the forecasting accuracy of inflation. This is investigated by adopting the models developed by (SW) (2002) and ($FHLR$). (2003, 2005, and 2014). These models are a generalized version of the New Keynesian Phillips curve. It is worth mentioning that according to Wiederholt (2015) the New Keynesian Phillips curve is the most widely used by macroeconomists at central banks. It states that, current period inflation depends on the output gap and expectations of future inflation. Demographics enter this model through expectations of future inflation. Studies have shown that the demographic structure of a country has a significant effect on people's expectations about future inflation. One notable among such studies was done by Shirakawa (2012), in investigating the relationship between demographic change and macroeconomic performance. He found that an ageing population leads to deflationary pressures, especially if the retirement age is not increase, as people will start saving more for retirement. On the contrary, a youthful population is associated with high inflation as most of them will be experiencing their peak in spending, especially on mortgage. Therefore, in other to isolate the contribution of demographics in forecasting inflation, four factor augmented regression models and the univarite $ARMA$ model is employed. The four models are specified as:

$$Y_{t+h} = \gamma + \sigma\hat{F}_t + \rho(L)Y_t + \pi\widehat{Demo} + v_{t+h} \tag{8}$$

$$Y_{t+h} = \omega + \emptyset\hat{F}_t + \sigma(L)Y_t + v_{t+h} \tag{9}$$

$$Y_{t+h} = \varphi + \theta(L)\hat{F}_t + \beta(L)Y_t + \partial(L)\widehat{Demo} + v_{t+h} \tag{10}$$

$$Y_{t+h} = \vartheta + \delta(L)\hat{F}_t + \alpha(L)Y_t + v_{t+h} \tag{11}$$

Where Y_t is the variable of interest (inflation rate), $\hat{F}_t$ are the principal components or factors from the conventional determinants of inflation, $\beta(L)$ is the lag polynomials of Y_t and v_{t+h} is h steps ahead forecast error and $\widehat{Demo}$ is the demographic principal component or factor, which is extracted from a group of 19 demographic variables. The idea is that the other four factors are the conventional determinants of inflation, and the demographic factor enters as the fifth factor to determine whether it can increase the forecast accuracy of inflation. As indicated in the equation 8 (SW_1) and equation 10 ($FHLR_1$) are estimated with a demographic factor while equation 9 (SW_2) and equation 11 ($FHLR_2$) are estimated without a demographic factor. According to Boivin and Ng (2005) the forecasting accuracy of factors depend both on how the factors are extracted and how they are used in forecasting. Using both static and dynamic factor models will help in determining the most efficient model in isolating the impact of demographics in forecasting UK inflation rate. The number of dynamic factor are determined by the information criteria developed by Bai and Ng (2002), whiles the number of $ARMA$ terms are determine by Bayesian Information Criterion (BIC). The univariate model use as the benchmark model is specified as:

$$Y_{t+h} = \alpha + \delta(L)Y_t + v_{t+h} \tag{12}$$

4.0 Results

This section looks at the analysis and interpretation of the findings of this study. A summary of the data and its specifications are also presented.

4.1 Data

The data, use in extracting the factors and forecasting inflation is divided into 5 groups. The productive sector variables, this is the output related sector of the UK economy, It is based on the national accounts and includes variables related to domestic productivity of the economy. External Sector variables, this is the part of the UK economy that deals with the economies of the rest of the world. It includes variables from all the countries whose trade with the UK is 5% or more of the UK Gross Domestic Product (GDP). The variables considered here are mainly, inflation rate, exchange rate, the average inflation rate of the G20 countries etc. Fiscal Policy variables capture the UK government spending and taxes that are used to influence their economy and notable among is the inflation rate. Monetary Policy variables, are the variables that are related to the Bank of England's management of interest rate and money supply in an attempt to influencing Economic growth, inflation rate etc. Demographics entails variables related to the amount and the features of the total population of the UK. It includes variables such as age, sex, economic status etc. The total number of variable I started with in each group were: The monetary policy group 21 variables, the productive sector accounts for 25 variables, the external sector variables consist of 21 variables, fiscal policy variables were 20 and the demographic variables were 19. The objective is to predict inflation using the factors extracted from these groups and to determine whether demographics improve the forecasting accuracy of the models. The data runs from 1989Q1 to 2015Q4, table 1 contains the composition of variables in each group and their source, and the list of all the variables in each group are in Table 7 in the appendix.

Table 1: The composition of variables in each group

Group	Number of variables	Source
Monetary Policy	21	Bank of England
Productive or real sector	25	National Statistics UK
External sector	21	OECD database
Fiscal Policy	20	National statistics UK
Demographics	19	National statistics UK

Table 1 reports the number of variables in each group and the source of the variables.

4.2 Data conversion

All the variables are converted into growth rates. This has the advantage of smoothening the linear trend of all the variables. Second, a test for stationarity is conducted to avoid using variables not stationary. Then all the variables were standardized with mean zero and unit variance. This is desirable as it prevent variables with relatively larger variances to be more influential in principal component analysis.

4.3 Grouping

The variables are divided into five groups, namely, the productive sector, external sector, fiscal policy, monetary policy and the demographics. This leads to only strongly correlated variables sharing the same group. In each group, the correlation coefficient between the variables were computed and variables with low correlations coefficients were dropped. Furthermore, variables with high uniqueness value were also dropped. This is in line with Bai and Ng (2008) who found that dropping variables that have a low correlation with the other variables increases the forecasting accuracy of the factors. Following Quah and Sargent (1993), and Stock and Watson (1993) one factor is extracted and/or retained from each group using principal component analysis. This is ideal as in principal component analysis majority of the variables all significantly loads on the first factor. For the dynamic factor model, the information criteria developed by Bai and Ng (2002, 2007) is used in determining the number of dynamic factors. This approach has the advantage of making the interpretation of factors easy.

4.4 Model Identification

The number of $ARMA$ terms in each of the forecasting models were determine by BIC. For static principal components, the SW (2002) model was adopted to model inflation and, an $AR(4)$ with static principal components was chosen. Similarly for the dynamic principal components the $FHLR$ (2003) model was employed, an $ARMA$ (3, 6) with dynamic principal components was chosen as the forecasting model. For the Benchmark $ARMA$ model an $ARMA$ (4, 3) model was employed according to the BIC information criteria.

4.5 Forecasting exercise

The out of-sample forecasting exercise was conducted by estimating all the five models using data from 1989Q1 to 2013Q4. This was the time UK population was experiencing consistent growth in its population Berrington (2014). In Each model a recursive forecast was done and each model was estimated in both a static and dynamic equations setting and a one step ahead to eight steps ahead forecast of the first difference of inflation was conducted starting from 2014Q1 to 2015Q4. The was the post population growth period, the time Bank of England started given more weight to demographic changes in its monetary policy decisions Vlieghe (2016) The recent financial crisis of 2007 to 2009 was controlled for in the initial estimation with a dummy, but was later dropped due to its insignificance. Similar approach was used for the in-sample forecast in which all the observations (1989Q1 to 2015Q4) were used in estimating the models before computing the forecast for the same horizons as that of the out of sample forecast.

The reader, should take note of the difference between static factor model and static forecasting equation and similarly, the difference between dynamic factor model and dynamic forecasting equation. The static and dynamic factor models are the models that use either a static factors or dynamic factors in estimating the parameters of the model. Since, the SW model used only static factors, we called it a static factor model. While the $FHLR$ models, only used the dynamic factors, it is called a dynamic factor model. On the contrary, the static and dynamic forecasting equations are talking about how the forecast from the dynamic factor model ($FHLR$) and the static factor model (SW) are generated. In dynamic forecasting, forecast are computed for a period by using the previously forecasted values, while static forecast uses the actual values rather than the forecasted values when computing the next period forecast. The use of the two types of equations will help in determining the robustness of the results.

Therefore, in each model two different sets of forecasting errors are generated at all the forecast horizons. The two factor models were estimated with and without a demographic factor in order to isolate its contribution in forecasting inflation. The $RMSE$ is used to determine the forecasting accuracy of each model, while the DM-test for equal forecasting error was used to test the significance of the difference in $RMSE$ in each model. At the end of the exercise, in each model and at all forecast horizons the calculated $RMSE$ is used to determine the forecasting accuracy of the models. And the DM-test for equal forecasting error is used to test for the significance of the difference in $RMSE$ by comparing all the models against each other.

The treatment of other factors, in forecasting inflation, is based on the notion that, they are the conventional factors that affect inflation. That is why they are included in all the 4 factor models. The goal is to isolate the contribution of the demographic factor in each model.

4.6 Discussion of forecasting results

Both the out of sample and in-sample forecast results are analyzed in this sub-section. The $RMSE$ is the main criterion in determining forecasting accuracy in this study. In each model the $RMSE$ is reported at all the eight forecast horizons. A relatively lower $RMSE$ compared to the other models indicates superior forecasting accuracy of that model.

4.6.1 Out of sample results

Table 2 reports the $RMSE$ of the out of sample forecast of the five models, in which all the models were set up as both a dynamic and static equation. All the four factor Augmented models outperformed the $ARMA$ model, this results are in line with Schumacher (2005), Cheung and Demers (2007), Lombardi and Maier (2011), Gillitzer and Kearns (2007), SW (2006), Eickmeier and Ziegler (200), Faust and Wright (2009) all of whom found that, factor models outperform the $ARMA$ model in macroeconomic forecasting. The SW_1 (2002) models with a demographic factor outperform the one without a demographic factor at all the forecast horizons. Similarly, $FHLR_1$ (2003) model with a demographic factor also outperforms the one without a demographic factor at all the forecasting horizons, the results are in line with the work done by Lindh and Malmberg (2000) and Juselius and Takats (2015) all of whom found that significant portion of the variation in inflation is due demographics in a panel studies on the relationship between Inflation and age structure of 22 European countries. Overall the $FHLR$ (2003) models out performs SW (2002) models at all forecasting horizons this result is similar to Ginters (2010) and $FHLR$ (2014) both of whom found that dynamic factor models outperform static factor models, however, it contradict the findings of Cheung and Demers (2007) who found that static factor model outperform dynamic factor model.

Table 2: $RMSE$ (out of sample forecast)

$Forecast\ horizon$	1	2	3	4	5	6	7	8
$ARMA\_DF$	0.543853	0.542177	0.539305	0.536697	0.536898	0.539606	0.536876	0.534176
$ARMA\_SF$	0.479238	0.478195	0.475864	0.473356	0.477677	0.481456	0.480801	0.478383
SW_1_DF	0.487434	0.485569	0.482980	0.480457	0.479080	0.485167	0.483220	0.481584
SW_1_SF	0.438537	0.436440	0.434210	0.431918	0.431379	0.439861	0.439414	0.437995
SW_2_DF	0.491188	0.490677	0.488140	0.485670	0.484400	0.492771	0.490914	0.489102
SW_2_SF	0.442403	0.441417	0.439063	0.436751	0.436304	0.448945	0.448627	0.446899
$FHLR_1\_DF$	0.424693	0.425896	0.423681	0.422679	0.426354	0.434431	0.432404	0.430259
$FHLR_1\_SF$	0.362795	0.370232	0.370261	0.376197	0.392379	0.411443	0.414132	0.417962
$FHLR_2\_DF$	0.490534	0.491427	0.488891	0.487584	0.490653	0.498212	0.496179	0.494121
$FHLR_2\_SF$	0.363062	0.385004	0.436708	0.488523	0.586339	0.694962	0.771113	0.874932

***Table 2** reports the RMSE of the five models used in conducting an out-of sample forecast of inflation. Where SF denotes the model used to forecast inflation is a static equation and DF denotes the model used in forecasting inflation is a dynamic equation.*

4.6.2 In-sample results

Table 3 reports the RMSE of the in sample forecast at all the forecast horizons. Unlike the out-of sample forecast, for the in-sample forecast, the full sample of data ranging from 1989Q1 to 2015Q4 is used in estimating the parameters of all the five models used in this study. To isolate the contribution of demographics in forecasting inflation, each of the factor models were estimated with and without a demographic factor.

Similar to the results found in the out of sample forecast, in all the four factor models. The two factor models with a demographic factor systematically out performs the corresponding two factor models without a demographic factor at all forecast horizons. The results are in line with Shirakawa (2012), who in studying the relationship between Macroeconomic performance and demographic change, found that demographics have a significant effect on the movement of inflation. According to Table 3, the factor models with a demographic factor significantly out performs the benchmark $ARMA$ model. In all the models employed in this study, the $FHLR$ models have a relatively superior forecast accuracy, than both the SW model and the $ARMA$ model. In comparing the $RMSE$ of the in-sample and the out of sample forecast, the out of sample forecast models have a relatively lower $RMSE$ than the in-sample forecast models. The behavior of the $RMSE's$ in the in-sample forecast are in line with the notion that, the longer the forecast horizon the worst the forecast becomes, as the $RMSE$ increases in each step ahead forecast. This is relatively, different from the behavior of the $RMSE$ from the out of sample forecasting models, in which at some forecast horizons the $RMSE$ tend to fall as the forecast horizon increases. However, the in-sample forecast results indicates that, demographics increases the forecasting accuracy of inflation. This is expected, as the demographic factor is highly significant in all the models it is included. This is in order with Lindh and Malmberg (2000) and Juselius and Takats (2015) in there panel studies, on forecasting European Union inflation in which both found demographic changes to have a significant effect on inflation.

Table 3: The RMSE (in sample forecast)

$Forecast\ horizon$	1	2	3	4	5	6	7	8
$ARMA\_DF$	0.549778	0.547864	0.544994	0.542275	0.542118	0.544343	0.541566	0.538874
$ARMA\_SF$	0.459670	0.457363	0.455322	0.453345	0.452815	0.453416	0.451552	0.449397
SW_1_DF	0.481400	0.478904	0.476327	0.473761	0.472087	0.471717	0.469256	0.467386
SW_1_SF	0.440984	0.438623	0.436548	0.434246	0.433434	0.433634	0.431580	0.430239
SW_2_DF	0.495398	0.493818	0.491214	0.488653	0.493818	0.486630	0.484141	0.482054
SW_2_SF	0.445927	0.443884	0.441548	0.439218	0.438368	0.439334	0.437144	0.435490
$FHLR_1\_DF$	0.427505	0.426865	0.424215	0.422086	0.425932	0.428255	0.425932	0.423521
$FHLR_1\_SF$	0.381789	0.379816	0.378047	0.376795	0.376898	0.387363	0.386782	0.385251
$FHLR_2\_DF$	0.436832	0.435892	0.433146	0.430998	0.432317	0.436831	0.434266	0.431682
$FHLR_2\_SF$	0.398870	0.398754	0.396813	0.396119	0.398696	0.402187	0.400160	0.398134

***Table 3** reports the RMSE of the five models used in conducting an in sample forecast of inflation. Where SF denotes the model used to forecast inflation is a static equation and DF denotes the model used in forecasting inflation is a dynamic equation. Where the forecast begins from 2014Q1 to 2015Q4.*

Table 4: DM-test for equal forecasting accuracy

$Models$	$T-Stat$	$P-values$	$Conclusion$
$ARMA$ vs SW_1	2.501844	0.005777	SW_1 *has superior forecast accuracy*
$ARMA$ vs SW_2	-0.238604	0.811413	*Both models have equal forecast accuracy*
$ARMA$ vs $FHLR_1$	3.073975	0.002112	$FHLR_1$ *has superior forecast accuracy*
$ARMA$ vs $FHLR_2$	-3.707716	0.000209	$FHLR_2$ *has superior forecast accuracy*
SW_1 vs SW_2	-1.649754	0.098993	SW_1 *has superior forecast accuracy*
$FHLR_1$ vs $FHLR_2$	-2.545916	0.010899	$FHLR_1$ *has superior forecast accuracy*
SW_1 vs $FHLR_1$	2.870126	0.004103	$FHLR_1$ *has superior forecast accuracy*
SW_2 vs $FHLR_2$	-2.177467	0.029473	$FHLR_2$ *has superior forecast accuracy*
SW_2 vs $FHLR_1$	2.245740	0.024721	$FHLR_1$ *has superior forecast accuracy*

***Table 4** reports the DM-test results of the five forecasting models compared to each other. This results does not depend on whether the forecasting equation is static and/ or dynamic.*

4.7 DM-test for equal forecasting accuracy

The root mean square error is use as the main criterion to determine the forecasting accuracy of the models. However, looking at the five different models employed, relying on the $RMSE$ as the criterion for forecasting accuracy on face value could be misleading. To determine whether the difference in $RMSE$ between the models is significant, the DM test for equal forecasting accuracy is employed. Table 4 and graphs 2 & 3 reports the results of the DM test for equal forecasting accuracy. The results indicate that both SW and $FHLR$ models with demographics have a superior forecasting accuracy relative to the same models without demographic factor. In comparing the $ARMA$ model to both the SW models and $FHLR$ models, the results also indicates that the difference in $RMSE$ between the models are significantly different, see graphs 4 & 5 in the appendix. In comparing the difference in $RMSE$ between SW and $FHLR$ model, the test results indicates that $FHLR$ model has a superior forecasting accuracy compared to the SW model as the difference in the $RMSE$ between the models are significantly different.

Figure 1: First difference of inflation (DCPI)

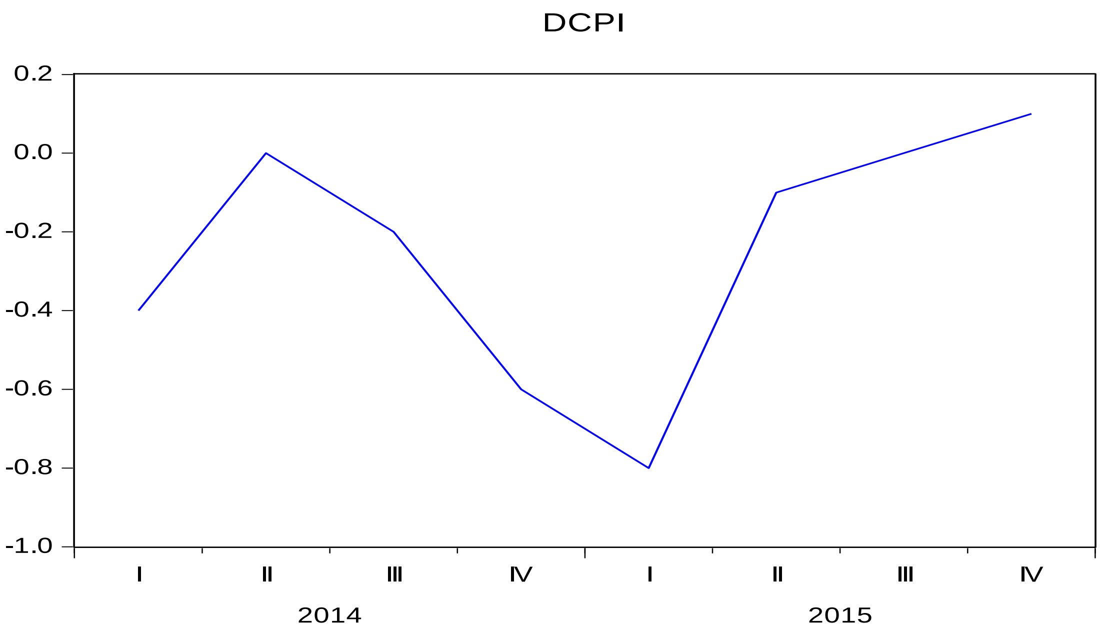

Figure 1 depicts the first difference of inflation forecasted in this study from 2014Q1 to 2015Q4, which corresponds to the period forecasted in this study.

Figure 2: DM-test ($FHLR_1$ vs $FHLR_2$)

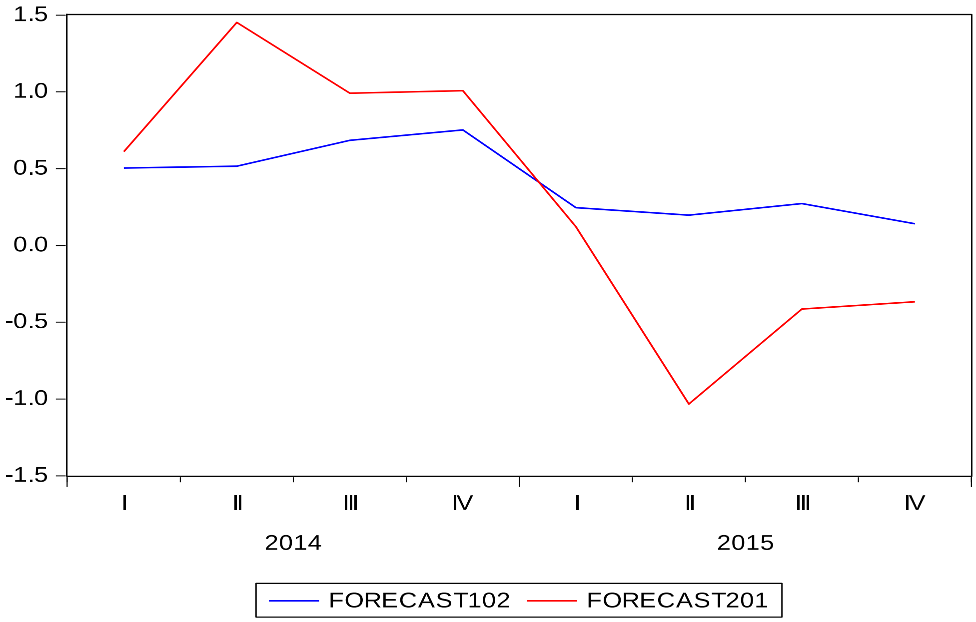

Figure 2 depicts the DM-test between the dynamic factor model with a demographic factor (FHLR1) and without demographic (FHLR2). Where forecast102 is the forecast from FHLR1 and forecast201 is the forecast from FHLR2.

Figure 3: DM-test (SW_1 vs SW_2)

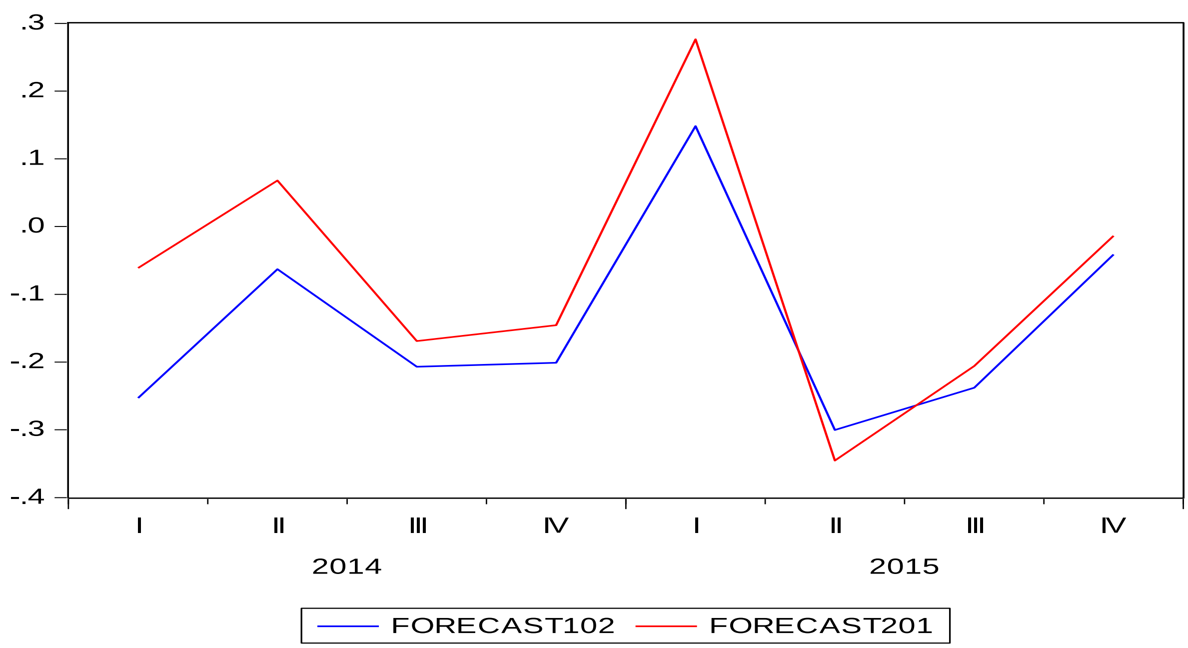

Figure 3 depicts the DM-test between the Static factor model with demographic factor (SW_1) and without demographic (SW_2). Where forecast 102 is the forecast from (SW_1) and forecast 201 is the forecast2 from SW_2.

4.8 Robustness checks

To verify whether the results obtained are not specific to a particular model and/ or dataset. The forecasting exercise is repeated relying on the benchmark information criteria to retain the factors. Each model is basically re-estimated with a different dataset. The following robust checks were conducted:

First, the information criteria is use to determine the number of factors to retain in each group and a forecasting model is conducted with the retained factors. Similar to the results from the empirical model, in both the SW and the $FHLR$ model, the models with a demographic factor have a lower $RMSE$ relative to the models without a demographic factor see tables 5, and this results are in line with the empirical model, as the models with a demographic factor have a superior forecasting accuracy since the difference in $RMSE$ is significant. And, the model that retained factors based on the information criteria have a relatively higher $RMSE$ to the model that retain only the first factor in each group. Similarly, the DM-test results also reveals that the empirical model has a superior forecast accuracy relative to the model that used factors retained in each group by the information criteria, see table 6.

Second, all the variables were put together in one group and the information criteria was used to determine the number of factors to retain. The $RMSE$ indicates that the empirical model has a lower $RMSE$ relative to the model in which all the variables are put in one group. However, the DM test results indicates that the difference in $RMSE$ is not significant.

Third, both the models constructed from the factors retained in the different groups and the one constructed from the factors retain in the unified group are compared to the $ARMA$ model. $RMSE$ Shows that both models outperform the $ARMA$ model. The DM-test result indicates that the factor models have a significantly lower $RMSE$ than the $ARMA$ models.

Table 5: The RMSE from both static and dynamic equation.

Forecast horizon	1	2	3	4	5	6	7	8
SW_{g1}_DF	0.439837	0.437475	0.435344	0.434991	0.449050	0.464467	0.467894	0.466892
SW_{g1}_SF	0.393190	0.391125	0.389364	0.390999	0.412772	0.439877	0.454127	0.461834
SW_{g2}_DF	0.462338	0.460537	0.458081	0.456353	0.460361	0.479129	0.479900	0.477532
SW_{g2}_SF	0.424277	0.422753	0.420522	0.419005	0.426922	0.447955	0.447328	0.445083
SW_{j1}_DF	0.538385	0.535497	0.532842	0.530411	0.528270	0.526092	0.523425	0.521824
SW_{j1}_SF	0.469976	0.468934	0.466554	0.464389	0.464620	0.463084	0.460734	0.460531
SW_{j2}_DF	0.518240	0.516860	0.514109	0.511553	0.509274	0.508087	0.505489	0.503427
SW_{j2}_SF	0.466736	0.464843	0.462373	0.460074	0.459535	0.460065	0.457715	0.456060

***Table 4** reports the RMSE of the factor models used to check the robustness of the empirical model. SW_{g1} and SW_{g2} are the models constructed with factors retain from each group using the information criteria. SW_{g1} Includes a demographic factor while SW_{g2}does not include a demographic factor. SW_{j1} and SW_{j2} are the model containing factor extracted from the case in which all the variables are put into only one group. The factors in SW_{j1} are extracted from group containing demographic variables and the factors in SW_{g2} does not include demographics variables in its extraction.*

Table 6: $DM - Test$ (between the empirical model and the alternative models)

Models	T-statistics	P-values	Conclusion
$ARMA$ vs SW_{g1}	2.622747	0.008722	SW_{g1}has superior forecasting accuracy
$ARMA$ vs SW_{g2}	-1.729643	0.083694	SW_{g2}has superior forecasting accuracy
SW_{g1} vs SW_{g2}	1.959370	0.068398	SW_{g1} has superior forecasting accuracy
$ARMA$ vs SW_{j2}	1.312363	0.089398	SW_{j2}has superior forecasting accuracy
SW_{j1} vs SW_{j2}	2.676183	0.008424	SW_{j1}has superior forecasting accuracy
SW_1 vs SW_{g1}	-2.495101	0.012592	SW_1 has superior forecasting accuracy
SW_1 vs SW_{j1}	-0.943699	0.345323	Both models have equal forecast accuracy
$FHLR_1$ vs SW_{j1}	2.461208	0.013847	$FHLR_1$has superior forecasting accuracy

Table 6 reports the DM-test for equal forecasting accuracy between the empirical models and the models use to check for robustness of the results.

The results above indicate that in forecasting UK inflations, demographic factor can increase the forecast accuracy of inflation, whiles both SW and $FHLR$ models outperform the simple $ARMA$ model. Furthermore, the $FHLR$ model has superior forecasting accuracy relative to the SW model.

5 Conclusion

This paper seeks to determine whether demographics can increase the forecast accuracy of United Kingdom inflation. This is determined by comparing two alternative factor augmented regression models to the benchmark $ARMA$ model. The variables are divided into five groups and in each group one factor is extracted. Each of the factor models were estimated with and without a demographic factor. According to the $RMSE$ from the alternative models, the models that contain a demographic factor has a lower RMSE relative to the models without a demographic factor. Furthermore, the $FHLR$ models has lower $RMSE$ relative to the SW model, but the SW model outperformed the $ARMA$ model.

In testing for the significant of the difference in $RMSE$ between the models, the SW model with a demographic factor has a superior forecast accuracy to the SW model without a demographic factor. Similarly, the $FHLR$ model with a demographic factor has a superior forecast accuracy relative to the $FHLR$ model without a demographic factor. Furthermore, the $FHLR$ models has a higher forecast accuracy relative to both the $ARMA$ and SW models, while the SW model outperform the $ARMA$ model.

Based on the $RMSE$ as the criteria for forecasting accuracy, demographics can increase the forecasting accuracy of UK inflation. And also, according to the DM-test for equal forecasting accuracy, the difference in $RMSE$ between the models with a demographic factor the ones without it is significantly difference. Thus, the results indicate that demographics can increase the forecast accuracy of UK inflation

Although, the results indicates that demographics can systematically increase the forecasting accuracy of UK inflation. The study can be extend further by modeling inflation with yearly variables, since the variation in demographic variables were very low. Among all the five groups the demographic group has the lowest standard deviation. Thus, further research can be done in this study in which yearly data is used, which is likely to have more variation than quarterly variables. This might provide further evidence as to whether demographics can actually increase the forecasting accuracy of inflation. Furthermore, the number variables in each group can be extended to capture more information in each group.

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7 Appendix

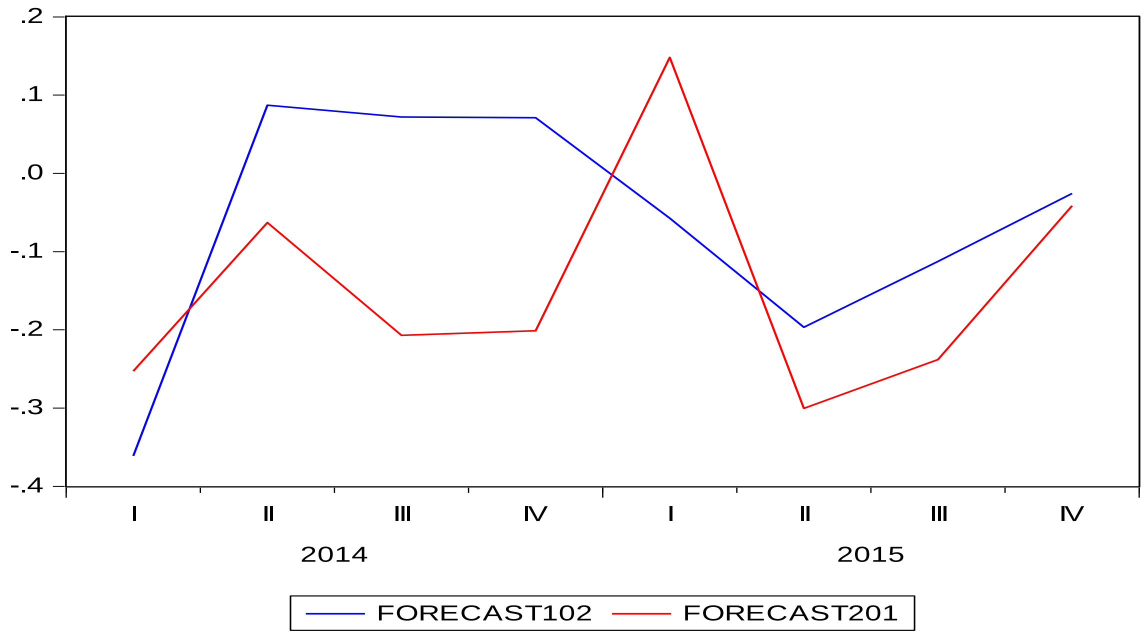
Table 7: List of variables

S/N	Monetary Policy Variables	Productive Sector Variables	Demographics Variables	Fiscal Policy Variables	External Factors
1	Short term interest rate	Inward Property Total Investment Level	Working age population (16-64)	Government Deficit	CPI USA
2	Long term interest rate	Consumption of fixed capital	Economic inactive(16-64)	Government Debt	CPI Germany
3	M1	Pension Schemes	Employment rate	Government Revenue	CPI China
4	M2	Total property income received	Female employment rate	Government reserves	CPI France
5	M3	Property income interest Total	Male employment rate	Capital taxes received from other sectors	CPI Switzerland
6	M4	Households: interest received	Economic active	Taxes on production and imports, receivable	CPI Ireland
7	Bonds issued by UK MFIs & other UK residents	Wages & salaries	Economic inactive	Taxes on income from employment	CPI Holland
8	Gross Saving	Total Primary Income Resources	Total weekly hours (millions)	Total domestic household final consumption one quarter growth rate	CPI average of OECD
9	Loans by UK MFIs	Changes in inventories	Employment rate (15-24)	Taxes on production & imports less subsidies as % of GDP	Exchange rate Dollars to Pound
10	Money Market Instruments issued by other UK residents	Households interest paid	Employment rate (25-54)	IMF UK gross external debt	Exchange rate Chf to Pound
11	Bonds issued by the UK central government	Gross disposable income	Employment rate (55-64)	Taxes on income	Exchange rate Yuan to Dollar

12	Deposits with UK Monetary Financial Instruments	Finished manufactures	Population under15	Net Borrowing	consumer opinion about UK inflation
13	Securities other than shares	Basic materials	Population age greater than 64	Taxes on production	pound/euro
14	Sterling treasury bills	Household final consumption expenditure	fertility rate	Taxes on production & imports: Other taxes on production	Resources: Imports Duties
15	Foreign currency deposits with UK banks	GDP(Expenditure) at current basic prices index no	Dependent population	Central government: total interest paid excl.	Imports goods annual growth rate
16	Short term loans	GDP: growth rate	Population women	Subsidies on products	Exports growth rate
17	Bonds issued by UK banks, building societies & other UK residents	Goss capital formation	Population men	Import duties	BOP Current Account Balance
18	MMIs issued by UK general government	GNI per capita	Unemployed Women age 15-24	Taxes on income and wealth	Balance of Payments
19	official bank rate	FDI Inward Property	men unemployed age 15-24	General Government: Final consumption expenditure	Capital Account Balance
20	Three months treasury bills	Food & drink growth rate			Crude oil import prices, US dollars per barrel
21	Interbank rates	Social assistance benefits in cash			Term of trade total ratio
22		Semi-manufactures			Total trade
23		Industrial production			
24		Oil price			

Note: Table reported that variables they are use in modeling inflation is this study.

Figure 4: DM-Test (ARMA vs SW1)



***Graph 4** depicts the DM-test between the benchmark ARMA (4, 3) model and the SW1. Where forecast102 is from the ARMA model and forecast201 is the forecast from SW1 model.*

Graph 5: DM-Test (ARMA vs FHLR1)

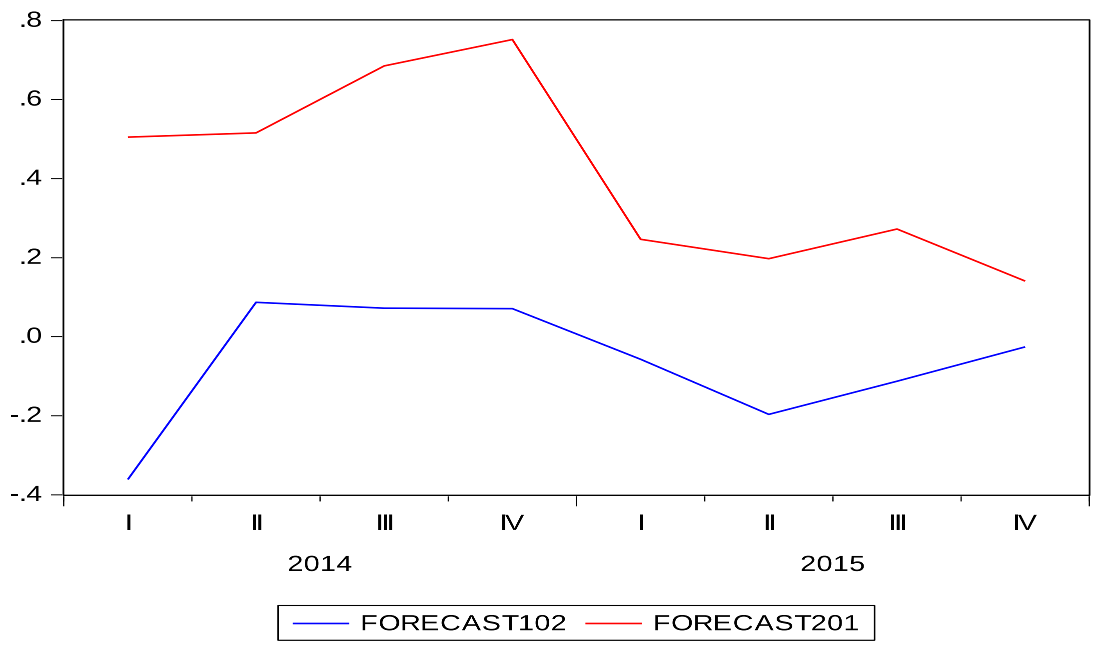


***Figure 5** depicts the DM-test between the benchmark ARMA model and the FHLR1 model. Where forecast102 is the forecast from the ARMA model and forecast201 is the forecast from FHLR1.*

Figure 6: DM-Test (SW1 vs SWJ1)

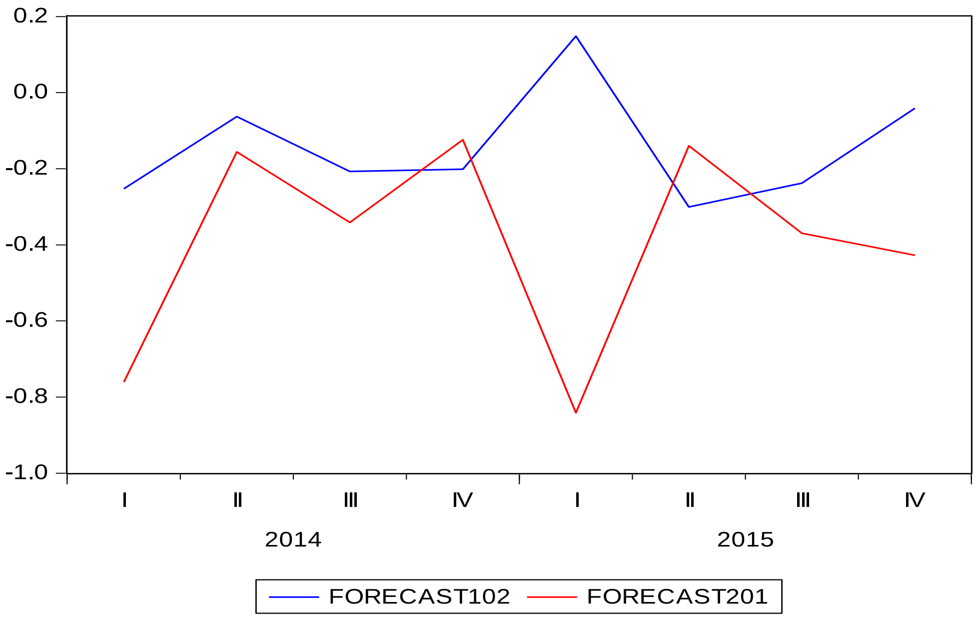


***Figure 6** depicts the DM-test between the SW1 model and the SWJ1 model. Where forecast102 is the forecast from the SW1 model and forecast201 is the forecast from SWJ1.*

Figure 7: DM-Test (SW1 vs SWg1)

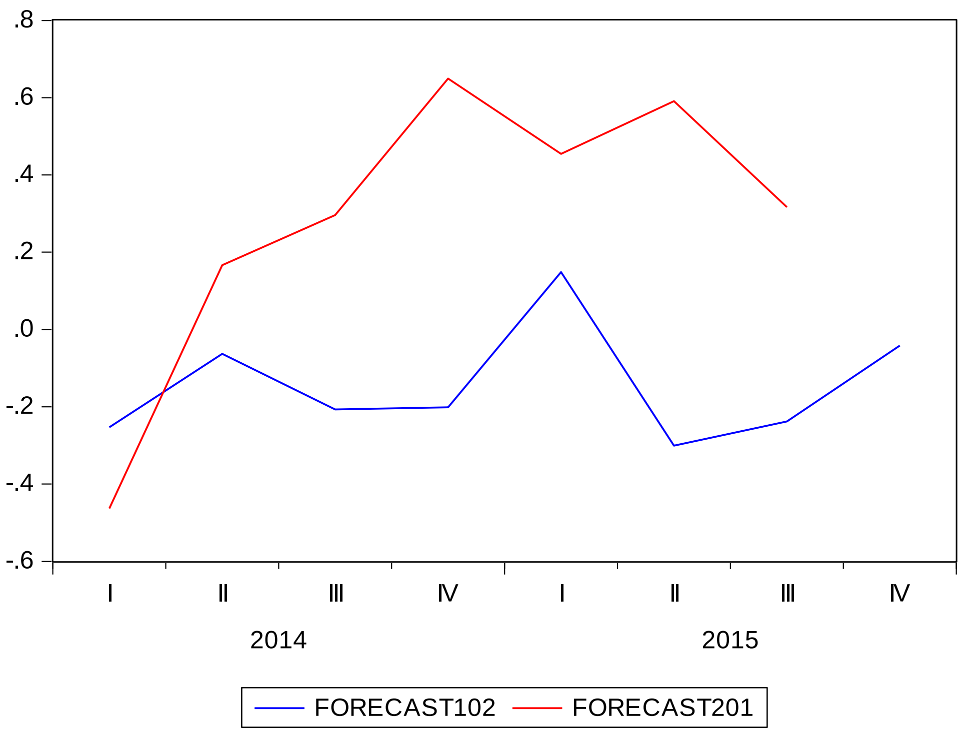


***Figure 7** depicts the DM-test between the SW1 model and the SWg1 model. Where forecast102 is the forecast from the SW1 model and forecast201 is the forecast from SWg1.*