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Producing Short-Term Forecasts of the Irish Economy: A Suite of Models Approach.

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Abstract

The Council's mandate includes endorsing, as it considers appropriate, the official macroeconomic forecasts of the Department of Finance on which the annual Budget and Stability Programme Update are based. As part of the endorsement process and for the purposes of its ongoing monitoring and analysis of the Irish economy, the Council's Secretariat produces its own Benchmark macroeconomic projections. This paper describes the short-run forecasting models used by the Secretariat for producing these projections. The general forecasting approach can be described as follows. Equations are used to forecast each component of the expenditure side of the Quarterly National Accounts. Multiple models are estimated for most components, with the simple model average used as an initial input into the formulation of the Benchmark projections. The out-of-sample forecasting performance of these models is assessed at each endorsement round. In addition to these model-based projections, other elements are considered. Discussions with the Council and other forecasting agencies help to guide any judgement that may be applied before arriving at the final Benchmark projections.

Section 1: Introduction

This working paper outlines the short-run forecasting methods used to produce the Secretariat's Benchmark projections for the Irish economy. The projections are produced to help carry out the Council's endorsement function.[1] As well as serving as a basis from which to compare the forecasts from the Department of Finance, the production of these projections also aids the Council's assessments by facilitating an improved understanding of macroeconomic conditions in the Irish economy. In particular, the detailed analysis of macroeconomic data that is required when producing forecasts can help identify important developments in the economy which may not be apparent from looking only at headline aggregates. The forecasting models also serve as a helpful input for illustrative simulation purposes, such as testing the sensitivity of macroeconomic and budgetary forecasts to external shocks.

There are several key dimensions to the Secretariat's approach to producing the Benchmarks. First, rather than a large-scale macroeconomic model, the models used as inputs to the projections consist of a large number of individual equations that model the expenditure and income side of the National Accounts, as well as the labour market. Large-scale macroeconomic models such as the ESRI's COSMO model[2] are designed for medium-term forecasting and assessing potential output and the cyclical position of the economy. Such models may not be ideally suited for the purposes of short-term forecasting, given the wide range of specific dynamics that can affect short-run developments.

In the spirit of Chan *et al* (1999), the Secretariat favours a *"suite of models"* approach. This involves the estimation of a number of models for individual expenditure components and sub-components where possible rather than relying on any single model. It is generally accepted that diversification can lead to more robust forecasts in the face of uncertainty and may also be more appropriate given the changing role of different macroeconomic drivers over time. There are obvious practical limits as to how informative any single model can be when forecasting. Empirical work (Bates and Granger, 1969; Stock and Watson, 1999) shows that the suite of models approach also tends to outperform single models. With this in mind, the average forecasts across the models are generally used, with equal weight given to each model, unless some models are performing exceptionally well or poorly for the recent period. By having a range of models for each sector of the economy and monitoring their relative performance, it is hoped that key developments in the economy will be captured.

Second, the models used for the Benchmark projections are subjected to rigorous testing. At the time of each endorsement round, an updated test of the models' out-of-sample forecasting performance is examined. Out-of-sample forecasting involves estimating the models/equations and then using these estimated parameters to forecast future quarters. As most of the models use quarterly data, iterative tests of the four-quarter-ahead forecasting performance are run to compare the in-sample forecasts to the actual outturns. Statistical measures of accuracy are used to determine their continued viability as forecasting tools, while the pattern of errors is used as a guide to explaining recent developments[3]. It is important to note that, although some models may fare more poorly than others for a time, they may prove useful in future as economic drivers captured by them return to prominence. For these reasons, models which once performed well but are no longer doing so are rarely dispensed with. For

[1] As outlined in IFAC (2013).
[2] See Bergin *et al* (2017) for a description.
[3] Annex 2.16 shows the Root Mean Squared Errors and the Theil's U2 statistic for the four quarter ahead forecasts.

example, one of the models of service imports has been performing poorly recently, but is still maintained.

The comparisons of in-sample forecasts and actual outturns shown in later sections use a rolling forecast window. This means that in all cases the models are trying to forecast the same number of quarters ahead (four). These in-sample forecasts are performed using data only available up until that point, e.g. an equation is estimated using data up until 2009Q1 and this is used to forecast 2010Q1. Given the current range of quarterly data available (1997Q1 – present), making use of all of the available data seems the most sensible strategy; hence equation estimations always start at the first available data point. However, this may change in future, as a greater quantity of historical quarterly data becomes available.

Third, model-based estimates are supported by additional inputs, as judgement plays an important role in short-term forecasting. In addition to discussions with Council members regarding preliminary forecasts, an important input into the preparation of the Benchmark projections involves a round of discussions with other external forecasters. Before each endorsement, the Secretariat holds discussions with the CSO and with forecasters coming from a mix of official institutions, financial sector and academic/research backgrounds. These inputs help to broaden the information set upon which the projections are formed. As with most forecasting agencies, models are also complemented by forecaster judgement. This reflects that some factors affecting the economy in the short term will not lend themselves to sufficient description by macroeconomic models. Judgement will also be influenced by high-frequency data which may not be included in the models themselves. The latest policy announcements and plans will also be reflected in the judgement applied to the forecasts. While judgement plays a key role in producing any forecasts, the focus of this paper is to outline the forecasting tools used to produce the model forecasts, after which judgement is applied.

The short-term forecasting tools described in this paper have been developed organically as the Secretariat has looked to expand its analytical capacity and there is ongoing work to widen/improve the set of tools employed. When forecasting capacity was initially being developed by the Secretariat, the Department of Finance, Central Bank and ESRI were all helpful in sharing their forecasting approaches. New models are added at the time of each endorsement round and these have a number of origins. Some are similar to those employed by the Department of Finance, while others are adaptations or refinements of these models. Additional models have been developed independently by the Council's Secretariat or in consultation with forecasting teams in other agencies such as the IMF, OECD and European Commission.

As always it is worth remembering that forecasters face unique challenges in interpreting the Irish National Accounts data. As has been well documented, the Irish Quarterly National Accounts are amongst the most heavily revised (Casey and Smyth, 2016) and the most volatile (McCarthy, 2004; and Conroy, 2015) in the OECD. The Secretariat continues to work to improve its understanding of the Irish economy. Each *Fiscal Assessment Report* provides an update of the macroeconomic assessment of the Council and a number of Boxes, Analytical Notes and Working Papers have been produced with the view to developing further insights on macroeconomic developments.

The rest of the paper is organised as follows: Section 2 provides an overview of the forecasting models used by the Council's Secretariat, Section 3 details consumption forecasting specifically, Section 4 considers investment, Section 5 describes the trade (exports and imports) models of the Irish economy, while Section 6 details the income and labour market models used. Section 7 examines some other issues that arise when forecasting the Irish economy.[4] Section 8 concludes.

[4] Note that there is no model used for government consumption. Assumptions from the Department of Finance are generally used for the purposes of the Benchmark projections, with the plausibility of these assessed on the basis of known budgetary plans and the latest CSO Quarterly National Accounts outturn data.

Section 2: Overview of Forecasting Models

This Section provides an overview of the short-term forecasting tools used by the Secretariat. The general approach is best described as a bottom-up approach, with components of the National Accounts and the labour market forecast at a disaggregated level where data allow. This approach is useful from a forecasting point of view, as it highlights developments that might otherwise be overlooked.[5] By being aware of such issues, the forecaster can apply informed judgement to the model forecast. This approach also aids the endorsement and assessment functions, as the Council is better placed to scrutinise the forecasts of the Department of Finance and the macroeconomic context which plays a key role in all aspects of the Council's mandate.

Short-term forecasts generally assume that the nature and capacity of production is fixed, while the utilisation of this capacity, demand-side conditions and various short-run shocks are determined by immediate developments. Over a longer forecast horizon, the Secretariat's suite of potential output models are used as a guide to supply-side capacity, as well as for highlighting potential overheating/imbalances in the economy. Also, in recent *Fiscal Assessment Reports* a modular approach to assessing potential imbalances in the economy has been taken. This entails looking at a range of indicators for signs of overheating, such as the labour market, credit conditions, external imbalances, investment indicators and the housing market. A separate working paper [Casey, forthcoming] describes how potential output is estimated and documents the models used.

The data used for the short-run forecasting models are predominantly quarterly in frequency and are disaggregated where possible, e.g. exports are split into goods and services. These series provide the most up-to-date picture of the economy and Quarterly National Accounts data – though prone to revision – are nonetheless found to be an unbiased indicator of latest developments (Casey and Smyth, 2016). Reflecting this, carryovers[6] and the quarterly profiles of the data can provide important information to the Secretariat when formulating the Benchmark projections as these can provide valuable and unbiased information. The forecasts of the Department of Finance and those produced by the Secretariat are both on an annual basis.

Generally, the forecasts from the short-run forecasting models are taken as an initial input for the forecasts of the current year (t) and of the year ahead (t+1)[7]. Each series is modelled in real terms, with a deflator modelled separately. Combining the real series and the deflator gives a forecast nominal value for each series.

Following the suite of models approach, multiple models or equations are estimated for each expenditure item. In most cases an Error Correction Mechanism (ECM) framework is used with short-run and long-run equations estimated for most variables along the following lines. In the following illustrative example, it is assumed that there are two explanatory variables (X_1 and X_2).

[5] As a recent example, services consumption has been performing quite poorly considering recent employment and income growth and the robust growth in goods consumption. If the forecaster were to only examine aggregate consumption, they may not become aware of some of these data issues. This is discussed further in Section 3.

[6] Carryovers refer to the growth rate that would be achieved were a series to remain at its current real, seasonally-adjusted level for the remaining quarters of this or next year.

[7] Thereafter, forecasts are based on the estimated potential output growth rate and the estimated cyclical position of the economy.

$$LN(Y_t) = \alpha_1 + \beta_1 LN(X_{1t}) + \beta_2 LN(X_{2t}) \quad (1)$$

$$\Delta LN(Y_t) = \alpha_2 + \beta_3 \Delta LN(X_{1t}) + \beta_4 \Delta LN(X_{2t}) + \beta_5 (LN(Y_{t-4}) - (\alpha_1 + \beta_1 LN(X_{1t-4}) + \beta_2 LN(X_{2t-4}))) \quad (2)$$

Where (1) describes the long-run relationship between Y and X_1 and X_2. Equation (2) describes the short-run relationship, with β_5 being the error correction term. The error correction term specifies the pace at which short-run developments return a variable to its long-run equilibrium level. The short-run equation here is modelling the year on year change in the quarterly series, i.e. $\Delta LN(Y_t) = LN(Y_t)$-$LN(Y_{t-4})$, hence the error correction mechanism appears with a four-quarter lag.

The error-correction approach is based on there being some long-run equilibrium for a series. When a series is significantly above this trend, it is assumed it will eventually fall back towards it; when it is below the trend, it will increase towards it. Identifying this long run trend in the series is central to this methodology. Some have suggested that this approach may be problematic when estimating over a sample that includes potential structural breaks like the recent financial crisis. While this may be a valid criticism in some instances, one can mitigate this problem/risk by testing for breaks in the long run equations and potentially using different explanatory variables or dummies if required.

Two observations are relevant in considering short-run equations such as (2). Firstly, as noted above, the dependent variable that is being modelled (for example goods imports) is a log year-on-year change i.e. $LN(MG_{2016Q1}) - LN(MG_{2015Q1})$. Secondly, as a result of this, seasonally adjusted data are not used. Due to the differencing method used, seasonality will not be present when examining changes in one quarter from the corresponding quarter in the previous year. Using seasonally-adjusted data has been attempted previously, but in all but two cases no significant forecasting advantage was found[8]. While the raw data used and hence the initial forecasts produced are not seasonally adjusted, these can easily be seasonally adjusted *ex-post*, giving smooth quarterly profiles[9].

The forecasting approach is concerned with estimating equations for the main expenditure components of the National Accounts. This mirrors the approach to producing short-term macroeconomic forecasts that is used by the ESRI, Department of Finance and the Central Bank of Ireland. The focus on expenditure-side aggregates is partially due to data availability as the CSO's Quarterly National Accounts provide only limited information on output trends[10] in the economy. An overview of the main expenditure-side equations that are used for forecasting is provided in Annex 1. Table 1 below outlines some of the variables used. It also gives the source information for many of the exogenous variables used and the external forecasts used to get future values of these variables.

[8] The two exceptions are goods and services consumption, where seasonally adjusted data are used for the long run equation and hence used as an input into the short run equation, identifying how far consumption is from equilibrium. This was the only item of the National Accounts where using seasonally adjusted data led to superior forecasting performance. This is hardly surprising, as investment and exports in Ireland are characterised by volatile patterns which are not obviously seasonal in nature. This is related to the concentration in sectors such as pharmaceuticals and ICT, for which production cycles vary dramatically and show little evidence of consistent seasonal patterns.

[9] This can be done while ensuring that the sum of the four quarters of the constructed seasonally adjusted forecast equals the four quarter sum of the original forecast, using seasonal adjustment methods in line with those used by statistical agencies. This is done using the statistical package R, which can be run through Eviews.

[10] In any event, data on the output side of the economy may be more useful for medium term forecasting and the supply side of the economy.

Figure 1: Flowchart of the forecasts

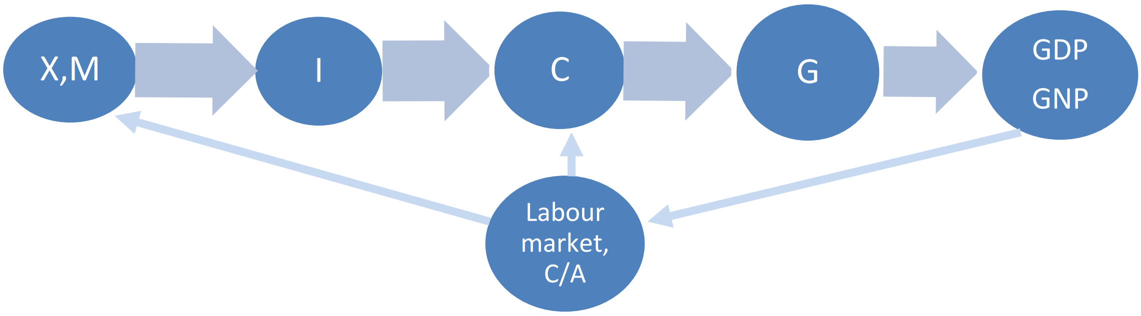


Table 1: Key assumptions/definitions table

	Data source	Description
Personal Disposable Income	Institutional sector accounts (CSO)	The raw data are in nominal terms. The variable used in consumption equations is in real terms, so the HICP is used to deflate it. Details of how forecasts of income are compiled can be found in Section 6.
Housing wealth	Central Bank of Ireland	The raw data are in nominal terms and is deflated using HICP. To forecast housing wealth, the stock of housing (consistent with the forecast of completions) and house prices are forecasted.
Financial wealth	Central Bank of Ireland	The raw data are in nominal terms and is deflated using HICP. A judgemental forecast is made to get future values of this exogenous input, generally growing at a similar pace to nominal GDP.
External demand for Irish goods exports	European Commission forecasts (when available), otherwise IMF forecasts	This variable reflects the trade weighted growth of goods imports in destination countries. Assumed future growth rates are taken from external agencies (EC, IMF). Trade weights are assumed constant over the forecast horizon.
External demand for Irish service exports	European Commission forecasts (when available), otherwise IMF forecasts	This variable reflects the trade weighted growth of service imports in destination countries. Assumed future growth rates are taken from external agencies (EC, IMF). Trade weights are assumed constant over the forecast horizon.

Real effective exchange rate	European Commission forecasts (when available), otherwise IMF forecasts	Future values of both inflation and exchange rates are needed to get real effective exchange rates. Forecasts for both inflation and exchange rates are taken from EC forecasts[11]. Trade weights in line with historical export shares are then used, which are held constant over the forecast horizon.
Housing Commencements	Department of Housing, Planning, Community and Local Government	Historical commencements data are used to forecast housing completions for a couple of quarters ahead. Thereafter commencements are not used so no forecast of future commencements is necessary.
Government Consumption	CSO and Department of Finance	Historical data are taken from the Quarterly National Accounts (QNA). The latest forecast of government consumption from the Department of Finance is often used in the Benchmark projections; however, this forecast will be scrutinised as part of the endorsement process.
EU goods export prices	European Commission forecasts (when available), otherwise IMF forecasts	The forecasts from the European Commission for the deflator on goods exports from the EU are used. If forecasts from the European Commission are not available, then forecasts from the IMF are used.
Brent crude oil prices	DataStream	Historical data are combined with futures contracts to get forecasts for the next two years. For the outer period, a 10-day moving average is used.
Construction output	National Income and Expenditure Accounts (CSO)	Historical data are taken from the National Accounts. Forecasts are compiled in line with forecasts for investment in the building and construction sector.

[11] Generally the forecasts for exchange rates will be flat after one or two years. This may be undesirable, particularly if the risks to particular exchange rate are considered to be heavily asymmetric.

Section 3: Consumption

In line with other aspects of the forecasting methodology, goods and services consumption are currently modelled separately. The main theoretical framework for forecasting consumption is the lifecycle approach to consumption and saving. This implies that households accumulate assets during their working lives in order to save for retirement and use assets to smooth consumption over their lifetime (Ando and Modigliani (1963)). With this in mind, consumption is modelled as a function of disposable income and total (net financial and net housing) wealth. When households have significant holdings of net assets, they have a reduced requirement to save for the future and hence their consumption should be boosted. Higher levels of disposable income should also lead to higher levels of consumption[12]. Other explanatory variables were also considered, such as retail sales and consumer confidence indices; however, these variables were not consistent predictors of consumption and hence are omitted. Future work could see these or other variables included.

By combining net financial wealth and net housing wealth into a single total net wealth variable, this imposes that the propensities to consume out of each of these two asset classes are equal. The wealth data we have are in nominal terms; to transfer this into real terms the HICP deflator is used. The measure of income used is real personal disposable income (institutional sector accounts)[13]. In aggregate, this should act as a good proxy for permanent income. In order to produce forecasts of goods and services consumption, income and both types of wealth need to be forecasted. Section 6 details how income and employment are forecasted. For housing wealth, the stock of housing and the price of housing need to be forecasted. The forecast of the stock comes from the completions forecast and the assumed rate of obsolescence of the existing stock. Prices are forecast on a judgemental basis. Forecasts of net financial wealth are judgement based also, usually growing at a similar rate to nominal GDP.

Long-run and short-run consumption equations are estimated. The residual on the long-run equations are then used as an input into the short-run equations (via the error correction mechanism). In effect, this error-correction mechanism will mean that consumption growth will be forecast to be higher when consumption lies below its long-run equilibrium level, and lower when it is above its long-run level. In some cases it is imposed that the long-run coefficients on income and wealth are assumed to sum to one, in line with Barrell and Davis (2007)[14].

The goods and services consumption data are not provided separately on a seasonally adjusted basis by the CSO. From a basic visual inspection, however, both series are clearly seasonal. Using the US census Bureau's X13 method, seasonally-adjusted series can be created. In implementing this methodology, it is imposed that the seasonally-adjusted data must add up to the same annual totals as the unadjusted data. The income data is also clearly seasonal, and hence it is also seasonally adjusted using the same process[15]. This seasonally-adjusted data that are created are then used for

[12] See section 6 for a description of how the labour market forecasts, including personal disposable income are compiled.
[13] This is made up of compensation of employees, gross operating surplus/mixed income, property income, social benefits and other transfers, minus taxation and social contributions.
[14] Referring to the constraining of the long-run coefficients, "This steady-state relationship links the consumption to income ratio to the wealth to income ratio. If either the demand for precautionary saving rises or the cost of holding wealth falls then we would expect the impact of wealth to change."
[15] For consistency, the measures of wealth are also seasonally adjusted, using the same methodology as applied to consumption and income.

the long-run equations which identify deviations of consumption from the expected long-run levels. In the short-run equation, the non-seasonally adjusted consumption data are used as the dependent variable, as it is the actual National Accounts data that the models are attempting to forecast.

For consumption of goods, there are three models used. The first and second models use real personal disposable income and real total wealth (housing and net financial combined) as predictors. The first model imposes that the long-run coefficients on income and wealth sum to one, with the result of a high (0.93) coefficient on income, thus implying a coefficient of 0.07 on wealth. In the short-run equation income, wealth and the error correction term are all statistically significant and correctly signed. The second model does not impose any restrictions on the long-run coefficients, with the coefficient on income somewhat lower (0.73) and the coefficient on wealth somewhat higher (0.11) when compared to the restricted model. In the second model the coefficients in the short-run equation are significant and correctly signed as was the case for the first model. For the third model, only income is used in the long-run equation, with wealth dropped from the specification. As before, the coefficients in the short-run equation are found to be correctly signed and statistically significant. The detailed equation specifications and full estimation results for all three models are shown in Annex 2.1.1.

Figure 2: Forecasting Real Goods Consumption Growth (%, Y-Y)
Estimation Sample Begins: 2003Q1, Estimation Sample Ends: 2006Q1 – 2015Q2, short-run equation, forecasting four quarters ahead.

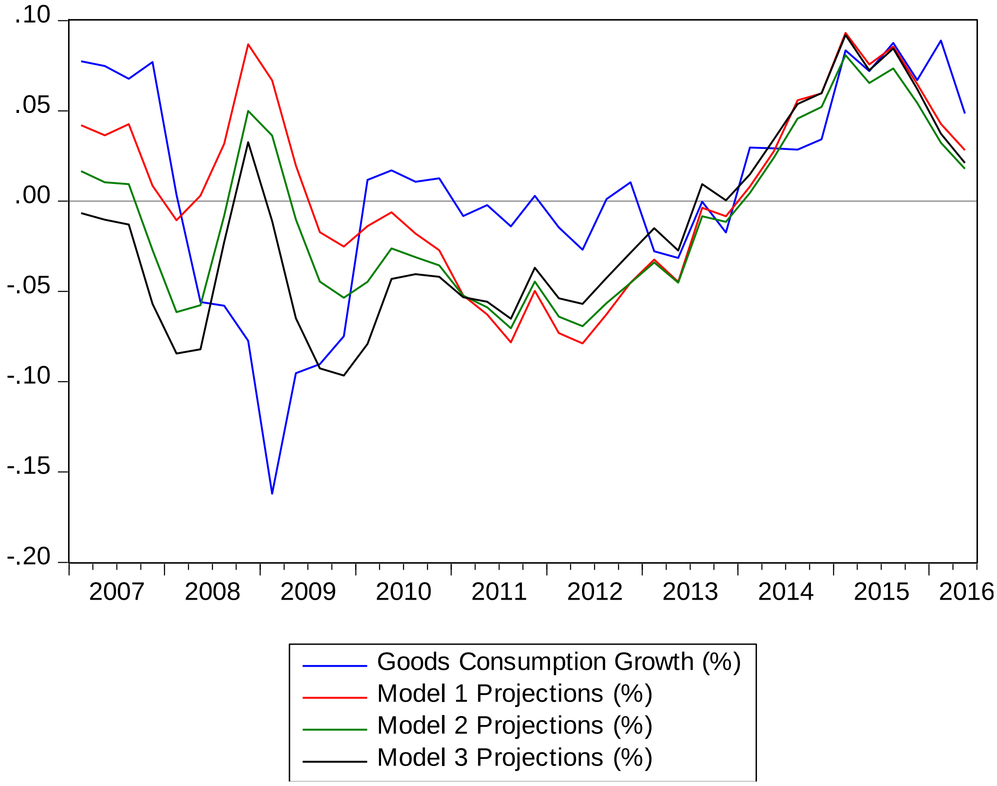


Figure 2 above shows the historical forecasting performance of these three models. In each case the models are trying to forecast goods consumption four quarters ahead when they have been estimated using only the data available up to that point in time, e.g., estimate the models using data up to 2007Q1 and use these parameters to forecast 2008Q1. Up until the last couple of quarters, all three models had been forecasting the recent growth quite well, with the strong growth in consumption of goods being fuelled by increases in disposable income and rising net financial wealth. Looking at formal measures of forecasting performance, the Theils U2 value is below one, indicating that each of the models outperforms a naïve forecast (the naïve forecast in this case is that the growth rate in four quarters' time will be the same as the current growth rate).

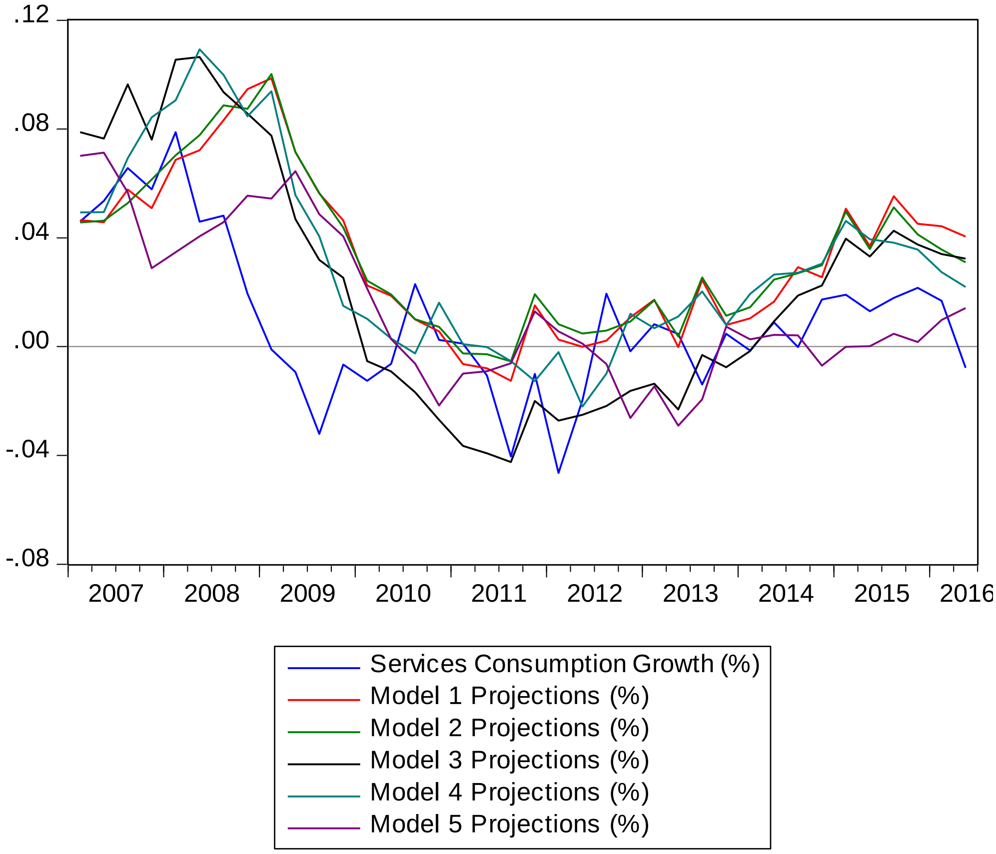
A similar approach is attempted in modelling services consumption. In the model one, disposable income and wealth are used as predictors, with no restrictions imposed. This leads to unsatisfactory results in the long-run equation, as the income coefficient is well above one (1.7) and the wealth coefficient is negative (-0.45) and statistically significant. The short-run equation is more along expected lines, with significant coefficients of the expected sign on income and the error-correction term and an insignificant coefficient on wealth. In the model two, the restriction that the long-run coefficients sum to one is imposed. This gives similar results to those in the unrestricted case, with a coefficient greater than one on income (1.4) and a negative coefficient (-0.4) on wealth. The short-run equation is also similar to that found in model one, with significant coefficients on income and the error correction term. Given that the long-run coefficient on wealth is found to be consistently the wrong sign, in model three we omit wealth from the long-run equation and only use income. Like in models one and two, a coefficient greater than one is estimated for income. In the short-run equation, all three variables (income, wealth and the error-correction term) are all correctly signed and significant.

Given that some of these long-run equations have given surprising results, a fourth model with no long-run equation or error-correction mechanism is estimated. A short-run equation using changes in disposable income, wealth and lagged services consumption is estimated. In this case, the lagged dependent variable is the only significant predictor, with income and wealth both positive but statistically insignificant. These results for services consumption are somewhat puzzling. The long-run income coefficient being above one could reflect that services consumption contains a higher degree of luxury items compared to goods consumption[16]. As a final approach to forecasting services consumption, a simple AR (2) model is specified. Estimates of all five models can be found in Annex 2.1.2.

Figure 3 below shows a test of the historical forecasting performance of these five models. As before, the five models are being used to try to forecast services consumption four quarters ahead. In recent quarters, the first four models appear to be substantially overestimating services consumption growth. This appears to be because services consumption growth has been much weaker recently than income growth. Given that there appears to be more of a divergence between services consumption and its standard predictors in recent times, it is perhaps less surprising that some of the long-run equations did not lead to coefficients of the expected sign and/or magnitude. The AR (2) model (model five), performs somewhat better in recent quarters. Looking at the formal measures of forecasting performance (Annex 2.8), the Root Mean Squared Errors (RMSE) of the models does not appear to be particularly poor relative to other models. However, looking at the Theils U2 statistic, all five models perform worse than a naïve forecast. The naïve forecast here is that the growth rate in four quarters time is the same as the current growth rate. Given the relatively poor recent forecasting performance, this is an area which will be a target for future work/development.

[16] Recreation/entertainment/education services would seem an obvious candidate, although this only made up 5% of total consumption in 2015. On the goods side, durables would seem the most obvious category to be very sensitive to income changes, and this made up less than 2.5% of consumption in 2015.

Figure 3: Forecasting Real Services Consumption Growth (%, Y-Y)
Estimation Sample Begins: 2003Q1, Estimation Sample Ends: 2006Q1 – 2015Q2, short-run equation, forecasting four quarters ahead.



The recent relative performances of goods and services consumption highlight some of the insights that can be gained by looking at the disaggregated data. This can give a better informed view of what drives the headline consumption figure. Given that just over half of consumption is now made up of services, it is important to understand what drives the diverging recent performance of goods and services consumption.

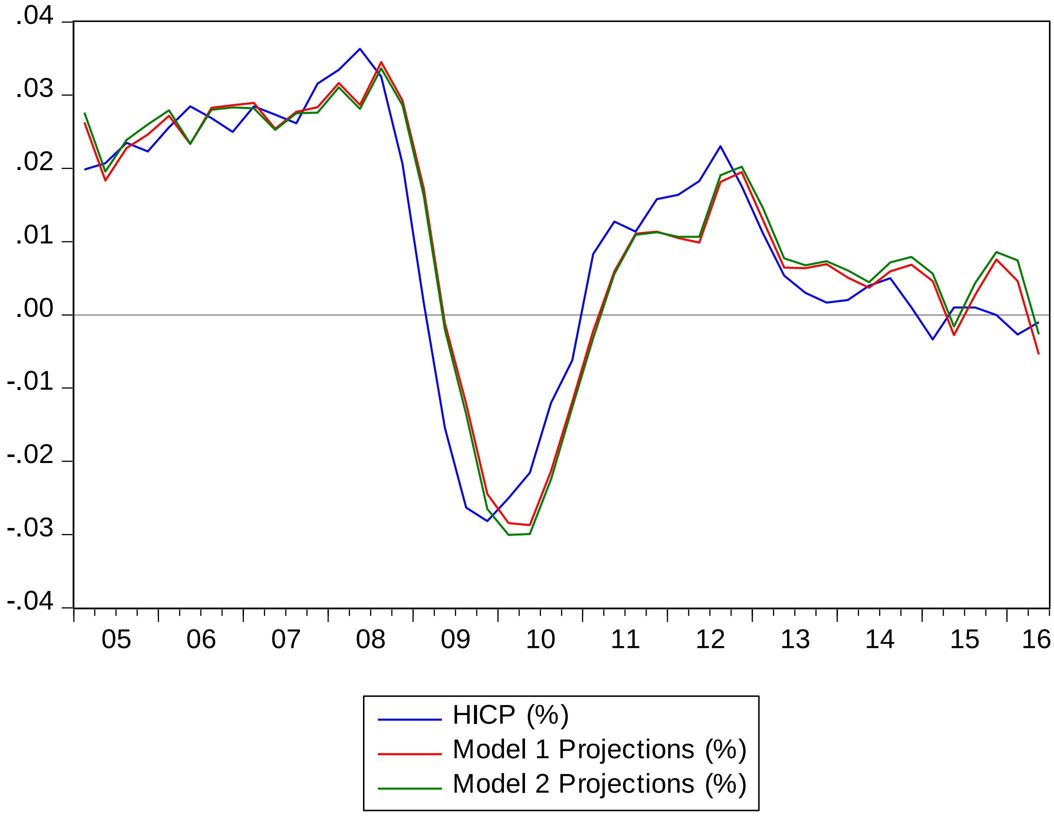
Like each item of the National Accounts and labour market that is forecasted, the model average forecast is complemented by judgement applied. In all cases, judgement is informed by a combination of factors. These factors include the direction of recent errors on model equations, current carryovers, quarterly profiles and other high frequency data which are not incorporated into the models estimated. For example, retail sales and consumer confidence indices are not included in models of consumption, but could influence judgement applied.

To derive a nominal series for consumption, the consumption deflator needs to be forecasted. The personal consumption deflator is split into three components: the part associated with rents, the part associated with FISIM[17] and the remainder (HICP). The weight placed on rents in this calculation comes from the share of imputed rents in overall consumption in the latest annual National Income and Expenditure Accounts.[18] The forecast for rent inflation is not model-based. In forecasting changes in HICP, two models are used (results detailed in Annex 2.1.3). The first model uses past changes in

[17] FISIM stands for Financial Intermediation Services Indirectly Measured. Forecasts for this component are informed by the margins on bank lending.
[18] This is 14% in the 2015 National Income and Expenditure Accounts.

the HICP and changes in activity (measured here by underlying domestic demand, given that GDP does not always accurately capture domestic activity in the economy) are used. The second model uses past changes in HICP and changes in real consumption. In both cases, changes in underlying domestic demand or consumption have small but significant impacts on the price level. The average of the two models is generally taken as the initial forecast, with judgement then applied as appropriate. Figure 4 below shows the four-quarter ahead forecasting performance of these two models over time, which seems to track the actual series quite closely.

Figure 4: Forecasting HICP (%, Y-Y Change).
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2004Q1 – 2015Q2.
Short-Run equation, forecasting four quarters ahead.



Section 4: Investment

Forecasts for investment are made using a bottom-up approach. Each of the main components of investment is modelled separately, in line with the detailed quarterly data published by the CSO. There are three broad categories of investment: building/construction, intangible assets and machinery and equipment. Building and construction can be split into four subcomponents which are each modelled separately: transfer costs, improvements, residential construction and commercial construction. Machinery and equipment is split into aircraft purchases and all other machinery and equipment investment (henceforth underlying machinery and equipment). Investment in aircraft and intangibles is largely imported (100 per cent for aircraft and around 80 per cent of intangibles[19]), hence these components of investment have no major impact on GDP[20]. With this in mind and given that investment in aircraft and intangibles are difficult to forecast, they are held constant over the forecast horizon. While this has no impact on the aggregate GDP/GNP forecast, it means that calculations of domestic vs. external sources of growth are not distorted by the activities of these sub-sectors.[21]

Investment in underlying machinery and equipment is modelled as a function of future values of external demand for Irish goods exports[22] and lagged values of itself. The rationale for using external demand is that investment in machinery and equipment takes place in order to give the capacity to produce goods to export. In using future values of external demand, the assumption is that investment decisions made now are based on expected future demand for goods produced in Ireland as opposed to current levels. As one would expect, there is a positive coefficient on future demand for Irish goods exports and the lagged dependent variable in both the long-run and short-run equations, while the error correction term is also found to be statistically significant. The estimation results are shown in Annex 2.2.1.

Figure 5 below shows the performance of the model in forecasting four quarters ahead. From this chart it is evident that this series is quite volatile and hence difficult to forecast, with the result that judgement will often necessarily play a larger role.[23] The forecasts for underlying machinery and equipment, along with the assumption that investment in aircraft remains flat, provides the overall forecast for total machinery and equipment investment.

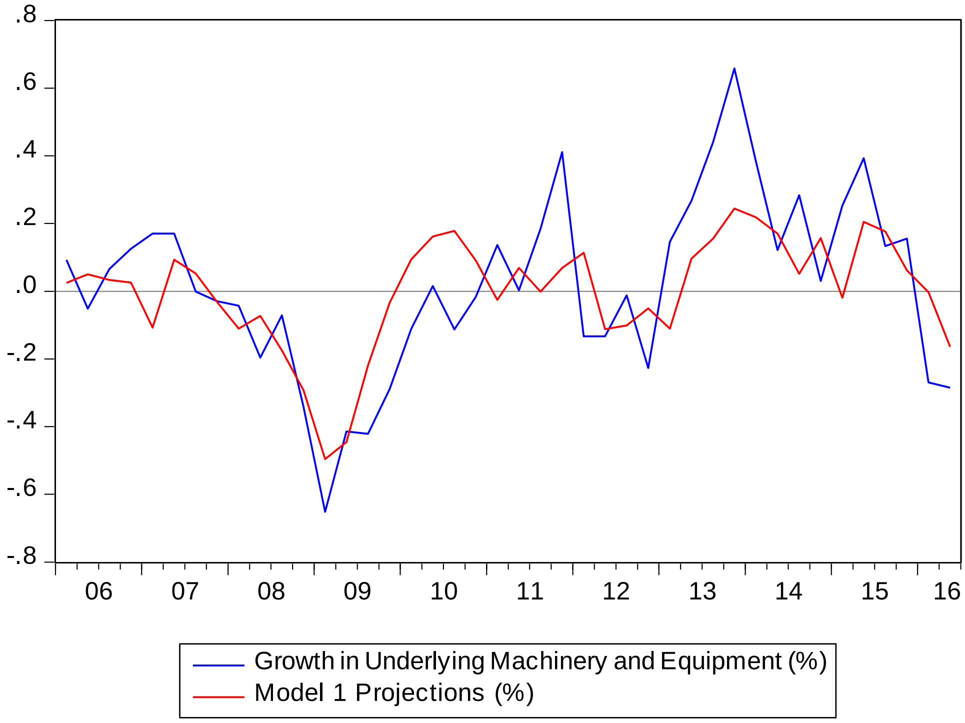
Looking at building and construction, forecasts of completions are a key input into forecasts of the building and construction sector. Firstly, new house completions are forecast on the basis of lagged housing commencements and registrations data from the Department of the Environment. While this gives a basis for forecasting several quarters ahead, some assumption is required for the pace of completions in later periods. One anchor for this is the estimated level of natural demand for housing. This is the level of housing completions needed to keep up with new household formation and obsolescence of the existing stock. There are a number of estimates of natural demand; Duffy *et al* (2014) estimated 25,000 per annum would be required. Duffy *et al* (2016) revised this up somewhat;

[19] On average, 80% of intangibles have been imported since 2012, although this is trending upwards.
[20] See IFAC (2015) Box C for details. The increase in imports cancels out the corresponding increase in investment
[21] As a result of this, domestic demand growth and underlying domestic demand growth will be equal over the forecast horizon.
[22] As detailed in table 1 above, this comes from forecasts of goods import growth in Irelands trading partners.
[23] Underlying machinery and equipment has the second-highest Root Mean Squared Errors (RMSE) of 0.181. See Table 2 for details.

with an estimate of 25,000 to 30,000 per annum out to 2024. Lyons (2017) estimates a much higher level of structural demand, in the region of 50,000 per annum. This higher level of natural demand is driven by assumed obsolescence rates and demographics. Given the current low level of completions, an element of judgement is involved in forecasting when completions will return to an assumed equilibrium level, which is informed by the estimates referenced above. Future work on more formal models for the building and construction sector are planned, with house/commercial property price-to-cost ratios a potential explanatory variable.

The forecast for investment in dwellings then follows from the forecast of completions, with a short-run equation relating changes in the two series (Annex 2.2.2). Improvements and transfer costs both depend on lagged completions and lagged dependent variables (Annex 2.2.3 and Annex 2.2.4). Commercial investment forecasts are judgement-based and reflect the latest industry forecasts as well as various market surveys and reports.

Figure 5: Forecasting Underlying Machinery and Equipment growth (%, Y-Y).
Estimation sample starts 1998Q2. Estimation Sample Ends: 2005Q4 -2015Q2.
Short-run equation, forecasting four quarters ahead.



It is worth noting that investment is by far the most difficult element of expenditure to model. This is reflected in Table 2 which shows the Root Mean Squared Errors (RMSE) of the various models, with the components of investment showing larger errors than consumption, exports or imports.

For each of the components forecasted above, a deflator must also be forecasted to get a nominal series. For the deflator on underlying machinery and equipment, changes in oil prices and the real effective exchange rate are used as well as ARMA terms. This reflects that external conditions drive not just the quantity of underlying machinery and equipment, but also its price. For residential and commercial investment deflators, ARMA models are used, after a number of alternatives were considered. For the deflator on transfer costs, a lagged dependent variable and wage inflation are used. A similar approach is taken for the improvements deflator with wage inflation and a lagged dependent variable used. Investment in intangible assets and aircraft are assumed constant both in nominal and real terms, so there is no model for the deflators in either case.

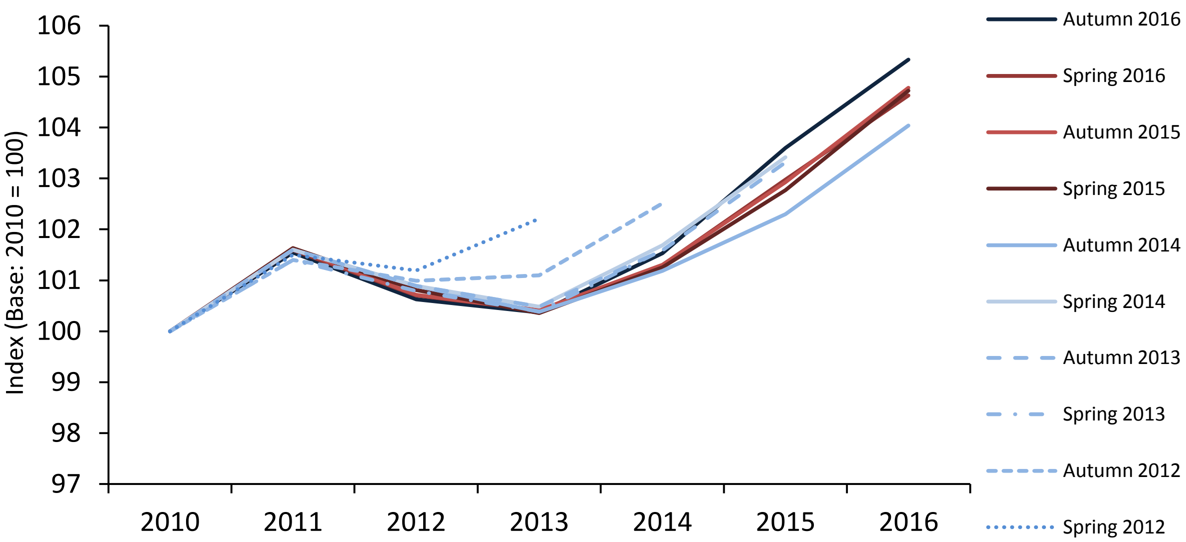
Section 5: Trade

Given the openness of the Irish economy and share of exports and imports in overall GDP, the projections of exports and imports are key drivers of the forecast for aggregate GDP. Exports of goods and services are modelled separately. An indicator of external demand is the key variable used to forecast goods exports and services exports. External demand is often calculated using GDP growth in main trading partners, with weights allocated in accordance with trade shares. An alternative approach is used here, focusing on the growth of goods imports and service imports in Ireland's trading partners rather than the GDP growth rates. Two indicators are constructed, one for goods exports and another for service exports.[24] This better reflects the demand for Irish exports than trading partners GDP as it focuses solely on the demand for Irish goods and services abroad.[25]

External agencies produce separate forecasts of goods imports and service imports for all of Ireland's main trading partners. Using a combination of these external forecasts (European Commission and IMF[26]), assumptions for external demand are calculated. The growth of goods imports and service imports for each country are combined with weights for each country. Weights are determined for each destination based on historical trade shares.

External demand is a critical background assumption required for the purposes of forecasting, particularly in a small open economy like Ireland. However, forecasts of growth for Ireland's major trading partners are prone to errors too, with the post-crisis period seeing a number of downward revisions to Euro Area growth by official agencies, for example (Figure 6). This is an important feature of the forecasts that the Council takes into consideration in assessing the risks around GDP growth projections.

Figure 6: Euro Area Real GDP (European Commission Forecast Vintages)



Source: European Commission Forecasts, Different Vintages

[24] Historical data on the destination of goods and service exports are used to calculate trade weights for goods and services.
[25] For example, if a major trading partner of Ireland was to experience much higher GDP growth due to an export boom, this would not necessarily lead to a surge in demand for Irish exports to that destination.
[26] When European Commission forecasts are not available, IMF forecasts are used, details in table 1, above.

Modelling Irish exports and imports has always been difficult due to the large share they make up of the economy and the high degree of concentration of the Irish export base. In particular, goods exports have proven to be problematic for forecasting in recent times, mainly due to contract manufacturing[27] activities. Previous *Pre Budget Statements* (IFAC 2016) and *Fiscal Assessment Reports* (IFAC 2015) have highlighted some of the problems that have arisen. These distortions have become much larger since the publication of the 2015 National Accounts. Nominal goods exports recorded in the National Accounts grew by 70% in 2015, while nominal goods exports captured by the monthly trade data grew by 20%[28]. This large step change in goods exports recorded in the National Accounts was not accompanied by a similar offsetting increase in imports, hence contributing to GDP growth of 26.3%. The monthly trade data is considered to better capture the actual goods exports from Ireland and hence plays a key role in informing judgement to be applied to the forecast of goods exports.

This change in the National Accounts has had substantial implications for modelling/forecasting goods exports. A previously estimated long-run equation of goods exports would now suggest that the equilibrium level of Irish exports is well below the current elevated level. This would impact on the forecasts given by the short-run equation, as the error-correction term would lead to forecasts of sharp falls in goods exports in subsequent quarters. How to deal with this data issue from a forecasting perspective depends on how one expects the base level to behave in future. The most likely scenario at the moment appears to be that the new higher base will remain and hence goods exports will then grow in line with changes in external conditions from this new base.

With this in mind, there are two obvious modifications that can be made to the usual error correction models used for forecasting. Firstly, one could insert a dummy from 2015Q1 and beyond in the long-run equation, reflecting that there is a once-off shift upward in goods exports which is expected to remain indefinitely[29]. Secondly, one could remove the long-run equation altogether and simply use a short-run equation which relates changes in goods exports to changes in world demand, exchange rates, etc. The first approach is taken, as this means that one can still easily see the long-run impact of a shock to external demand or exchange rates on goods exports.

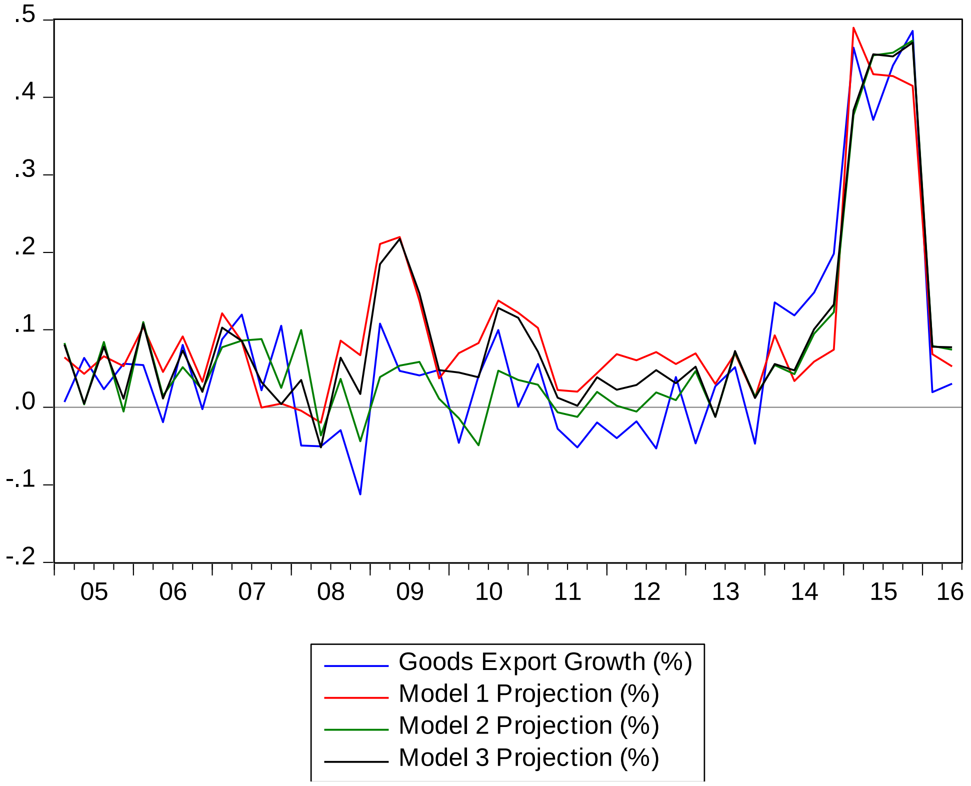
In line with this approach, three models are estimated and the average of the three forecasts produced is taken as an initial input into the Benchmark projections (Annex 2.3.1). In the model one, goods exports are modelled as a function of external demand and the real effective exchange rate. External demand is highly significant in both the long and short-run, while the real effective exchange rate is only statistically significant in the short-run. As a result of this, in model two the real effective exchange rate is dropped and lagged goods exports is used as well as external demand. In this case, both external demand and the lagged dependent variable are significant in the long-run equation. Model three uses external demand, the real effective exchange rate and lagged goods exports. In this case, while all three variables are correctly signed in the long-run equation, real effective exchange rates are not statistically significant. In all three models, the dummy variables are statistically significant and correctly signed in both the short-run and long-run equations.

[27] Contract manufacturing activities occur when an Irish-resident firm (not necessarily Irish-owned) contracts a manufacturer overseas to produce a good for supply to an end-client abroad. While contract manufacturing activity had taken place in previous years, it had previously been largely GDP-neutral, with the increase in goods exports largely being offset by a corresponding increase in service imports (mainly royalties/licences).
[28] This gap gives an indication of the scale of the increase in contract manufacturing related activities in 2015.
[29] A dummy is also inserted in the short run equation; this takes a value of one in the period 2015Q1-2015Q4 to capture the extraordinary growth rates in these quarters.

In previous cases forecasting performance has been assessed by looking at four-quarter ahead forecasts. This is a way of testing the out of sample forecasting of an equation[30]. Doing this when including a dummy for a time period is misleading. For example, when trying to forecast goods exports for 2015Q1 using data up to and including 2014Q1, one would not have been able to estimate the impact of the dummy which was to operate from 2015Q1 on. With this in mind, Figure 7 below shows four-quarter ahead forecasts up until and including 2014Q4. Thereafter, the "forecast" values are within sample fits rather than out-of-sample forecasts. It is also evident from Figure 7 that even prior to the step-change in this series, goods export growth was quite difficult to forecast, with some large swings from quarter to quarter which were not explained by changes in the standard predictors (external demand, effective exchange rates, etc). The dummy appears to have captured the step change in goods exports recorded in the 2015 National Accounts. Looking at the RMSE and the Theil's U2 statistics (Table 2), it appears that these models are performing relatively well.

In addition to the models described above, judgement is applied to arrive at the final projection. Other sources of data like the monthly trade data play a key role in any judgement which may be applied. In any event, the monthly trade data may provide better guidance as to the level and/or change in goods exports actually being produced in Ireland for export.

Figure 7: Forecasting Goods Exports growth (%, Y-Y)
Estimation sample Begins 1999Q1. Estimation sample Ends: 2004Q1 -2015Q2.
Short-Run Equation, forecasting four quarters ahead.

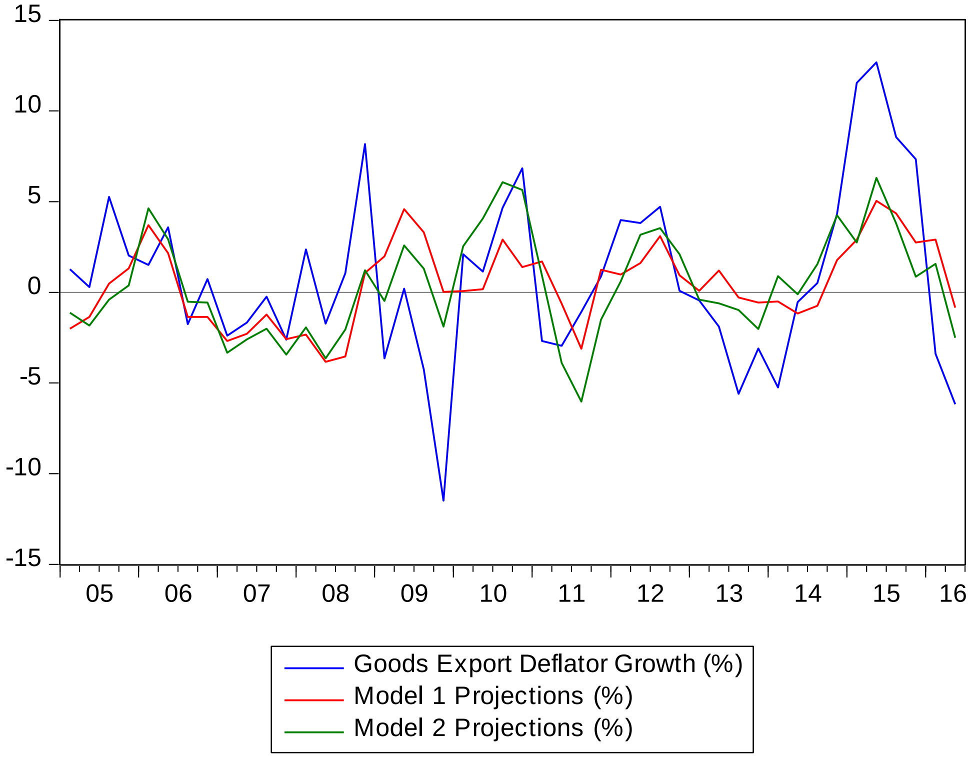


To model the deflator on goods exports, two models are estimated (Annex 2.6.1). The first includes the Euro/US dollar exchange rate. As many of the exports of goods from Ireland are priced in dollars and/or are exported by US-owned multinational enterprises, this variable can explain a lot of the variation in this deflator. In 2015, there was strong growth in the goods export deflator, most of which

[30] The model/equation is estimated using data up until time t, this is then used to forecast values out to t+4.

could be explained by the weakening of the Euro against the Dollar[31]. For the second model, the goods import deflator as well as the Euro/US exchange rate is used. This reflects that many intermediate inputs used to produce goods which are subsequently exported are imports.

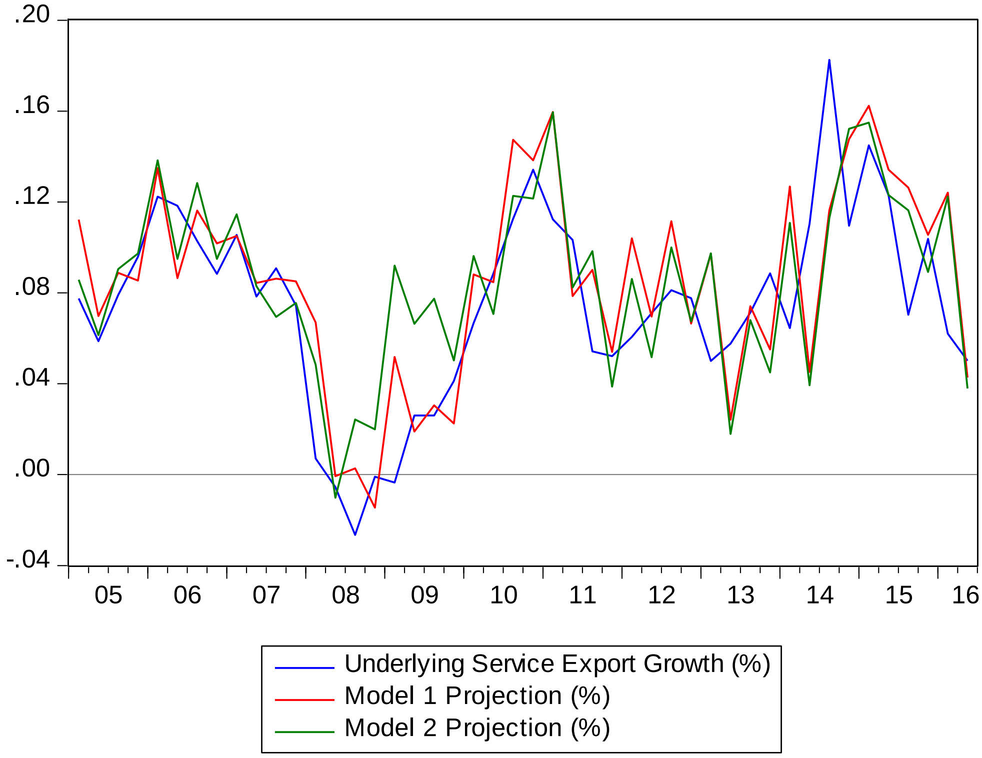
Figure 8: Forecasting Goods Exports Deflator growth (%, Y-Y)
Estimation Sample Begins 1999Q1 Estimation Sample Ends 2004Q1 -2015Q2.
Short-Run Equation, forecasting four quarters ahead.



On the services side, service exports are split into those related to tourism and all other service exports (henceforth underlying service exports). There are two models of underlying service exports used (Annex 2.3.2). The first uses external demand, the real effective exchange rate and a lagged dependent variable in the long-run equation. All the variables are found to be correctly signed, with the real effective exchange rate and the lagged dependent variable statistically significant. In the short-run, all variables are correctly signed and significant, including the error correction term. The second model uses a lagged dependent variable and external demand, with only the lagged dependent variable statistically significant. Generally, an average of the two models is taken as an initial input into the Benchmark projections. This model forecast is then combined with other considerations including discussions with the Council and recent forecast errors to give the final forecast. Both models appear to be performing relatively well in recent quarters, as stronger external demand and a more favourable exchange rate have coincided with the recent growth in service exports (Figure 9).

[31] The Euro depreciated by 16.5% against the dollar in 2015.

Figure 9: Forecasting Service Exports growth (%, Y-Y)
Estimation Sample begins: 1999Q2 Estimation Sample Ends: 2004Q1 -2015Q2
Short-Run Equation, forecasting four quarters ahead.



For the services export deflator, changes in the services import deflator and lagged changes of the dependent variable are used, as well as a time trend. This reflects the import content of service exports.

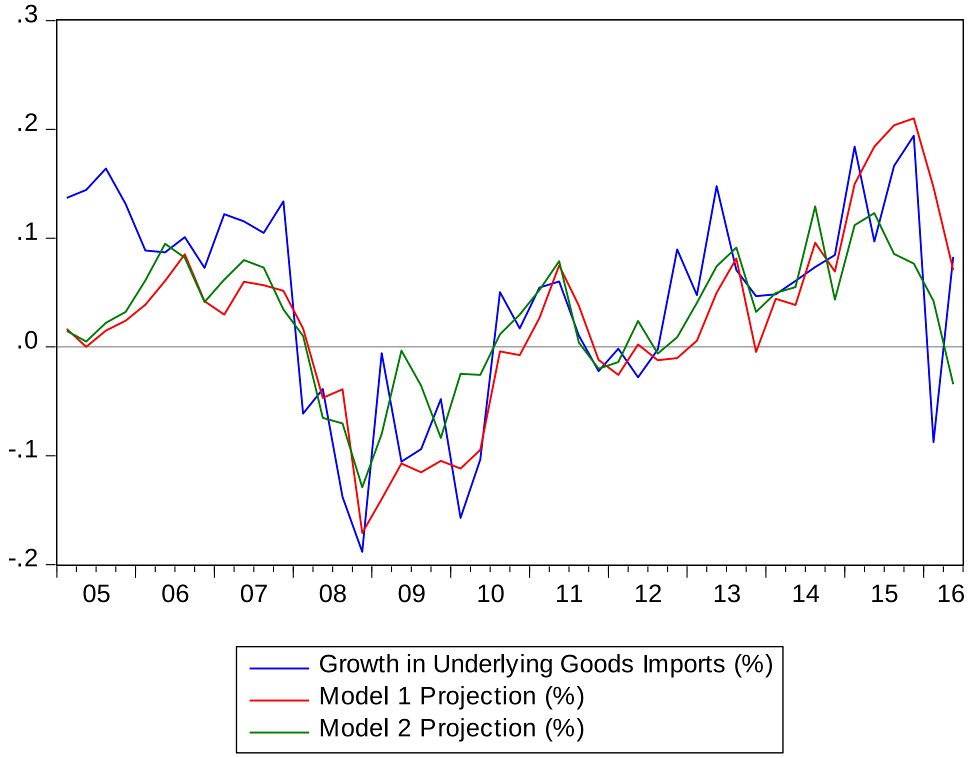
For tourism exports, an indirect approach is taken. First, the number of visitors to Ireland from abroad is forecasted. This is done using weighted forecasts of external real GDP per capita growth in Ireland's main tourism export markets. The weightings applied reflect the previous visitor numbers to Ireland and their origin. After tourist visits are forecasted, a simple equation is used to translate this into tourism exports. Adding this to the underlying service exports gives a forecast for total service exports.

In terms of imports, goods and service imports are forecasted separately. On the goods side, it is underlying goods imports which are modelled (this excludes aircraft which, as was noted earlier, are part of investment and hence are GDP neutral). Two models of underlying goods imports are used. Firstly a simple model using underlying final demand[32] and lagged values of goods imports is estimated (Annex 2.4.1). Final demand should give an indication of domestic activity and hence the demand for imported goods. Both variables carry the expected sign and are significant both in the short-run and long-run equations. The second model of underlying goods imports uses underlying service exports, underlying investment and a lagged dependent variable. The rationale for this is that both investment and service exports can be import intensive. All three variables are found to be significant and correctly signed in the long-run and short-run equations. Other variables such as the

[32] Underlying final demand is defined here as personal consumption plus government expenditure plus underlying investment (excluding aircraft and intangibles) plus stock changes.

real effective exchange rate were used for some estimations, but were not found to be significantly correlated with goods imports.

Figure 10: Forecasting Goods Imports growth (%, Y-Y)
Estimation Sample Begins: 1999Q4 Estimation Sample Ends 2004Q1-2015Q2.
Short-Run equation, forecasting four quarters ahead.

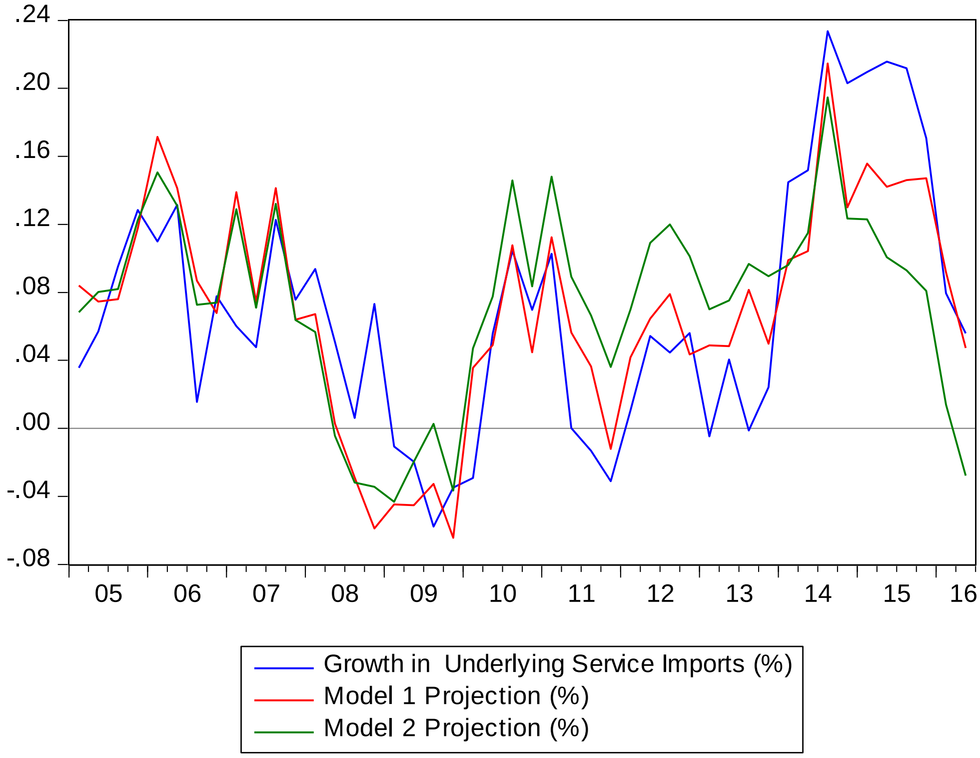


The goods import deflator is modelled using oil prices, the Euro/US dollar exchange rate and EU goods export prices. Many imports into Ireland come from the US and/or from US-owned firms and hence the exchange rate can have a significant impact. Oil is a significant part of goods imports into Ireland and its price is quite volatile, and hence it makes a significant contribution to changes in the goods imports deflator. Finally, EU goods export prices are included to reflect the impact of EU price changes on Irish import prices.

For service imports, an adjustment is also made, with imports of intangible assets removed. Two models are used for this series (Annex 2.4.2), with a model average normally used. Underlying final demand, personal consumption and goods exports are all used as explanatory variables. This reflects that part of consumption is made up of imported services while imported services also frequently represent an input to goods exporting industries (support services for firms, royalties/licenses imports etc). Figure 11 below shows the historical forecasting performance of the two models, which broadly track the recent strong growth in underlying service imports.

As was the case for goods imports, other variables such as the real effective exchange rate were used in some estimations, but were not found to be significant predictors and hence are omitted. For the service import deflator, two models are used. The first uses the Euro/US dollar exchange rate as well as lagged values of the service import deflator. The second model uses changes in the goods export deflator in addition to the variables used in the first model.

Figure 11: Forecasting Underlying Service Import growth (%, Y-Y)
Estimation Sample Begins 2000Q4. Estimation Sample Ends 2004Q1 - 2015Q2,
Short-Run equation, forecasting four quarters ahead.



Section 6: Labour Market and Income Projections

The forecasts of the labour market depend on the forecasts of the expenditure side of the economy, as outlined in the previous sections. Starting with employment, forecasts are based on the projections for labour demand, captured by the growth of the economy. While in many countries GDP may be a good proxy for labour demand, in Ireland this is not always the case. Changes in Irish GDP are often due to the activities in the multinational sector and hence may not accurately reflect demand for domestic labour. While there is substantial employment in multinationals based in Ireland, the output or value added of these firms is much less employment intensive than in the rest of the Irish economy. Given that this is the case, using a measure of activity which is heavily influenced by these firms may not be a good measure of demand for labour in Ireland.

With this in mind, the more domestically focused elements of the Irish economy are used to forecast employment. From the expenditure side, domestic demand is used as it captures much of the activity in the Irish economy, without being distorted by some of the issues in the trade data (as discussed in section 5 above). This measure includes personal consumption, government consumption and investment[33]. From the output side, construction output and output in the distribution, transport, software and communications sector are used. While there is a substantial multinational presence in the software sector, this aggregate sector is mainly populated by domestic firms and hence is quite employment intensive.

Three models of employment are used (details in Annex 2.5.1). Model one uses domestic demand and construction activity as proxies for labour demand. In the long-run equation underlying domestic demand is found to be statistically significant, with construction activity marginally outside a 10% level. In the short-run equation, changes in domestic demand and construction activity are found to be significant, as well as the error correction term.

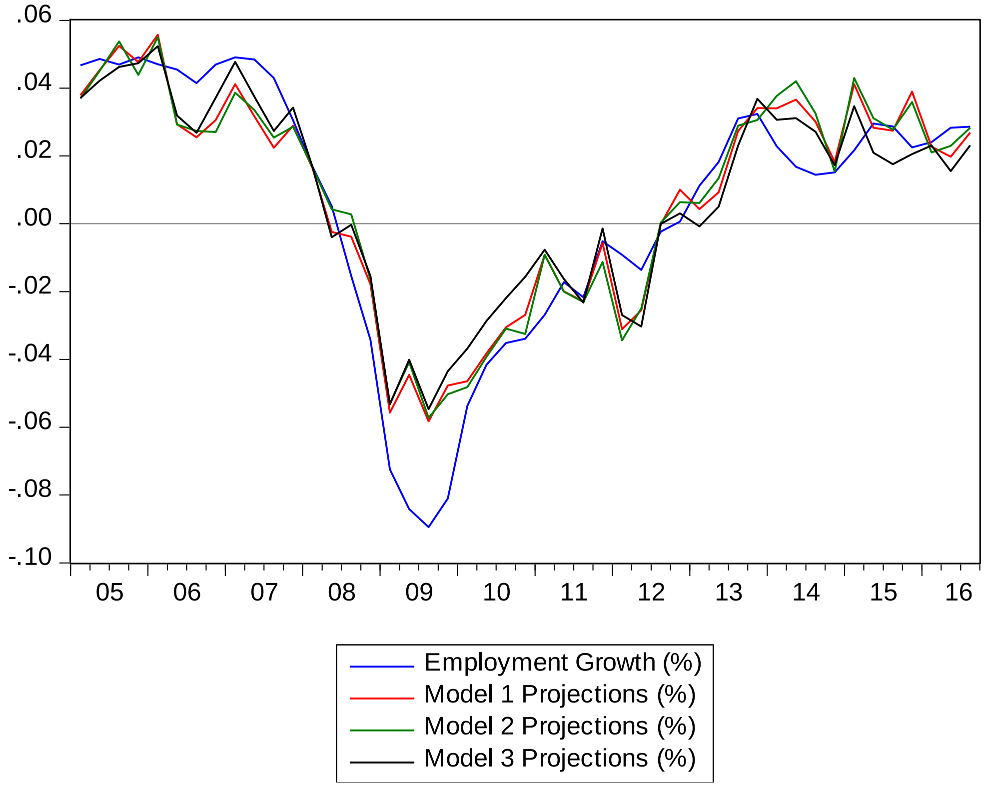
Model two does not use any long run or error correction framework; it simply relates changes in employment to changes in underlying domestic demand and construction activity. The coefficients on both underlying domestic demand and construction activity are found to be correctly signed and statistically significant.

Model three uses underlying domestic demand, output in the industrial (excluding construction) sector and output in the Distribution, Transport, Software and Communications (DTSC) sector. In the long-run equation, both domestic demand and output in the DTSC sector are found to be positive and significant. By contrast, industrial (excluding construction) output is found to be negatively signed and significant. It is perhaps not so surprising that this sector is not strongly positively associated with employment, as it may partly reflect the recent contract manufacturing activities of multinationals based in Ireland. In the short-run the industrial coefficient is also negative, albeit not significantly so. The error-correction term is also incorrectly (positively) signed.

Figure 12 shows the forecasting performance of the three models described above, in each case the models are forecasting four quarters ahead. Recent model forecasts have tracked actual employment growth quite closely, indicating that the measures of the output or expenditure side of the economy are consistent with recent improvements in the labour market.

[33] Underlying domestic demand may be used in future, as it excludes investment in aircraft and intangible assets.

Figure 12: Forecasting Employment growth (%, Y-Y)
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2004Q1 - 2015Q3,
Short-Run equation, forecasting four quarters ahead.

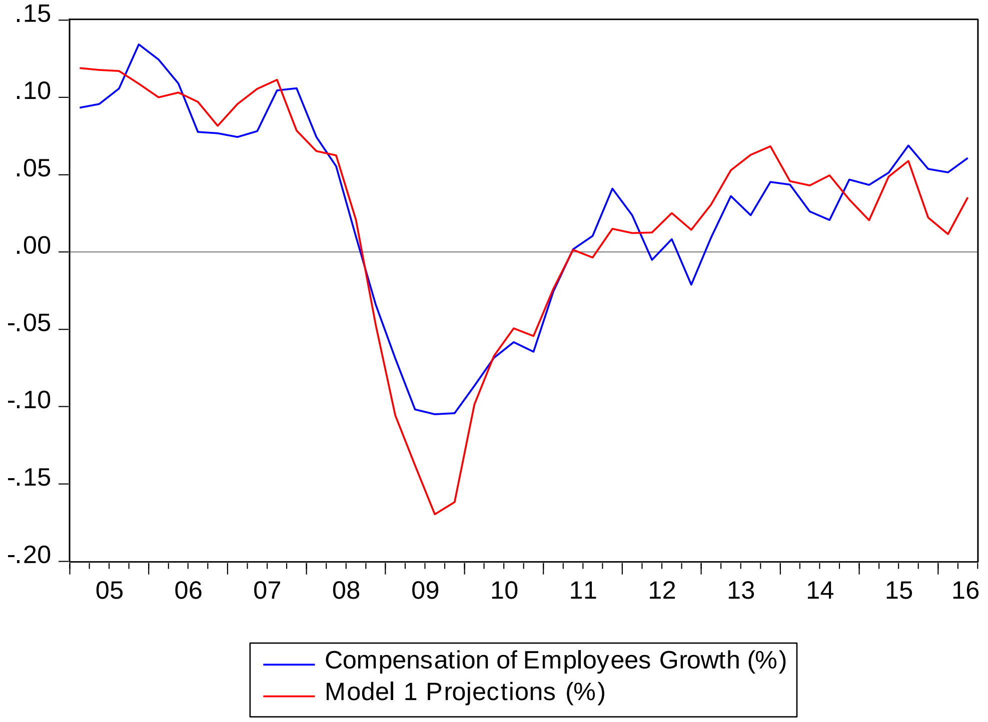


After employment has been forecast, the level of unemployment is next to be projected. A similar set of variables is used to model unemployment (domestic demand, construction output and output in the DTSC sector). In addition to the model output, it is noteworthy that the unemployment rate has been steadily falling recently and can provide a useful background to assess model projections. Using elements of the macroeconomic projections as a predictor for employment/unemployment helps to make sure that these forecasts are consistent. As a formal check on the consistency of these projections, Okun's law equations are examined. Projections for the labour force are based on examining the age cohorts of the population and their likely participation rates, which tend to change slowly in normal times.

Turning to incomes, data on wage growth have often been difficult to interpret with contradictory signals coming from the estimate of non-agricultural wage growth in the national accounts, and the growth in average earnings reported in the survey-based Earnings and Labour Costs (see Box A, IFAC (2014)). Given the uncertainty regarding historical data, forecasting has proven challenging. The variable modelled is compensation of employees[34] (as per the Institutional Sector Accounts). This is modelled on the basis of consumer inflation (HICP), employment and seasonal dummies. While there are a number of models maintained on an ongoing basis, only the favoured model is documented in Annex 2.5.2. Figure 13 below shows the four-quarters ahead forecasting performance of this model. Compensation of employees is a key input into personal disposable income which is used in forecasting consumption as detailed in section 3 above.

[34] A forecast of compensation per employee is then implied by dividing compensation of employees by the forecast of employees.

Figure 13: Forecasting Compensation of Employees growth (%, Y-Y)
Estimation Sample Begins 2000Q1. Estimation Sample Ends 2004Q1 - 2015Q3,
Short-Run equation, forecasting four quarters ahead.



Section 7: Other Issues Arising

This section considers some other issues that arise when compiling a short-run forecast of the Irish economy. Stock changes make up a part of GDP and have made substantial contributions to growth in recent years[35]. There is no explicit model of these changes; a judgemental forecast is made with respect to this item. Stock changes are generally held constant over the forecast period unless there is good reason to think they will change significantly. This does not imply that the stock level is held constant but rather that the change in stocks (i.e. the flow) is held constant. This ensures that stock changes make no contribution to GDP growth.

All of the items described above are forecasted on the basis of quarterly data.[36] There are trade-offs when examining quarterly data as opposed to annual, such as timeliness, extent of revision and volatility. Given the timing of the two forecast sets produced by the secretariat (March and September), examining the quarterly data is key as the annual National Accounts for a given year are released with a significant lag (in June/July of the following year).[37] While partially reflected in the quarterly models of each of the components, carryovers are a key part of the judgement element of the forecasts. For example the strong growth in the second half of 2016 led to a carryover of 4% for 2017. A large carryover of this scale provides significant additional information about the likely future path of GDP (and its components) and can inform the judgment used to arrive at the final forecast for that year. As there is no systematic bias in the revisions to the Quarterly National Accounts, quarterly profiles and carryovers give unbiased information that can assist in the forecasting process.

Multiple Iterations

In practice, the approach outlined here does not produce real GDP estimates that are simply the aggregate of a single iteration of all components. Instead, several iterations are undertaken to arrive at a final set of model estimates.

A useful way to explain the role of multiple iterations is the example of employment growth. In the approach outlined here, employment is forecast, in part, as a function of expected underlying domestic demand. However, in order to arrive at expectations for underlying domestic demand, it is necessary to have some initial estimate of employment expectations. This is because estimates of employment influence personal disposable income growth in the economy and personal disposable income growth acts as an explanatory variable underpinning personal consumption – a key component of underlying domestic demand. The initial estimate may be a previous set of forecasts or it may be informed by judgement or by other forecasting tools. A possible drawback of the short-term forecasting outlined here is the extent to which it is allowed to be unduly influenced by the *ex-ante* expectations used. This can be mitigated by using alternative satellite models or consistency checks.

[35] Stock changes contributed 1.3pp in 2014 with a negative contribution of 0.8pp in 2015.

[36] The one exception is tourism exports, which due to data constraints is forecast on an annual basis and then interpolated to give quarterly values.

[37] The National Accounts for 2015 were published by the CSO on 12 July 2016. Only a selection of the standard National Accounts tables were published in this release. For example, detailed tables on income, investment and General Government expenditure and revenue for 2015 were not published until October 2016.

Consistency Checks

The suite of models approach results in a set of initial model estimates that form the starting point for the Benchmark projections. A number of consistency checks can then be applied to examine the coherency of these. The Council's Secretariat employ additional models to examine the consistency of initial estimates with other known or theoretical relationships. Though not detailed here, the Secretariat has employed consistency checks that, for example, examine the implied relationships between productivity and wages and the relationship between employment and the composition of growth among other things.

Section 8: Conclusions

While this paper describes the forecasting methodologies employed at this time, there is ongoing work on expanding the tools used and testing the existing ones. Models are re-estimated and the forecasting performance is reassessed at each forecasting round. This is essential both to continue to produce the best quality Benchmark forecasts possible, but also to be better placed to scrutinise the forecasts of the Department of Finance.

In conclusion, this paper describes the short-run forecasting models used by the Secretariat for producing its own Benchmark macroeconomic forecasts and assessing the forecasts of the Department of Finance. The approach taken is to forecast disaggregated components of the income and expenditure side of the National Accounts as well as the labour market. This is done using individual equations for each component. In many instances multiple equations are estimated and the average forecast across the equations is used. The forecasting performance of the equations is tested at each forecasting round and examples can be found in Annex 2.

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Annex 1: Description of NIE Aggregates Modelled

$$GDP(Y) = C + I + G + (X - M) + Stocks + Stat$$

Where C = Consumption, I = Investment, G = Government, X = Exports, M = Imports, $Stocks$ = Stock changes and $Stat$ = Statistical discrepancy.

Goods and services consumption are modelled separately.

$$C = CG + CS$$

Where CG = Goods consumption and CS = Services consumption[38].

Government consumption is taken as exogenous, based on the forecasts provided by the Department of Finance. The plausibility of these forecasts are assessed based on known budgetary plans and the latest Quarterly National Accounts data.

There are three main components of investment which are each modelled separately as follows:

$$I = B\&C + M\&E + Int$$

Where $B\&C$ = Building and construction = Dwellings + Improvements + Transfer Costs + Commercial.

$M\&E$ = Machinery and equipment = Aircraft + underlying M&E.

Int = Intangible assets.

Exports and imports of goods and services are modelled separately: $X = XG + XS$

XG = Exports of goods, XS = Exports of services.

$$M = MG + MS$$

MG = Imports of goods, MS = Imports of Services.

$$MS = MSU + Int$$

MSU = Underlying service imports.

$$MG = MGU + Aircraft$$

MGU = Underlying Goods imports.

UDD = Underlying domestic demand.

$$UDD = C + B\&C + Underlying\ M\&E + G$$

Unless otherwise stated log differences refer to year on year differences, i.e.

$\Delta\text{LN}(Z_t) = \text{LN}(Z_t) - \text{LN}(Z_{t-4})$

[38] CG_{SA} and CS_{SA} denote seasonally adjusted goods and services consumption.

Annex 2: Detailed Estimation Results

2.1.1: Goods Consumption

Dependent Variable: Consumption of goods.

Model 1: Explanatory variables: Personal disposable income and wealth (both in real terms).

Long Run: $\mathrm{LN}(CG_{SA\,t}) = -1.05 + 0.93{*}\mathrm{LN}(PDI_t) + 0.07{*}\mathrm{LN}(Wealth_t)$

Short Run: $\Delta\mathrm{LN}(CG_t) = -0.00 + 0.71{*}\Delta\mathrm{LN}(PDI_t) + 0.25{*}\Delta\mathrm{LN}(Wealth_t)$ $-0.70{*}(\mathrm{LN}(CG_{SA\,t-4})$ - $\mathrm{LN}(CG^{*}_{SA\,t-4}))$

Dependent Variable: LPCGR_SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2002Q1 2016Q2
Included observations: 58 after adjustments
LPCGR_SA = C(1) + C(2)*LRPDI_SA + (1-C(2))*LRNFHWEALTH_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.046692	0.133592	-7.835016	0.0000
C(2)	0.933313	0.041629	22.41992	0.0000

R-squared	0.823204	Mean dependent var	9.159352
Adjusted R-squared	0.820047	S.D. dependent var	0.077339
S.E. of regression	0.032808	Akaike info criterion	-3.962423
Sum squared resid	0.060276	Schwarz criterion	-3.891373
Log likelihood	116.9103	Hannan-Quinn criter.	-3.934747
F-statistic	260.7487	Durbin-Watson stat	0.293279
Prob(F-statistic)	0.000000		

Dependent Variable: DLPCGR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCGR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*(LPCGR_SA(-4) - (BETA80 + BETA81*LRPDI_SA(-4) + (1-BETA81)
*LRNFHWEALTH_SA(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.002455	0.004263	-0.575850	0.5673
C(7)	0.710009	0.123690	5.740236	0.0000
C(8)	0.253277	0.052138	4.857773	0.0000
C(9)	-0.702764	0.130457	-5.386939	0.0000

R-squared	0.760208	Mean dependent var	0.016921
Adjusted R-squared	0.745820	S.D. dependent var	0.055887
S.E. of regression	0.028176	Akaike info criterion	-4.229493
Sum squared resid	0.039695	Schwarz criterion	-4.082161
Log likelihood	118.1963	Hannan-Quinn criter.	-4.172672
F-statistic	52.83792	Durbin-Watson stat	0.510235
Prob(F-statistic)	0.000000		

Dependent Variable: Consumption of goods.

Model 2: Explanatory variables: Personal disposable income and wealth (both in real terms).

Long Run: $\mathrm{LN}(CG_{SA\,t}) = 0.47 + 0.73$*$\mathrm{LN}(PDI_t)$ +0.11*$\mathrm{LN}(Wealth_t)$

Short Run: $\Delta\mathrm{LN}(CG_t) =$ -$0.00 + 0.64$*$\Delta\mathrm{LN}(PDI_t) + 0.22$*$\Delta\mathrm{LN}\ (Wealth_t)$ -$0.66(\mathrm{LN}(CG_{SA\,t-4})$-$\mathrm{LN}(CG^*_{SA\,t-4}))$

Dependent Variable: LPCGR_SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2002Q1 2016Q2
Included observations: 58 after adjustments
LPCGR_SA = C(1) + C(2)*LRPDI_SA + C(3)*LRNFHWEALTH_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.474812	0.504374	0.941388	0.3506
C(2)	0.728730	0.076291	9.552034	0.0000
C(3)	0.106288	0.040768	2.607120	0.0117

R-squared	0.849682	Mean dependent var	9.159352
Adjusted R-squared	0.844216	S.D. dependent var	0.077339
S.E. of regression	0.030525	Akaike info criterion	-4.090188
Sum squared resid	0.051248	Schwarz criterion	-3.983614
Log likelihood	121.6155	Hannan-Quinn criter.	-4.048675
F-statistic	155.4461	Durbin-Watson stat	0.282366
Prob(F-statistic)	0.000000		

Dependent Variable: DLPCGR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCGR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*(LPCGR_SA(-4) - (BETA82 + BETA83*LRPDI_SA(-4) + (BETA84)
*LRNFHWEALTH_SA(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.001135	0.004440	-0.255738	0.7992
C(7)	0.636271	0.126113	5.045252	0.0000
C(8)	0.221111	0.055651	3.973160	0.0002
C(9)	-0.663521	0.142632	-4.651973	0.0000

R-squared	0.735512	Mean dependent var	0.016921
Adjusted R-squared	0.719642	S.D. dependent var	0.055887
S.E. of regression	0.029592	Akaike info criterion	-4.131468
Sum squared resid	0.043783	Schwarz criterion	-3.984136
Log likelihood	115.5496	Hannan-Quinn criter.	-4.074648
F-statistic	46.34806	Durbin-Watson stat	0.454697
Prob(F-statistic)	0.000000		

Dependent Variable: Consumption of goods.

Model 3: Explanatory variables: Personal disposable income and wealth (both in real terms).

Long Run: $\mathrm{LN}(CG_{SA\,t}) = 0.72 + 0.85*\mathrm{LN}(PDI_t)$

Short Run: $\Delta\mathrm{LN}(CG_t) = -0.00 + 0.77*\Delta\mathrm{LN}(PDI_t) + 0.17*\Delta\mathrm{LN}(Wealth_t) -0.68*(\mathrm{LN}(CG_{SA\,t-4}) - \mathrm{LN}(CG^{*}_{SA\,t-4}))$

Dependent Variable: LPCGR_SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2001Q1 2016Q2
Included observations: 62 after adjustments
LPCGR_SA = C(1) + C(2)*LRPDI_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.716531	0.444935	1.610418	0.1126
C(2)	0.845054	0.044580	18.95592	0.0000

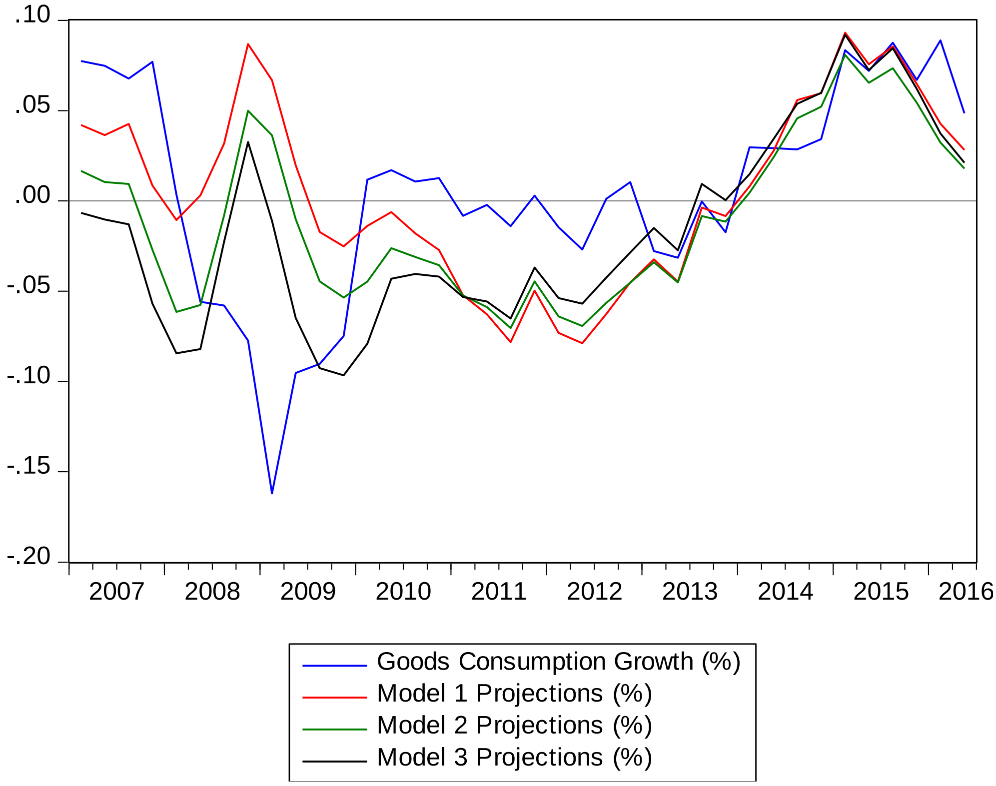
R-squared	0.856914	Mean dependent var	9.150341
Adjusted R-squared	0.854529	S.D. dependent var	0.082438
S.E. of regression	0.031442	Akaike info criterion	-4.049590
Sum squared resid	0.059318	Schwarz criterion	-3.980973
Log likelihood	127.5373	Hannan-Quinn criter.	-4.022649
F-statistic	359.3268	Durbin-Watson stat	0.297426
Prob(F-statistic)	0.000000		

Dependent Variable: DLPCGR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCGR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*(LPCGR_SA(-4) - (BETA85 + BETA86*LRPDI_SA(-4)))

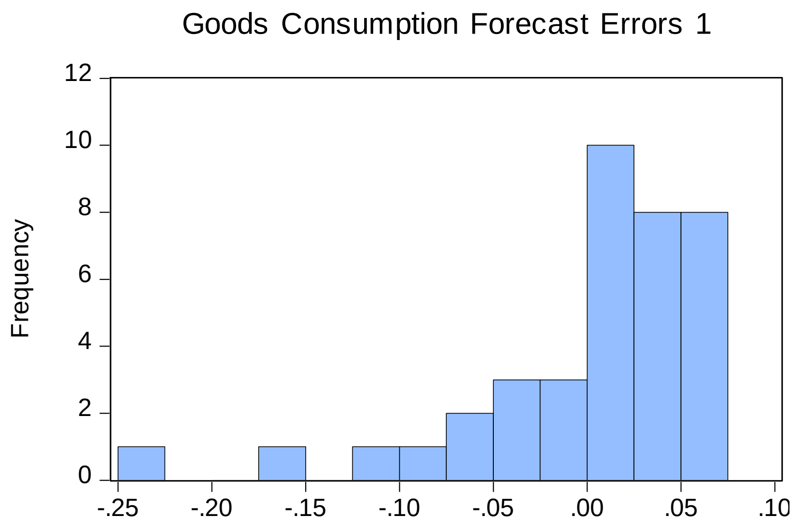
	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.003237	0.004525	-0.715395	0.4777
C(7)	0.766255	0.136853	5.599094	0.0000
C(8)	0.174575	0.058090	3.005277	0.0041
C(9)	-0.678953	0.144219	-4.707776	0.0000

R-squared	0.737426	Mean dependent var	0.016921
Adjusted R-squared	0.721671	S.D. dependent var	0.055887
S.E. of regression	0.029484	Akaike info criterion	-4.138733
Sum squared resid	0.043466	Schwarz criterion	-3.991400
Log likelihood	115.7458	Hannan-Quinn criter.	-4.081912
F-statistic	46.80748	Durbin-Watson stat	0.479923
Prob(F-statistic)	0.000000		

Forecasting Real Goods Consumption Growth (%, Y-Y)
Estimation Sample Begins: 2003Q1, Estimation Sample Ends: 2006Q1 – 2015Q2,
short run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 2003Q1. In the first case the estimation sample ends at 2006Q1, this equation is then used to forecast 2007Q1. The end date of the estimation is then pushed out to 2006Q2 and this equation is used to forecast 2007Q2. This process is repeated for each of the three models and produces the projections graphed above along with the actual outturns.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6
4
2
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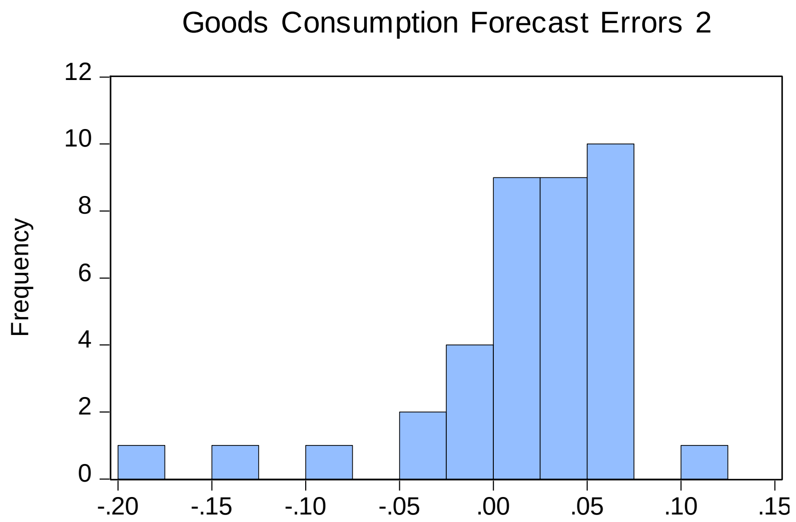
-.25
-.20
-.15
-.10
-.05
.00
.05
.10


Goods Consumption Forecast Errors 2
Frequency
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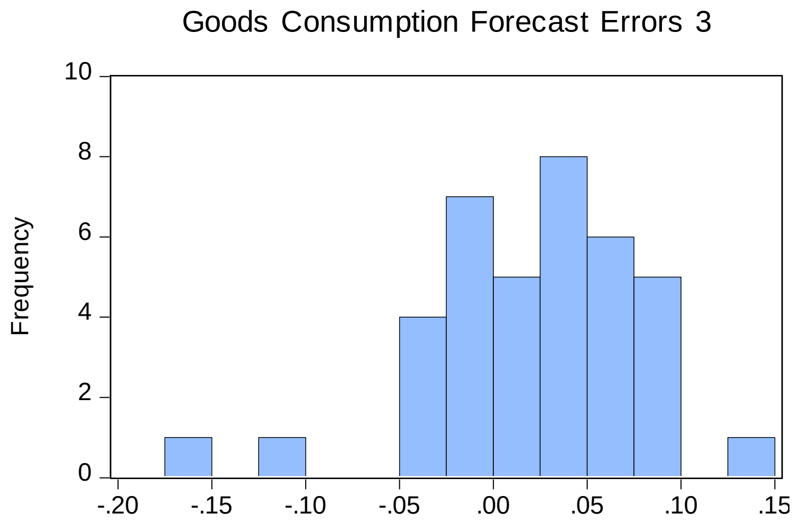
10
8
6
4
2
0
-.20
-.15
-.10
-.05
.00
.05
.10
.15


Goods Consumption Forecast Errors 3
Frequency
10
8
6
4
2
0
-.20
-.15
-.10
-.05
.00
.05
.10
.15

2.1.2: Services Consumption

Dependent Variable: Consumption of services.

Model 1: Explanatory variables: Personal disposable income and wealth (both in real terms).

Long Run: $\mathrm{LN}(CS_{SA\,t})$ = -1.59 + 1.70*LN(PDI_t) -0.46*LN($Wealth_t$)

Short Run: ΔLN(CS_t) = 0.01 + 0.57*ΔLN(PDI_t) -0.01*ΔLN($Wealth_t$) -0.47*(LN($CS_{SA\,t-4}$)-LN($CS^*_{SA\,t-4}$))

Dependent Variable: LPCSR_SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2002Q1 2016Q2
Included observations: 58 after adjustments
LPCSR_SA = C(1) + C(2)*LRPDI_SA + C(3)*LRNFHWEALTH_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.592989	0.649881	-2.451201	0.0174
C(2)	1.700263	0.098300	17.29675	0.0000
C(3)	-0.456372	0.052530	-8.687883	0.0000

R-squared	0.861365	Mean dependent var	9.372362
Adjusted R-squared	0.856324	S.D. dependent var	0.103764
S.E. of regression	0.039331	Akaike info criterion	-3.583247
Sum squared resid	0.085083	Schwarz criterion	-3.476673
Log likelihood	106.9142	Hannan-Quinn criter.	-3.541734
F-statistic	170.8623	Durbin-Watson stat	0.687849
Prob(F-statistic)	0.000000		

Dependent Variable: DLPCSR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCSR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*(LPCSR_SA(-4) - (BETA90 + BETA91*LRPDI_SA(-4) + (BETA92)
*LRNFHWEALTH_SA(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.014270	0.002877	4.960524	0.0000
C(7)	0.570002	0.087128	6.542140	0.0000
C(8)	-0.009889	0.038169	-0.259097	0.7966
C(9)	-0.468748	0.078755	-5.951986	0.0000

R-squared	0.661904	Mean dependent var	0.023225
Adjusted R-squared	0.641618	S.D. dependent var	0.032520
S.E. of regression	0.019468	Akaike info criterion	-4.968918
Sum squared resid	0.018950	Schwarz criterion	-4.821586
Log likelihood	138.1608	Hannan-Quinn criter.	-4.912098
F-statistic	32.62901	Durbin-Watson stat	1.264972
Prob(F-statistic)	0.000000		

Dependent Variable: Consumption of services.

Model 2: Explanatory variables: Personal disposable income and wealth (both in real terms).

Long Run: $\mathrm{LN}(CS_{SA\,t}) = 0.66 + 1.40*\mathrm{LN}(PDI_t)$ -0.40*$\mathrm{LN}(Wealth_t)$

Short Run: $\Delta\mathrm{LN}(CS_t) = 0.02 + 0.49*\Delta\mathrm{LN}(PDI_t)$ - $0.03*\Delta\mathrm{LN}(Wealth_t)$ -0.40*($\mathrm{LN}(CS_{SA\,t-4})$- $\mathrm{LN}(CS^*_{SA\,t-4})$)

Dependent Variable: LPCSR_SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2002Q1 2016Q2
Included observations: 58 after adjustments
LPCSR_SA = C(1) + C(2)*LRPDI_SA + (1-C(2))*LRNFHWEALTH_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.656234	0.176161	3.725184	0.0005
C(2)	1.397830	0.054894	25.46417	0.0000

R-squared	0.829219	Mean dependent var	9.372362
Adjusted R-squared	0.826170	S.D. dependent var	0.103764
S.E. of regression	0.043262	Akaike info criterion	-3.409197
Sum squared resid	0.104811	Schwarz criterion	-3.338147
Log likelihood	100.8667	Hannan-Quinn criter.	-3.381521
F-statistic	271.9061	Durbin-Watson stat	0.396559
Prob(F-statistic)	0.000000		

Dependent Variable: DLPCSR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCSR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*(LPCSR_SA(-4) - (BETA93 + BETA94*LRPDI_SA(-4) + (1-BETA94)
*LRNFHWEALTH_SA(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.015341	0.002839	5.403785	0.0000
C(7)	0.485245	0.080957	5.993853	0.0000
C(8)	-0.028724	0.038794	-0.740433	0.4625
C(9)	-0.402192	0.065756	-6.116406	0.0000

R-squared	0.669579	Mean dependent var	0.023225
Adjusted R-squared	0.649754	S.D. dependent var	0.032520
S.E. of regression	0.019246	Akaike info criterion	-4.991881
Sum squared resid	0.018520	Schwarz criterion	-4.844549
Log likelihood	138.7808	Hannan-Quinn criter.	-4.935061
F-statistic	33.77406	Durbin-Watson stat	1.128219
Prob(F-statistic)	0.000000		

Dependent variable: Consumption of services.

Model 3: Explanatory variables: Personal disposable income and wealth (both in real terms).

Long Run: $\mathrm{LN}(CS_{SA\,t}) =$ -2.64 + 1.20*LN(PDI_t)

Short Run: $\Delta\mathrm{LN}(CS_t) = 0.02 + 0.25{*}\Delta\mathrm{LN}(PDI_t) + 0.11{*}\ \Delta\mathrm{LN}(Wealth_t)$ -0.31*(LN($CS_{SA\,t-4}$) - LN($CS^{*}_{SA\,t-4}$))

Dependent Variable: LPCSR_SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2001Q1 2016Q2
Included observations: 62 after adjustments
LPCSR_SA = C(1) + C(2)*LRPDI_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-2.639193	0.882109	-2.991911	0.0040
C(2)	1.201599	0.088382	13.59546	0.0000

R-squared	0.754939	Mean dependent var	9.353012
Adjusted R-squared	0.750854	S.D. dependent var	0.124887
S.E. of regression	0.062336	Akaike info criterion	-2.680813
Sum squared resid	0.233150	Schwarz criterion	-2.612196
Log likelihood	85.10522	Hannan-Quinn criter.	-2.653873
F-statistic	184.8367	Durbin-Watson stat	0.153177
Prob(F-statistic)	0.000000		

Dependent Variable: DLPCSR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCSR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*(LPCSR_SA(-4) - (BETA95 + BETA96*LRPDI_SA(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.018700	0.002429	7.700119	0.0000
C(7)	0.247102	0.066584	3.711126	0.0005
C(8)	0.105370	0.030347	3.472133	0.0011
C(9)	-0.312794	0.036667	-8.530774	0.0000

R-squared	0.764753	Mean dependent var	0.023225
Adjusted R-squared	0.750638	S.D. dependent var	0.032520
S.E. of regression	0.016239	Akaike info criterion	-5.331612
Sum squared resid	0.013185	Schwarz criterion	-5.184280
Log likelihood	147.9535	Hannan-Quinn criter.	-5.274792
F-statistic	54.18089	Durbin-Watson stat	1.222428
Prob(F-statistic)	0.000000		

Dependent variable: Consumption of services.

Model 4: Explanatory variables: Personal disposable income and wealth (both in real terms).

Short Run: $\Delta \mathrm{LN}(CS_t) = 0.00 + 0.07{*}\Delta \mathrm{LN}(PDI_t) + 0.04{*}\Delta \mathrm{LN}(Wealth_t) + 0.70{*}\Delta \mathrm{LN}(CS_{t-1})$

Dependent Variable: DLPCSR
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 17:03
Sample (adjusted): 2003Q1 2016Q2
Included observations: 54 after adjustments
DLPCSR = C(5) + C(7)*DLRPDI+ C(8)*DLRNFHWEALTH + C(9)
*DLPCSR(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.003658	0.002997	1.220649	0.2279
C(7)	0.073643	0.079083	0.931218	0.3562
C(8)	0.044996	0.032297	1.393192	0.1697
C(9)	0.701471	0.093130	7.532147	0.0000

R-squared	0.729398	Mean dependent var	0.023225
Adjusted R-squared	0.713162	S.D. dependent var	0.032520
S.E. of regression	0.017417	Akaike info criterion	-5.191599
Sum squared resid	0.015167	Schwarz criterion	-5.044267
Log likelihood	144.1732	Hannan-Quinn criter.	-5.134779
F-statistic	44.92441	Durbin-Watson stat	2.377366
Prob(F-statistic)	0.000000		

Dependent variable: Consumption of services.

Model 5: AR (2) model.

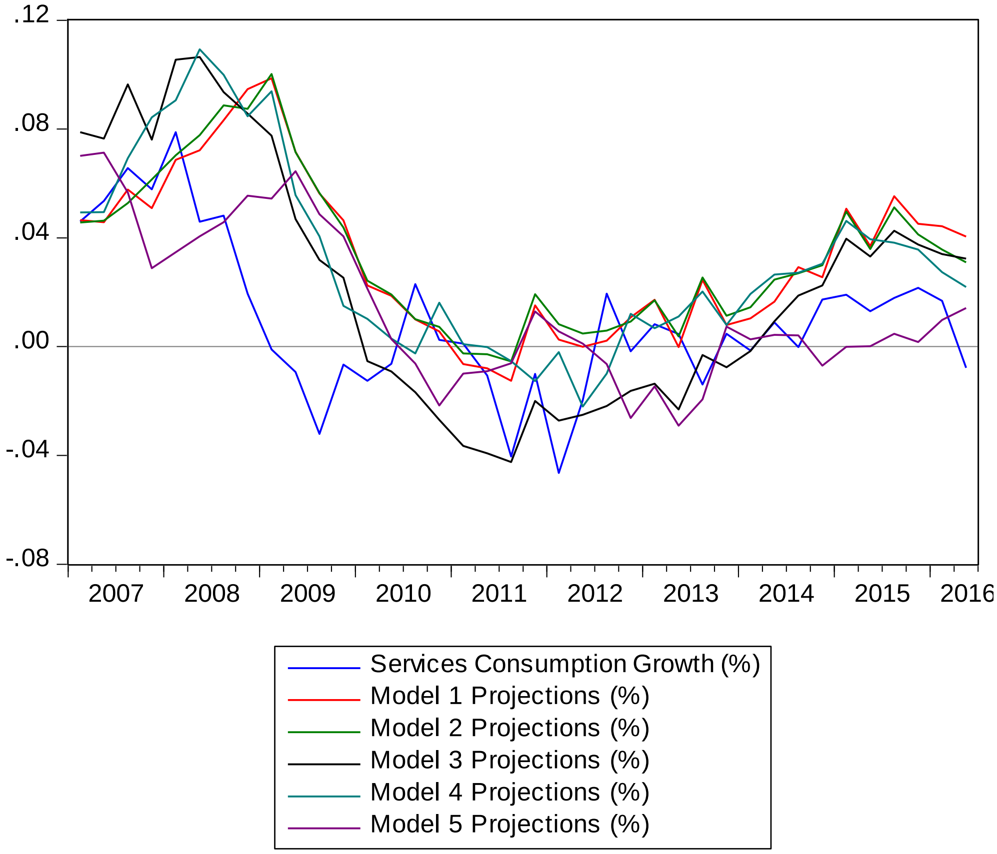
Dependent Variable: DLPCSR
Method: ARMA Maximum Likelihood (BFGS)
Date: 02/14/17 Time: 16:39
Sample: 2002Q1 2016Q2
Included observations: 58
Convergence achieved after 6 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.612411	0.154466	3.964692	0.0002
AR(2)	0.317385	0.143952	2.204796	0.0317
SIGMASQ	0.000313	6.37E-05	4.918332	0.0000

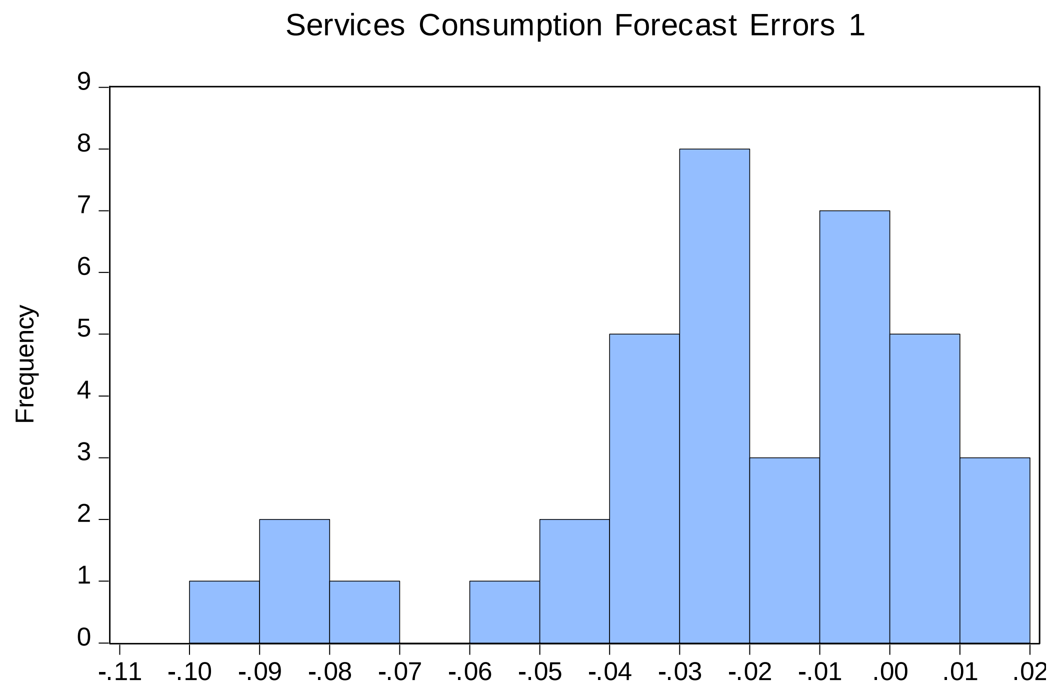
R-squared	0.712278	Mean dependent var	0.026088
Adjusted R-squared	0.701816	S.D. dependent var	0.033290
S.E. of regression	0.018178	Akaike info criterion	-5.094992
Sum squared resid	0.018175	Schwarz criterion	-4.988417
Log likelihood	150.7548	Hannan-Quinn criter.	-5.053479
Durbin-Watson stat	1.985456		

Inverted AR Roots	.95	-.34

Forecasting Real Services Consumption Growth (%, Y-Y)
Estimation Sample Begins: 2003Q1, Estimation Sample Ends: 2006Q1 – 2015Q2,
short-run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 2003Q1. In the first case the estimation sample ends at 2006Q1, this equation is then used to forecast 2007Q1. The end date of the estimation is then pushed out to 2006Q2 and this equation is used to forecast 2007Q2. This process is repeated for each of the three models and produces the projections graphed above along with the actual outturns.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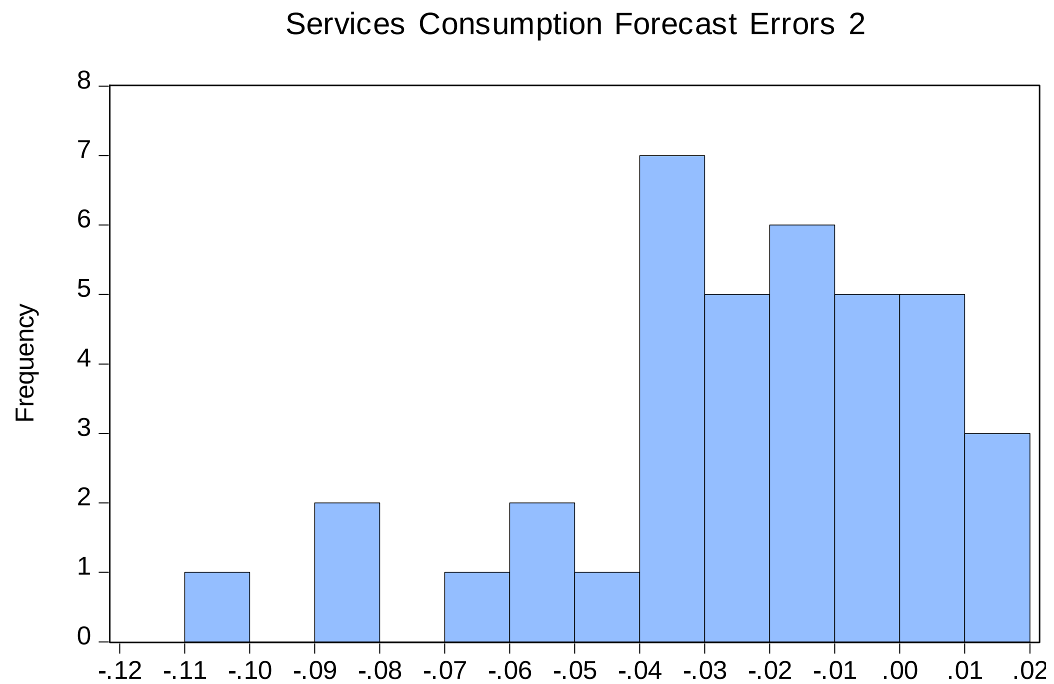
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-.01
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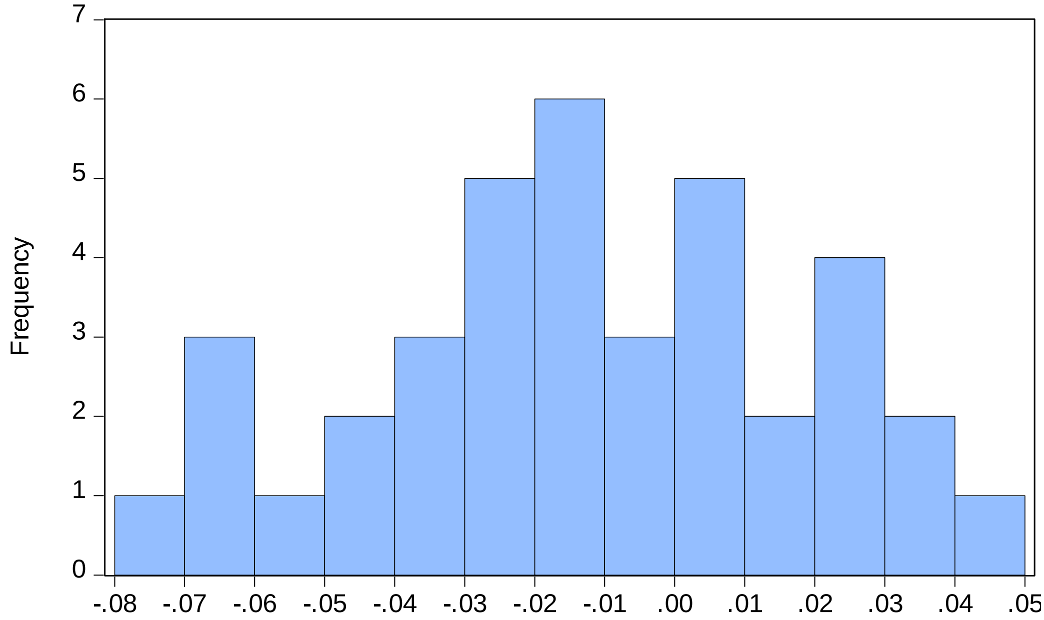
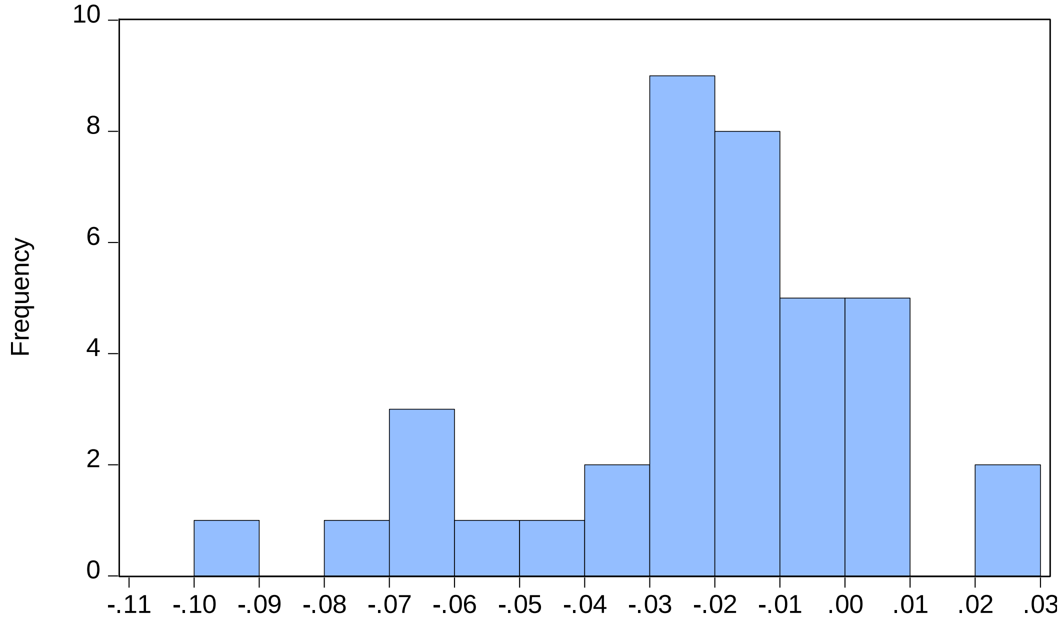
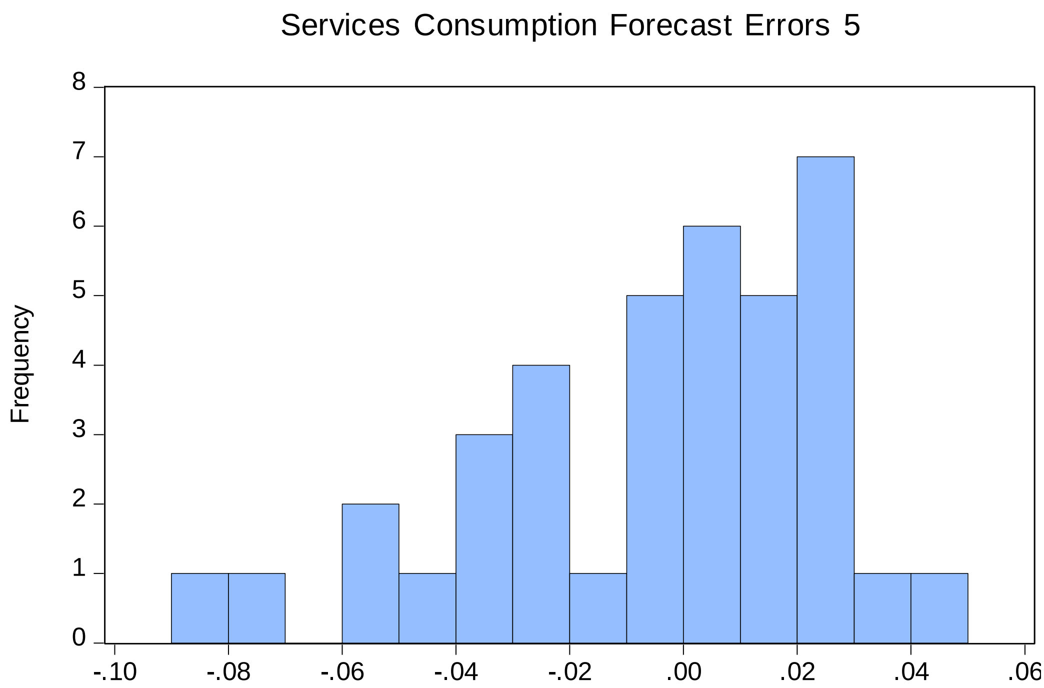
.01
.02

Services Consumption Forecast Errors 3



Services Consumption Forecast Errors 4




Services Consumption Forecast Errors 5
Frequency
8
7
6
5
4
3
2
1
0
-.10
-.08
-.06
-.04
-.02
.00
.02
.04
.06

2.1.3: HICP

Dependent variable: HICP.

Model 1: Explanatory variables: Lagged HICP and Consumption (goods and services).

Long run $\mathrm{LN}(HICP_t) = -0.07 + 0.88 * \mathrm{LN}(HICP_{t-1}) + 0.06 * \mathrm{LN}(C_{SA\,t})$

Short run $\Delta\mathrm{LN}(HICP_t) = -0.00 + 0.92 * \Delta\mathrm{LN}(HICP_{t-1}) + 0.07 * \Delta\mathrm{LN}(C_t) - 0.39 * (\mathrm{LN}(HICP_{t-4}) - \mathrm{LN}(HICP^*_{t-4}))$

Dependent Variable: LHICP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 16:29
Sample: 1999Q1 2016Q2
Included observations: 70
LHICP = C(1) + C(2)*LHICP(-1) + C(3)*LPCR_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.068954	0.092167	-0.748137	0.4570
C(2)	0.884401	0.028526	31.00387	0.0000
C(3)	0.060044	0.021227	2.828655	0.0062

R-squared	0.996151	Mean dependent var	4.518704
Adjusted R-squared	0.996036	S.D. dependent var	0.096927
S.E. of regression	0.006102	Akaike info criterion	-7.318363
Sum squared resid	0.002495	Schwarz criterion	-7.221999
Log likelihood	259.1427	Hannan-Quinn criter.	-7.280086
F-statistic	8670.304	Durbin-Watson stat	1.779194
Prob(F-statistic)	0.000000		

Dependent Variable: DLHICP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 16:29
Sample: 1999Q1 2016Q2
Included observations: 70
DLHICP = C(5) + C(6)*DLHICP(-1) + C(7)*DLPCR + C(8)*(LHICP(-4) -
(BETA100 + BETA200*LHICP(-5) + BETA300*LPCR_SA(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.000863	0.000849	-1.016301	0.3132
C(6)	0.915228	0.034697	26.37784	0.0000
C(7)	0.068943	0.016438	4.194201	0.0001
C(8)	-0.390614	0.106161	-3.679461	0.0005

R-squared	0.942761	Mean dependent var	0.019118
Adjusted R-squared	0.940159	S.D. dependent var	0.020010
S.E. of regression	0.004895	Akaike info criterion	-7.745812
Sum squared resid	0.001581	Schwarz criterion	-7.617326
Log likelihood	275.1034	Hannan-Quinn criter.	-7.694776
F-statistic	362.3536	Durbin-Watson stat	1.416938
Prob(F-statistic)	0.000000		

Dependent variable: HICP.

Model 2: Explanatory variables: Lagged HICP and Underlying Domestic Demand.

Long run $\mathrm{LN}(HICP_t) = 0.01 + 0.94^*\mathrm{LN}(HICP_{t-1}) + 0.02^*\mathrm{LN}(UDD_{SA\,t})$

Short run $\Delta\mathrm{LN}(HICP_t) = \text{-}0.00 + 0.92^*\Delta\mathrm{LN}(HICP_{t-1}) + 0.05^*\Delta\mathrm{LN}(UDD_t)$ -0.40*($HICP_{t-4}$-$HICP^{*}_{t-4}$)

Dependent Variable: LHICP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 16:29
Sample: 1999Q1 2016Q2
Included observations: 70
LHICP = C(1) + C(2)*LHICP(-1) + C(3)*LUDD_SA

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.011926	0.075383	0.158209	0.8748
C(2)	0.941011	0.011575	81.29367	0.0000
C(3)	0.024902	0.010346	2.406944	0.0188

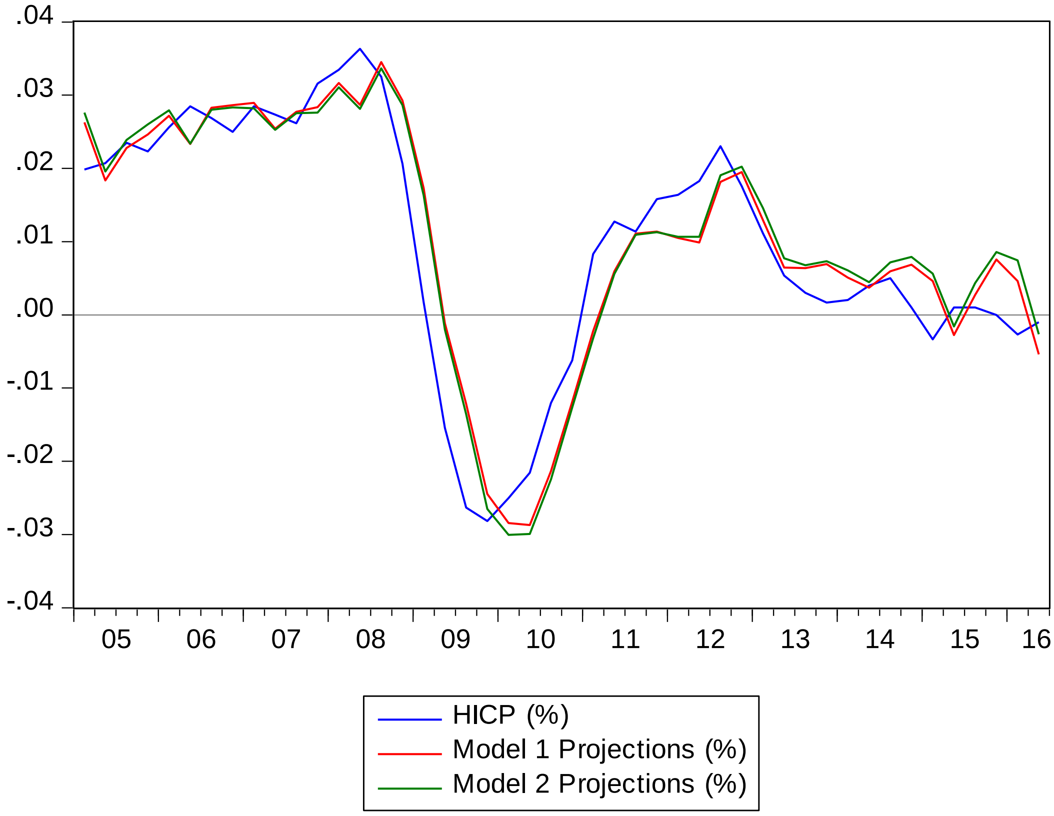
R-squared	0.996034	Mean dependent var	4.518704
Adjusted R-squared	0.995916	S.D. dependent var	0.096927
S.E. of regression	0.006194	Akaike info criterion	-7.288483
Sum squared resid	0.002571	Schwarz criterion	-7.192119
Log likelihood	258.0969	Hannan-Quinn criter.	-7.250206
F-statistic	8414.079	Durbin-Watson stat	1.822330
Prob(F-statistic)	0.000000		

Dependent Variable: DLHICP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16 Time: 16:29
Sample: 1999Q1 2016Q2
Included observations: 70
DLHICP = C(5) + C(6)*DLHICP(-1) + C(7)*DLUDD + C(8)*(LHICP(-4) -
(BETA101 + BETA201*LHICP(-5) + BETA301*LUDD_SA(-4)))

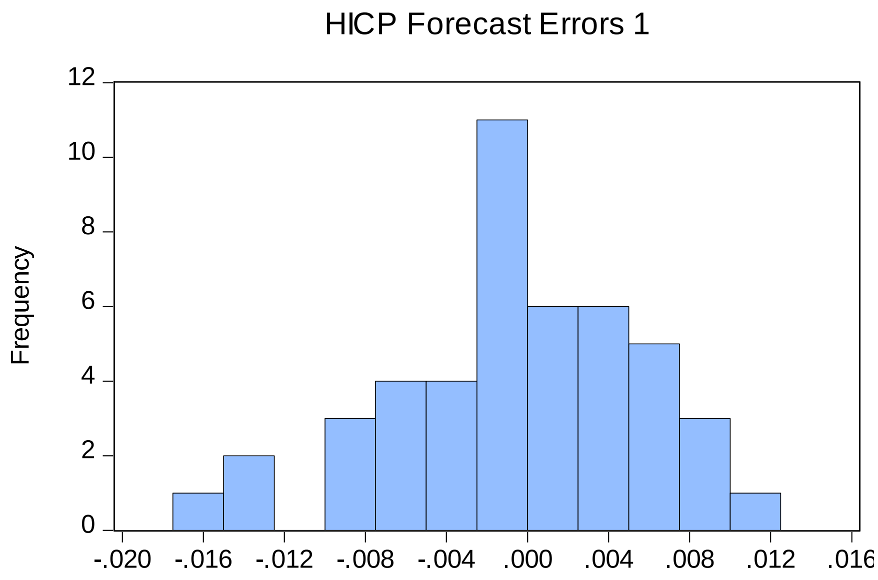
	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-4.68E-05	0.000855	-0.054713	0.9565
C(6)	0.917160	0.036160	25.36370	0.0000
C(7)	0.051241	0.012980	3.947691	0.0002
C(8)	-0.395250	0.104173	-3.794161	0.0003

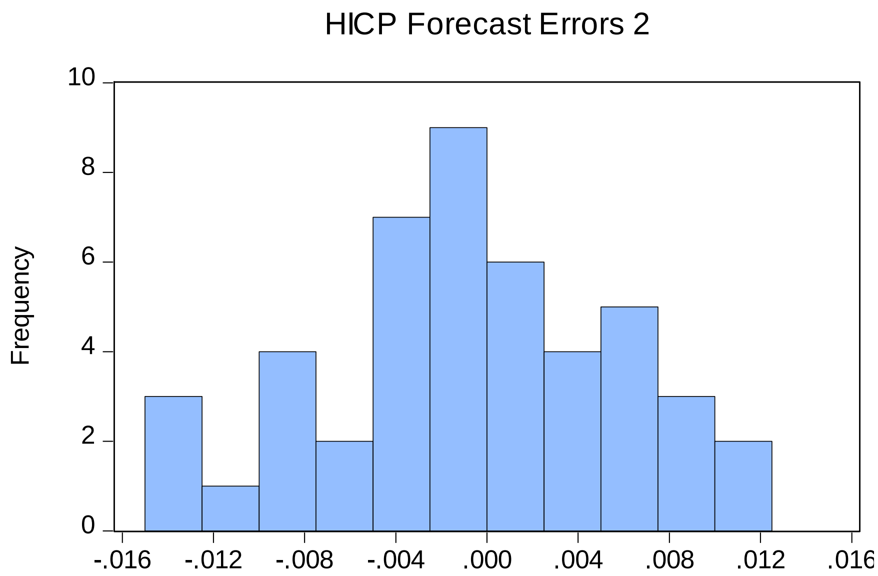
R-squared	0.940183	Mean dependent var	0.019118
Adjusted R-squared	0.937465	S.D. dependent var	0.020010
S.E. of regression	0.005004	Akaike info criterion	-7.701764
Sum squared resid	0.001653	Schwarz criterion	-7.573279
Log likelihood	273.5617	Hannan-Quinn criter.	-7.650728
F-statistic	345.7912	Durbin-Watson stat	1.322391
Prob(F-statistic)	0.000000		

Forecasting HICP (%, Y-Y Change).
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2004Q1 – 2015Q2.
Short-Run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1999Q1. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for both of the models and produces the projections graphed above along with the actual outturns.


HICP Forecast Errors 1
Frequency
12
10
8
6
4
2
0
-.020
-.016
-.012
-.008
-.004
.000
.004
.008
.012
.016


HICP Forecast Errors 2
Frequency
10
8
6
4
2
0
-.016
-.012
-.008
-.004
.000
.004
.008
.012
.016

2.2.1: Investment, machinery and equipment

Dependent variable: Underlying machinery and equipment investment (excludes aircraft).

Explanatory variables: Lagged underlying machinery and equipment and expected future external demand for Irish goods exports.

$$\mathrm{LN}(\mathrm{MNEU}_t) = 2.55 + 0.18{*}\mathrm{LN}(External\ Demand\ Goods_{t+1}) + 0.53{*}\mathrm{LN}(\mathrm{MNEU}_{t-1})$$

$$\Delta\mathrm{LN}(MNEU_t) = -0.03 + 1.01{*}\Delta\mathrm{LN}(External\ Demand\ Goods_{t+1}) + 0.58{*}\Delta\mathrm{LN}(MNEU_{t-1}) - 0.25{*}(\mathrm{LN}(MNEU_{t-4}) - \mathrm{LN}(MNEU^{*}_{t-4}))$$

Dependent Variable: LMNEU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/06/16 Time: 17:11
Sample (adjusted): 1997Q2 2016Q2
Included observations: 77 after adjustments
LMNEU = C(1) + C(2)*LGMTPINDEX(1) + C(3)*LMNEU(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.554409	0.862810	2.960570	0.0041
C(2)	0.177307	0.136343	1.300452	0.1975
C(3)	0.528632	0.098118	5.387707	0.0000

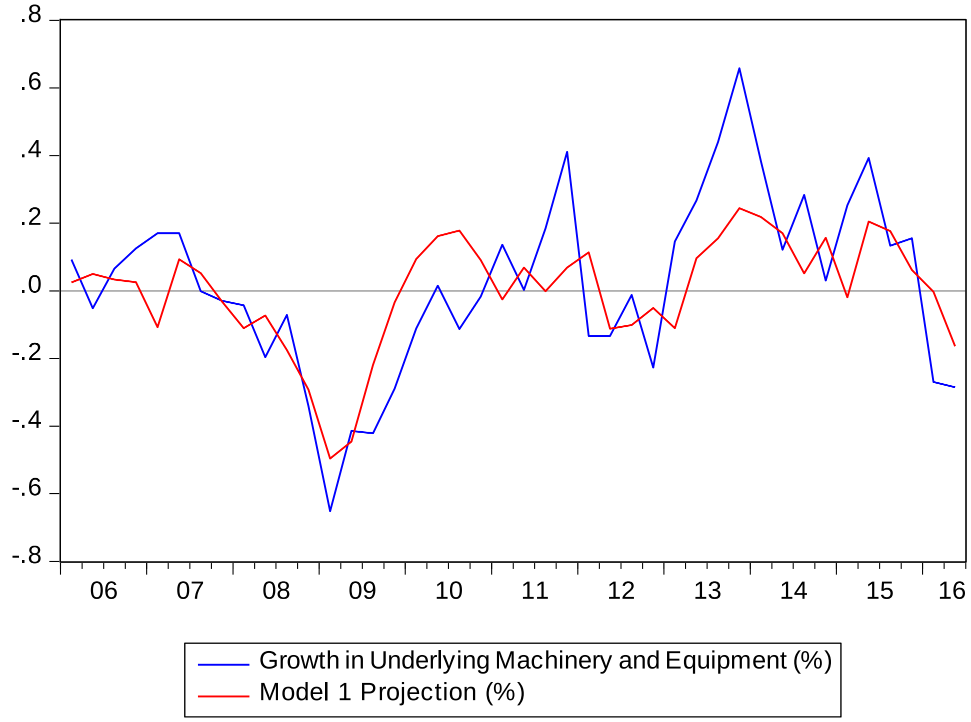
R-squared	0.331103	Mean dependent var	7.325381
Adjusted R-squared	0.313025	S.D. dependent var	0.294395
S.E. of regression	0.244006	Akaike info criterion	0.054938
Sum squared resid	4.405897	Schwarz criterion	0.146255
Log likelihood	0.884901	Hannan-Quinn criter.	0.091464
F-statistic	18.31493	Durbin-Watson stat	2.049927
Prob(F-statistic)	0.000000		

Dependent Variable: DLMNEU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/06/16 Time: 17:11
Sample (adjusted): 1998Q2 2016Q2
Included observations: 73 after adjustments
DLMNEU = C(4) + C(5)*DLGMTP(1) +C(6)*DLMNEU(-1) + C(7)*(LMNEU(-4)
- (BETA58 + BETA59*LGMTPINDEX(-3) + BETA60*LMNEU(-5)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(4)	-0.032644	0.021561	-1.514011	0.1346
C(5)	1.007283	0.329884	3.053444	0.0032
C(6)	0.581012	0.085772	6.773880	0.0000
C(7)	-0.250106	0.074017	-3.379023	0.0012

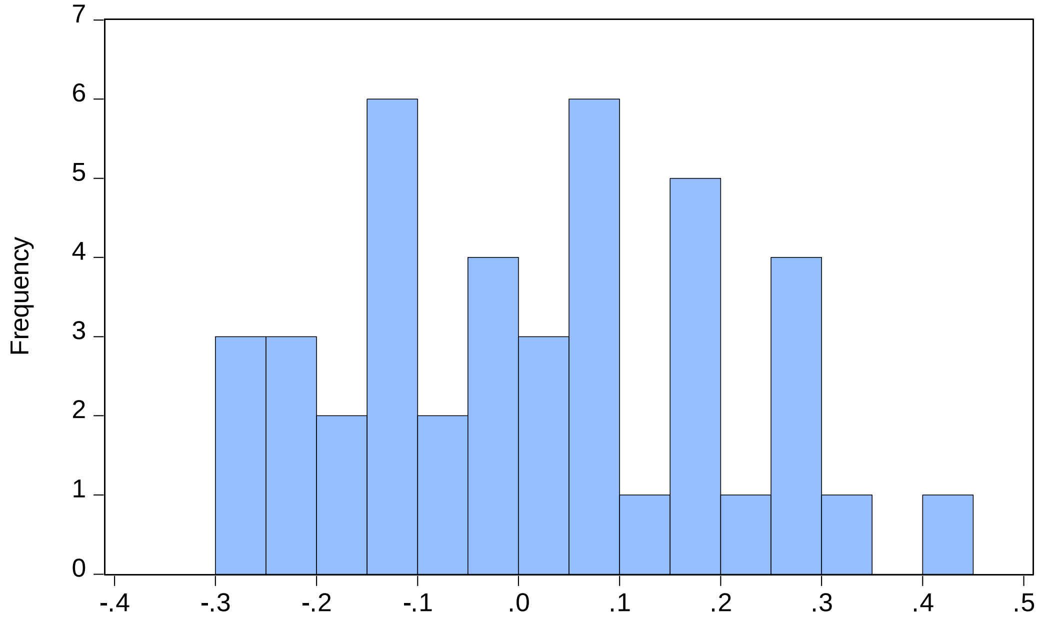
R-squared	0.563321	Mean dependent var	0.030939
Adjusted R-squared	0.544335	S.D. dependent var	0.225067
S.E. of regression	0.151927	Akaike info criterion	-0.877601
Sum squared resid	1.592638	Schwarz criterion	-0.752097
Log likelihood	36.03245	Hannan-Quinn criter.	-0.827586
F-statistic	29.67023	Durbin-Watson stat	2.175521
Prob(F-statistic)	0.000000		

Forecasting Underlying Machinery and Equipment growth (%, Y-Y).
Estimation Sample Begins 1998Q2. Estimation Sample Ends 2005Q1 – 2015Q2.
Short-Run equation, forecasting four quarters ahead.



In every case the estimation sample begins in 1998Q2. In the first case the estimation sample ends at 2005Q1, this equation is then used to forecast 2006Q1. The end date of the estimation is then pushed out to 2005Q2 and this equation is used to forecast 2006Q2. This process is repeated and produces the projection graphed above along with the actual outturns.

Underlying M&E Errors



2.2.2: Investment, Dwellings

Dependent variable: Annual percentage change in dwellings.

Explanatory variable: Annual percentage change in completions.

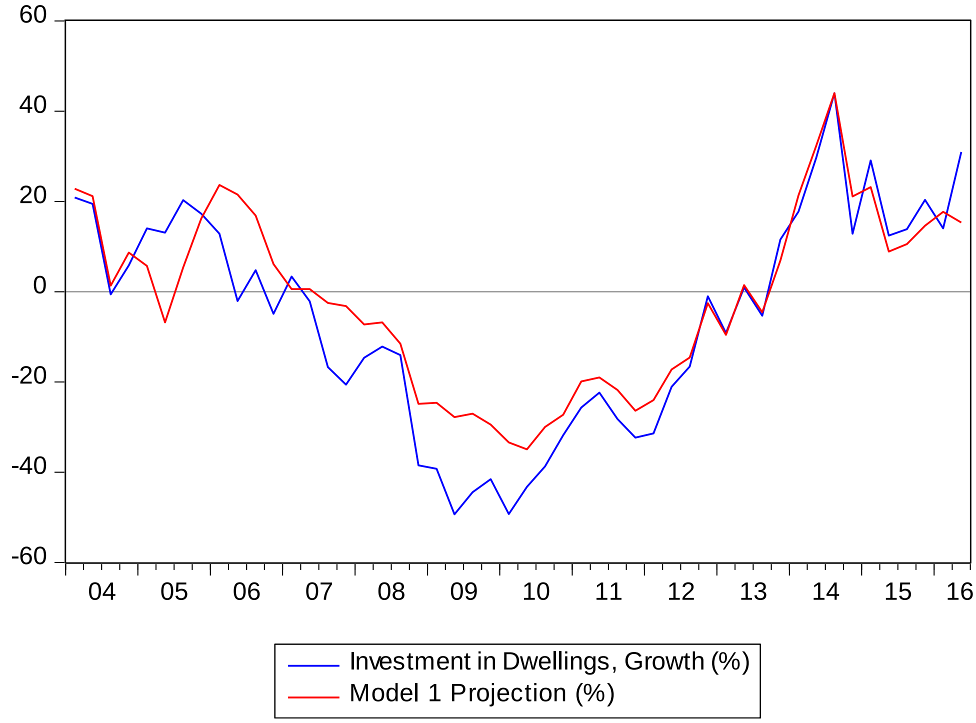
$$100^*\left(\frac{Dwellings_t}{Dwellings_{t-4}}-1\right) = 1.29 + 0.86^*\left(100^*\left(\frac{Completions_t}{Completions_{t-4}}-1\right)\right)$$

Dependent Variable: PCYDWELL
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 10:10
Sample: 1999Q1 2016Q2
Included observations: 70
PCYDWELL = C(88) + C(89)*(COMPS_F/COMPS_F(-4)-1)*100

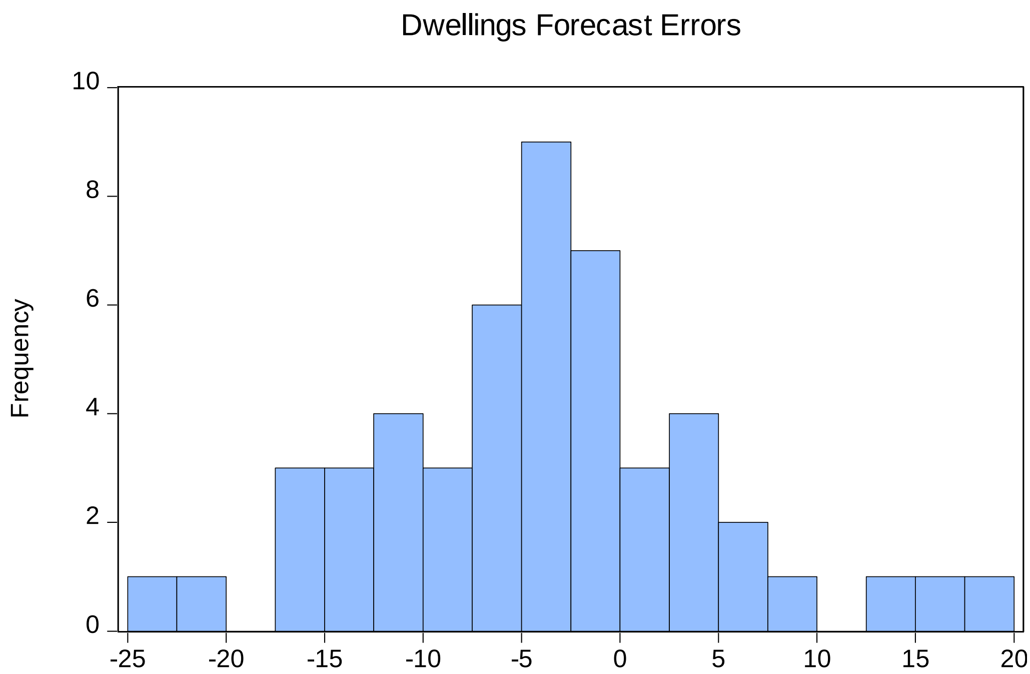
	Coefficient	Std. Error	t-Statistic	Prob.
C(88)	1.290886	0.789423	1.635228	0.1066
C(89)	0.864945	0.032495	26.61803	0.0000

R-squared	0.912430	Mean dependent var	-1.086734
Adjusted R-squared	0.911142	S.D. dependent var	22.01467
S.E. of regression	6.562367	Akaike info criterion	6.628735
Sum squared resid	2928.397	Schwarz criterion	6.692978
Log likelihood	-230.0057	Hannan-Quinn criter.	6.654253
F-statistic	708.5196	Durbin-Watson stat	0.949084
Prob(F-statistic)	0.000000		

Forecasting Dwellings growth (%, Y-Y).
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2003Q1 – 2015Q2.
Short-Run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1999Q1. In the first case the estimation sample ends at 2003Q1, this equation is then used to forecast 2004Q1. The end date of the estimation is then pushed out to 2003Q2 and this equation is used to forecast 2004Q2. This process is repeated and produces the projection graphed above along with the actual outturns.



2.2.3: Investment, improvements

Dependent variable: Improvements.

Explanatory variables: Completions and lagged improvements.

$$\mathrm{LN}(Improvements_t) = 0.54 + 0.03{*}\mathrm{LN}(Completions_t) + 0.87{*}\mathrm{LN}(Improvements_{t-1})$$

$$\Delta\mathrm{LN}(Improvements_t) = 0.00 + 0.01{*}\Delta\mathrm{LN}(Completions_t) + 0.88{*}\Delta\mathrm{LN}(Improvements_{t-1}) - 1.04{*}(\mathrm{LN}(Improvements_{t-4}) - \mathrm{LN}(Improvements^{*}_{t-4}))$$

Dependent Variable: LIMPROVS
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 09:19
Sample (adjusted): 1997Q2 2016Q2
Included observations: 77 after adjustments
LIMPROVS = C(1) + C(2)*LCOMPS + C(3)*LIMPROVS(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.536483	0.275465	1.947554	0.0553
C(2)	0.034611	0.013589	2.547028	0.0129
C(3)	0.865784	0.049857	17.36543	0.0000

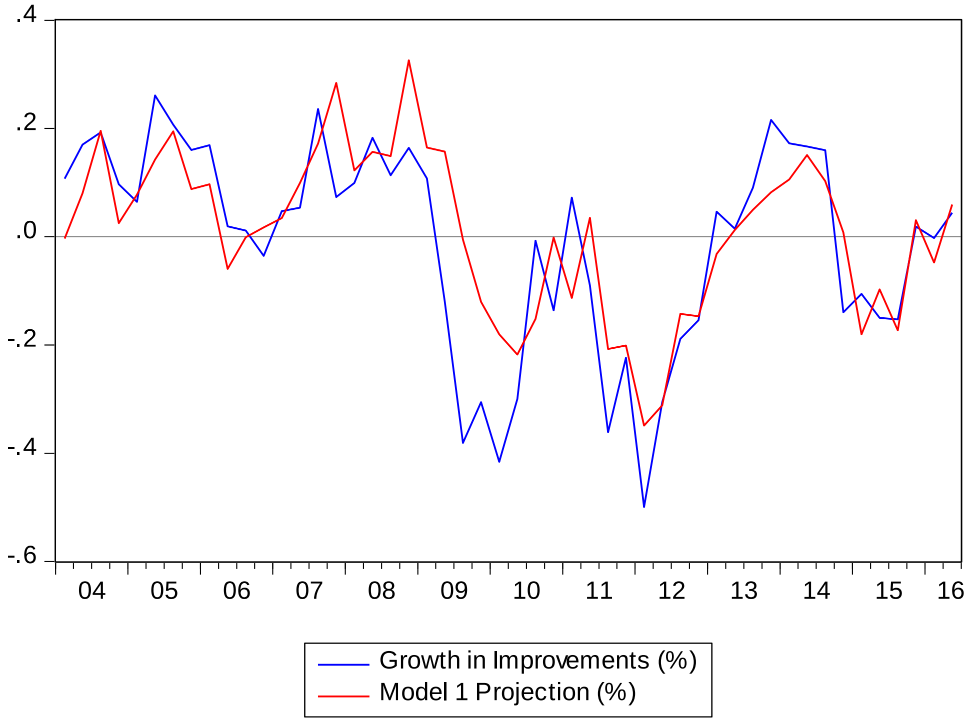
R-squared	0.864501	Mean dependent var	6.330263
Adjusted R-squared	0.860839	S.D. dependent var	0.231694
S.E. of regression	0.086432	Akaike info criterion	-2.020737
Sum squared resid	0.552815	Schwarz criterion	-1.929420
Log likelihood	80.79839	Hannan-Quinn criter.	-1.984211
F-statistic	236.0652	Durbin-Watson stat	2.379425
Prob(F-statistic)	0.000000		

Dependent Variable: DLIMPROVS
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 09:19
Sample (adjusted): 1998Q2 2016Q2
Included observations: 73 after adjustments
DLIMPROVS = C(4) + C(5)*DLCOMPS_F +C(6)*DLIMPROVS(-1) + C(7)
*(LIMPROVS(-4) - (BETA58 + BETA59*LCOMPS(-4) + BETA60
*LIMPROVS(-5)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(4)	0.001329	0.010504	0.126520	0.8997
C(5)	0.010717	0.041262	0.259735	0.7958
C(6)	0.881668	0.071943	12.25517	0.0000
C(7)	-1.040376	0.131633	-7.903592	0.0000

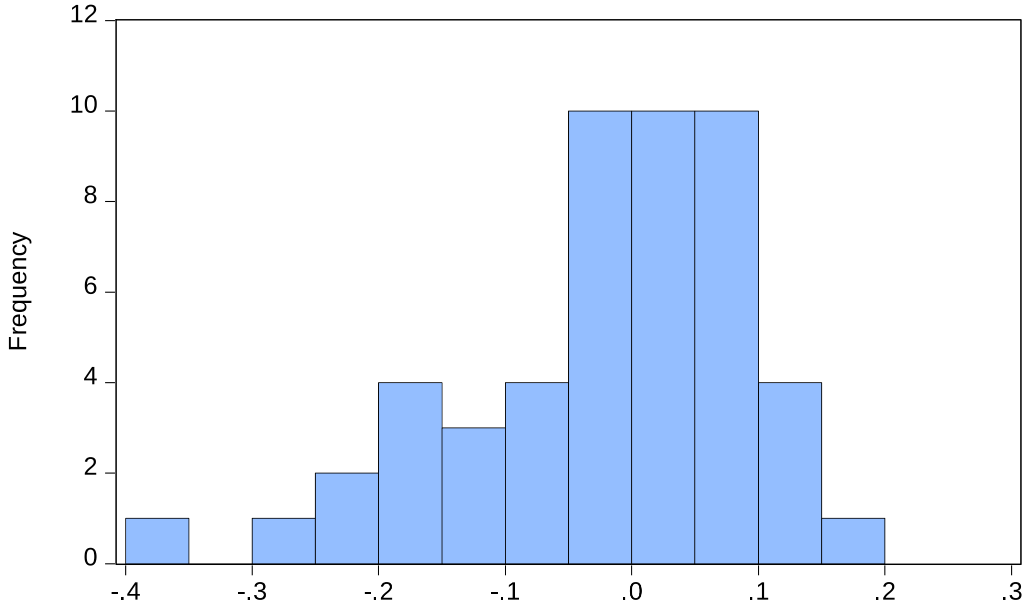
R-squared	0.744668	Mean dependent var	-0.006259
Adjusted R-squared	0.733567	S.D. dependent var	0.170013
S.E. of regression	0.087756	Akaike info criterion	-1.975279
Sum squared resid	0.531376	Schwarz criterion	-1.849774
Log likelihood	76.09769	Hannan-Quinn criter.	-1.925263
F-statistic	67.07876	Durbin-Watson stat	2.451847
Prob(F-statistic)	0.000000		

Forecasting Improvements growth (%, Y-Y).
Estimation Sample Begins 1998Q2. Estimation Sample Ends 2003Q1 – 2015Q2.
Short-Run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1998Q2. In the first case the estimation sample ends at 2003Q1, this equation is then used to forecast 2004Q1. The end date of the estimation is then pushed out to 2003Q2 and this equation is used to forecast 2004Q2. This process is repeated and produces the projection graphed above along with the actual outturns.

Improvements Forecast Errors



2.2.4: Investment, Transfer Costs

Dependent variable: Transfer costs.

Explanatory variables: Lagged completions and lagged transfer costs.

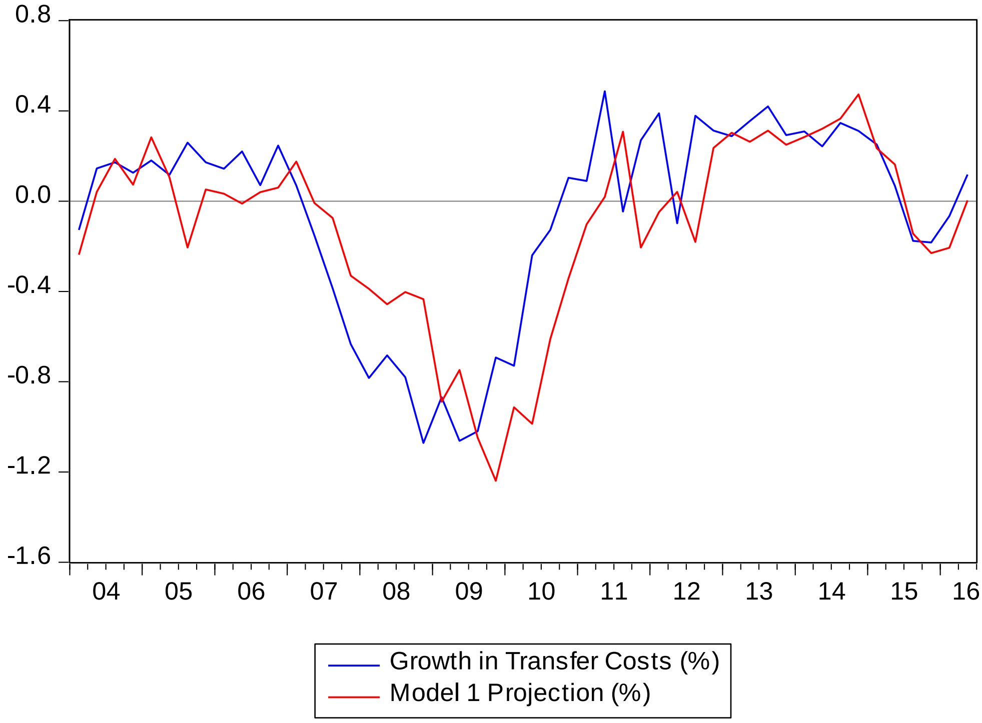
$$\Delta\text{LN}(Tcosts_t) = 0.00 - 0.47{*}\Delta\text{LN}(Completions_{t-4}) + 0.66{*}\Delta\text{LN}(Completions_{t-1}) + 0.79{*}\Delta\text{LN}(Tcosts_{t-1}) - 0.18{*}\Delta\text{LN}(Tcosts_{t-4})$$

Dependent Variable: DLTCOSTS
Method: Least Squares
Date: 12/07/16 Time: 10:44
Sample: 1999Q1 2016Q2
Included observations: 70

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002900	0.023152	0.125255	0.9007
DLCOMPS_F(-4)	-0.473939	0.156821	-3.022165	0.0036
DLCOMPS_F(-1)	0.656267	0.186378	3.521156	0.0008
DLTCOSTS(-1)	0.789448	0.093397	8.452592	0.0000
DLTCOSTS(-4)	-0.179501	0.103823	-1.728921	0.0886

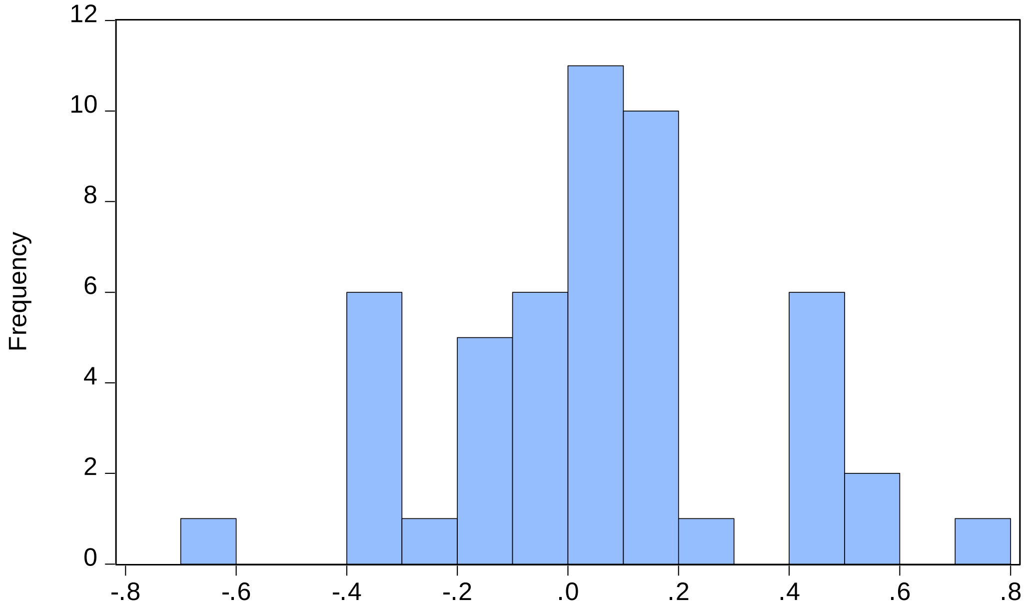
R-squared	0.785579	Mean dependent var	-0.024911
Adjusted R-squared	0.772384	S.D. dependent var	0.385936
S.E. of regression	0.184127	Akaike info criterion	-0.477635
Sum squared resid	2.203673	Schwarz criterion	-0.317029
Log likelihood	21.71724	Hannan-Quinn criter.	-0.413840
F-statistic	59.53538	Durbin-Watson stat	2.528303
Prob(F-statistic)	0.000000		

Forecasting Transfer Costs growth (%, Y-Y).
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2003Q1 – 2015Q2.
Short-Run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1999Q1. In the first case the estimation sample ends at 2003Q1, this equation is then used to forecast 2004Q1. The end date of the estimation is then pushed out to 2003Q2 and this equation is used to forecast 2004Q2. This process is repeated and produces the projection graphed above along with the actual outturns.

Transfer Costs Forecast Errors



2.3.1: Exports, Goods

Dependent variable: Goods exports.

Model 1: Explanatory variables: External demand for goods exports, the real effective exchange rate and a dummy variable (2015Q1).

$\text{LN}(Goods\ Exports_t) = 6.04 + 0.81 * \text{LN}(External\ Demand\ Goods_t)$ -0.03*$\text{LN}(REER_t)$ + 0.45*$Dum15Q1_t$

Dependent Variable: LGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 11/30/16 Time: 16:04
Sample: 1999Q1 2016Q2
Included observations: 70
LGX = C(1) + C(2)*LGMTPINDEX + C(3)*LREER + C(4)*GXDUM

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	6.038031	0.462990	13.04138	0.0000
C(2)	0.813677	0.062643	12.98907	0.0000
C(3)	-0.035251	0.096033	-0.367067	0.7147
C(4)	0.446065	0.047479	9.395049	0.0000

R-squared	0.898370	Mean dependent var	10.07496
Adjusted R-squared	0.893750	S.D. dependent var	0.243634
S.E. of regression	0.079415	Akaike info criterion	-2.172814
Sum squared resid	0.416245	Schwarz criterion	-2.044328
Log likelihood	80.04848	Hannan-Quinn criter.	-2.121778
F-statistic	194.4710	Durbin-Watson stat	1.314703
Prob(F-statistic)	0.000000		

$\Delta\text{LN}(Goods\ Exports_t) = 0.03 + 0.30 * \Delta\text{LN}(External\ Demand\ Goods_t)$ -0.26*$\Delta\text{LN}(REER_t)$ +0.40*$\Delta Dum15Q1_t$ -0.52*($Goods\ Exports_{t-4}$-$Goods\ Exports^*_{t-4}$)

Dependent Variable: DLGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/02/16 Time: 13:00
Sample: 1999Q1 2016Q2
Included observations: 70
DLGX = C(5) + C(6)*DLGMTP + C(7)*DLNREER +C(8)*DDUMMY + C(9)
*(LGX(-4) - (BETA1000 + BETA1001*LGMTPINDEX(-4) + BETA1002
*LREER(-4) +BETA1003*GXDUM(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.025189	0.008884	2.835476	0.0061
C(6)	0.301848	0.122971	2.454623	0.0168
C(7)	-0.263298	0.114387	-2.301814	0.0246
C(8)	0.401208	0.035307	11.36328	0.0000
C(9)	-0.515439	0.083884	-6.144677	0.0000

R-squared	0.767467	Mean dependent var	0.069320
Adjusted R-squared	0.753157	S.D. dependent var	0.121246
S.E. of regression	0.060239	Akaike info criterion	-2.712249
Sum squared resid	0.235867	Schwarz criterion	-2.551642
Log likelihood	99.92872	Hannan-Quinn criter.	-2.648454
F-statistic	53.63252	Durbin-Watson stat	1.327848
Prob(F-statistic)	0.000000		

Dependent variable: Goods exports

Model 2: Explanatory variables: External demand for goods exports, lagged goods exports and dummy variable (2015Q1).

$\text{LN}(Goods\ Exports_t) = 2.75$ $+0.33$*$\text{LN}(External\ Demand\ Goods_t)$
$+0.56$*$\text{LN}(Goods\ Exports_{t-1})$ $+\ 0.24$*$Dum15Q1_t$

Dependent Variable: LGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/01/16 Time: 15:13
Sample: 1999Q1 2016Q2
Included observations: 70
LGX = C(1) + C(2)*LGMTPINDEX + C(3)*LGX(-1) + C(4)*GXDUM

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.752903	0.534440	5.151009	0.0000
C(2)	0.327569	0.086285	3.796364	0.0003
C(3)	0.559297	0.084920	6.586176	0.0000
C(4)	0.239775	0.044075	5.440124	0.0000

R-squared	0.938550	Mean dependent var	10.07496
Adjusted R-squared	0.935757	S.D. dependent var	0.243634
S.E. of regression	0.061752	Akaike info criterion	-2.675927
Sum squared resid	0.251681	Schwarz criterion	-2.547441
Log likelihood	97.65744	Hannan-Quinn criter.	-2.624891
F-statistic	336.0131	Durbin-Watson stat	2.309936
Prob(F-statistic)	0.000000		

$\Delta\text{LN}(Goods\ Exports_t) = 0.01$ $+0.20$*$\Delta\text{LN}(External\ Demand\ Goods_t)$
$+0.38$*$\Delta\text{LN}(Goods\ Exports_{t-1})$ $+0.32$*$\Delta Dum15Q1_t$ -0.81*($Goods\ Exports_{t-4}$-
$Goods\ Exports^*_{t-4}$)

Dependent Variable: DLGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/02/16 Time: 13:00
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
DLGX = C(5) + C(6)*DLGMTP + C(7)*DLGX(-1) +C(9)*DDUMMY + C(8)
*(LGX(-4) - (BETA1004 + BETA1005*LGMTPINDEX(-4) + BETA1006
*LGX(-5) +BETA1007*GXDUM(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.014442	0.008658	1.668151	0.1002
C(6)	0.204331	0.115377	1.770978	0.0813
C(7)	0.381378	0.071903	5.304060	0.0000
C(9)	0.323604	0.036559	8.851672	0.0000
C(8)	-0.805965	0.115810	-6.959383	0.0000

R-squared	0.804835	Mean dependent var	0.068786
Adjusted R-squared	0.792637	S.D. dependent var	0.122051
S.E. of regression	0.055579	Akaike info criterion	-2.872332
Sum squared resid	0.197695	Schwarz criterion	-2.710440
Log likelihood	104.0954	Hannan-Quinn criter.	-2.808104
F-statistic	65.98176	Durbin-Watson stat	2.066740
Prob(F-statistic)	0.000000		

Dependent variable: Goods Exports.

Model 3: Explanatory variables: External demand for goods exports, real effective exchange rate, lagged goods exports and dummy variable (2015Q1).

$\mathrm{LN}(Goods\ Exports_t) = 2.87$ +0.33*$\mathrm{LN}(External\ Demand\ Goods_t)$ -0.03*$\mathrm{LN}(REER_{t-1})$ + 0.56*$\mathrm{LN}(Goods\ Exports_{t-1})$ + 0.23*$Dum15Q1_t$

Dependent Variable: LGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/01/16 Time: 15:31
Sample: 1999Q1 2016Q2
Included observations: 70
LGX = C(1) + C(2)*LGMTPINDEX + C(3)*LREER + C(4)*LGX(-1) + C(5)
*GXDUM

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.873698	0.604204	4.756170	0.0000
C(2)	0.334256	0.088147	3.792019	0.0003
C(3)	-0.032944	0.075136	-0.438463	0.6625
C(4)	0.559121	0.085445	6.543620	0.0000
C(5)	0.229930	0.049708	4.625619	0.0000

R-squared	0.938731	Mean dependent var	10.07496
Adjusted R-squared	0.934961	S.D. dependent var	0.243634
S.E. of regression	0.062134	Akaike info criterion	-2.650309
Sum squared resid	0.250938	Schwarz criterion	-2.489702
Log likelihood	97.76080	Hannan-Quinn criter.	-2.586514
F-statistic	248.9736	Durbin-Watson stat	2.323826
Prob(F-statistic)	0.000000		

$\Delta\text{LN}(Goods\ Exports_t) = 0.01 + 0.20{*}\Delta\text{LN}(External\ Demand\ Goods_t)$
$+0.35{*}\Delta\text{LN}(Goods\ Exports_{t-1})\quad -0.20{*}\Delta\text{LN}(REER_t) + 0.30{*}\Delta Dum15Q1 -$
$0.78{*}(\text{LN}(Goods\ Exports_{t-4}) - \text{LN}(Goods\ Exports^{*}_{t-4}))$

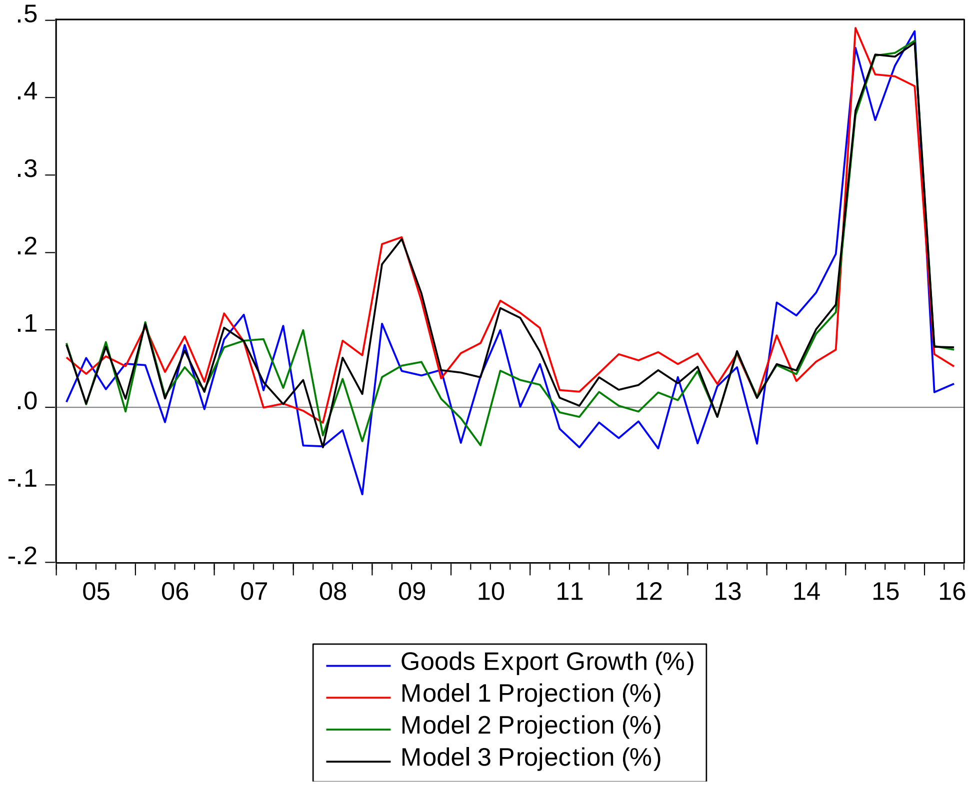
Dependent Variable: DLGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/02/16 Time: 13:00
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
DLGX = C(5) + C(6)*DLGMTP + C(7)*DLGX(-1) +C(8)*DLNREER +C(10)
DDUMMY + C(9)(LGX(-4) - (BETA1008 + BETA1009*LGMTPINDEX(
-4) + BETA1010*LREER(-4) + BETA1011*LGX(-5) +BETA1012
*GXDUM(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.015564	0.008484	1.834388	0.0713
C(6)	0.195175	0.113161	1.724757	0.0895
C(7)	0.352988	0.071947	4.906243	0.0000
C(8)	-0.196141	0.105183	-1.864754	0.0669
C(10)	0.302206	0.036984	8.171337	0.0000
C(9)	-0.777103	0.114145	-6.808042	0.0000

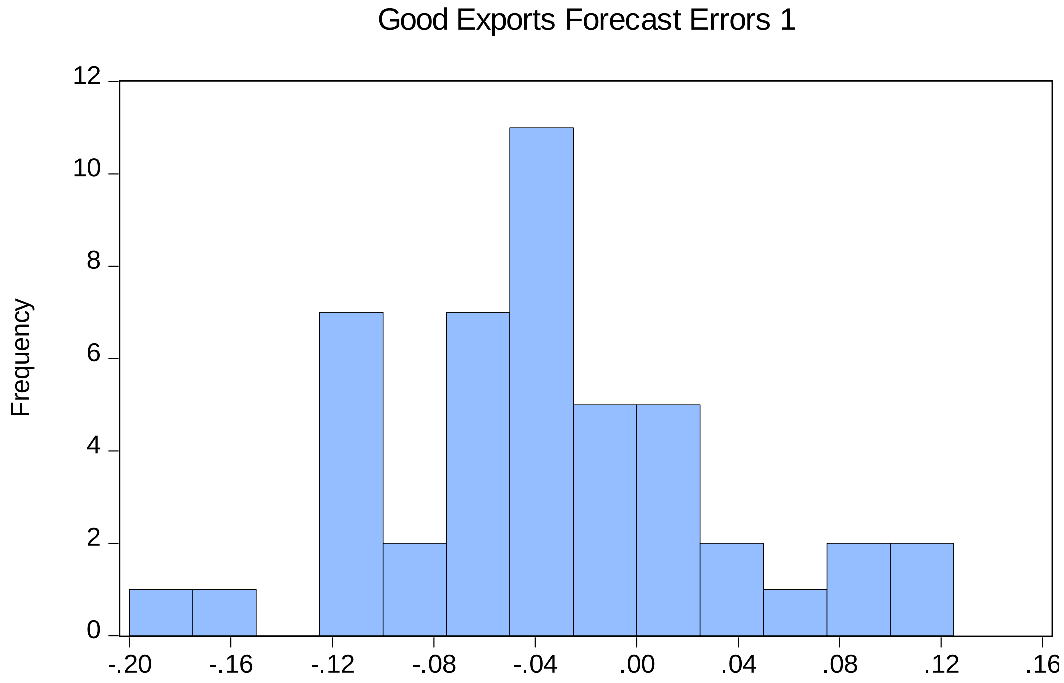
R-squared	0.815328	Mean dependent var	0.068786
Adjusted R-squared	0.800671	S.D. dependent var	0.122051
S.E. of regression	0.054491	Akaike info criterion	-2.898611
Sum squared resid	0.187066	Schwarz criterion	-2.704340
Log likelihood	106.0021	Hannan-Quinn criter.	-2.821537
F-statistic	55.62898	Durbin-Watson stat	2.039580
Prob(F-statistic)	0.000000		

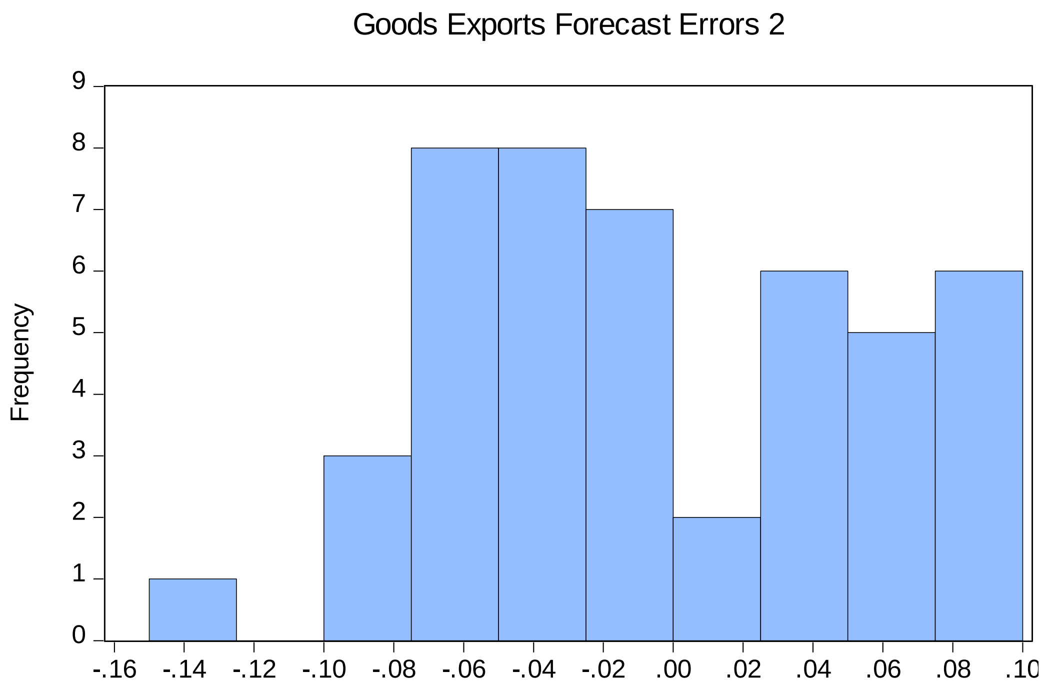
Forecasting Goods Exports growth (%, Y-Y)

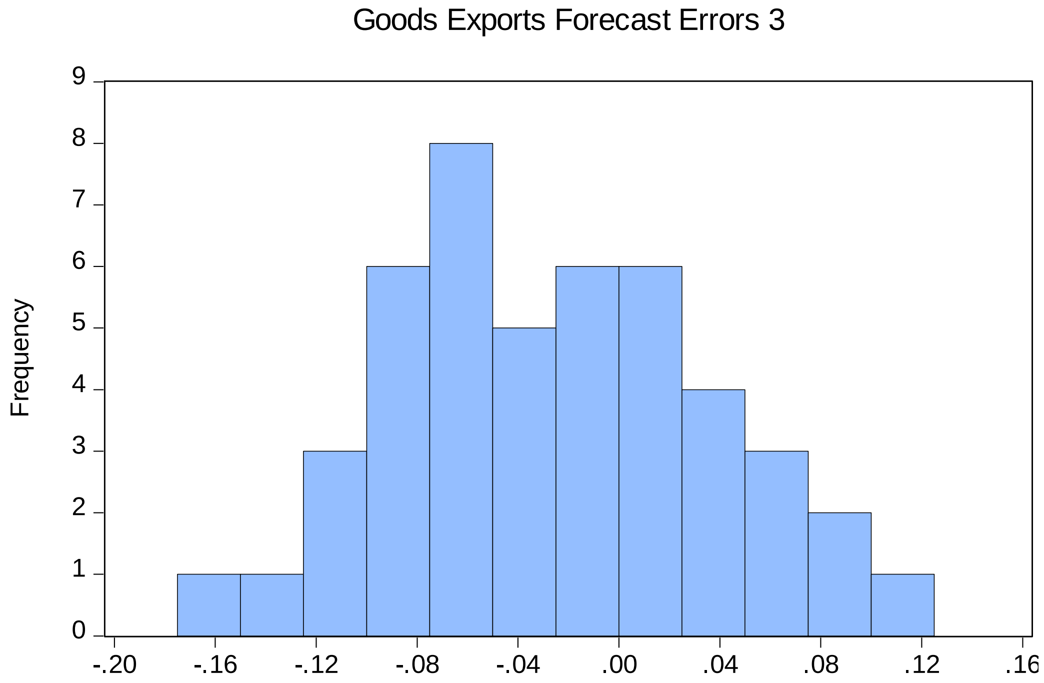
Estimation sample Begins 1999Q2. Estimation sample Ends: 2004Q1 -2015Q2.
Short-Run Equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1999Q2. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for each of the three models and produces the projections graphed above along with the actual outturns.


Good Exports Forecast Errors 1
Frequency
12
10
8
6
4
2
0
-.20
-.16
-.12
-.08
-.04
.00
.04
.08
.12
.16


Goods Exports Forecast Errors 2
Frequency
9
8
7
6
5
4
3
2
1
0
-.16
-.14
-.12
-.10
-.08
-.06
-.04
-.02
.00
.02
.04
.06
.08
.10



Goods Exports Forecast Errors 3
Frequency
9
8
7
6
5
4
3
2
1
0
-.20
-.16
-.12
-.08
-.04
.00
.04
.08
.12
.16

2.3.2: Exports, Services

Dependent variable: Service exports (excluding tourism).

Model 1: Explanatory variables: Lagged service exports, external demand for service exports and the real effective exchange rate.

$\mathrm{LN}(Service\ Exports_t) = 0.76 + 0.90*\mathrm{LN}\ (Service\ Exports_{t-1})\ +$
$0.13*\mathrm{LN}(External\ Demand\ Servcies_t)$ - $0.09*\mathrm{LN}\ (REER_t)$

$\Delta\mathrm{LN}(Service\ Exports_t) = 0.01$ $+0.71*\Delta\mathrm{LN}\ (Service\ Exports_{t-1})\ \ +$
$0.33*\Delta\mathrm{LN}(External\ Demand\ Servcies_t)$ $-0.17*\Delta\mathrm{LN}(REER_t)$ - $0.27*(\mathrm{LN}(Service\ Exports_{t-4})$-
$\mathrm{LN}(Service\ Exports^{*}_{t-4}))$

Dependent Variable: LSXU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 11/22/16 Time: 12:10
Sample: 1999Q1 2016Q2
Included observations: 70
LSXU = C(1) + C(2)*LSXU(-1) + C(3)*LSMTPINDEX + C(4)*LREER

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.762044	0.328622	2.318904	0.0235
C(2)	0.900073	0.061052	14.74273	0.0000
C(3)	0.128814	0.136926	0.940752	0.3503
C(4)	-0.093757	0.053766	-1.743797	0.0859

R-squared	0.981390	Mean dependent var	9.662797
Adjusted R-squared	0.980544	S.D. dependent var	0.395965
S.E. of regression	0.055231	Akaike info criterion	-2.899150
Sum squared resid	0.201328	Schwarz criterion	-2.770664
Log likelihood	105.4702	Hannan-Quinn criter.	-2.848114
F-statistic	1160.169	Durbin-Watson stat	3.048347
Prob(F-statistic)	0.000000		

Dependent Variable: DLSXU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 11/22/16 Time: 12:10
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
DLSXU = C(5) + C(6)*DLSXU(-1) +C(7)*DLSMTP + C(8)*DLNREER + C(9)
*(LSXU(-4) - (BETA7 + BETA8*LSXU(-5) + BETA9*LSMTPINDEX(-4) +
BETA10*LREER(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.010018	0.007377	1.358037	0.1792
C(6)	0.710940	0.071770	9.905783	0.0000
C(7)	0.332970	0.160021	2.080785	0.0415
C(8)	-0.172093	0.064666	-2.661277	0.0098
C(9)	-0.271093	0.080657	-3.361085	0.0013

R-squared	0.796206	Mean dependent var	0.099330
Adjusted R-squared	0.783469	S.D. dependent var	0.078194
S.E. of regression	0.036386	Akaike info criterion	-3.719557
Sum squared resid	0.084733	Schwarz criterion	-3.557665
Log likelihood	133.3247	Hannan-Quinn criter.	-3.655329
F-statistic	62.51059	Durbin-Watson stat	2.661234
Prob(F-statistic)	0.000000		

Dependent variable: Service exports (excluding tourism).

Model 2: Explanatory variables: Lagged service exports, external demand for service exports and real effective exchange rate.

$\mathrm{LN}(Service\ Exports_t) = 0.32 + 0.92^{*}\mathrm{LN}\ (Service\ Exports_{t-1})\ +$
$0.10^{*}\mathrm{LN}(External\ Demand\ Servcies_t)$

$\Delta\mathrm{LN}(Service\ Exports_t) = 0.01\ {+0.73}^{*}\Delta\mathrm{LN}\ (Service\ Exports_{t-1})$
$+0.33^{*}\Delta\mathrm{LN}(External\ Demand\ Servcies_t)$ -0.16*$\Delta\mathrm{LN}(REER_t)$ - 0.26*(LN($Service\ Exports_{t-4}$)-
LN($Service\ Exports^{*}_{t-4}$))

Dependent Variable: LSXU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 11/22/16 Time: 12:10
Sample: 1999Q1 2016Q2
Included observations: 70
LSXU = C(1) + C(2)*LSXU(-1) + C(3)*LSMTPINDEX

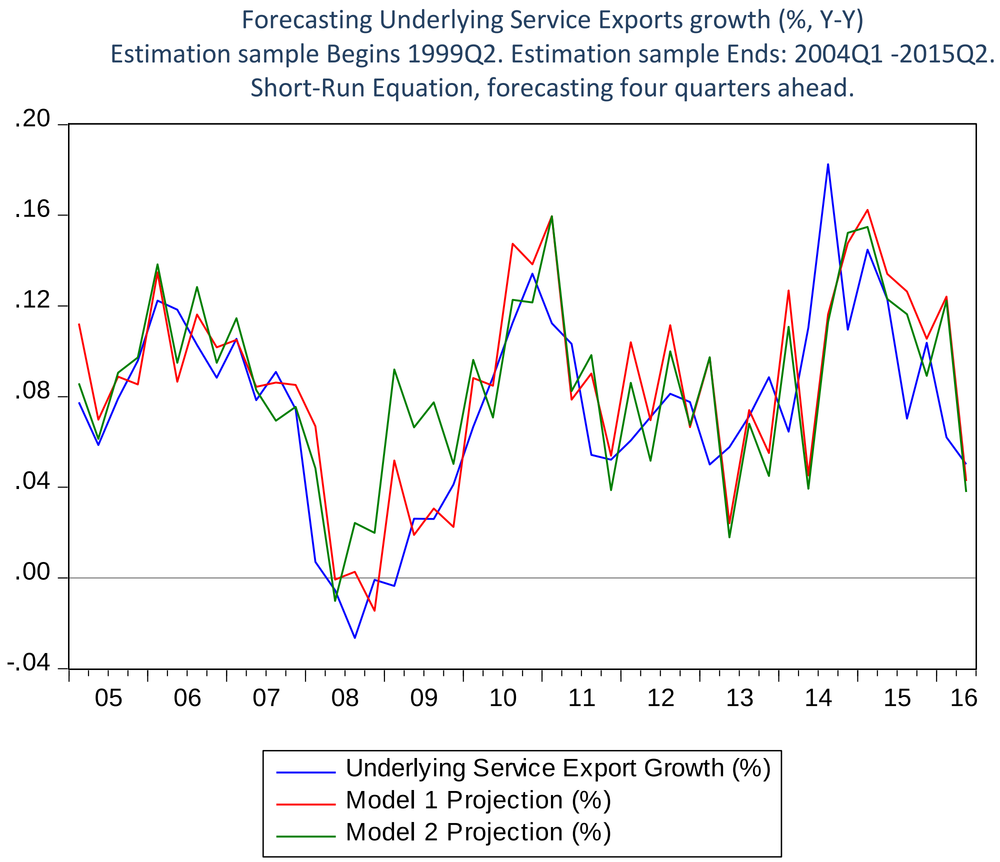
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.318662	0.211338	1.507833	0.1363
C(2)	0.915942	0.061283	14.94620	0.0000
C(3)	0.100878	0.138041	0.730778	0.4675

R-squared	0.980533	Mean dependent var	9.662797
Adjusted R-squared	0.979952	S.D. dependent var	0.395965
S.E. of regression	0.056066	Akaike info criterion	-2.882678
Sum squared resid	0.210604	Schwarz criterion	-2.786314
Log likelihood	103.8937	Hannan-Quinn criter.	-2.844401
F-statistic	1687.336	Durbin-Watson stat	2.941191
Prob(F-statistic)	0.000000		

Dependent Variable: DLSXU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 11/22/16 Time: 12:10
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
DLSXU = C(4) + C(5)*DLSXU(-1) +C(6)*DLSMTP + C(7)*DLNREER + C(8)
*(LSXU(-4) - (BETA11 + BETA12*LSXU(-5) + BETA13*LSMTPINDEX(
-4)))

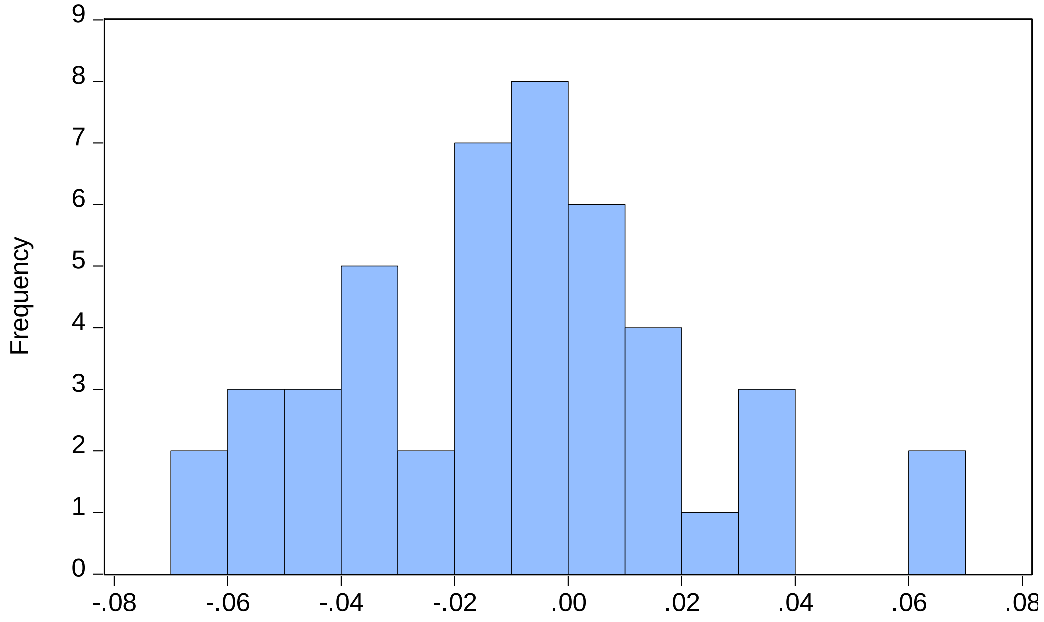
	Coefficient	Std. Error	t-Statistic	Prob.
C(4)	0.008042	0.007487	1.074012	0.2869
C(5)	0.730099	0.072859	10.02067	0.0000
C(6)	0.330630	0.160568	2.059133	0.0436
C(7)	-0.162278	0.064792	-2.504593	0.0148
C(8)	-0.264048	0.080344	-3.286473	0.0016

R-squared	0.794855	Mean dependent var	0.099330
Adjusted R-squared	0.782033	S.D. dependent var	0.078194
S.E. of regression	0.036507	Akaike info criterion	-3.712948
Sum squared resid	0.085294	Schwarz criterion	-3.551057
Log likelihood	133.0967	Hannan-Quinn criter.	-3.648720
F-statistic	61.99343	Durbin-Watson stat	2.685075
Prob(F-statistic)	0.000000		

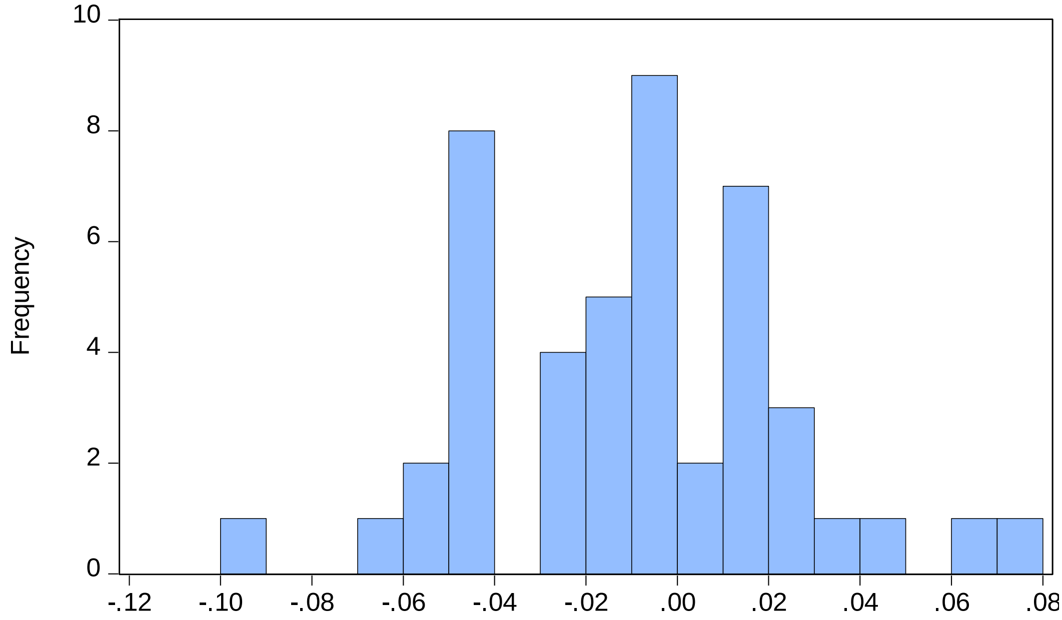


In all cases the estimation sample begins in 1999Q2. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for both of the models and produces the projections graphed above along with the actual outturns.

Underlying Service Exports Forecast Errors 1



Underlying Service Exports Forecast Errors 2



2.4.1: Imports, Goods

Dependent variable: Underlying Goods Imports (excludes aircraft).

Model 1: Explanatory variables: Underlying final demand (excludes investment in aircraft and intangibles) and lagged underlying goods imports (excludes aircraft).

$\text{LN}\ (Goods\ Imports_t) = 0.54 + 0.40{*}\text{LN}\ (Underlying\ Final\ Demand_t)\ {+}0.41{*}\text{LN}\ (Goods\ Imports_{t-1})$

$\Delta\text{LN}(Goods\ Imports_t) = \text{-}0.02\ {+}0.83{*}\Delta\text{LN}(Underlying\ Final\ Demand_t)\ {+}0.24{*}\Delta\text{LN}(Goods\ Imports_{t-1})\ \text{-}\ 0.59{*}(\text{LN}(Goods\ Imports_{t-4})\text{-}\text{LN}(Goods\ Imports^*_{t-4}))$

Dependent Variable: LGMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 14:59
Sample (adjusted): 1999Q1 2016Q2
Included observations: 70 after adjustments
LGMU = C(1) + C(2)*LFDU + C(3)*LGMU(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.541598	0.554385	0.976936	0.3321
C(2)	0.403375	0.091835	4.392381	0.0000
C(3)	0.413621	0.115727	3.574098	0.0007

R-squared	0.798727	Mean dependent var	9.564349
Adjusted R-squared	0.792719	S.D. dependent var	0.159927
S.E. of regression	0.072812	Akaike info criterion	-2.359965
Sum squared resid	0.355205	Schwarz criterion	-2.263601
Log likelihood	85.59877	Hannan-Quinn criter.	-2.321688
F-statistic	132.9403	Durbin-Watson stat	1.941568
Prob(F-statistic)	0.000000		

Dependent Variable: DLGMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 15:08
Sample (adjusted): 1999Q4 2016Q2
Included observations: 67 after adjustments
DLGMU = C(4) + C(5)*DLFDU +C(6)*DLGMU(-1) + C(7)*(LGMU(-4) -
(BETA14 + BETA15*LFDU(-4) +BETA16*LGMU(-3)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(4)	-0.019008	0.010935	-1.738221	0.0871
C(5)	0.833764	0.189502	4.399766	0.0000
C(6)	0.238863	0.108410	2.203338	0.0312
C(7)	-0.587708	0.118541	-4.957825	0.0000

R-squared	0.622260	Mean dependent var	0.039732
Adjusted R-squared	0.604273	S.D. dependent var	0.100526
S.E. of regression	0.063237	Akaike info criterion	-2.625996
Sum squared resid	0.251935	Schwarz criterion	-2.494372
Log likelihood	91.97085	Hannan-Quinn criter.	-2.573912
F-statistic	34.59386	Durbin-Watson stat	1.816731
Prob(F-statistic)	0.000000		

Dependent variable: Underlying Goods Imports (excludes aircraft).

Model 2: Explanatory variables: Underlying investment (excludes investment in aircraft and intangible assets), underlying service exports (excludes tourism) and lagged underlying goods imports (excludes aircraft).

$\mathrm{LN}(Goods\ Imports_t) = 2.44 + 0.23 {*} \mathrm{LN}(Underlying\ Service\ Exports_t)$
$+ 0.14 {*} \mathrm{LN}(Underlying\ Investment_t) + 0.39 {*} \mathrm{LN}\ (Goods\ Imports_{t-1})$

$\Delta\mathrm{LN}(Goods\ Imports_t) = -0.02 + 0.49 {*} \Delta\mathrm{LN}(Underlying\ Service\ Exports_t)$
$+1.14 {*} \Delta\mathrm{LN}(Underlying\ Investment_{t-1}) + 0.39 {*} \Delta\mathrm{LN}(Goods\ Imports_{t-1}) - 0.58 {*}$
$(\mathrm{LN}(Goods\ Imports_{t-4}) - \mathrm{LN}(Goods\ Imports^{*}_{t-4}))$

Dependent Variable: LGMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 15:08
Sample: 1999Q1 2016Q2
Included observations: 70
LGMU = C(1) + C(2)*LSXU_F + C(3)*LGFCFU + C(4)*LGMU(-1)

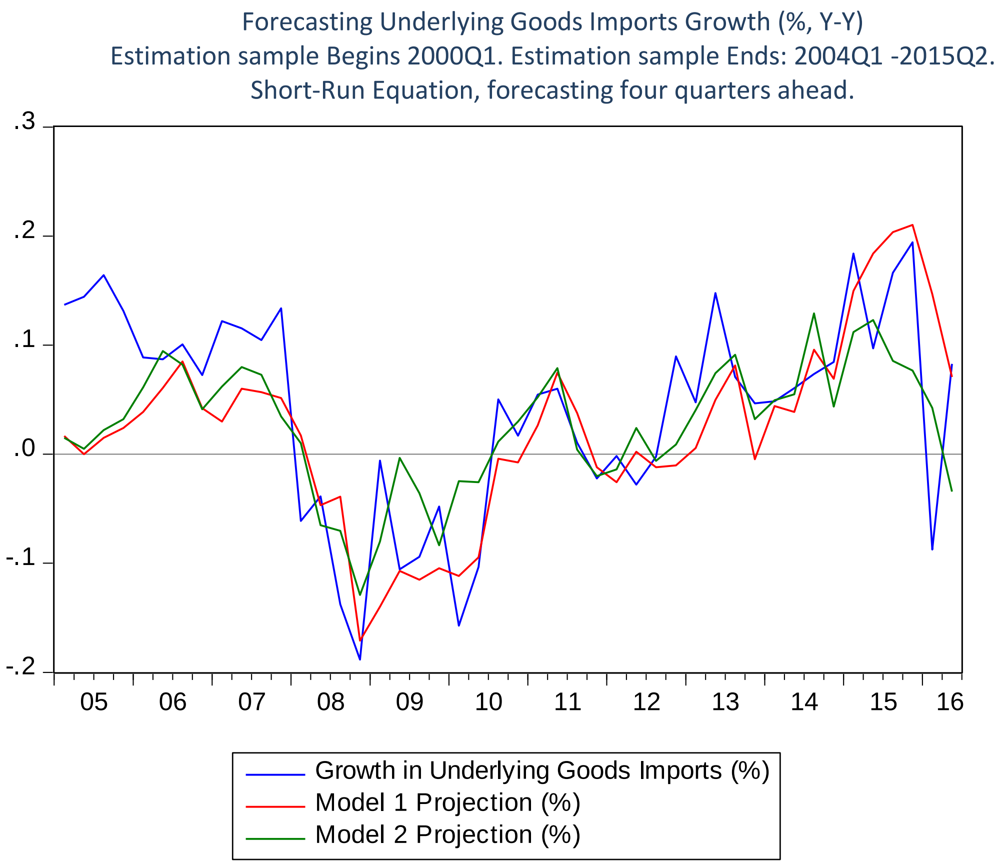
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.441776	0.600760	4.064482	0.0001
C(2)	0.229737	0.043156	5.323410	0.0000
C(3)	0.136658	0.038208	3.576707	0.0007
C(4)	0.390045	0.102895	3.790702	0.0003

R-squared	0.818648	Mean dependent var	9.564349
Adjusted R-squared	0.810405	S.D. dependent var	0.159927
S.E. of regression	0.069636	Akaike info criterion	-2.435617
Sum squared resid	0.320048	Schwarz criterion	-2.307132
Log likelihood	89.24659	Hannan-Quinn criter.	-2.384581
F-statistic	99.31098	Durbin-Watson stat	1.967783
Prob(F-statistic)	0.000000		

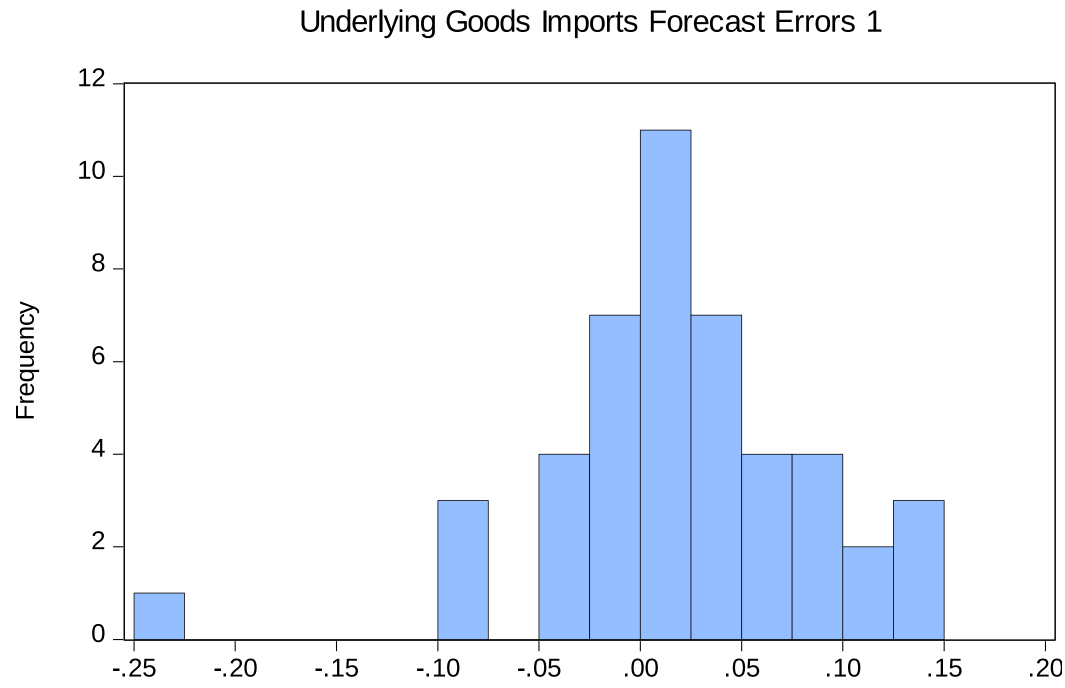
Dependent Variable: DLGMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16   Time: 15:08
Sample (adjusted): 2000Q1 2016Q2
Included observations: 66 after adjustments
DLGMU = C(5) + C(6)*DLSXU +C(7)*DLGFCFU + C(8)*DLGMU(-1) + C(9)
*(LGMU(-4) - (BETA17 + BETA18*LSXU(-4) + BETA19*LGFCFU(-4) +
BETA20*LGMU(-5)))

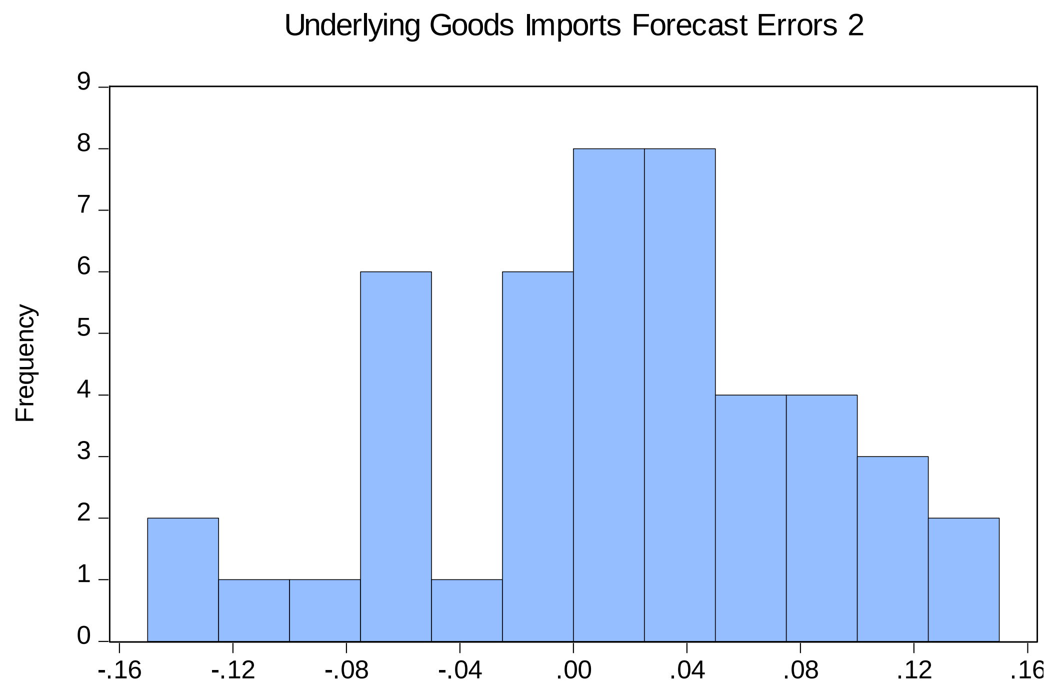
	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.024569	0.013309	-1.846015	0.0697
C(6)	0.491096	0.125883	3.901218	0.0002
C(7)	1.135846	0.453298	2.505739	0.0149
C(8)	0.386498	0.090879	4.252882	0.0001
C(9)	-0.584015	0.114467	-5.102056	0.0000

R-squared	0.663772	Mean dependent var	0.038001
Adjusted R-squared	0.641724	S.D. dependent var	0.100285
S.E. of regression	0.060027	Akaike info criterion	-2.715310
Sum squared resid	0.219798	Schwarz criterion	-2.549427
Log likelihood	94.60523	Hannan-Quinn criter.	-2.649762
F-statistic	30.10612	Durbin-Watson stat	2.039147
Prob(F-statistic)	0.000000		



In all cases the estimation sample begins in 2000Q1. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for both of the models and produces the projections graphed above along with the actual outturns.





2.4.2: Imports, Service

Dependent variable: Service imports (excludes intangible assets).

Model 1: Explanatory variables: Underlying final demand (excludes investment in aircraft and intangible assets) and service exports.

$\text{LN}(Service\ Imports_t) = \text{-3.59} + 0.69\text{*LN}\ (Underlying\ Final\ Demand_t)\ +$
$0.48\text{*LN}(Service\ Exports_t)$

$\Delta\text{LN}(Service\ Imports_t) = \text{-0.02}\ + 0.80\text{*}\Delta\text{LN}\ (Underlying\ Final\ Demand_t)$
$+ 0.62\text{*}\Delta\text{LN}(Service\ Exports_t)\ \text{- } 0.69\text{*(LN}(Service\ Imports_{t-4})\text{-LN}(Service\ Imports^*_{t-4}))$

Dependent Variable: LSMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 17:06
Sample (adjusted): 1999Q4 2016Q2
Included observations: 67 after adjustments
LSMU = C(1) + C(2)*LFDU_F + C(3)*LSXU_F

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-3.594864	0.709086	-5.069717	0.0000
C(2)	0.694494	0.087703	7.918701	0.0000
C(3)	0.480590	0.044537	10.79070	0.0000

R-squared	0.980707	Mean dependent var	9.809278
Adjusted R-squared	0.980104	S.D. dependent var	0.297777
S.E. of regression	0.042002	Akaike info criterion	-3.458438
Sum squared resid	0.112909	Schwarz criterion	-3.359721
Log likelihood	118.8577	Hannan-Quinn criter.	-3.419375
F-statistic	1626.631	Durbin-Watson stat	1.530044
Prob(F-statistic)	0.000000		

Dependent Variable: DLSMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 17:06
Sample (adjusted): 2000Q4 2016Q2
Included observations: 63 after adjustments
DLSMU = C(5) + C(6)*DLFDU_F +C(7)*DLSXU_F + C(9)*(LSMU(-4) -
(BETA24 + BETA25*LFDU_F(-4) + BETA26*LSXU_F(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.017585	0.009052	-1.942686	0.0568
C(6)	0.804183	0.105308	7.636463	0.0000
C(7)	0.619892	0.110892	5.590069	0.0000
C(9)	-0.694076	0.120048	-5.781653	0.0000

R-squared	0.775047	Mean dependent var	0.073736
Adjusted R-squared	0.763608	S.D. dependent var	0.079012
S.E. of regression	0.038416	Akaike info criterion	-3.619308
Sum squared resid	0.087071	Schwarz criterion	-3.483236
Log likelihood	118.0082	Hannan-Quinn criter.	-3.565790
F-statistic	67.75888	Durbin-Watson stat	1.472564
Prob(F-statistic)	0.000000		

Dependent variable: Service imports (excludes intangible assets).

Model 2: Explanatory variables: Personal consumption and service exports.

$\mathrm{LN}(Service\ Imports_t) =$ -0.11 + 0.27*$\mathrm{LN}(Consumption_t)$ + 0.75*$\mathrm{LN}(Service\ Exports_t)$

$\Delta\mathrm{LN}(Service\ Imports_t) =$ -0.01 +0.66*$\Delta\mathrm{LN}$ $(Consumption_t)$ +0.76*$\Delta\mathrm{LN}(Service\ Exports_t)$ - 0.49*($\mathrm{LN}(Service\ Imports_{t-4})$-$\mathrm{LN}(Service\ Imports^*_{t-4})$)

Dependent Variable: LSMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 17:15
Sample: 1999Q1 2016Q2
Included observations: 70
LSMU = C(1) + C(2)*LPCE_F + C(3)*LSXU_F

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.108875	0.684965	-0.158950	0.8742
C(2)	0.269774	0.095252	2.832208	0.0061
C(3)	0.746073	0.033498	22.27215	0.0000

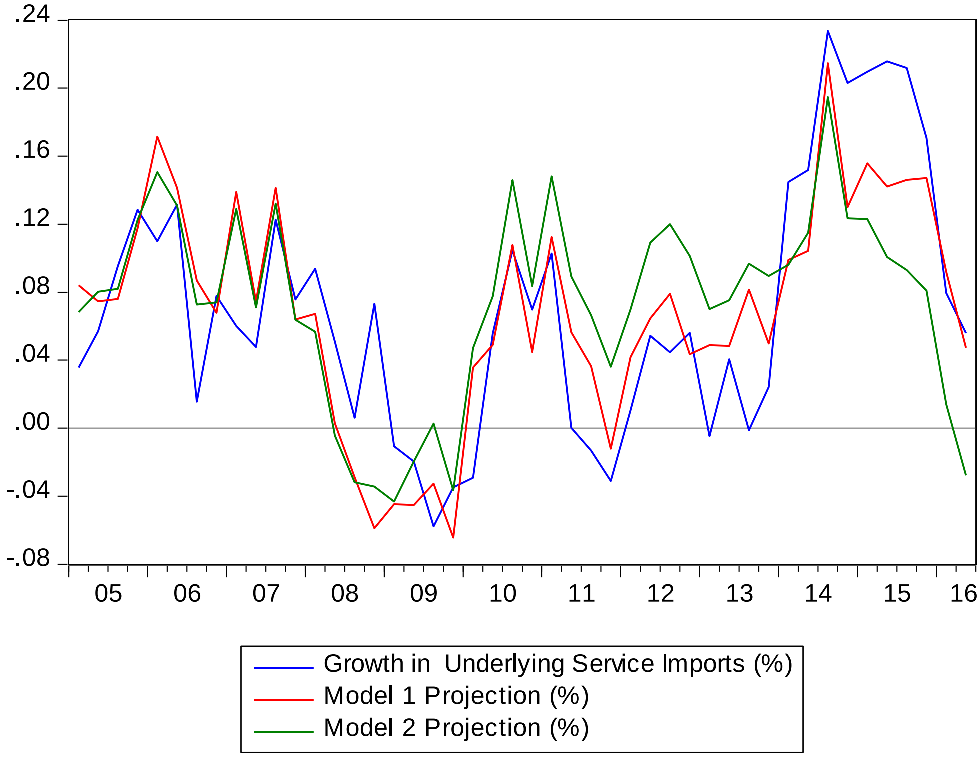
R-squared	0.972896	Mean dependent var	9.775471
Adjusted R-squared	0.972087	S.D. dependent var	0.332937
S.E. of regression	0.055624	Akaike info criterion	-2.898477
Sum squared resid	0.207303	Schwarz criterion	-2.802113
Log likelihood	104.4467	Hannan-Quinn criter.	-2.860200
F-statistic	1202.485	Durbin-Watson stat	0.615070
Prob(F-statistic)	0.000000		

Dependent Variable: DLSMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16 Time: 17:15
Sample (adjusted): 2000Q1 2016Q2
Included observations: 66 after adjustments
DLSMU = C(5) + C(6)*DLPCE_F +C(7)*DLSXU_F + C(9)*(LSMU(-4) -
(BETA28 + BETA29*LPCE_F(-4) + BETA30*LSXU_F(-4)))

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	-0.006831	0.010431	-0.654828	0.5150
C(6)	0.656544	0.185649	3.536479	0.0008
C(7)	0.757042	0.119927	6.312532	0.0000
C(9)	-0.491297	0.124440	-3.948072	0.0002

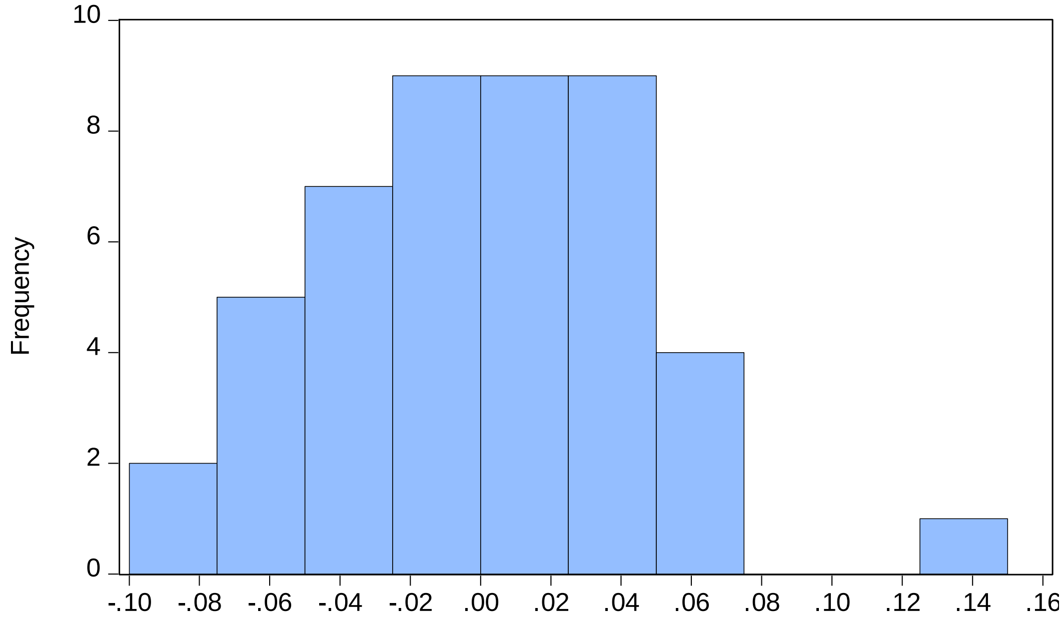
R-squared	0.706635	Mean dependent var	0.082266
Adjusted R-squared	0.692440	S.D. dependent var	0.086794
S.E. of regression	0.048134	Akaike info criterion	-3.170947
Sum squared resid	0.143649	Schwarz criterion	-3.038241
Log likelihood	108.6413	Hannan-Quinn criter.	-3.118509
F-statistic	49.78024	Durbin-Watson stat	0.750447
Prob(F-statistic)	0.000000		

Forecasting Underlying Service Imports growth (%, Y-Y)
Estimation sample Begins 2000Q1. Estimation sample Ends: 2004Q1 -2015Q2.
Short-Run Equation, forecasting four quarters ahead.

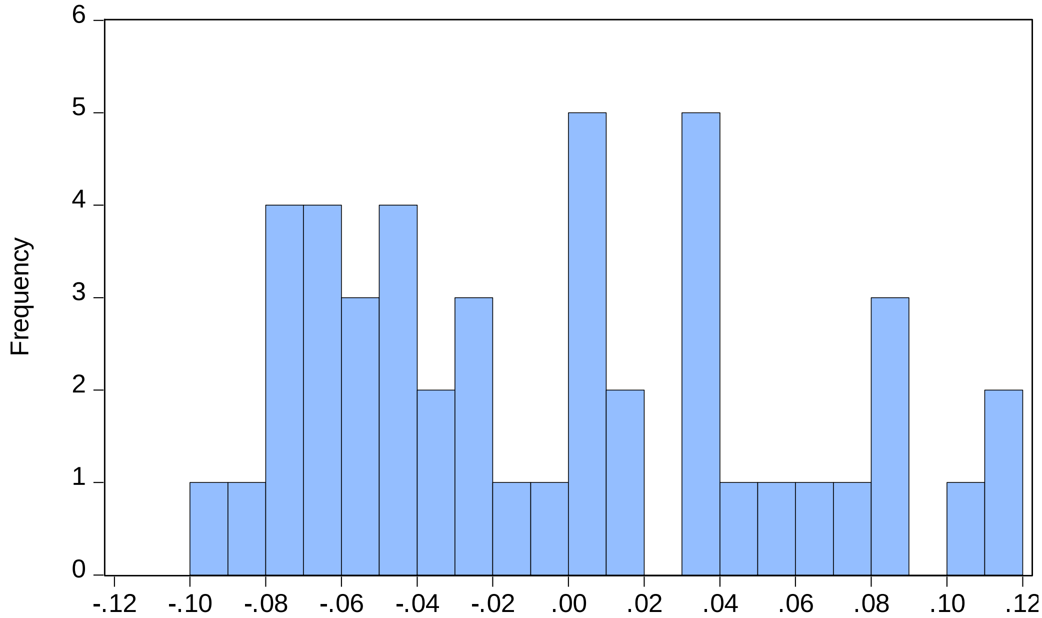


In all cases the estimation sample begins in 2000Q1. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for both of the models and produces the projections graphed above along with the actual outturns.

Underlying Service Imports Forecast Errors 1



Underlying Service Imports Forecast Errors 2



2.5.1: Employment

Dependent variable: Employment.

Model 1: Explanatory variables: Underlying domestic demand (excludes investment in aircraft and intangible assets) and construction output.

$$LN(Employment_t) = 1.23 + 0.60*LN(Underlying\ Domestic\ Demand_t) + 0.01*LN(Construction\ Output_t)$$

$$\Delta\mathrm{LN}(Employment_t) = 0.00 + 0.52*\Delta\mathrm{LN}(Underlying\ Domestic\ Demand_t) + 0.05*\Delta\mathrm{LN}(Construction\ Output_t) - 0.20*(LN(Employment_{t-4}) - LN(Employment^*_{t-4}))$$

Dependent Variable: LOG(EMPLOYMENT)
Method: Least Squares
Date: 02/02/17 Time: 15:46
Sample (adjusted): 1998Q1 2016Q3
Included observations: 75 after adjustments
LNEMP = C(1) + C(2)*LNUDD + C(3)*LNCONS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.226712	0.157517	7.787801	0.0000
C(2)	0.598115	0.015892	37.63575	0.0000
C(3)	0.013156	0.008009	1.642718	0.1048

R-squared	0.957030	Mean dependent var	7.532281
Adjusted R-squared	0.955836	S.D. dependent var	0.086482
S.E. of regression	0.018174	Akaike info criterion	-5.138447
Sum squared resid	0.023782	Schwarz criterion	-5.045747
Log likelihood	195.6917	Hannan-Quinn criter.	-5.101433
F-statistic	801.7927	Durbin-Watson stat	1.881108
Prob(F-statistic)	0.000000		

Dependent Variable: DLNEMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/02/17 Time: 15:46
Sample (adjusted): 1999Q1 2015Q3
Included observations: 67 after adjustments
DLNEMP = C(1) + C(2)*DLNUDD + C(3)*DLNCONS +C(4)*RES_EMP1(-4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.002414	0.001928	1.252485	0.2150
C(2)	0.515808	0.051249	10.06469	0.0000
C(3)	0.053759	0.021484	2.502324	0.0149
C(4)	-0.200022	0.073942	-2.705100	0.0088

R-squared	0.918254	Mean dependent var	0.014736
Adjusted R-squared	0.914362	S.D. dependent var	0.036543
S.E. of regression	0.010694	Akaike info criterion	-6.180424
Sum squared resid	0.007205	Schwarz criterion	-6.048800
Log likelihood	211.0442	Hannan-Quinn criter.	-6.128340
F-statistic	235.8941	Durbin-Watson stat	1.287920
Prob(F-statistic)	0.000000		

Dependent variable: Employment.

Model 2: Explanatory variables: Underlying domestic demand (excludes investment in aircraft and intangibles) and construction output.

$$\Delta \mathrm{LN}(Employment_t) = 0.00 + 0.52 * \Delta \mathrm{LN}(Underlying\ Domestic\ Demand_t) + 0.06 * \Delta \mathrm{LN}(Construction\ Output_t)$$

Dependent Variable: DLNEMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/02/17 Time: 15:46
Sample (adjusted): 1999Q1 2015Q3
Included observations: 67 after adjustments
DLNEMP = C(1) + C(2)*DLNUDD + C(3)*DLNCONS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.002422	0.002020	1.198813	0.2350
C(2)	0.515440	0.053719	9.595128	0.0000
C(3)	0.058929	0.022430	2.627276	0.0108

R-squared	0.908759	Mean dependent var	0.014736
Adjusted R-squared	0.905908	S.D. dependent var	0.036543
S.E. of regression	0.011209	Akaike info criterion	-6.100388
Sum squared resid	0.008042	Schwarz criterion	-6.001670
Log likelihood	207.3630	Hannan-Quinn criter.	-6.061325
F-statistic	318.7209	Durbin-Watson stat	1.300598
Prob(F-statistic)	0.000000		

Dependent variable: Employment.

Model 3: Explanatory variables: Underlying domestic demand (excludes investment in aircraft and intangibles), Industrial output (excludes construction) and output from the Distribution, Transport, Software and Communications (DTSC) sector.

$LN(Employment_t) = 1.26+ 0.60*LN(Underlying\ Domestic\ Demand_t)$ - 0.01$*LN(Industrial\ Output_t)$ +0.01 *LN($DTSC_t$)

ΔLN$(Employment_t)$ = -0.00 +0.61*$\Delta LN(Underlying\ Domestic\ Demand_t)$ - 0.01*$\Delta LN(Industry\ Output_t)$ +0.05*$\Delta LN(DTSC_t)$ -0.2*($LN(Employment_{t-4})$- $LN(Employment^*_{t-4})$)

Dependent Variable: LOG(EMPLOYMENT)
Method: Least Squares
Date: 02/02/17 Time: 15:46
Sample (adjusted): 1998Q1 2016Q3
Included observations: 75 after adjustments
LNEMP = C(1) + C(2)*LNUDD + C(3)*LNIND + c(4)*LNDTSC

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.256770	0.168339	7.465711	0.0000
C(2)	0.599096	0.026283	22.79372	0.0000
C(3)	-0.007020	0.012299	-0.570763	0.5700
C(4)	0.013422	0.022013	0.609765	0.5440

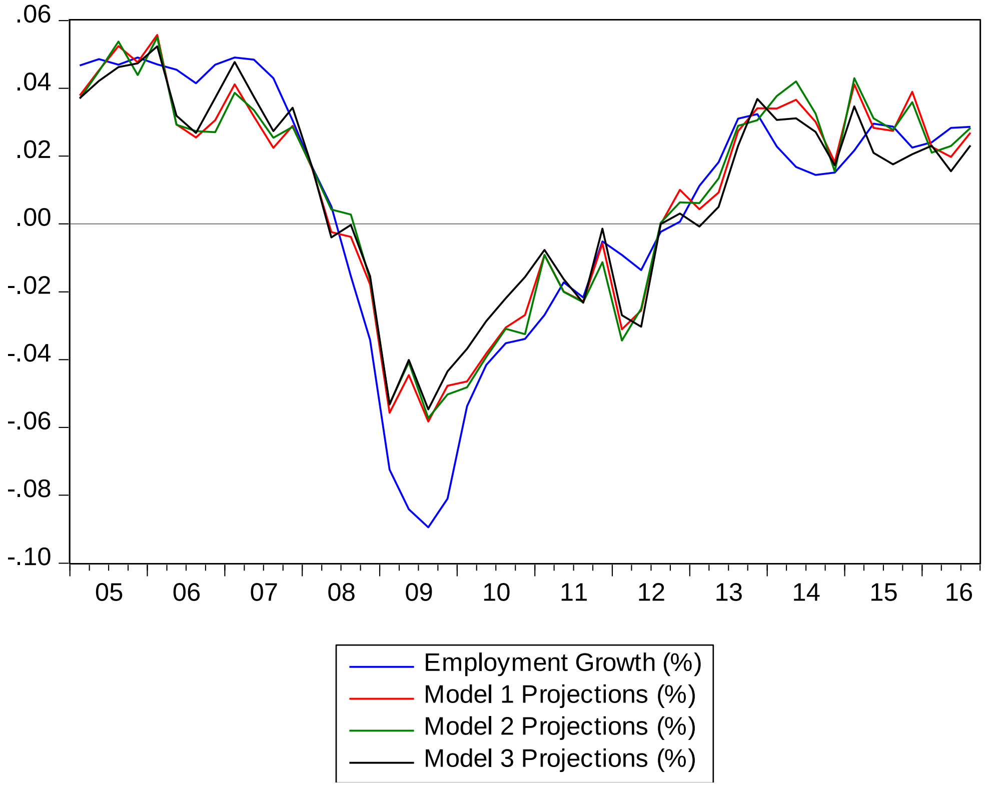
R-squared	0.955704	Mean dependent var	7.532281
Adjusted R-squared	0.953832	S.D. dependent var	0.086482
S.E. of regression	0.018582	Akaike info criterion	-5.081383
Sum squared resid	0.024516	Schwarz criterion	-4.957783
Log likelihood	194.5518	Hannan-Quinn criter.	-5.032031
F-statistic	510.6144	Durbin-Watson stat	1.788421
Prob(F-statistic)	0.000000		

Dependent Variable: DLNEMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/02/17 Time: 15:46
Sample (adjusted): 1999Q1 2015Q3
Included observations: 67 after adjustments
DLNEMP = C(1) + C(2)*DLNUDD + C(3)*DLNIND + C(4)*DLNDTSC + C(5)
*RES_EMP3(-4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.001495	0.001702	-0.878552	0.3830
C(2)	0.611596	0.035251	17.34997	0.0000
C(3)	-0.014667	0.009499	-1.543981	0.1277
C(4)	0.051979	0.036617	1.419527	0.1608
C(5)	-0.198887	0.074979	-2.652575	0.0101

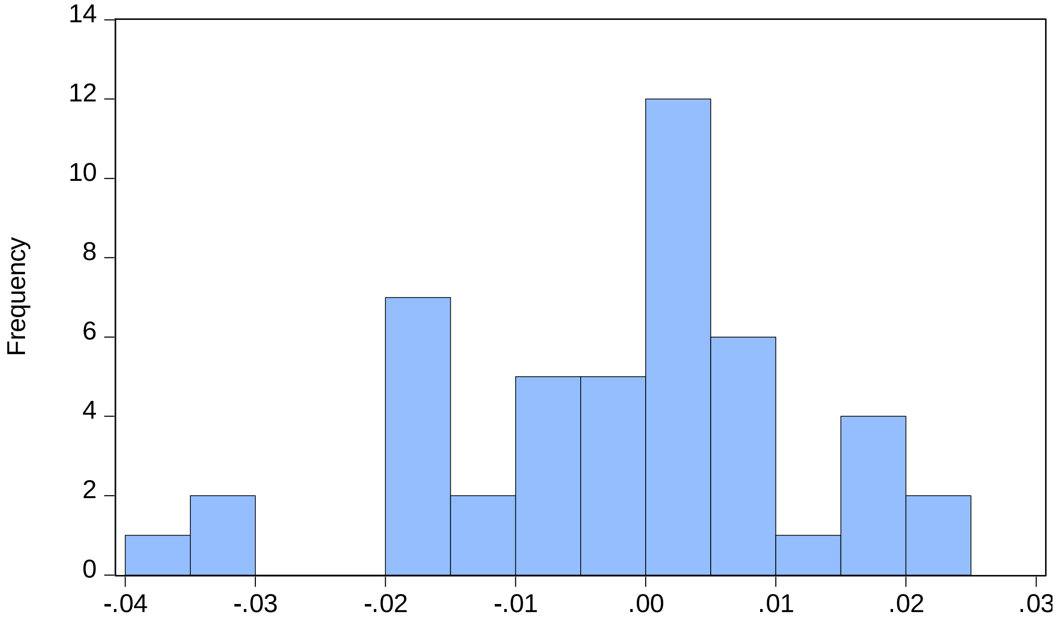
R-squared	0.913886	Mean dependent var	0.014736
Adjusted R-squared	0.908330	S.D. dependent var	0.036543
S.E. of regression	0.011064	Akaike info criterion	-6.098512
Sum squared resid	0.007590	Schwarz criterion	-5.933983
Log likelihood	209.3001	Hannan-Quinn criter.	-6.033407
F-statistic	164.4935	Durbin-Watson stat	1.380896
Prob(F-statistic)	0.000000		

Forecasting Employment growth (%, Y-Y)
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2004Q1 - 2015Q3,
Short-Run equation, forecasting four quarters ahead.

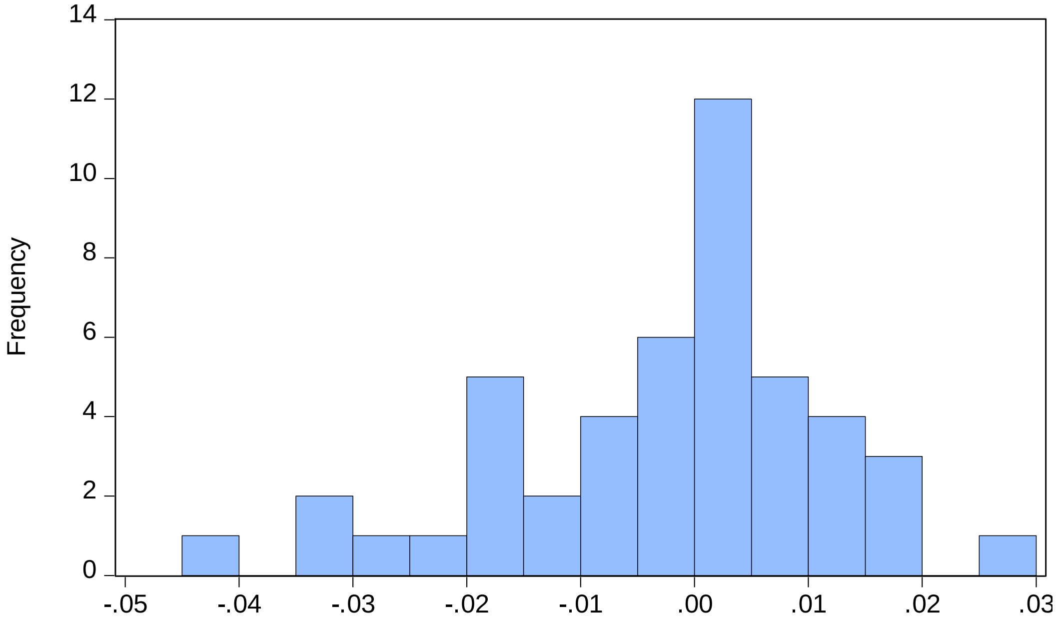


In all cases the estimation sample begins in 1999Q1. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for each of the three models and produces the projections graphed above along with the actual outturns.

Employment Forecast Errors 1



Employment Forecast Errors 2




Employment Forecast Errors 3
Frequency
0
1
2
3
4
5
6
7
8
-.05
-.04
-.03
-.02
-.01
.00
.01
.02

2.5.2: Compensation of Employees

Dependent variable: Compensation of employees (wage bill).

Explanatory variables: HICP and employment.

$LN(CE_t)$ = -6.43 +1.74*$LN(HICP_t)$ +1.09*$LN(Employment_t)$

$\Delta LN(CE_t)$ = 0.01 +1.15*ΔLN $(HICP_t)$ +1.27*$\Delta LN(Employment_t)$ - 0.47*(CE_{t-4}-CE^*_{t-4}))

Dependent Variable: LOG(CE)
Method: Least Squares
Date: 02/02/17 Time: 15:46
Sample (adjusted): 1999Q1 2016Q2
Included observations: 70 after adjustments
LNCE= C(1)+C(2)*LNHICP + C(3)*LNEMP

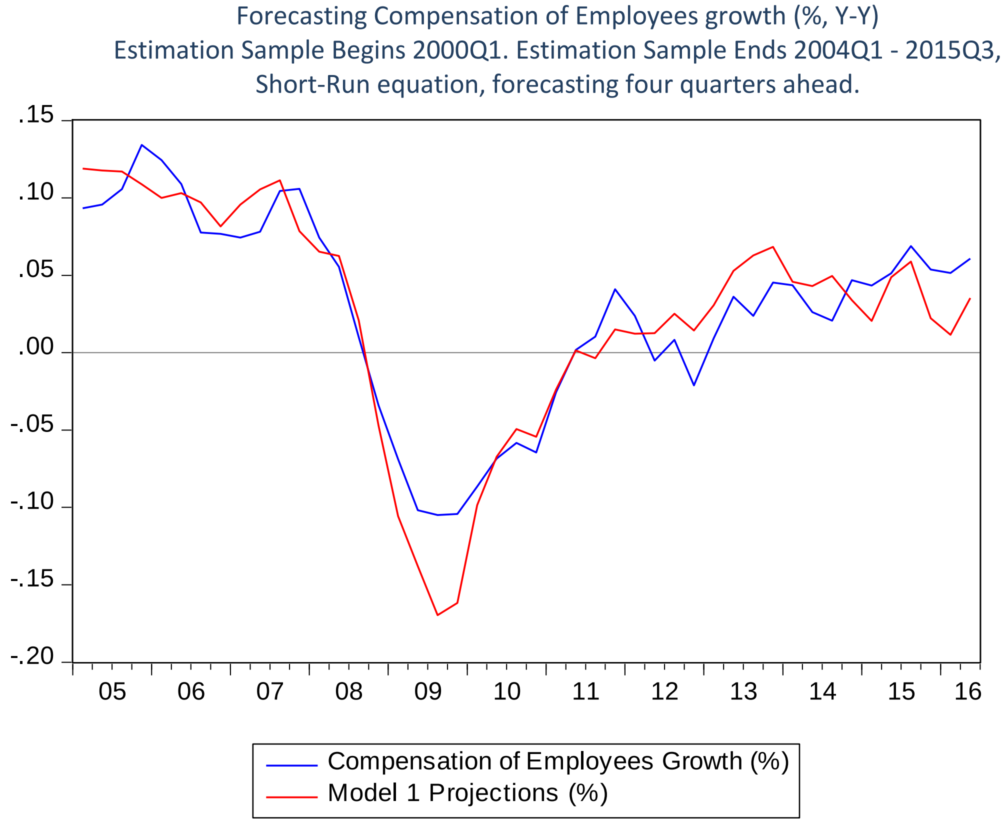
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-6.428926	0.274732	-23.40073	0.0000
C(2)	1.742694	0.038833	44.87661	0.0000
C(3)	1.090011	0.051218	21.28164	0.0000

R-squared	0.993156	Mean dependent var	9.667231
Adjusted R-squared	0.992952	S.D. dependent var	0.237143
S.E. of regression	0.019909	Akaike info criterion	-4.953424
Sum squared resid	0.026555	Schwarz criterion	-4.857060
Log likelihood	176.3698	Hannan-Quinn criter.	-4.915147
F-statistic	4861.600	Durbin-Watson stat	0.898805
Prob(F-statistic)	0.000000		

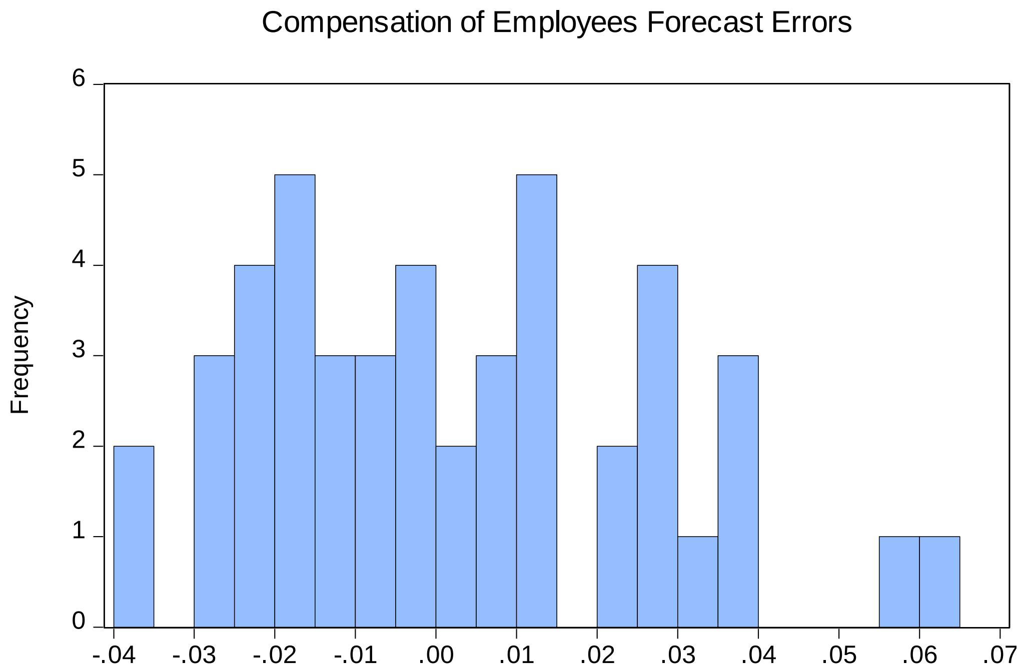
Dependent Variable: DLCE
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/02/17 Time: 16:37
Sample (adjusted): 2000Q1 2016Q2
Included observations: 66 after adjustments
DLCE = C(1) +C(2)*DLHICP +C(3)*DLNEMP +C(4)*RES_CE10(-4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.009490	0.002937	3.231351	0.0020
C(2)	1.150504	0.130982	8.783706	0.0000
C(3)	1.273290	0.075649	16.83154	0.0000
C(4)	-0.469008	0.122936	-3.815047	0.0003

R-squared	0.934168	Mean dependent var	0.047786
Adjusted R-squared	0.930983	S.D. dependent var	0.063452
S.E. of regression	0.016670	Akaike info criterion	-5.291764
Sum squared resid	0.017228	Schwarz criterion	-5.159057
Log likelihood	178.6282	Hannan-Quinn criter.	-5.239325
F-statistic	293.2654	Durbin-Watson stat	0.781266
Prob(F-statistic)	0.000000		



In all cases the estimation sample begins in 2000Q1. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated and produces the projections graphed above along with the actual outturns.



2.6.1: Goods Export Deflator

Model 1: Dependent variable: Goods Export Deflator.

Explanatory variables: Euro/US exchange rate.

$$100^* \left(\frac{XGD_t}{XGD_{t-4}} -1\right) = 0.52 -0.27 *(100^* \left(\frac{USexch_t}{USexch_{t-4}} -1\right))$$

Dependent Variable: PCYGXP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/17/17 Time: 14:41
Sample: 1999Q1 2016Q2
Included observations: 70
PCYGXP = C(1) + C(2)*PCYUSD

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.515874	0.440191	1.171933	0.2453
C(2)	-0.270358	0.041980	-6.440168	0.0000

R-squared	0.378858	Mean dependent var	0.353474
Adjusted R-squared	0.369724	S.D. dependent var	4.631381
S.E. of regression	3.676851	Akaike info criterion	5.470146
Sum squared resid	919.3079	Schwarz criterion	5.534388
Log likelihood	-189.4551	Hannan-Quinn criter.	5.495664
F-statistic	41.47576	Durbin-Watson stat	1.109284
Prob(F-statistic)	0.000000		

Model 2: Dependent variable: Goods Export Deflator.

Explanatory variables: Euro/US exchange rate, goods import deflator.

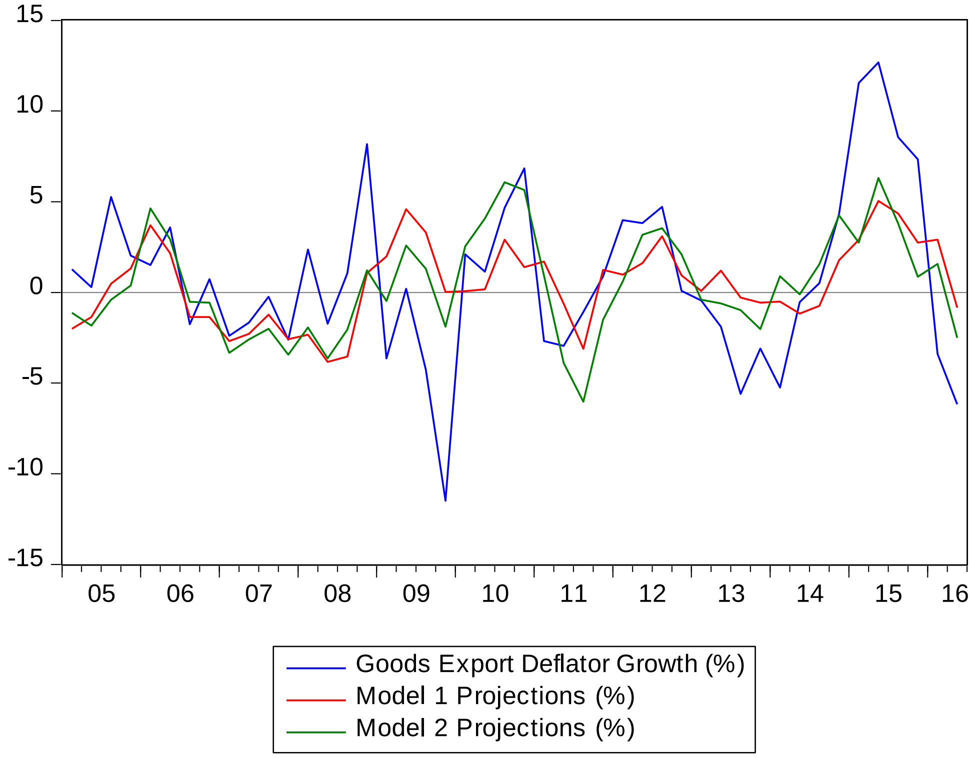
$$100^* \left(\frac{XGD_t}{XGD_{t-4}} -1\right) = 0.43 -0.22 *(100^* \left(\frac{USexch_t}{USexch_{t-4}} -1\right)) + 0.31^*\left(\frac{MGD_t}{MGD_{t-4}} -1\right)$$

Dependent Variable: PCYGXP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/17/17 Time: 14:41
Sample: 1999Q1 2016Q2
Included observations: 70
PCYGXP = C(1) + C(2)*PCYUSD +C(3)*PCYGMP

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.436083	0.381810	1.142147	0.2575
C(2)	-0.220627	0.037794	-5.837597	0.0000
C(3)	0.306267	0.063107	4.853148	0.0000

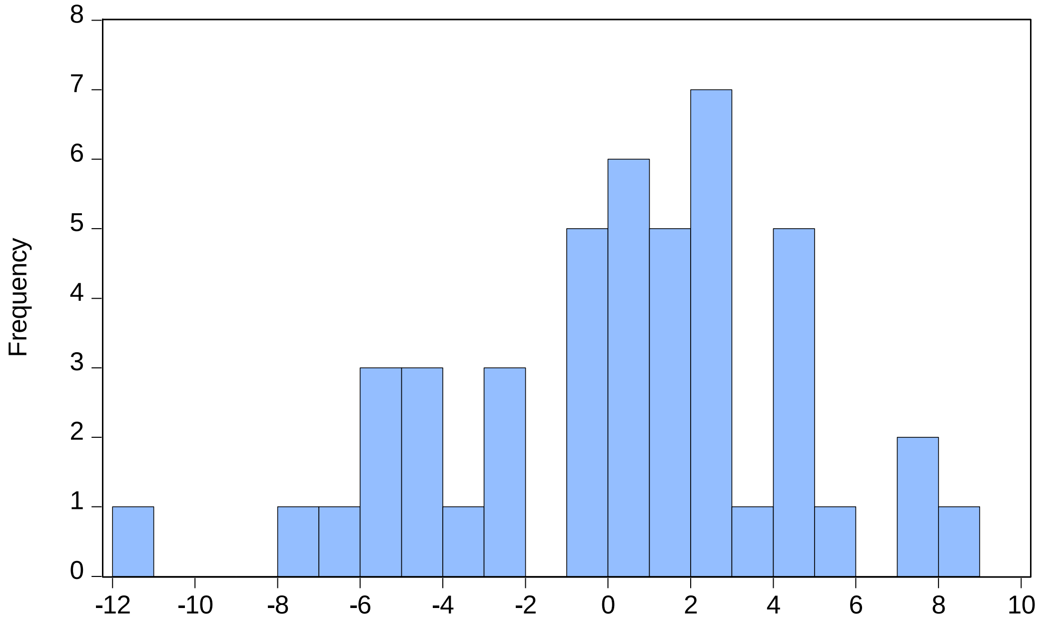
R-squared	0.540418	Mean dependent var	0.353474
Adjusted R-squared	0.526699	S.D. dependent var	4.631381
S.E. of regression	3.186243	Akaike info criterion	5.197474
Sum squared resid	680.1939	Schwarz criterion	5.293838
Log likelihood	-178.9116	Hannan-Quinn criter.	5.235751
F-statistic	39.39238	Durbin-Watson stat	1.179211
Prob(F-statistic)	0.000000		

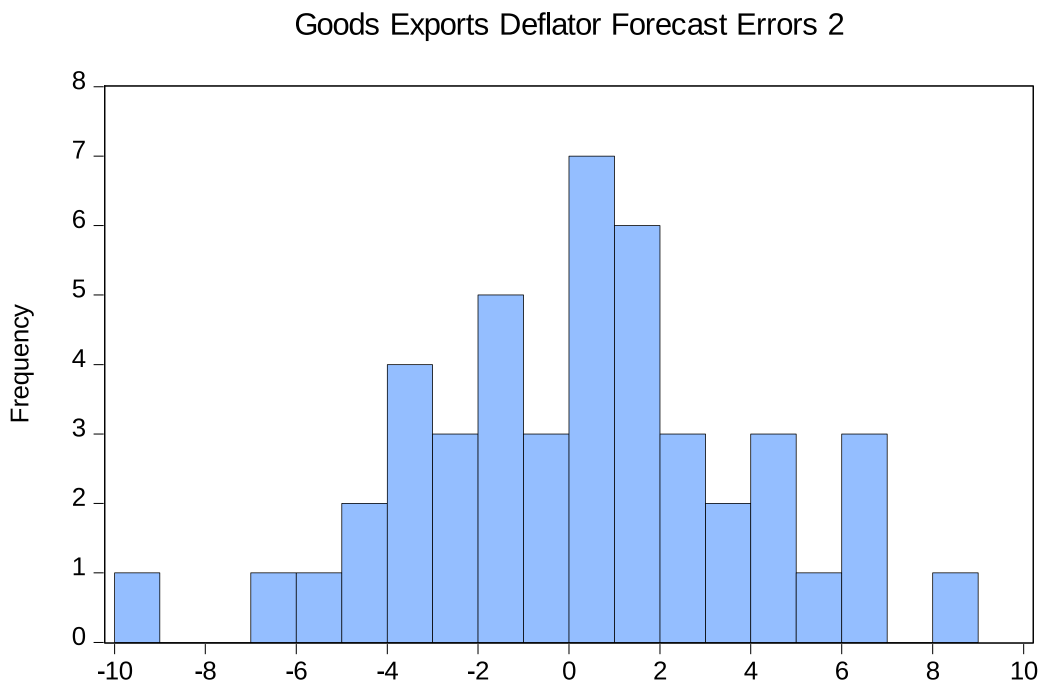
Forecasting Goods Export Deflator growth (%, Y-Y)
Estimation Sample Begins 1999Q1. Estimation Sample Ends 2004Q1 - 2015Q3,
Short-Run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1999Q1. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for both models and produces the projections graphed above along with the actual outturns.

Goods Exports Deflator Forecast Errors 1




Goods Exports Deflator Forecast Errors 2
Frequency
8
7
6
5
4
3
2
1
0
-10
-8
-6
-4
-2
0
2
4
6
8
10

2.6.2: Service Export Deflator

Model 1: Dependent variable: Service export deflator.

Explanatory variables: Service import deflator, time trend and lagged service export deflator.

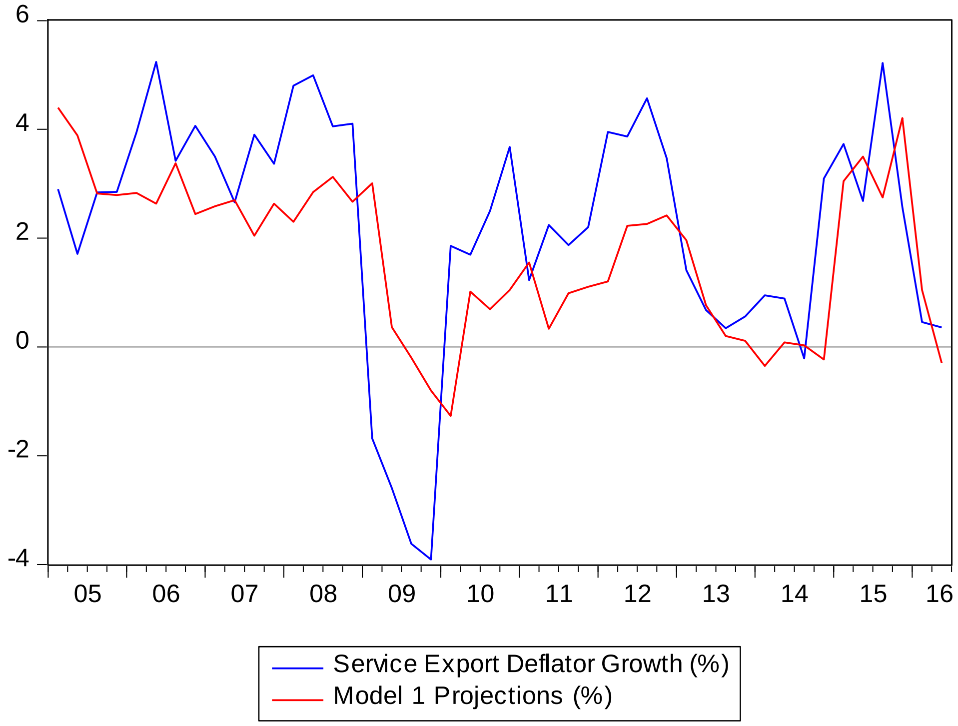
$$100^*\left(\frac{XSD_t}{XSD_{t-4}}-1\right) = 2.5 + 0.25^*\left(100^*\left(\frac{MSD_{t-1}}{MSD_{t-5}}-1\right)\right) + 0.55\ ^*\left(100^*\left(\frac{XSD_{t-1}}{XSD_{t-5}}-1\right)\right) - 0.04^*Trend$$

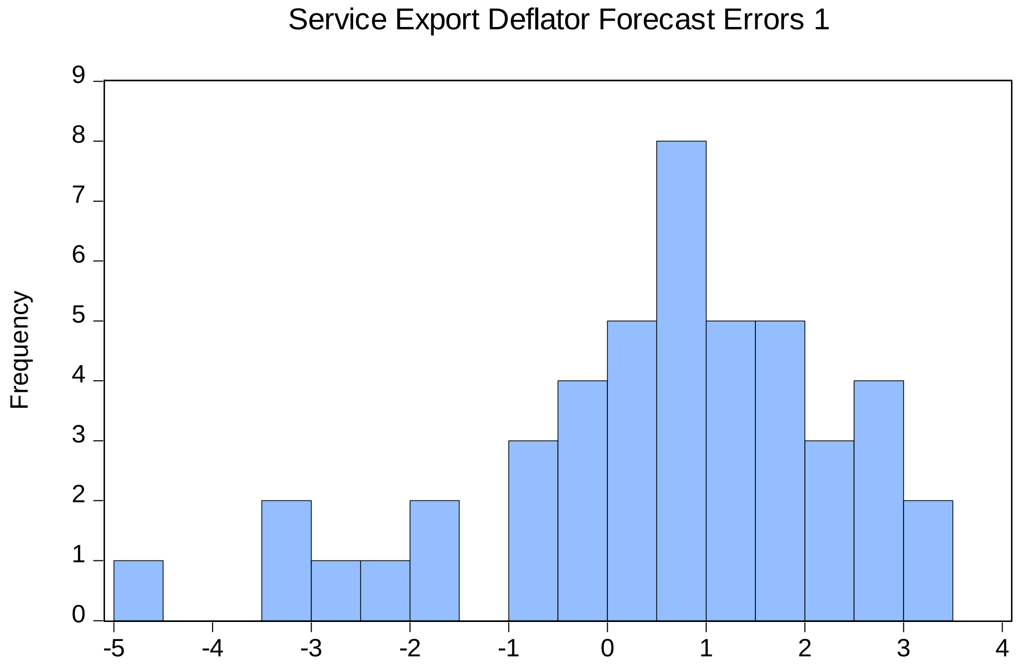
Dependent Variable: PCYSXP
Method: Least Squares
Date: 02/15/17 Time: 15:31
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.516877	1.144212	2.199659	0.0314
PCYSMP	0.246766	0.134052	1.840825	0.0702
PCYSXP(-1)	0.548907	0.099327	5.526251	0.0000
@TREND	-0.035677	0.017820	-2.002013	0.0495

R-squared	0.565112	Mean dependent var	3.671192
Adjusted R-squared	0.545040	S.D. dependent var	3.533417
S.E. of regression	2.383314	Akaike info criterion	4.631084
Sum squared resid	369.2121	Schwarz criterion	4.760597
Log likelihood	-155.7724	Hannan-Quinn criter.	4.682466
F-statistic	28.15460	Durbin-Watson stat	1.866221
Prob(F-statistic)	0.000000		

Forecasting Service export Deflator growth (%, Y-Y)
Estimation Sample Begins 1999Q2. Estimation Sample Ends 2004Q1 - 2015Q2,
Short-Run equation, forecasting four quarters ahead.




Service Export Deflator Forecast Errors 1
Frequency
0
1
2
3
4
5
6
7
8
9
-5
-4
-3
-2
-1
0
1
2
3
4

2.7.1: Goods Import Deflator

Model 1: Dependent variable: Goods import deflator.

Explanatory variables: Brent oil price, real effective exchange rate, EU goods export prices and lagged goods import prices.

$$100^* (\frac{MGD_t}{MGD_{t-4}} -1) = -1.37 + 0.04^*(100^* (\frac{Brent_t}{Brent_{t-4}} -1)) - 0.18 ^*(100^* (\frac{REER_t}{REER_{t-4}} -1)) + 0.15^*(100^* (\frac{EUGXD_t}{EUGXD_{t-4}} -1)) +0.47 ^*(100^* (\frac{MGD_{t-1}}{MGD_{t-5}} -1))$$

Dependent Variable: PCYGMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/15/17 Time: 16:22
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
PCYGMP = C(1) + C(2)*PCYBRENT + C(3)*PCYREER + C(4)*PCYEUGXP +
C(5)*PCYGMP(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.372025	0.700055	-1.959883	0.0544
C(2)	0.040956	0.017139	2.389694	0.0198
C(3)	-0.180188	0.085407	-2.109761	0.0388
C(4)	0.145216	0.119463	1.215568	0.2286
C(5)	0.471275	0.106939	4.406960	0.0000

R-squared	0.519479	Mean dependent var	0.209264
Adjusted R-squared	0.489446	S.D. dependent var	6.349071
S.E. of regression	4.536604	Akaike info criterion	5.931939
Sum squared resid	1317.170	Schwarz criterion	6.093831
Log likelihood	-199.6519	Hannan-Quinn criter.	5.996167
F-statistic	17.29719	Durbin-Watson stat	1.603771
Prob(F-statistic)	0.000000		

Model 2: Dependent variable: Goods import deflator.

Explanatory variables: Brent oil price, real effective exchange rate and lagged goods import prices.

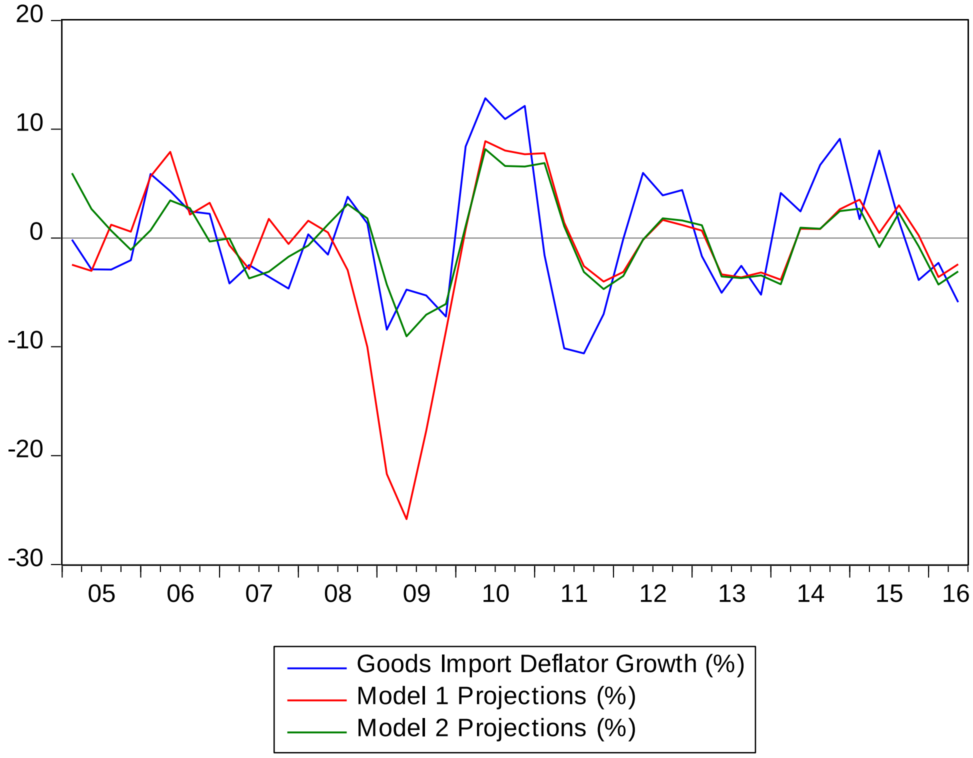
$$100^{*}\left(\frac{MGD_t}{MGD_{t-4}}-1\right)=-0.92+0.05^{*}\left(100^{*}\left(\frac{Brent_t}{Brent_{t-4}}-1\right)\right)-0.19^{*}\left(100^{*}\left(\frac{REER_t}{REER_{t-4}}-1\right)\right)$$
$$+0.53^{*}\left(100^{*}\left(\frac{MGD_{t-1}}{MGD_{t-5}}-1\right)\right)$$

Dependent Variable: PCYGMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/15/17 Time: 16:22
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
PCYGMP = C(1) + C(2)*PCYBRENT + C(3)*PCYREER + C(5)*PCYGMP(-1)

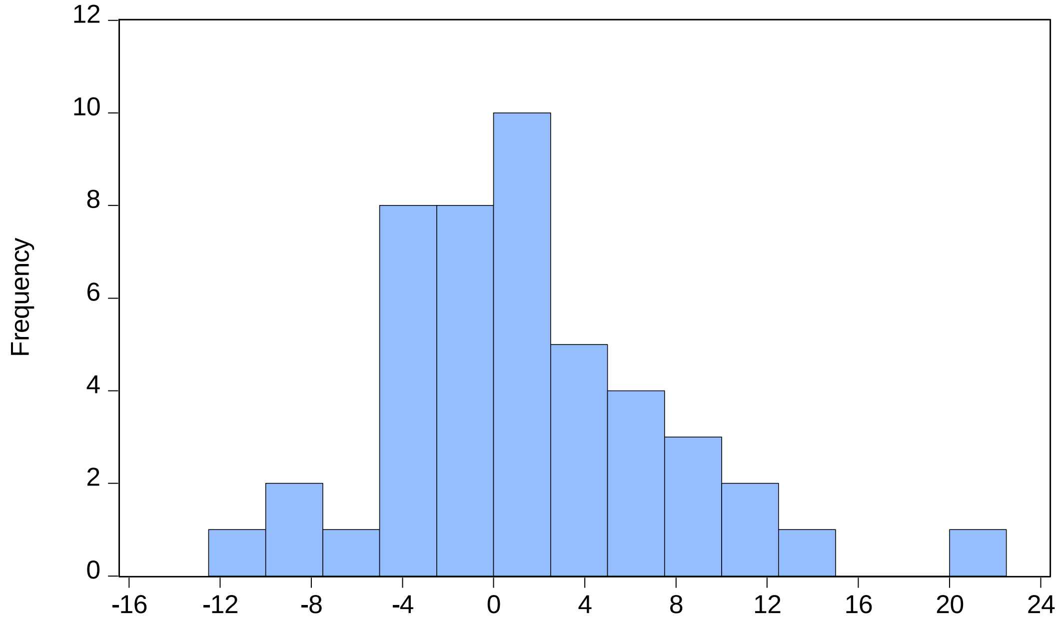
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.920902	0.595764	-1.545751	0.1270
C(2)	0.053379	0.013809	3.865425	0.0003
C(3)	-0.186141	0.085579	-2.175088	0.0333
C(5)	0.533681	0.094153	5.668217	0.0000

R-squared	0.508385	Mean dependent var	0.209264
Adjusted R-squared	0.485695	S.D. dependent var	6.349071
S.E. of regression	4.553241	Akaike info criterion	5.925778
Sum squared resid	1347.580	Schwarz criterion	6.055292
Log likelihood	-200.4394	Hannan-Quinn criter.	5.977161
F-statistic	22.40575	Durbin-Watson stat	1.635706
Prob(F-statistic)	0.000000		

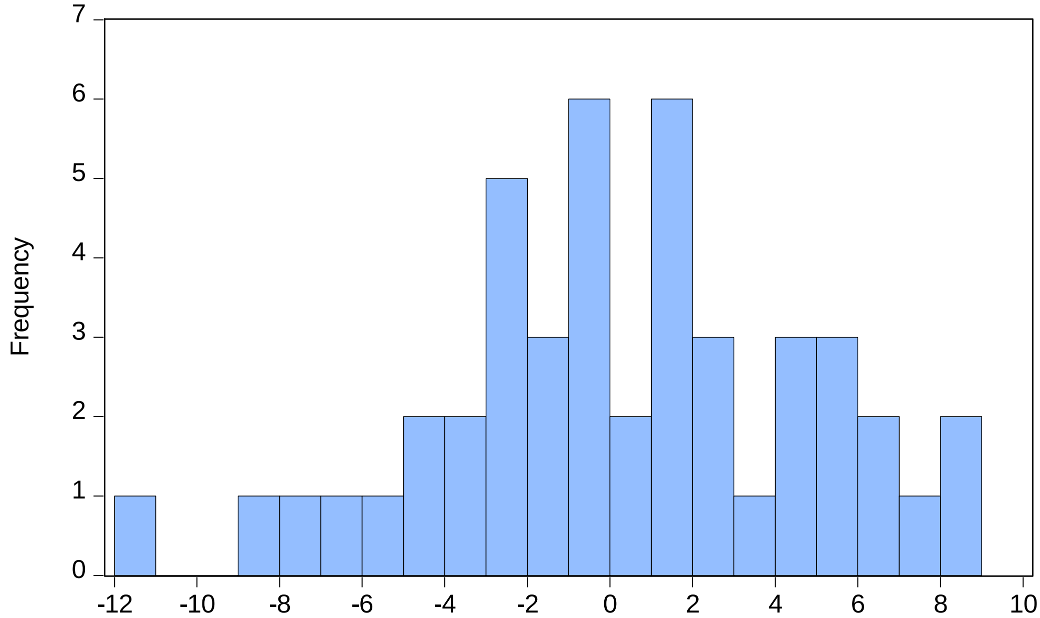
Forecasting Service export Deflator growth (%, Y-Y)
Estimation Sample Begins 1999Q2. Estimation Sample Ends 2004Q1 - 2015Q2,
Short-Run equation, forecasting four quarters ahead.



Goods Import Deflator Forecast Errors 1



Goods Import Deflator Forecast Errors 2



2.7.2: Service Import Deflator

Model 1: Dependent variable: Service Import Deflator.

Explanatory variables: Euro/US exchange rate and lagged service import deflator.

$$100^*\ (\frac{MSD_t}{MSD_{t-4}}\text{ -1}) = 1.03\ \text{-0.02}\ ^*(100^*\ (\frac{USexch_t}{USexch_{t-4}}\text{ -1})) + 0.57^*(100^*\ (\frac{MSD_{t-1}}{MSD_{t-5}}\text{ -1}))$$

Dependent Variable: PCYSMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/17/17 Time: 16:23
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
PCYSMP = C(1) + C(2)*PCYUSD + C(3)*PCYSMP(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.027274	0.347515	2.956053	0.0043
C(2)	-0.018632	0.022194	-0.839507	0.4042
C(3)	0.570851	0.096035	5.944183	0.0000

R-squared	0.394675	Mean dependent var	2.584890
Adjusted R-squared	0.376332	S.D. dependent var	2.337550
S.E. of regression	1.846025	Akaike info criterion	4.106451
Sum squared resid	224.9153	Schwarz criterion	4.203586
Log likelihood	-138.6726	Hannan-Quinn criter.	4.144988
F-statistic	21.51621	Durbin-Watson stat	2.160253
Prob(F-statistic)	0.000000		

Model 2: Dependent variable: Service Import Deflator.

Explanatory variables: Euro/US exchange rate, goods export deflator and lagged service import deflator.

$$100^* \left(\frac{MSD_t}{MSD_{t-4}} - 1\right) = 1.07 + 0.06^*\left(100^* \left(\frac{USexch_t}{USexch_{t-4}} - 1\right)\right) + 0.50^*\left(100^* \left(\frac{MSD_{t-1}}{MSD_{t-5}} - 1\right)\right)$$

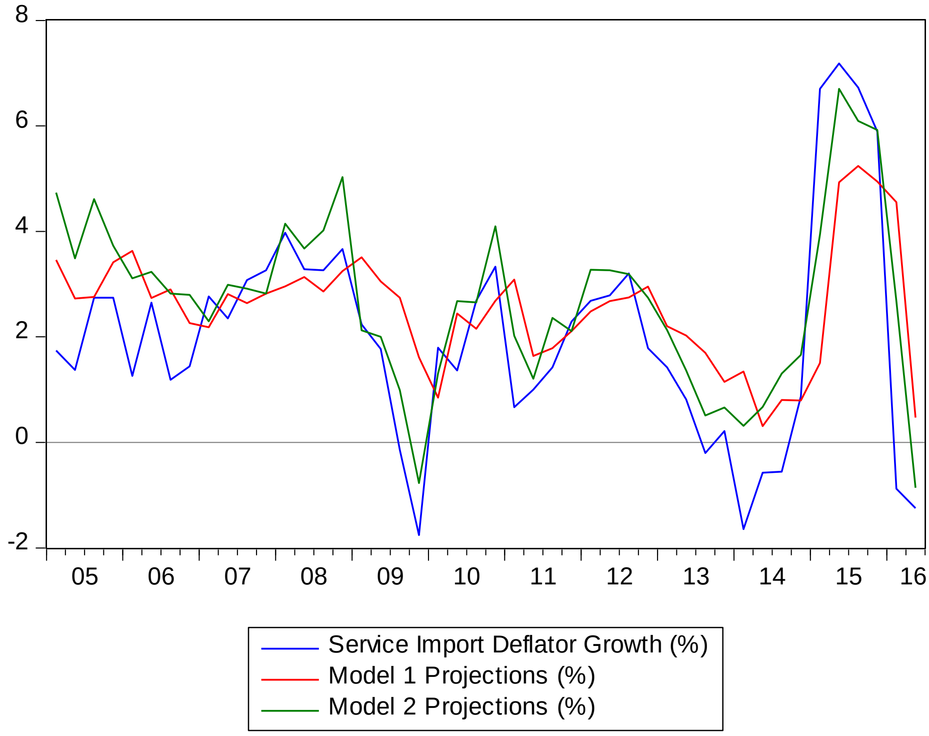
$$+ 0.31^*\left(100^*\left(\frac{XGD_t}{XGD_{t-4}} - 1\right)\right)$$

Dependent Variable: PCYSMP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/17/17 Time: 16:23
Sample (adjusted): 1999Q2 2016Q2
Included observations: 69 after adjustments
PCYSMP = C(1) + C(2)*PCYUSD + C(3)*PCYSMP(-1) + C(4)*PCYGXP

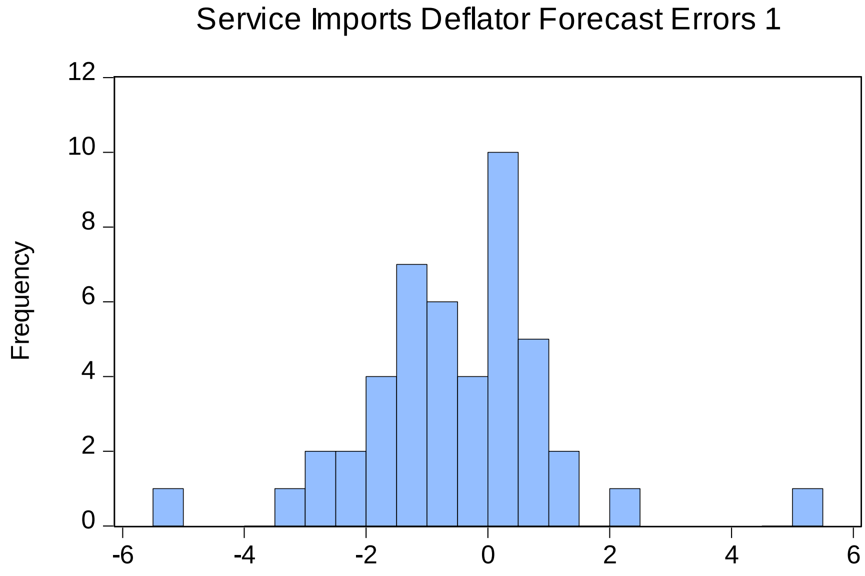
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.070136	0.272860	3.921920	0.0002
C(2)	0.061442	0.021348	2.878184	0.0054
C(3)	0.498894	0.076193	6.547740	0.0000
C(4)	0.313692	0.048335	6.489915	0.0000

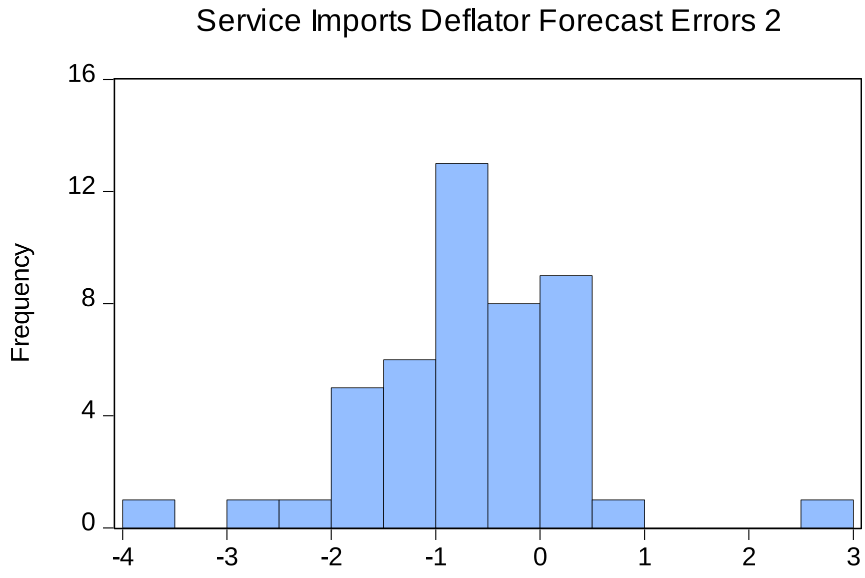
R-squared	0.632688	Mean dependent var	2.584890
Adjusted R-squared	0.615735	S.D. dependent var	2.337550
S.E. of regression	1.449026	Akaike info criterion	3.635883
Sum squared resid	136.4790	Schwarz criterion	3.765397
Log likelihood	-121.4380	Hannan-Quinn criter.	3.687266
F-statistic	37.32042	Durbin-Watson stat	2.006953
Prob(F-statistic)	0.000000		

Forecasting Service Import Deflator growth (%, Y-Y).
Estimation Sample Begins 1999Q2. Estimation Sample Ends 2004Q1 - 2015Q3,
Short-Run equation, forecasting four quarters ahead.



In all cases the estimation sample begins in 1999Q2. In the first case the estimation sample ends at 2004Q1, this equation is then used to forecast 2005Q1. The end date of the estimation is then pushed out to 2004Q2 and this equation is used to forecast 2005Q2. This process is repeated for both models and produces the projections graphed above along with the actual outturns.


Service Imports Deflator Forecast Errors 1
Frequency
12
10
8
6
4
2
0
-6
-4
-2
0
2
4
6


Service Imports Deflator Forecast Errors 2
Frequency
16
12
8
4
0
-4
-3
-2
-1
0
1
2
3

2.8: Forecast Evaluation

Table 2 shows the root mean squared errors and the Theils U2 statistic of the various models used. These were computed by assessing the errors on the four quarter ahead forecasts. These forecasts are made by estimating the equations using the data available up until time t, and then forecasting time period t+4. The dependent variables modelled are year on year percentage changes. The formula for calculating the Root Mean Squared Errors (RMSE) is given below:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

Theil's U2 measures the accuracy of forecasts. Specifically, here it is measuring performance against a naïve forecast. The naïve forecast used here is that growth four quarters ahead will be the same as it is currently. If the statistic is less than one, then the forecasting model outperforms this naïve forecast. This is the case for almost all the models specified. If the Theil's U2 statistic is greater than one that indicates that the naïve forecast has superior forecasting performance. The formula is given below, where $\hat{y}_t$= model forecast growth rate for time t, which was finalised using data up until time t-4. The denominator has y_t as the forecast for time period t+4, as the naïve forecast in this case is that the growth rate in four quarters time will be the same as the current growth rate.

$$U_2 = \sqrt{\frac{\frac{1}{N}\sum_{t=1}^{n}(\frac{\hat{y}_{t+4} - y_{t+4}}{y_t})^2}{\frac{1}{N}\sum_{t=1}^{n}(\frac{y_t - y_{t+4}}{y_t})^2}}$$

Table 2: Root Mean Squared Errors (RMSE) and Theil's U2 statistic

	RMSE	Theil's U2
Goods Consumption Model 1	0.064	0.93
Goods Consumption Model 2	0.059	0.86
Goods Consumption Model 3	0.057	0.83
Services Consumption Model 1	0.037	1.90
Services Consumption Model 2	0.037	1.75
Services Consumption Model 3	0.033	1.69
Services Consumption Model 4	0.033	1.09
Services Consumption Model 5	0.030	1.09
HICP Model 1	0.0061	0.33
HICP Model 2	0.0063	0.34
Underlying M&E	0.181	0.52
Improvements	0.115	0.43
Transfer costs	0.283	0.69
Dwellings	0.096	0.52
Goods exports Model 1	0.076	0.49
Goods exports Model 2	0.058	0.37
Goods exports Model 3	0.067	0.44
Service exports underlying Model 1	0.032	0.55
Service exports underlying Model 2	0.034	0.59
Underlying goods imports Model 1	0.071	0.57
Underlying goods imports Model 2	0.066	0.56
Service imports Model 1	0.045	0.48
Service imports Model 2	0.060	0.65
Employment Model1	0.014	0.42
Employment Model2	0.014	0.44
Employment Model3	0.015	0.44
Compensation of employees (wage bill)	0.024	0.42
Goods Export Deflator Model 1	0.041	0.53
Goods Export Deflator Model 2	0.037	0.47
Service Imports Deflator Model 1	0.017	0.53
Service Imports Deflator Model 2	0.012	0.38
Service Exports Deflator	0.018	0.53
Goods Import Deflator Model 1	0.060	0.56
Goods Import Deflator Model 2	0.040	0.40