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. 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 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. 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

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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. Section 8 concludes.

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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. 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 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). 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 $X_2$).

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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.
\[ \ln(Y_t) = \alpha_1 + \beta_1 \ln(X_{1t}) + \beta_2 \ln(X_{2t}) \]  

(1)

\[ \Delta \ln(Y_t) = \alpha_2 + \beta_3 \Delta \ln(X_{1t}) + \beta_4 \Delta \ln(X_{2t}) + \beta_5 (\ln(Y_{t-4}) - (\alpha_1 + \beta_1 \ln(X_{1t-4}) + \beta_2 \ln(X_{2t-4}))) \]  

(2)

Where (1) describes the long-run relationship between \( Y \) and \( X_1 \) and \( X_2 \). Equation (2) describes the short-run relationship, with \( \beta_5 \) 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. While the raw data used and hence the initial forecasts produced are not seasonally adjusted, these can easily be seasonally adjusted \textit{ex-post}, giving smooth quarterly profiles.

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 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.

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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

<table>
<thead>
<tr>
<th>Data source</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal Disposable Income</td>
<td>Institutional sector accounts (CSO)</td>
</tr>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td>Housing wealth</td>
<td>Central Bank of Ireland</td>
</tr>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td>Financial wealth</td>
<td>Central Bank of Ireland</td>
</tr>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td>External demand for Irish goods exports</td>
<td>European Commission forecasts (when available), otherwise IMF forecasts</td>
</tr>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td>External demand for Irish service exports</td>
<td>European Commission forecasts (when available), otherwise IMF forecasts</td>
</tr>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td>Real effective exchange rate</td>
<td>European Commission forecasts (when available), otherwise IMF forecasts</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-------------------------------------------------</td>
</tr>
<tr>
<td>Housing Commencements</td>
<td>Department of Housing, Planning, Community and Local Government</td>
</tr>
<tr>
<td>Government Consumption</td>
<td>CSO and Department of Finance</td>
</tr>
<tr>
<td>EU goods export prices</td>
<td>European Commission forecasts (when available), otherwise IMF forecasts</td>
</tr>
<tr>
<td>Brent crude oil prices</td>
<td>DataStream</td>
</tr>
<tr>
<td>Construction output</td>
<td>National Income and Expenditure Accounts (CSO)</td>
</tr>
</tbody>
</table>

\(^{11}\) 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. 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). 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). 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. This seasonally-adjusted data that are created are then used for

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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)

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.
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).
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;\(^{24}\)

\(^{19}\) 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 Ireland’s 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.

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. 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.

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), 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

Historical data on the destination of goods and service exports are used to calculate trade weights for goods and services.

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.

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.\(^{27}\) 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. 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.

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

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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\textsuperscript{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)
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).

\textsuperscript{31} The Euro depreciated by 16.5\% against the dollar in 2015.
Figure 9: Forecasting Service Exports growth (% Y-Y)
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\textsuperscript{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

\textsuperscript{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)
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. 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.

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33 Underlying domestic demand may be used in future, as it excludes investment in aircraft and intangible assets.
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 and non-agricultural wage growth in the survey-based survey of 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\(^3\) (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.

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\(^3\) 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\(^\text{35}\). 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.\(^\text{36}\) 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).\(^\text{37}\) 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.
References


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.

\[ \Delta LN(Z_t) = LN(Z_t) - LN(Z_{t-1}) \]

\(^{38}\) \( CG_{SA} \) 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: $\ln(C_{t}) = -1.05 + 0.93\ln(PDI_{t}) + 0.07\ln(Wealth_{t})$

Short Run: $\Delta\ln(C_{t}) = -0.00 + 0.71\Delta\ln(PDI_{t}) + 0.25\Delta\ln(Wealth_{t}) - 0.70(\ln(C_{t-4}) - \ln(C_{t-4}))$

**Dependent Variable:** LPCGR\_SA

Method: Least Squares (Gauss-Newton / Marquardt steps)

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<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
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<td>-7.835016</td>
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<td>C(2)</td>
<td>0.933313</td>
<td>22.41992</td>
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R-squared: 0.823204
Adjusted R-squared: 0.820047
S.E. of regression: 0.032808
Akaike info criterion: -3.962423
Schwarz criterion: -3.891373
Log likelihood: 116.9103
Durbin-Watson stat: 0.293279
Prob(F-statistic): 0.000000

**Dependent Variable:** DLPCGR

Method: Least Squares (Gauss-Newton / Marquardt steps)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
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<td>C(5)</td>
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<td>C(7)</td>
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<td>C(8)</td>
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<td>C(9)</td>
<td>-0.702764</td>
<td>-5.386939</td>
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R-squared: 0.760208
Adjusted R-squared: 0.745820
S.E. of regression: 0.028176
Akaike info criterion: -4.229493
Schwarz criterion: -4.082161
Log likelihood: 118.1963
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: \(\ln(CG_{SA,t}) = 0.47 + 0.73\ln(PDI_t) + 0.11\ln(Wealth_t)\)

Short Run: \(\Delta \ln(CG_t) = -0.00 + 0.64\Delta \ln(PDI_t) + 0.22\Delta \ln(Wealth_t) - 0.66(\ln(CG_{SA,t-4}) - \ln(CG_{SA,t-4}^-))\)

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

\[\text{LPCGR-SA} = C(1) + C(2)\text{LRPDI-SA} + C(3)\text{LRNFHWEALTH-SA}\]

<table>
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<th>Coefficient</th>
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<td>C(3)</td>
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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 crit. -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

\[\text{DLPCGR} = C(5) + C(7)\Delta LRPDI + C(8)\Delta LRNFHWEALTH + C(9)\Delta(\text{LPCGR-SA}(-4)) - (\text{BETA82} + \text{BETA83}LRPDI-SA(-4) + \text{BETA84}LRNFHWEALTH-SA(-4))\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
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</table>

R-squared 0.735512  Mean dependent var 0.016921
Adjusted R-squared 0.719642  S.D. dependent var 0.055887
S.E. of regression 0.029590  Akaike info criterion -4.131468
Sum squared resid 0.043783  Schwarz criterion -3.984136
Log likelihood 115.5496  Hannan-Quinn crit. -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: \( \ln(C_{SA,t}) = 0.72 + 0.85 \ln(PDI_t) \)

Short Run: \( \Delta \ln(C_{SA,t}) = -0.00 + 0.77 \Delta \ln(PDI_t) + 0.17 \Delta \ln(Wealth_t) - 0.68 (\ln(C_{SA,t-4}) - \ln(C_{SA,t-4})) \)

---

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.716531</td>
<td>0.444935</td>
<td>1.610418</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.845054</td>
<td>0.044580</td>
<td>18.95592</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.856914</td>
<td>Mean dependent var</td>
<td>9.150341</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.854529</td>
<td>S.D. dependent var</td>
<td>0.082438</td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.031442</td>
<td>Akaike info criterion</td>
<td>-4.049590</td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.059318</td>
<td>Schwarz criterion</td>
<td>-3.980973</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>127.5373</td>
<td>Hannan-Quinn criter.</td>
<td>-4.022649</td>
</tr>
<tr>
<td>F-statistic</td>
<td>359.3268</td>
<td>Durbin-Watson stat</td>
<td>0.297426</td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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)) )

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>-0.003237</td>
<td>0.004525</td>
<td>-0.715395</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.766255</td>
<td>0.136853</td>
<td>5.599094</td>
</tr>
<tr>
<td>C(8)</td>
<td>0.174575</td>
<td>0.058090</td>
<td>3.005277</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.678953</td>
<td>0.144219</td>
<td>-4.707776</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.737426</td>
<td>Mean dependent var</td>
<td>0.016921</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.721671</td>
<td>S.D. dependent var</td>
<td>0.055887</td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.029484</td>
<td>Akaike info criterion</td>
<td>-4.138733</td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.031442</td>
<td>Schwarz criterion</td>
<td>-3.980973</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>115.7458</td>
<td>Hannan-Quinn criter.</td>
<td>-4.022649</td>
</tr>
<tr>
<td>F-statistic</td>
<td>46.80748</td>
<td>Durbin-Watson stat</td>
<td>0.479923</td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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.
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: \( \ln(CS_{SA_t}) = -1.59 + 1.70 \ln(PDI_t) - 0.46 \ln(Wealth_t) \)

Short Run: \( \Delta \ln(CS_t) = 0.01 + 0.57 \Delta \ln(PDI_t) - 0.01 \Delta \ln(Wealth_t) - 0.47(\ln(CS_{SA_{t-4}}) - \ln(CS_{SA_{t-4}})) \)

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

\[\text{LPCSR}_{SA} = C(1) + C(2) \times \text{LRPDI}_{SA} + C(3) \times \text{LRNFHWEALTH}_{SA} \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-1.592969</td>
<td>0.649881</td>
<td>-2.345201</td>
</tr>
<tr>
<td>C(2)</td>
<td>1.700263</td>
<td>0.098300</td>
<td>17.29675</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.456372</td>
<td>0.052530</td>
<td>-8.687883</td>
</tr>
</tbody>
</table>

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

\[\text{DLPCSR} = C(5) + C(7) \times \text{DLRPDI} + C(8) \times \text{DLRNHFWEALTH} + C(9) \times (\text{LPCSR}_{SA_{-4}} - (BETA90 + BETA91 \times \text{LRPDI}_{SA_{-4}} + (BETA92 \times \text{LRNFHWEALTH}_{SA_{-4}})) \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.014270</td>
<td>0.002877</td>
<td>4.960524</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.570002</td>
<td>0.087128</td>
<td>6.452140</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.009889</td>
<td>0.038169</td>
<td>-0.259097</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.468748</td>
<td>0.078755</td>
<td>-5.951986</td>
</tr>
</tbody>
</table>

R-squared 0.661904  Mean dependent var 0.023225
Adjusted R-squared 0.641618  S.D. dependent var 0.325200
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: \( \ln(C_{S_{at}}) = 0.66 + 1.40 \ln(PDI_t) - 0.40 \ln(Wealth_t) \)

Short Run: \( \Delta \ln(C_t) = 0.02 + 0.49 \Delta \ln(PDI_t) - 0.03 \Delta \ln(Wealth_t) - 0.40(\ln(C_{S_{at-4}}) - \ln(C_{S_{at-4}})) \)

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

\[ LPCSR_{SA} = C(1) + C(2) \times LRPDI_{SA} + (1 - C(2)) \times LRNFHWEALTH_{SA} \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.656234</td>
<td>0.176161</td>
<td>3.725184</td>
</tr>
<tr>
<td>C(2)</td>
<td>1.397830</td>
<td>0.054894</td>
<td>25.46417</td>
</tr>
</tbody>
</table>

R-squared 0.829219
Adjusted R-squared 0.826170
S.E. of regression 0.043262
Log likelihood 271.9061

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

\[ DLPCSR = C(5) + C(7) \times DLRPDI + C(8) \times DLRFHWEALTH + C(9) \times (LPCSR_{SA(-4)} - (BETA93 + BETA94 \times LRPDI_{SA(-4)} + (1 - BETA94) \times LRNFHWEALTH_{SA(-4)}) \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.015341</td>
<td>0.002839</td>
<td>5.403785</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.485245</td>
<td>0.080957</td>
<td>5.993853</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.028724</td>
<td>0.038794</td>
<td>-0.740433</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.402192</td>
<td>0.065756</td>
<td>-6.116406</td>
</tr>
</tbody>
</table>

R-squared 0.669579
Adjusted R-squared 0.649754
S.E. of regression 0.019246
Log likelihood 138.7808

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: $\ln(C_{S,t}) = -2.64 + 1.20*\ln(PDI_t)$

Short Run: $\Delta\ln(C_{S,t}) = 0.02 + 0.25*\Delta\ln(PDI_t) + 0.11*\Delta\ln(Wealth_t) -0.31*(\ln(C_{S,t-4}) - \ln(C_{S,t-4}))$

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-2.639193</td>
<td>0.882109</td>
<td>-2.991911</td>
</tr>
<tr>
<td>C(2)</td>
<td>1.201599</td>
<td>0.088382</td>
<td>13.59546</td>
</tr>
</tbody>
</table>

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)*DLRNHFWEALTH + C(9)*(LPCSR_SA(-4) - (BETA95 + BETA96*LRPDI_SA(-4)))

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.018700</td>
<td>0.002429</td>
<td>7.700119</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.247102</td>
<td>0.066584</td>
<td>3.711126</td>
</tr>
<tr>
<td>C(8)</td>
<td>0.105370</td>
<td>0.030347</td>
<td>3.472133</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.312794</td>
<td>0.036667</td>
<td>-8.530774</td>
</tr>
</tbody>
</table>

R-squared    0.764753  Mean dependent var 0.023225
Adjusted R-squared 0.750638  S.D. dependent var 0.032620
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: $\Delta \ln(CS_t) = 0.00 + 0.07 \times \Delta \ln(PDI_t) + 0.04 \times \Delta \ln(Wealth_t) + 0.70 \times \Delta \ln(CS_{t-1})$

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

\[ DLPCSR = C(5) + C(7) \times DLRPDI + C(8) \times DLRFWEALHT + C(9) \times DLPCSR(-1) \]

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.003658</td>
<td>0.002997</td>
<td>1.220649</td>
<td>0.2279</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.073643</td>
<td>0.079083</td>
<td>0.931218</td>
<td>0.3562</td>
</tr>
<tr>
<td>C(8)</td>
<td>0.044996</td>
<td>0.032297</td>
<td>1.393192</td>
<td>0.1697</td>
</tr>
<tr>
<td>C(9)</td>
<td>0.701471</td>
<td>0.093130</td>
<td>7.532147</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared: 0.729398
Adjusted R-squared: 0.713162
S.E. of regression: 0.017417
Akaike info criterion: -5.191599
Hannan-Quinn criter.: -5.134779

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1)</td>
<td>0.612411</td>
<td>0.154466</td>
<td>3.964692</td>
<td>0.0002</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.317385</td>
<td>0.143952</td>
<td>2.204796</td>
<td>0.0317</td>
</tr>
<tr>
<td>SIGMASQ</td>
<td>0.000313</td>
<td>6.37E-05</td>
<td>4.918332</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared: 0.712278
Adjusted R-squared: 0.701816
S.E. of regression: 0.018178
Akaike info criterion: -5.094992
Hannan-Quinn criter.: -5.053479

Inverted AR Roots: .95  -.34
Forecasting Real Services Consumption Growth (% Y-Y)


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.
Services Consumption Forecast Errors 5
2.1.3: HICP

Dependent variable: HICP.

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

Long run \( \ln(HICP_t) = -0.07 + 0.88*\ln(HICP_{t-1}) + 0.06*\ln(CSA_t) \)

Short run \( \Delta\ln(HICP_t) = -0.00 + 0.92*\Delta\ln(HICP_{t-1}) + 0.07*\Delta\ln(C_t) - 0.39*(\ln(HICP_{t-4}) - \ln(HICP_{t-4})) \)

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-0.068954</td>
<td>0.092167</td>
<td>-0.748137</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.884401</td>
<td>0.028526</td>
<td>31.00387</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.060044</td>
<td>0.021227</td>
<td>2.828655</td>
</tr>
</tbody>
</table>

- 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
- Schwarz criterion: -7.221999
- Hannan-Quinn criter.: -7.280086
- Durbin-Watson stat: 1.779194
- F-statistic: 8670.304
- 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*HICP(-5) + BETA300*LPCR_SA(-4)))

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>-0.000863</td>
<td>0.000849</td>
<td>-1.016301</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.915228</td>
<td>0.034697</td>
<td>26.37784</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.068943</td>
<td>0.016438</td>
<td>4.194201</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.390614</td>
<td>0.106161</td>
<td>-3.679461</td>
</tr>
</tbody>
</table>

- 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
- Schwarz criterion: -7.617326
- Hannan-Quinn criter.: -7.694776
- Durbin-Watson stat: 1.416938
- F-statistic: 362.3536
- Prob(F-statistic): 0.000000
Dependent variable: HICP.

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

Long run \( \ln(HICP_t) = 0.01 + 0.94\ln(HICP_{t-1}) + 0.02\ln(UDD_{stat}) \)

Short run \( \Delta \ln(HICP_t) = -0.00 + 0.92\Delta \ln(HICP_{t-1}) + 0.05\Delta \ln(UDD_t) - 0.40(HICP_{t-4}HICP_{t-4}) \)

### Dependent Variable: LHICP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16   Time: 16:29
Sample: 1999Q1 2016Q2
Included observations: 70

\[ LHICP = C(1) + C(2)\times LHICP(-1) + C(3)\times LUDD_SA \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.011926</td>
<td>0.075383</td>
<td>0.158209 0.8748</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.941011</td>
<td>0.011575</td>
<td>81.29367 0.0000</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.024902</td>
<td>0.010346</td>
<td>2.406944 0.0188</td>
</tr>
</tbody>
</table>

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
Log likelihood 258.0969
F-statistic 8414.079

### Dependent Variable: DLHICP
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/06/16   Time: 16:29
Sample: 1999Q1 2016Q2
Included observations: 70

\[ DLHICP = C(5) + C(6)\times DLHICP(-1) + C(7)\times DLUDD + C(8)\times (LHICP(-4) - (BETA101 + BETA201\times LHICP(-5) + BETA301\times LUDD_SA(-4))) \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>-4.68E-05</td>
<td>0.000855</td>
<td>-0.054713 0.9565</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.917160</td>
<td>0.036160</td>
<td>25.36370 0.0000</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.051241</td>
<td>0.012980</td>
<td>3.947691 0.0002</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.395250</td>
<td>0.104173</td>
<td>-3.794161 0.0003</td>
</tr>
</tbody>
</table>

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
Log likelihood 273.5617
F-statistic 345.7912
Forecasting HICP (% Y-Y Change).
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.
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.

\[
\ln(MNEU_t) = 2.55 + 0.18\ln(\text{External Demand Goods}_{t+1}) + 0.53\ln(MNEU_{t-1})
\]

\[
\Delta\ln(MNEU_t) = -0.03 + 1.01\Delta\ln(\text{External Demand Goods}_{t+1}) + 0.58\Delta\ln(MNEU_{t-1}) - 0.25\ln(MNEU_{t-4}) - \ln(MNEU_{t-4})
\]

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)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>2.554409</td>
<td>0.862810</td>
<td>2.960570</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.177307</td>
<td>0.136343</td>
<td>1.300452</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.528632</td>
<td>0.098118</td>
<td>5.387707</td>
</tr>
</tbody>
</table>

R-squared 0.331103
Adjusted R-squared 0.313025
S.E. of regression 0.244006
Akaike info criterion 0.054938
Schwarz criterion 0.146255
Hannan-Quinn criter. 0.091464

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(-1) + BETA58 + BETA59*LGMTPINDEX(-3) + BETA60*LMNEU(-5))

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(4)</td>
<td>-0.032644</td>
<td>0.021561</td>
<td>-1.514011</td>
</tr>
<tr>
<td>C(5)</td>
<td>1.007283</td>
<td>0.329884</td>
<td>3.053444</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.581012</td>
<td>0.085772</td>
<td>6.773880</td>
</tr>
<tr>
<td>C(7)</td>
<td>-0.250106</td>
<td>0.074017</td>
<td>-3.379023</td>
</tr>
</tbody>
</table>

R-squared 0.563321
Adjusted R-squared 0.544335
S.E. of regression 0.293345
Akaike info criterion 0.091464
Schwarz criterion 0.182597
Hannan-Quinn criter. 0.091464

Prob(F-statistic) 0.000000
Forecasting Underlying Machinery and Equipment growth (%, Y-Y).
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.
2.2.2: Investment, Dwellings

Dependent variable: Annual percentage change in dwellings.

Explanatory variable: Annual percentage change in completions.

\[ 100^* \left( \frac{\text{Dwellings}_{t}}{\text{Dwellings}_{t-4}} - 1 \right) = 1.29 + 0.86^* \left( 100^* \left( \frac{\text{Completions}_{t}}{\text{Completions}_{t-4}} - 1 \right) \right) \]

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

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(88)</td>
<td>1.290886</td>
<td>0.789423</td>
<td>1.635228</td>
<td>0.1066</td>
</tr>
<tr>
<td>C(89)</td>
<td>0.864945</td>
<td>0.032495</td>
<td>26.61803</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

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.
Short-Run equation, forecasting four quarters ahead.

![Graph showing investment in dwellings, growth (%) and model 1 projection (%).]
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.

Dwellings Forecast Errors

![Dwellings Forecast Errors](image-url)
### 2.2.3: Investment, improvements

**Dependent variable:** Improvements.

**Explanatory variables:** Completions and lagged improvements.

\[
\ln(\text{Improvements}_t) = 0.54 + 0.03\ln(\text{Completions}_t) + 0.87\ln(\text{Improvements}_{t-1})
\]

\[
\Delta\ln(\text{Improvements}_t) = 0.00 + 0.01\Delta\ln(\text{Completions}_t) + 0.88\Delta\ln(\text{Improvements}_{t-1}) - 1.04(\ln(\text{Improvements}_{t-4}) - \ln(\text{Improvements}_{t-4}))
\]

**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

\[\text{LIMPROVS} = C(1) + C(2)\text{*LCOMPS} + C(3)\text{*LIMPROVS}(-1)\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.536483</td>
<td>0.275465</td>
<td>1.947554</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.034611</td>
<td>0.013589</td>
<td>2.547028</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.865784</td>
<td>0.049857</td>
<td>17.36543</td>
</tr>
</tbody>
</table>

**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

\[\text{Prob(F-statistic)}\]

**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

\[\text{DLIMPROVS} = C(4) + C(5)\text{*DLCOMPS}_F + C(6)\text{*DLIMPROVS}(-1) + C(7)\]

\[\text{*}(\text{LIMPROVS}(-4) - (\text{BETA58} + \text{BETA59*LCOMPS}(-4) + \text{BETA60*LIMPROVS}(-5)))\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(4)</td>
<td>0.001329</td>
<td>0.010504</td>
<td>0.126520</td>
</tr>
<tr>
<td>C(5)</td>
<td>0.010717</td>
<td>0.041262</td>
<td>0.259735</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.881668</td>
<td>0.071943</td>
<td>12.25517</td>
</tr>
<tr>
<td>C(7)</td>
<td>-1.040376</td>
<td>0.131633</td>
<td>-7.903592</td>
</tr>
</tbody>
</table>

**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** 236.0652  **Durbin-Watson stat** 2.451847

**Prob(F-statistic)** 0.000000
Forecasting Improvements growth (%, Y-Y).
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 outcomes.
2.2.4: Investment, Transfer Costs

Dependent variable: Transfer costs.

Explanatory variables: Lagged completions and lagged transfer costs.

\[
\Delta \ln(T\text{costs}_t) = 0.00 - 0.47\Delta \ln(\text{Completions}_{t-4}) + 0.66\Delta \ln(\text{Completions}_{t-1}) + 0.79\Delta \ln(T\text{costs}_{t-1}) - 0.18\Delta \ln(T\text{costs}_{t-4})
\]

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

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

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 (% \( Y - Y \)).


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).

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

Dependent Variable: LGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 11/30/16   Time: 16:04
Sample: 1999Q1 2016Q2
Included observations: 70

$$LGX = \text{C}(1) + \text{C}(2)\text{LGMPINDEX} + \text{C}(3)\text{LREER} + \text{C}(4)\text{GXDUM}$$

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>6.038031</td>
<td>0.462990</td>
<td>13.04138</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.813677</td>
<td>0.062643</td>
<td>12.98907</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.035251</td>
<td>0.096033</td>
<td>-0.367067</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.446065</td>
<td>0.047479</td>
<td>9.395049</td>
</tr>
</tbody>
</table>

| 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 |                  |       |

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

Dependent Variable: DLGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/02/16   Time: 13:00
Sample: 1999Q1 2016Q2
Included observations: 70

$$DLGX = \text{C}(5) + \text{C}(6)\text{DLGMPINDEX} + \text{C}(7)\text{DLNREER} + \text{C}(8)\text{DDUMMY} + \text{C}(9)\text{LGX}_{t-4} - (\text{BETA1000} + \text{BETA1001}\text{LGMPINDEX}_{t-4} + \text{BETA1002}\text{LREER}_{t-4} + \text{BETA1003}\text{GXDUM}_{t-4})$$

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.025189</td>
<td>0.008884</td>
<td>2.835476</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.301848</td>
<td>0.122971</td>
<td>2.454623</td>
</tr>
<tr>
<td>C(7)</td>
<td>-0.263298</td>
<td>0.114387</td>
<td>-2.301814</td>
</tr>
<tr>
<td>C(8)</td>
<td>0.401208</td>
<td>0.035307</td>
<td>11.36328</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.515439</td>
<td>0.083884</td>
<td>-6.144677</td>
</tr>
</tbody>
</table>

| 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 | 0.416245 | Schwarz criterion | -2.044328 |
| 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


\[ \ln(\text{Goods Exports}_t) = 2.75 + 0.33*\ln(\text{External Demand Goods}_t) + 0.56*\ln(\text{Goods Exports}_{t-1}) + 0.24*\text{Dum15Q1}_t \]

Dependent Variable: LGX
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/01/16   Time: 15:13
Sample: 1999Q1 2016Q2
Included observations: 70

\[ \text{LGX} = C(1) + C(2)*\text{LGMPINDEX} + C(3)*\text{LGX(-1)} + C(4)*\text{GXDUM} \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>2.752903</td>
<td>0.534440</td>
<td>5.151009</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.327569</td>
<td>0.086285</td>
<td>3.796364</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.559297</td>
<td>0.084920</td>
<td>6.586176</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.239775</td>
<td>0.044075</td>
<td>5.440124</td>
</tr>
</tbody>
</table>

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
Schwarz criterion -2.547441
Hannan-Quinn crit. -2.624891
Durbin-Watson stat 2.309936
Prob(F-statistic) 0.000000

\[ \Delta \ln(\text{Goods Exports}_t) = 0.01 + 0.20*\Delta \ln(\text{External Demand Goods}_t) + 0.38*\Delta \ln(\text{Goods Exports}_{t-1}) + 0.32*\Delta \text{Dum15Q1}_t - 0.81*(\text{Goods Exports}_{t-4} - \text{Goods Exports}_{t-4}) \]

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

\[ \text{DLGX} = C(5) + C(6)*\text{DLGMTP} + C(7)*\text{DLGX(-1)} + C(9)*\text{DDUMMY} + C(8)*(\text{LGX(-4)} - (\text{BETA1004} + \text{BETA1005}*\text{LGMPINDEX(-4)} + \text{BETA1006} * \text{LGX(-5)} + \text{BETA1007} * \text{GXDUM(-4)})) \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.014442</td>
<td>0.008658</td>
<td>1.668151</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.204331</td>
<td>0.115377</td>
<td>1.770978</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.381378</td>
<td>0.071903</td>
<td>5.304060</td>
</tr>
<tr>
<td>C(9)</td>
<td>0.323604</td>
<td>0.036559</td>
<td>8.851672</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.805965</td>
<td>0.115810</td>
<td>-6.959383</td>
</tr>
</tbody>
</table>

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
Schwarz criterion -2.710440
Hannan-Quinn crit. -2.808104
Durbin-Watson stat 2.066740
Prob(F-statistic) 0.000000
Dependent variable: Goods Exports.


$$\ln(Goods\ Exports_{t}) = 2.87 + 0.33\ln(External\ Demand\ Goods_{t}) - 0.03\ln(REER_{t-1}) + 0.56\ln(Goods\ Exports_{t-1}) + 0.23\times Dum15Q1_{t}$$

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>2.873698</td>
<td>0.604204</td>
<td>4.756170</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.334256</td>
<td>0.088147</td>
<td>3.792019</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.032944</td>
<td>0.075136</td>
<td>-0.438463</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.559121</td>
<td>0.085445</td>
<td>6.543620</td>
</tr>
<tr>
<td>C(5)</td>
<td>0.229930</td>
<td>0.049708</td>
<td>4.625619</td>
</tr>
</tbody>
</table>

R-squared: 0.938731
Adjusted R-squared: 0.934961
S.E. of regression: 0.062134
Akaike info criterion: -2.650309
Schwarz criterion: -2.489702
Log likelihood: 97.76080
Hannan-Quinn criter.: -2.586514
Durbin-Watson stat: 248.9736
Prob(F-statistic): 0.000000
\[
\Delta \ln(\text{Goods Exports}_t) = 0.01 + 0.20 \Delta \ln(\text{External Demand Goods}_t) + 0.35 \Delta \ln(\text{Goods Exports}_{t-1}) - 0.20 \Delta \ln(\text{REER}_t) + 0.30 \Delta \text{Dum15Q1} - 0.78 \ln(\text{Goods Exports}_{t-4}) - \ln(\text{Goods Exports}_{t-4})
\]

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

\[
\text{DLGX} = C(5) + C(6) \times \text{DLGMP} + C(7) \times \text{DLGX}_{(t-1)} + C(8) \times \text{DLNREER} + C(10) \times \text{DDUMMY} + C(9) \times (\ln(\text{LGX}_{(t-4)}) - \text{BETA1008} + \text{BETA1009} \times \text{LGMPINDEX}_{(t-4)} + \text{BETA1010} \times \text{LREER}_{(t-4)} + \text{BETA1011} \times \text{LGX}_{(t-5)} + \text{BETA1012} \times \text{GXDUM}_{(t-4)})
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.015564</td>
<td>0.008484</td>
<td>1.834388</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.195175</td>
<td>0.113161</td>
<td>1.724757</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.352988</td>
<td>0.071947</td>
<td>4.906243</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.196141</td>
<td>0.105183</td>
<td>-1.864754</td>
</tr>
<tr>
<td>C(10)</td>
<td>0.302206</td>
<td>0.036984</td>
<td>8.171337</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.777103</td>
<td>0.114145</td>
<td>-6.808042</td>
</tr>
</tbody>
</table>

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)
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.
### 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.

\[ \ln(\text{Service} \ \text{Exports}_t) = 0.76 + 0.90 \ln(\text{Service} \ \text{Exports}_{t-1}) + 0.13 \ln(\text{External \ Demand} \ \text{Service} \ \text{Services}_t) - 0.09 \ln(\text{REER}_t) \]

\[ \Delta \ln(\text{Service} \ \text{Exports}_t) = 0.01 + 0.71 \Delta \ln(\text{Service} \ \text{Exports}_{t-1}) + 0.33 \Delta \ln(\text{External \ Demand} \ \text{Services}_t) - 0.17 \Delta \ln(\text{REER}_t) - 0.27(\ln(\text{Service} \ \text{Exports}_{t-4}) - \ln(\text{Service} \ \text{Exports}_{t-5})) \]

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1) 0.762044</td>
<td>0.328622</td>
<td>2.318904</td>
<td>0.0235</td>
</tr>
<tr>
<td>C(2) 0.900073</td>
<td>0.061052</td>
<td>14.74273</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(3) 0.128814</td>
<td>0.136926</td>
<td>0.940752</td>
<td>0.3503</td>
</tr>
<tr>
<td>C(4) -0.093757</td>
<td>0.053766</td>
<td>-1.743797</td>
<td>0.0859</td>
</tr>
</tbody>
</table>

**R-squared 0.981390**  
Mean dependent var 9.662797

**Adjusted R-squared 0.980544**  
S.D. dependent var 0.395965

**S.E. of regression 0.201328**  
Akaike info criterion -2.899150

**Sum squared resid 0.055231**  
Schwarz criterion -2.770664

**Log likelihood 105.4702**  
Hannan-Quinn criterion -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)))

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>0.010018</td>
<td>0.007377</td>
<td>1.358037</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.710940</td>
<td>0.071770</td>
<td>9.905783</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.332970</td>
<td>0.160021</td>
<td>2.080785</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.172093</td>
<td>0.064666</td>
<td>-2.661277</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.271093</td>
<td>0.080657</td>
<td>-3.361085</td>
</tr>
</tbody>
</table>

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.

\[
\ln(\text{Service Exports}_t) = 0.32 + 0.92*\ln(\text{Service Exports}_{t-1}) + 0.10*\ln(\text{External Demand Servcies}_t)
\]

\[
\Delta \ln(\text{Service Exports}_t) = 0.01 + 0.73*\Delta \ln(\text{Service Exports}_{t-1}) + 0.33*\Delta \ln(\text{External Demand Servcies}_{t}) - 0.16*\Delta \ln(\text{REER}_t) - 0.26*(\ln(\text{Service Exports}_{t-4}) - \ln(\text{Service Exports}_{t-4}))
\]

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.318662</td>
<td>0.211338</td>
<td>1.507833</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.915942</td>
<td>0.061283</td>
<td>14.94620</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.100878</td>
<td>0.138041</td>
<td>0.730778</td>
</tr>
</tbody>
</table>

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 | 103.3247 | 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)))

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(4)</td>
<td>0.008042</td>
<td>0.007487</td>
<td>1.074012</td>
</tr>
<tr>
<td>C(5)</td>
<td>0.730099</td>
<td>0.072859</td>
<td>10.02067</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.330630</td>
<td>0.160568</td>
<td>2.059133</td>
</tr>
<tr>
<td>C(7)</td>
<td>-0.162278</td>
<td>0.064792</td>
<td>-2.504593</td>
</tr>
<tr>
<td>C(8)</td>
<td>-0.264048</td>
<td>0.080344</td>
<td>-3.286473</td>
</tr>
</tbody>
</table>

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
Schwarz criterion: -3.551057
Hannan-Quinn criter.: -3.648720
Durbin-Watson stat: 2.685075
Log likelihood: 133.0967
Prob(F-statistic): 0.000000

Forecasting Underlying Service Exports growth (%), Y-Y
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 of the models and produces the projections graphed above along with the actual outcomes.

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).

\[
\text{LN}(\text{Goods Imports}_t) = 0.54 + 0.40\times\text{LN}(\text{Underlying Final Demand}_t) + 0.41\times\text{LN}(\text{Goods Imports}_{t-1})
\]

\[
\Delta\text{LN}(\text{Goods Imports}_t) = -0.02 + 0.83\times\Delta\text{LN}(\text{Underlying Final Demand}_t)
\]

\[
+ 0.24\times\Delta\text{LN}(\text{Goods Imports}_{t-1}) - 0.59\times[\text{LN}(\text{Goods Imports}_{t-4}) - \text{LN}(\text{Goods Imports}_{t-4})]
\]

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)\times LFDU + C(3)\times LGMU(-1)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.541598</td>
<td>0.554385</td>
<td>0.976936</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.403375</td>
<td>0.091835</td>
<td>4.392381</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.413621</td>
<td>0.115727</td>
<td>3.574098</td>
</tr>
</tbody>
</table>

R-squared: 0.798727
Adjusted R-squared: 0.792719
S.E. of regression: 0.072812
Akaike info criterion: -2.345965
Schwarz criterion: -2.263601
Hannan-Quinn criter.: -2.321688
F-statistic: 132.9403
Prob(F-statistic): 9.564349

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)\times DLFDU + C(6)\times DLGMU(-1) + C(7)\times (LGMU(-4) - (BETA14 + BETA15\times DLFDU(-4) + BETA16\times LGMU(-3)) )

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(4)</td>
<td>-0.019008</td>
<td>0.010935</td>
<td>-1.738221</td>
</tr>
<tr>
<td>C(5)</td>
<td>0.833764</td>
<td>0.189502</td>
<td>4.399766</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.238863</td>
<td>0.108410</td>
<td>2.203338</td>
</tr>
<tr>
<td>C(7)</td>
<td>-0.587708</td>
<td>0.118541</td>
<td>-4.957825</td>
</tr>
</tbody>
</table>

R-squared: 0.622260
Adjusted R-squared: 0.604273
S.E. of regression: 0.063237
Akaike info criterion: -2.625996
Schwarz criterion: -2.494372
Hannan-Quinn criter.: -2.573912
F-statistic: 34.59386
Prob(F-statistic): 1.941568
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).

\[
\text{LN}(\text{Goods Imports}_t) = 2.44 + 0.23 \cdot \text{LN}(\text{Underlying Service Exports}_t) + 0.14 \cdot \text{LN}(\text{Underlying Investment}_t) + 0.39 \cdot \text{LN}(\text{Goods Imports}_{t-1})
\]

\[
\Delta \text{LN}(\text{Goods Imports}_t) = -0.02 + 0.49 \cdot \Delta \text{LN}(\text{Underlying Service Exports}_t) + 1.14 \cdot \Delta \text{LN}(\text{Underlying Investment}_{t-1}) + 0.39 \cdot \Delta \text{LN}(\text{Goods Imports}_{t-1}) - 0.58 \cdot (\text{LN}(\text{Goods Imports}_{t-4}) - \text{LN}(\text{Goods Imports}_{t-4}))
\]

Dependent Variable: LGMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16   Time: 15:08
Sample: 1999Q1 2016Q2
Included observations: 70

\[
\text{LGMU} = C(1) + C(2) \cdot \text{LSXU_F} + C(3) \cdot \text{LGFCFU} + C(4) \cdot \text{LGMU}(-1)
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>2.441776</td>
<td>0.600760</td>
<td>4.064482</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.229737</td>
<td>0.043156</td>
<td>5.323410</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.136658</td>
<td>0.038208</td>
<td>3.576707</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.390045</td>
<td>0.102895</td>
<td>3.790702</td>
</tr>
</tbody>
</table>

R-squared 0.818648  Mean dependent var 9.564349
Adjusted R-squared 0.810405  S.D. dependent var 0.159927
S.E. of regression 0.069638  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  

$$DLGMU = C(5) + C(6) * DLSXU + C(7) * DLGFCFU + C(8) * DLGMU(-1) + C(9) \times (LGEMU(-4) \times (BETA17 + BETA18 * LSXU(-4) + BETA19 * LGFCFU(-4) + BETA20 * LGEMU(-5)))$$  

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>-0.024569</td>
<td>-1.846015</td>
<td>0.0697</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.491096</td>
<td>3.901218</td>
<td>0.0002</td>
</tr>
<tr>
<td>C(7)</td>
<td>1.135846</td>
<td>2.505739</td>
<td>0.0149</td>
</tr>
<tr>
<td>C(8)</td>
<td>0.386498</td>
<td>4.252882</td>
<td>0.0001</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.584015</td>
<td>-5.102056</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared          0.663772  
Adjusted R-squared 0.641724  
S.E. of regression 0.125883  
Akaike info criterion 2.505739  
Schwarz criterion   2.549427  
Log likelihood      94.60523  
Hannan-Quinn criter. 2.49762  
Durbin-Watson stat  2.039147  
Prob(F-statistic)   0.000000  

Forecasting Underlying Goods Imports Growth (% Y-Y)  
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 Goods Imports Forecast Errors 1

Underlying Goods Imports Forecast Errors 2
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.

\[
\ln(\text{Service Imports}_t) = -3.59 + 0.69 \ln(\text{Underlying Final Demand}_t) + 0.48 \ln(\text{Service Exports}_t)
\]

\[
\Delta \ln(\text{Service Imports}_t) = -0.02 + 0.80 \Delta \ln(\text{Underlying Final Demand}_t) + 0.62 \Delta \ln(\text{Service Exports}_t) - 0.69 \ln(\text{Service Imports}_{t-4}) - \ln(\text{Service Imports}_{t-4})
\]

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-3.594864</td>
<td>0.709086</td>
<td>-5.069717</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.694494</td>
<td>0.087703</td>
<td>7.918701</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.480590</td>
<td>0.044537</td>
<td>10.79070</td>
</tr>
</tbody>
</table>

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
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)*LFDU_F + C(7)*LSXU_F + C(9)*(LSMU(-4) - (BETA24 + BETA25*LFDU_F(-4) + BETA26*LSXU_F(-4))

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>-0.017585</td>
<td>0.009052</td>
<td>-1.942686</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.804183</td>
<td>0.105308</td>
<td>7.636463</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.619892</td>
<td>0.110892</td>
<td>5.590069</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.694076</td>
<td>0.120048</td>
<td>-5.781653</td>
</tr>
</tbody>
</table>

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
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.

\[ \ln(\text{Service Imports}_t) = -0.11 + 0.27*\ln(\text{Consumption}_t) + 0.75*\ln(\text{Service Exports}_t) \]

\[ \Delta \ln(\text{Service Imports}_t) = -0.01 + 0.66*\Delta \ln(\text{Consumption}_t) + 0.76*\Delta \ln(\text{Service Exports}_t) - 0.49*(\ln(\text{Service Imports}_{t-4}) - \ln(\text{Service Imports}_{t-4})) \]

Dependent Variable: LSMU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 12/07/16   Time: 17:15
Sample: 1999Q1 2016Q2
Included observations: 70

\[ \text{LSMU} = C(1) + C(2)*\text{LPCE}_F + C(3)*\text{LSXU}_F \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-0.108875</td>
<td>-0.158950</td>
<td>0.8742</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.269774</td>
<td>2.832208</td>
<td>0.0061</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.746073</td>
<td>22.27215</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

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. -2.862000
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

\[ \text{DLSMU} = C(5) + C(6)*\text{DLPCE}_F + C(7)*\text{DLSXU}_F + C(9)*\text{LSMU}(-4) - (\text{BETA28} + \text{BETA29}*\text{LPCE}_F(-4) + \text{BETA30})*\text{LSXU}_F(-4) \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(5)</td>
<td>-0.006831</td>
<td>-0.654828</td>
<td>0.5150</td>
</tr>
<tr>
<td>C(6)</td>
<td>0.656544</td>
<td>3.536479</td>
<td>0.0008</td>
</tr>
<tr>
<td>C(7)</td>
<td>0.757042</td>
<td>6.312532</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(9)</td>
<td>-0.491297</td>
<td>-3.948072</td>
<td>0.0002</td>
</tr>
</tbody>
</table>

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)
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.
### 2.5.1: Employment

**Dependent variable:** Employment.

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

\[
LN(\text{Employment}_t) = 1.23 + 0.60*LN(\text{Underlying Domestic Demand}_t) + 0.01*LN(\text{Construction Output}_t)
\]

\[
\Delta LN(\text{Employment}_t) = 0.00 + 0.52*\Delta LN(\text{Underlying Domestic Demand}_t) + 0.05*\Delta LN(\text{Construction Output}_t) - 0.20*(LN(\text{Employment}_{t-4})-LN(\text{Employment}^*_{t-4}))
\]

**Dependent Variable:** LOG(EMPLOYMENT)

**Method:** Least Squares

**Date:** 02/02/17  **Time:** 15:46

**Sample (adjusted):** 1998Q1 2016Q3

**Included observations:** 75 after adjustments

\[
\text{LNEMP} = C(1) + C(2)\cdot\text{LNUDD} + C(3)\cdot\text{LNCONS}
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>1.226712</td>
<td>0.157517</td>
<td>7.787801</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.598115</td>
<td>0.015892</td>
<td>37.63575</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.013156</td>
<td>0.008009</td>
<td>1.642718</td>
</tr>
</tbody>
</table>

**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  **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

\[
\text{DLNEMP} = C(1) + C(2)\cdot\text{DLNUDD} + C(3)\cdot\text{DLNCONS} + C(4)\cdot\text{RES_EMP1}(-4)
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.002414</td>
<td>0.001928</td>
<td>1.252485</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.515808</td>
<td>0.051249</td>
<td>10.06469</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.053759</td>
<td>0.021484</td>
<td>2.502324</td>
</tr>
<tr>
<td>C(4)</td>
<td>-0.200022</td>
<td>0.073942</td>
<td>-2.705100</td>
</tr>
</tbody>
</table>

**R-squared** 0.957030  **Mean dependent var** 0.014736  **Adjusted R-squared** 0.955836  **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  **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.

\[ \Delta \ln(\text{Employment}_t) = 0.00 + 0.52 \Delta \ln(\text{Underlying Domestic Demand}_t) \\
+ 0.06 \Delta \ln(\text{Construction Output}_t) \]

---

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

\[ \text{DLNEMP} = C(1) + C(2) \cdot \text{DLNUDD} + C(3) \cdot \text{DLNCONS} \]

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.002422</td>
<td>0.002020</td>
<td>1.198813</td>
<td>0.2350</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.515440</td>
<td>0.053719</td>
<td>9.595128</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.058929</td>
<td>0.022430</td>
<td>2.627276</td>
<td>0.0108</td>
</tr>
</tbody>
</table>

R-squared: 0.908759
Mean dependent var: 0.014736

---

Adj. 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.

\[ \ln(\text{Employment}_t) = 1.26 + 0.60 \ln(\text{Underlying Domestic Demand}_t) - 0.01 \ln(\text{Industrial Output}_t) + 0.01 \ln(\text{DTSC}_t) \]

\[ \Delta \ln(\text{Employment}_t) = -0.00 + 0.61 \Delta \ln(\text{Underlying Domestic Demand}_t) - 0.01 \Delta \ln(\text{Industry Output}_t) + 0.05 \Delta \ln(\text{DTSC}_t) - 0.2(\ln(\text{Employment}_{t-4}) - \ln(\text{Employment}_{t-4})) \]

Dependent Variable: LOG(EMPLOYMENT)
Method: Least Squares
Date: 02/02/17   Time: 15:46
Sample (adjusted): 1998Q1 2016Q3
Included observations: 75 after adjustments
\[ \ln(\text{EMPLOYMENT}) = C(1) + C(2) \ln(\text{UD}) + C(3) \ln(\text{IO}) + C(4) \ln(\text{DTSC}) \]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>1.256770</td>
<td>0.168339</td>
<td>7.465711</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.599096</td>
<td>0.026283</td>
<td>22.79372</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.007020</td>
<td>0.012299</td>
<td>-0.57063</td>
<td>0.5700</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.013422</td>
<td>0.022013</td>
<td>0.609765</td>
<td>0.5440</td>
</tr>
</tbody>
</table>

R-squared 0.955704  Mean dependent var 7.532281
Adjusted R-squared 0.953832  S.D. dependent var 0.086482
S.E. of regression 22.79372
Sum squared resid 0.024516
Log likelihood 194.5518
Hannan-Quinn criter. 5.032031

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
\[ \Delta \ln(\text{EMPLOYMENT}) = C(1) + C(2) \Delta \ln(\text{UD}) + C(3) \Delta \ln(\text{IO}) + C(4) \Delta \ln(\text{DTSC}) + C(5) \Delta \ln(\text{EMPLOYMENT}_{t-4}) \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-0.001495</td>
<td>0.001702</td>
<td>-0.878552</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.611596</td>
<td>0.035251</td>
<td>17.34997</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.014667</td>
<td>0.009499</td>
<td>-1.543981</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.051979</td>
<td>0.036617</td>
<td>1.419527</td>
</tr>
<tr>
<td>C(5)</td>
<td>-0.198887</td>
<td>0.074979</td>
<td>-2.652575</td>
</tr>
</tbody>
</table>

R-squared 0.955704  Mean dependent var 7.532281
Adjusted R-squared 0.953832  S.D. dependent var 0.086482
S.E. of regression 22.79372
Sum squared resid 0.024516
Log likelihood 194.5518
Hannan-Quinn criter. 5.032031

81
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 outcomes.
Employment Forecast Errors 1

Employment Forecast Errors 2
### 2.5.2: Compensation of Employees

**Dependent variable:** Compensation of employees (wage bill).

**Explanatory variables:** HICP and employment.

\[
LN(CE_t) = -6.43 + 1.74*LN(HICP_t) + 1.09*LN(Employment_t)
\]

\[
\Delta LN(CE_t) = 0.01 + 1.15*\Delta LN(HICP_t) + 1.27*\Delta LN(Employment_t) - 0.47*(CE_{t-4} - CE_{t-4})
\]

---

**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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-6.428926</td>
<td>0.274732</td>
<td>-23.40073</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(2)</td>
<td>1.742694</td>
<td>0.038833</td>
<td>44.87661</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(3)</td>
<td>1.090011</td>
<td>0.051218</td>
<td>21.28164</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared 0.993156
Adjusted R-squared 0.992952
S.E. of regression 0.019909
Akaike info criterion -4.953424
Schwarz criterion -4.857060
Log likelihood 176.3698
Hannan-Quinn criter. 0.898805

**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)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.009490</td>
<td>0.002937</td>
<td>3.231351</td>
</tr>
<tr>
<td>C(2)</td>
<td>1.192952</td>
<td>0.130982</td>
<td>8.783706</td>
</tr>
<tr>
<td>C(3)</td>
<td>1.273290</td>
<td>0.075649</td>
<td>16.83154</td>
</tr>
<tr>
<td>C(4)</td>
<td>-0.469008</td>
<td>0.122936</td>
<td>-3.815047</td>
</tr>
</tbody>
</table>

R-squared 0.934168
Adjusted R-squared 0.932303
S.E. of regression 0.016670
Akaike info criterion -5.291764
Schwarz criterion -5.159057
Log likelihood 178.6282
Hannan-Quinn criter. 0.781266
Forecasting Compensation of Employees growth (%, Y-Y)
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 and produces the projections graphed above along with the actual outturns.

Compensation of Employees Forecast Errors
2.6.1: Goods Export Deflator

Model 1: Dependent variable: Goods Export Deflator.

Explanatory variables: Euro/US exchange rate.

\[
100 \times \left( \frac{X_{GD_t}}{X_{GD_{t-4}}} - 1 \right) = 0.52 - 0.27 \times \left(100 \times \frac{US_{Exch_t}}{US_{Exch_{t-4}}} - 1\right)
\]

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

\[
PCYGXP = C(1) + C(2) \times PCYUSD
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.515874</td>
<td>0.440191</td>
<td>1.171933</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.270358</td>
<td>0.041980</td>
<td>-6.440168</td>
</tr>
</tbody>
</table>

R-squared: 0.378858
Adjusted R-squared: 0.369724
S.E. of regression: 3.676851
Akaike info criterion: 5.470146
Schwarz criterion: 5.534388
Hannan-Quinn crit.: 5.495664
Durbin-Watson stat: 1.109284

Model 2: Dependent variable: Goods Export Deflator.

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

\[
100 \times \left( \frac{X_{GD_t}}{X_{GD_{t-4}}} - 1 \right) = 0.43 - 0.22 \times \left(100 \times \frac{US_{Exch_t}}{US_{Exch_{t-4}}} - 1\right) + 0.31 \times \left(100 \times \frac{MG_{D_t}}{MG_{D_{t-4}}} - 1\right)
\]

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

\[
PCYGXP = C(1) + C(2) \times PCYUSD + C(3) \times PCYGMP
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.436083</td>
<td>0.381810</td>
<td>1.142147</td>
</tr>
<tr>
<td>C(2)</td>
<td>-0.220627</td>
<td>0.037794</td>
<td>-5.837597</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.306267</td>
<td>0.063107</td>
<td>4.853148</td>
</tr>
</tbody>
</table>

R-squared: 0.540148
Adjusted R-squared: 0.526699
S.E. of regression: 3.186243
Akaike info criterion: 4.631381
Schwarz criterion: 5.293838
Hannan-Quinn crit.: 5.395664
Durbin-Watson stat: 1.179211
Forecasting Goods Export Deflator growth (% Y-Y)

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.
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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>2.516877</td>
<td>1.144212</td>
<td>2.199659</td>
<td>0.0314</td>
</tr>
<tr>
<td>PCYSMP</td>
<td>0.246766</td>
<td>0.134052</td>
<td>1.840825</td>
<td>0.0702</td>
</tr>
<tr>
<td>PCYSXP(-1)</td>
<td>0.548907</td>
<td>0.099327</td>
<td>5.526251</td>
<td>0.0000</td>
</tr>
<tr>
<td>@TREND</td>
<td>-0.035677</td>
<td>0.017820</td>
<td>-2.002013</td>
<td>0.0495</td>
</tr>
</tbody>
</table>

R-squared: 0.565112
Adjusted R-squared: 0.545040
S.D. dependent var: 3.671192
Mean dependent var: 3.533417
Akaike info criterion: 4.631084
Schwarz criterion: 4.760597
Hannan-Quinn crit.: 4.682466
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.
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.

\[
100^* \left( \frac{M_{D_{t-4}}}{M_{D_{t-5}}} - 1 \right) = -1.37 + 0.04^* \left( 100^* \left( \frac{B_{ent_{t}}}{B_{ent_{t-4}}} - 1 \right) \right) - 0.18^* \left( 100^* \left( \frac{R_{EER_{t}}}{R_{EER_{t-4}}} - 1 \right) \right) + 0.15^* \left( 100^* \left( \frac{E_{U_{G_{D_{t-4}}}}}{E_{U_{G_{D_{t-5}}} - 1}} \right) \right) + 0.47^* \left( 100^* \left( \frac{M_{D_{t-1}}}{M_{D_{t-5}}} - 1 \right) \right)
\]

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

\[
PCYGMP = C(1) + C(2) \cdot PCYBRENT + C(3) \cdot PCYREER + C(4) \cdot PCYEUGXP + C(5) \cdot PCYGMP(-1)
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-1.372025</td>
<td>0.700055</td>
<td>-1.959883</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.040956</td>
<td>0.017139</td>
<td>2.389694</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.180188</td>
<td>0.085407</td>
<td>-2.108761</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.145216</td>
<td>0.119463</td>
<td>1.215568</td>
</tr>
<tr>
<td>C(5)</td>
<td>0.471275</td>
<td>0.106939</td>
<td>4.406960</td>
</tr>
</tbody>
</table>

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.

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

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)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-0.920902</td>
<td>-1.545751</td>
<td>0.1270</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.053379</td>
<td>3.865425</td>
<td>0.0003</td>
</tr>
<tr>
<td>C(3)</td>
<td>-0.186141</td>
<td>-2.175088</td>
<td>0.0333</td>
</tr>
<tr>
<td>C(5)</td>
<td>0.533681</td>
<td>5.668217</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

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.

\[
100^* \left( \frac{MSD_t}{MSD_{t-4}} - 1 \right) = 1.03 - 0.02^* \left( 100^* \left( \frac{USech_t}{USech_{t-4}} - 1 \right) \right) + 0.57^* \left( 100^* \left( \frac{MSD_t}{MSD_{t-5}} - 1 \right) \right)
\]

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)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>1.027274</td>
<td>0.347515</td>
<td>2.956053</td>
</tr>
<tr>
<td>C(2)</td>
<td>-0.018632</td>
<td>0.022194</td>
<td>-0.839507</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.570851</td>
<td>0.096035</td>
<td>5.944183</td>
</tr>
</tbody>
</table>

R-squared 0.394675
Adjusted R-squared 0.376332
Mean dependent var 2.584890
S.D. dependent var 2.337550
Akaike info criterion 4.106451
Schwarz criterion 4.203586
Hannan-Quinn criter. 4.144988
Durbin-Watson stat 2.160253
Model 2: Dependent variable: Service Import Deflator.

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

\[
100 \times \left( \frac{MSD_t}{MSD_{t-4}} - 1 \right) = 1.07 + 0.06 \times \left( 100 \times \left( \frac{US_{xch_t}}{US_{xch_{t-4}}} - 1 \right) \right) + 0.50 \times \left( 100 \times \left( \frac{MSD_{t-1}}{MSD_{t-5}} - 1 \right) \right) + 0.31 \times \left( 100 \times \left( \frac{XGD_t}{XGD_{t-4}} - 1 \right) \right)
\]

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

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>1.070136</td>
<td>0.272860</td>
<td>3.921920</td>
</tr>
<tr>
<td>C(2)</td>
<td>0.061442</td>
<td>0.021348</td>
<td>2.878184</td>
</tr>
<tr>
<td>C(3)</td>
<td>0.498894</td>
<td>0.076193</td>
<td>6.547740</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.313692</td>
<td>0.048335</td>
<td>6.489915</td>
</tr>
</tbody>
</table>

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

Service Imports Deflator Forecast Errors 2
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.

$$U_2 = \sqrt{\frac{1}{N} \sum_{t=1}^{n} \left( \frac{\hat{y}_{t+4} - y_{t+4}}{y_t} \right)^2}$$
Table 2: Root Mean Squared Errors (RMSE) and Theil’s U2 statistic

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