# Inside the "Upside Down": Estimating Ireland's Output Gap


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**Abstract**

This paper attempts to identify estimates of Ireland's output gap that are relevant for fiscal policy. In contrast to standard approaches, we focus on measures of domestic economic activity, given its relatively more tax-rich nature. We examine and test various methods based on univariate/ multivariate filters and principal components analysis, comparing our estimates with those of the EU commonly agreed methodology. We find that our results are stable; are less complex in structure; are able to explain price and wage inflation; and – most importantly – yield estimates that are more plausible for Ireland.

Keywords: Macroeconomic Modelling, Potential Output, Output Gap



This report can be downloaded at www.fiscalcouncil.ie

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## Section 1: Introduction

This paper attempts to identify estimates of the output gap for the Irish economy. The output gap is a summary indicator describing the gap between the economy's actual level of output and the level of output that would be expected if the economy were at its most efficient – that is, at full capacity.

A number of challenges face us: Ireland's small, open nature; the presence of large foreign-owned multinational enterprises; and a tendency for Ireland to demonstrate characteristics more like that of a regional economy. Recognising these challenges, we prioritise measures that focus on domestic activity – an approach warranted given its relatively more tax-rich nature. By comparison, standard approaches, such as the EU commonly agreed methodology (Havik *et al.*, 2014), focus on GDP.

As it is not directly observed, the output gap has to be estimated on the basis of available indicators and assumptions about the path of potential output. Given the significant uncertainty surrounding output gap estimates, it would be unwise to focus on any single approach. Individual approaches are likely to be driven by specific inputs or assumptions that can fail to deliver answers that are consistently plausible. We therefore adopt a "suite of models approach" that emphasises the use of a range of alternative estimation techniques rather than relying on any single approach. This can be helpful when faced with uncertainty, and is shown to outperform single models in a forecasting context.

Determining the current budgetary stance and its sustainability requires an understanding of the cyclical position of the economy and its potential growth rate. An economy operating above its potential (i.e., where the output gap is positive) would be expected to show stronger government balances than one in steady state. Revenues would be expected to be higher, and cyclical expenditure on areas like unemployment benefits would be expected to be lower. It is also important to have a medium-term view as to economic growth prospects in the context of expenditure planning and debt sustainability assessments – something that estimates of potential output can help to determine.

## Section 2: Relevant Literature

There are a large number of issues commonly faced when attempting to estimate the output gap and potential output, and a diverse literature has evolved reflecting the challenges involved. Three methods of estimating the output gap that we focus on can be classified as: (1) statistical filters; (2) production functions; and (3) cyclical indicators.

This section gives an overview of the literature on these approaches for estimating the output gap and also discusses the literature on the suite of models approach to deal with uncertainty.

### 2.1 Statistical Filters

Statistical tools such as the Hodrick-Prescott filter (Hodrick and Prescott, 1981) and the Kalman filter can be used to extract a smoothed trend from an output series. If the trend approximates the path of potential output, then the output gap can be measured as the gap between the trend and actual level of output.

There are three common criticisms of these approaches:

- First, they incorporate little, if any, theoretical foundation and draw on limited economic information. As such, they are said to represent purely statistical approaches.
- Second, some of the dynamics of trends produced may not be sensible for economic variables. The dynamics assumed in an HP filter may be an unreasonable representation of the underlying data-generating process and structural breaks may be smoothed to an unreasonable degree (Hamilton, 2017; Ódor and Jurašeková Kucserová, 2014).
- Third, the so-called “end-point problem” can – with some filters – result in estimates that are highly biased at the ends of the sample. This occurs in a fashion that is typically procyclical (i.e., the smoothed series tends to be close to the observed data at the beginning and end of the estimation sample). In practice, sufficient new observations are required before a satisfactory decomposition of data into its trend and cycle components may be achieved. This problem is often offset – though not eliminated – by extending historical data with forecast observations.[2]

[2] Mohr (2005) notes that this bias can occur even “if the forecast itself is unbiased and the forecast error is a random white noise process”. This reflects the fact that the implied errors in the computation of the trend are unlikely to share the more desirable features (white noise, and random) of the forecasts errors. The filter model of course differs from the model that underlies the forecast.

There have been efforts to introduce some additional information to statistical filters, while drawing on economic theory. Statistical filters can be extended to include additional economic variables that contain some information about the cycle. The latter are generally termed “multivariate filters”.

A seminal work in this area is presented in Borio *et al.,* (2013; 2014) where additional variables are incorporated in a multivariate filter setting that also employs Bayesian techniques for the US, UK and Spain. A mix of financial variables (credit growth, real interest rates, and housing prices) and other economic variables (capacity utilisation measures, inflation, and unemployment rates) are considered in order to better filter out underlying trends from the cycle. The approach is also availed of in work such as Darvas and Simon (2015) for twelve EU economies and five non-EU economies; in Alberola *et al.,* (2014) for Spain; and in Ódor and Jurašeková Kucserová (2014) for Slovakia.

Other variables incorporated in the multivariate setting include the current account, financial and asset/commodity prices. The current account is incorporated as a means of identifying the absorption cycle (Bénétrix and Lane, 2015) where the assumed relationship with the economic cycle is negative, unlike that posited for financial variables. Dobrescu and Salman (2011) and Lendvai *et al.,* (2011) emphasise the role of the current account deficit in augmenting fiscal cycles, for example. Bornhorst *et al.*, (2011) argue for consideration of asset and commodity price cycles (e.g., oil prices in heavily resource-dependent countries or, alternatively, real estate and equity prices).

Though multivariate filters help to address the problem of a lack of theoretical foundations, they may still have a number of conceptual weaknesses. A key issue is whether financial cycles can be identified in real-time (Blagrave *et al.*, 2015).

## 2.2 Production Functions

Estimates of potential may also be obtained based on assumptions regarding the potential level of factor inputs like capital and labour along with Total Factor Productivity – the efficiency with which factor inputs are used to produce output. This approach is currently agreed by EU member states and used by the European Commission (EC) in assessing compliance with legislated fiscal rules (Havik *et al.*, 2014) – hereafter, we refer to this agreed EU approach as the Commonly Agreed Methodology (CAM). Other organisations such as the OECD also currently employ variants of the production function approach (Turner *et al.*, 2016; Johansson *et al.*, 2013; Giorno *et al.*, 1995).

There are a number of weaknesses to production function approaches such as the CAM. These particularly relate to how labour, capital and total factor productivity are incorporated. It should be noted that some of these drawbacks are often well recognised by users of the approach, such as in the official documentation of the CAM (Havik *et al.*, 2014).[3] We first discuss the general issue of its applicability to open economies. We then discuss some of the specific issues recognised in the literature as being problematic for each of the potential factor inputs:

**Applicability to open economies:** The production function approach can disregard certain behaviours of open economies where excess demand may be absorbed by the trade balance or, more broadly, by the current account balance. This phenomenon is consistent with the absorption cycle (Lendvai *et al.*, 2011). Sharp deteriorations in these balances were evident in Ireland, Greece, Latvia, and Spain prior to the great recession (Darvas, 2013). In this vein, Darvas (2015) shows that the size of revisions to CAM-based output gap estimates are correlated with the variability of the current account balance, suggesting that important information is not utilised in the EC and IMF output gap estimates.

**Capital:** Approaches such as the CAM see growth in the level of the actual net capital stock as driving the capital contribution to potential output. However, identifying sustainable levels of output linked to capital may be complicated. First, there are significant issues involved in measuring the capital stock accurately (OECD, 2001) with major challenges posed by the openness of capital (Fratzscher and Bussiere, 2004; Obstfeld, 1985). Unsustainable developments, such as asset price bubbles in the housing sector, can also distort capital contributions to potential output. For example, investments into housing may boost capital levels, thus inflating potential output as measured. However, the actual effects on an economy's potential might best be considered unsustainable over the long term.

**Labour:** The contribution from labour inputs in the production function approach is often centred on the identification of the NAWRU (Non-Accelerating Wage Rate of Unemployment) – essentially the level of unemployment that keeps inflation constant. Currently, the CAM production function obtains the implied trend unemployment rate based on a version of an accelerationist Phillips curve. Combining this with trend labour force levels gives trend employment levels, which, together with trend average hours

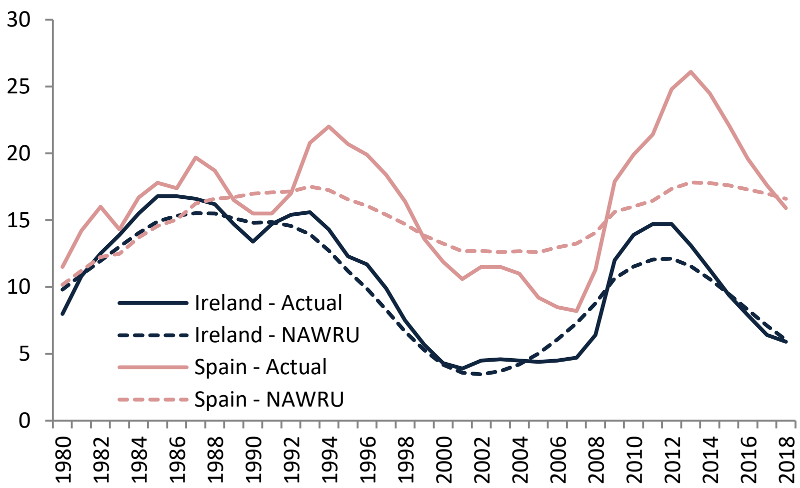
[3] For example, see "Box 1: NAWRU versus Structural Unemployment" of Havik *et al* (2014).

worked, gives the total potential level of factor inputs from the labour side (i.e., trend total hours worked).

The estimation of the NAWRU has been a focal point for recent criticism of the production function approach employed under the CAM (e.g., Fiormanti, 2016; Darvas and Simon, 2015). For Spain, the NAWRU is forecast to be 16.6 per cent for 2018, with actual unemployment at 15.9 per cent (European Commission, 2017).[4] For Ireland, the CAM-based NAWRU estimate for 2016 was 8.3 per cent at the time of writing, while actual unemployment was 7.9 per cent. These estimates suggest that excess employment was evident, or, as Darvas (2013) note, that almost all of those unemployed are regarded as useless from the perspective of the production potential of the economy. The plausibility of these results is questionable in the absence of clear wage pressures. However, without observing the actual rate of unemployment that would be consistent with constant inflation, it is difficult to dispute the validity of such estimates.

**Figure 1: NAWRU and Actual Unemployment Rates**

% labour force




*Sources:* European Commission Spring 2017 Estimates (AMECO database).

Perhaps more concerning is the extent to which the estimates can tend to track actual unemployment for some economies (Figure 1). Rather than identifying a persistent trend unemployment rate, the NAWRU appears to more closely approximate the actual unemployment rate (87 per cent of the observations for Ireland since 1980 fall between +/- 2 percentage points of the actual rate). This tendency occurs whenever actual unemployment experiences sharp swings, even in the absence of developments that might explain rapid shifts in structural unemployment. For example, the NAWRU

[4] Estimates are obtained from the Spring 2017 forecasts produced by the European Commission.

estimates for Ireland in the late 2000s onwards rise and fall sharply in step with actual unemployment rates, despite the absence of major labour market reforms that might explain such drastic changes in the NAWRU.

There are also arguments that the standard Phillips curve approach on which NAWRU estimates are founded should be extended. Recent decades have seen inflation become less sensitive to unemployment changes. This is partly due to inflation expectations becoming better anchored. The presence of credible inflation-targeting central banks is an often cited reason for this anchoring. Such developments would argue for approaches like that of Rusticelli *et al.,* (2015) that try to incorporate some anchoring of inflation expectations around the central bank's inflation objective (provided that the data are consistent with this).

A further issue is the influence of migration flows on estimates of potential output. Net inward migration can boost labour inputs and hence potential output estimates in the production function approach. However, these flows can also dampen the traditional Phillips curve relationship between output (or unemployment) and inflation. This dampening effect arises due to the additional labour supply prompted by migration, which can serve to limit the expected inflationary pressures that might arise when unemployment is low. In smaller economies – like Ireland – it can play a proportionally greater role, as migration flows can make up a relatively large share of the total labour force (Section 3). In turn, this can add to difficulties in discerning a stable level of unemployment at which inflation does not change (the NAWRU) and, hence, in distinguishing between cyclical and trend developments.

**Total Factor Productivity (TFP):** The CAM production function approach identifies trend TFP as the smoothed time series of the Solow residual. The latter is obtained from actual real GDP data based on assumed output elasticities of capital and labour inputs.[5]

A key challenge when attempting to identify trend TFP is the instability of the estimates toward the end of the sample period. The CAM addresses this problem with two solutions: (1) forecasts are incorporated to overcome the end-point problem by effectively extending out the sample used; and (2) a Kalman filter is used rather than an HP filter as it is understood to suffer relatively less from end-point bias. This is thanks in large part to its ability to incorporate economic information from elsewhere, unlike the typical HP filter approach. The CAM draws on a time series for capacity utilisation to

[5] The CAM assumes that these are approximately ⅓ and ⅔, respectively.

help the Kalman filter to identify estimates, given that this may have additional information about the TFP cycle.

Notwithstanding these useful innovations, problems remain. First, bias in the forecast observations can prompt changes in the trend series produced (for historical and forecast years) so that the addition of forecasts may be unhelpful (or worse, misleading). Second, regardless of any bias in the forecasts, there is a tendency for estimates to converge on forecasts. Rather than overcoming end-point bias, therefore, the effect of including forecasts may simply be to push end-point bias out to later periods in the forecast horizon. Third, augmenting the series with information from the capacity utilisation series may be helpful provided that the series offers some useful informational content. However, such surveys have their limitations: data are not available for forecast periods; the surveys are often limited to manufacturing sectors; and the quality of information provided may be poor. For example, it can be unclear who responds to the survey and how exactly they interpret its questions (Bauer and Deily, 1988). For Ireland, limitations are especially pronounced, given that the series itself has been discontinued, with the last observation collected in 2008 (Clancy, 2013).[6]

### 2.3 Cyclical Indicators

Another useful approach for estimating the output gap is to account for a wide range of indicators of the cyclical position of the economy. Such an approach is currently used by agencies like the Office for Budget Responsibility (OBR) in the UK (Murray, 2014; Pybus, 2011) and it is also shown to be usefully applied to measure the Euro Area aggregate business cycle (Altissimo *et al.*, 2001).

Indicators are chosen so as to reflect cyclical factors and may include a variety of survey measures of spare capacity and recruitment difficulties as well as measures of earnings growth. Prior information on sectoral shares or statistical techniques may be used to derive weights for each of the indicators in order to produce an overall measure akin to an output gap. One approach to the estimation process, based on the method of principal components, involves assigning weights to each of the indicators employed so that the derived output gap series explains as much of the variability of the data as possible.

[6] Clancy (2013) develops a composite PMI variable to proxy for the capacity utilisation series in its absence. This builds on work by Planas *et al* (2010) showing a very high degree of cross-correlation between the PMI and capacity utilisation measures, with a very strong relationship between them in Ireland (>0.80).

The Cyclical Indicators approach has the advantage of being able to overcome the usual reliance on output estimates that can be frequently prone to substantial revisions. This is particularly an issue for Irish GDP data, which are shown to have among the largest revisions in the OECD (Casey and Smyth, 2016). In addition, because the indicators chosen to underpin the output gap estimate derived are typically data that tend to be unrevised, this means that real time estimates are unlikely to differ very much from those which might be estimated at another point in time (Murray, 2014).

A difficulty posed by the approach is that cyclical indicators identified need to be combined and weighted to produce an aggregate output gap; this is not a straightforward process. Indicators are typically very different and require transformations to produce comparable series. Furthermore, it is not necessarily obvious what an appropriate weight might be for each given series. More fundamentally, the indicators selected themselves might not provide a full enough picture of cyclical developments.

### 2.4 Suite of Models Approach

A number of challenges confront us in estimating the output gap for Ireland. First, there are the usual uncertainties involved in arriving at estimates of an unobservable like potential output. Second, such uncertainties are arguably greater for small, open economies, particularly when standard measures of economic activity like GDP are subject to substantial distortions from a large foreign-owned multinational sector. Third, common approaches for measuring the output gap are each subject to their own limitations.

We adopt a “suite of models approach” as an attempt to overcome the uncertainties faced. The diversification afforded by this approach is one way of reinforcing the robustness of the estimates produced. There are obvious practical limits to the informational content of any single model, while the relevance of any single model paradigm may also vary over time (e.g., following the recent financial crisis). In addition, there may be a number of specific factors that we may be interested in, which individual models may fail to address if relied upon in isolation.

It is generally accepted that diversification can lead to more robust forecasts/estimates in the face of uncertainty. Empirical work by Bates and Granger (1969) and Stock and Watson (1999) shows that the suite of models approach tends to outperform single models in a forecasting sense. The approach is usefully applied for short-term forecasting in the Irish case (Conroy and Casey, 2017).

A similar approach is advocated by the OBR (2011) for the UK output gap given the assertion that “it would be unwise to base an assessment of economic prospects on any single approach alone” (p.6). With output gap estimates, as with forecasts, there are obvious practical limits as to how informative any single approach can be. By having a range of models that incorporate different information about the cycle, it is hoped that key developments in relation to the cyclical position of the economy will be captured.

## Section 3: Issues Relevant for Ireland's Output Gap

Producing output gap estimates for an economy always presents difficulties because of its unobservable nature, as well as other common problems. These problems are well documented in the literature (Section 2). However, estimating the output gap for the Irish economy poses considerable difficulties, which we explore further in this section.

Some of the key features to consider when determining an output gap for Ireland include: (i) the openness of the economy, (ii) its small size, (iii) the presence of large foreign-owned multinational enterprises, and (iv) the regional nature of the Irish economy.[7] In particular, the first three factors entail that large changes in activity can result from a small set of large exporting enterprises. Owing partly to their strong integration in global supply chains, such enterprises are capable of varying their production substantially with little impact on domestic factor inputs or domestic capacity utilisation.

Ideally, any approach to measuring Ireland's output gap would allow for a separation of the business cycle relevant for domestic sectors, which are less integrated in the global economy, from those activities that are highly integrated (e.g., those sectors marked by a greater presence of foreign-owned multinational enterprises). It is also important to try to recognise the regional nature of Ireland's economy – in particular the importance of sizeable labour market flows into and out of Ireland, with consequent impacts on the procyclicality of potential output estimates.

### 3.1 Openness

Ireland's integration with the global economy is among the highest observed internationally. In terms of the scale of traded activity relative to the size of the economy, Ireland ranks second highest in the OECD, both in terms of GNP and GDP (Figure 2).

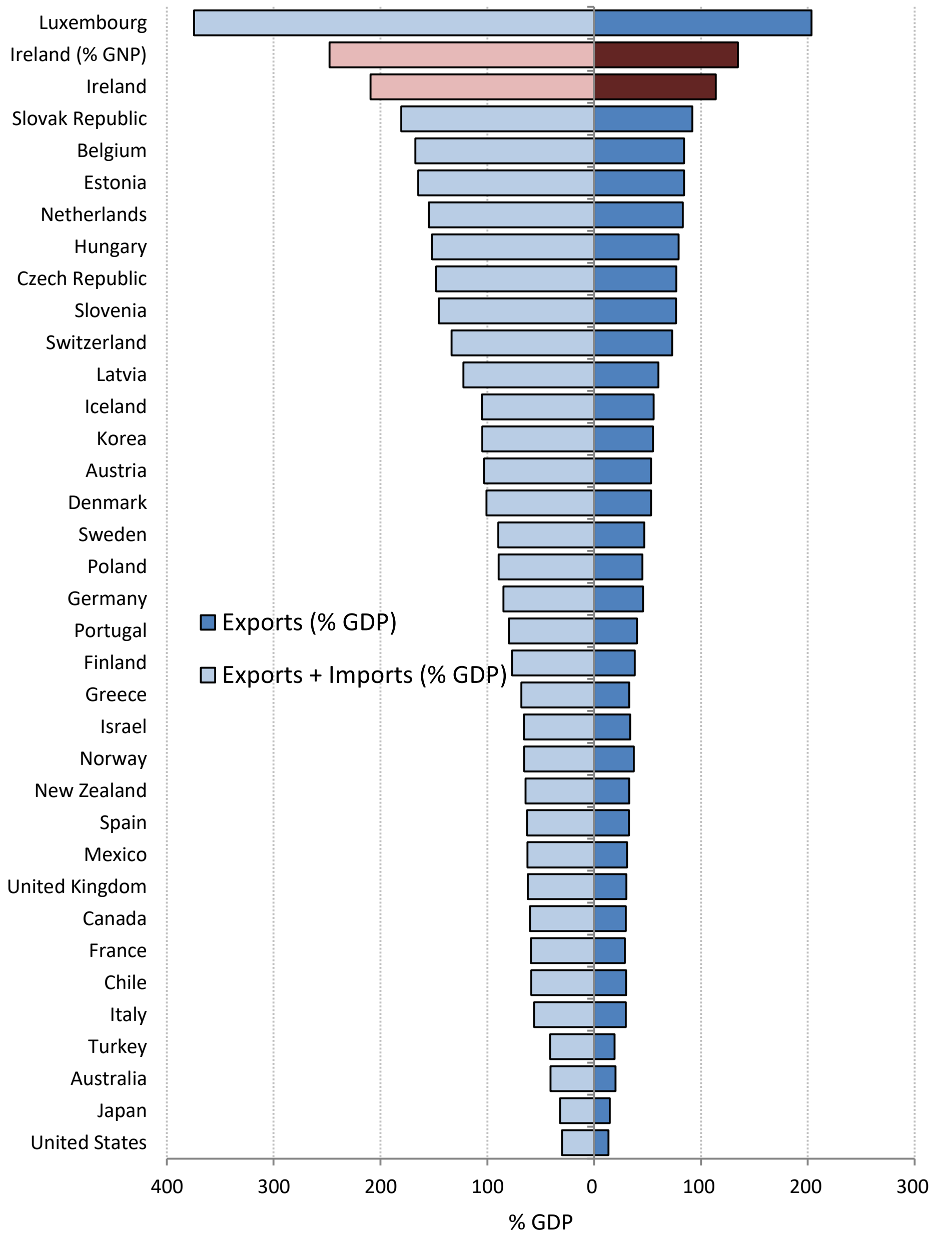
### 3.2 Small Size

Based on 2014 data, Ireland is in the bottom 20 per cent of OECD countries in terms of size (based on working age population). Looking at size on the basis of levels of GDP in US dollars, Ireland ranks 24th among 35 OECD countries, while using GNP just for Ireland, it ranks 27th (Figure 3).

[7] By regional, we mean that the economy – much like regions – can display patterns of migration flows, which are sizeable enough to result in large impacts on the labour market.

## Figure 2: Openness Indicators

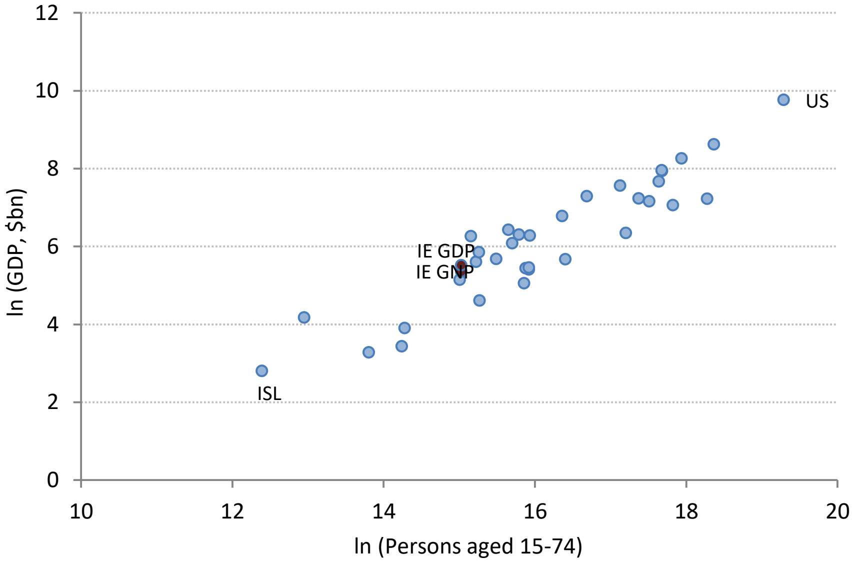
% GDP unless stated (2014)




*Sources:* OECD data and author's workings.
*Notes:* Openness indicators used are nominal exports as a share of GDP and nominal exports + imports as a share of GDP.

**Figure 3: Size Indicators, 2014**

Natural logarithm levels (ln)




*Sources*: OECD data and author's workings.
*Notes*: Size indicators are GDP ($ billions) and working age population (age 15-74) as of 2014; both in natural log levels.

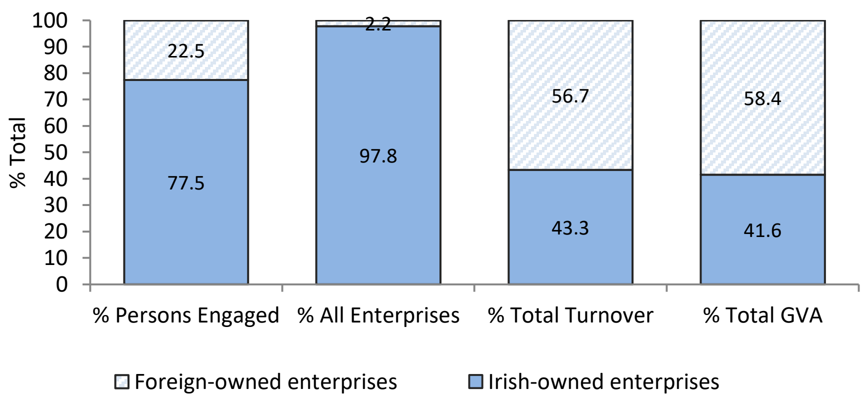
## 3.3 Presence of Large Foreign-Owned Multinational Enterprises

Another important feature of the Irish economy is the role of highly productive sectors where foreign-owned multinational enterprises dominate.

On the one hand, an estimated 2.2 per cent of enterprises in the business economy in Ireland for 2012 are foreign-owned, yet these enterprises account for an estimated 58.4 per cent of total GVA (Figure 4). On the other hand, resident-owned enterprises account for 97.8 per cent of such enterprises, but less than half (41.6 per cent) of total GVA.

**Figure 4: Irish Business Economy**

% of respective totals (2012)




*Sources*: CSO Business in Ireland 2012 and author's workings.

This dichotomy might lead to a characterisation of Ireland as having a two-speed economy. One part of the economy is marked by strong growth and high productivity. These activities are concentrated in “modern” exporting sectors that have comparatively stronger integration in global value chains. The other part of the economy is marked by weaker growth in relatively less productive and less globally integrated “traditional” sectors of the economy.

The characterisation could follow that the traditional sector is primarily comprised of Irish-owned enterprises, while the modern sector is dominated by foreign-owned multinational enterprises. Yet this characterisation would be a crude one. Often sectors that we would recognise as being traditional in terms of the nature of their output (such as the food and beverage industry) may also contain enterprises that would, on closer inspection, be identified as modern or highly productive in nature.[8]

The problem for those discerning developments in Irish economic activity has to some extent become one of trying to isolate in a meaningful way the underlying performance of the economy. Efforts have focussed on stripping out distortions related to sectors that provide little in the way of changes to more tangible or “real” variables like employment, wages or corporation tax. Numerous attempts have been made to achieve this. Most recently, this has included the development of an alternative indicator of Irish economic activity: “modified GNI” or “GNI*” (CSO, 2017).[9] However, the outcomes from various alternatives have varied in their ability to capture the underlying activity that users have in mind.

In this paper, we focus on alternative measures of economic activity that are more closely linked to the domestic economy than real GDP. This is an attempt to arrive at meaningful measures of on economic activity that is cleaned of some of the distortions with little impact on variables like domestic incomes, employment or corporation tax receipts. Our objective is to identify changes in activity that will have some bearing on the underlying budgetary position.

[8] Indeed, recent years have seen foreign-owned multinational enterprises involved in food production also being represented in what is perceived as the traditional sector. Moreover, the production practices of enterprises in traditional sectors may be often be highly advanced as in modern sectors.

[9] GNI* is an aggregate that is designed to more accurately capture national income of Irish residents compared to GDP, given that GDP is prone to distortions from foreign-owned multinational enterprises. GNI* differs from actual GNI in that it excludes (i) the depreciation of foreign-owned, but Irish-resident, capital assets (specifically, intellectual property and aircraft leasing assets) and (ii) the undistributed profits of firms that have re-domiciled to Ireland.

In particular, adequate recognition should be given to the fact that a small set of enterprises can vary their production substantially with little change in domestic capacity utilisation, hence supporting much greater levels of potential output. An ideal approach would allow for some degree of separation between the business cycle that is relevant for domestic economic activity that is less integrated in the global economy from that activity which is highly integrated.

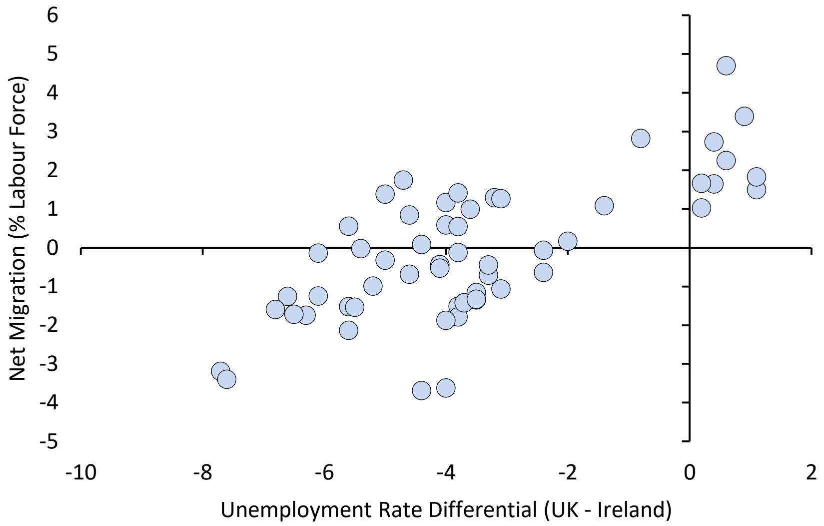
### 3.4 Ireland as a Regional Economy

A further complication is the tendency for Ireland to demonstrate characteristics more like that of a regional economy than a typical national economy. This is in part a reflection of its small and open nature. Behaviours such as periods of self-reinforcing growth may be evidenced, for example, when inward migration supports scale economies and incomes, thus attracting further inward flows.

This has been referenced in relation to the positive association observed between Irish net inward migration flows (as % of total labour force) and the relative unemployment rates for Ireland and the UK (Figure 5).

**Figure 5: Net Irish Migration and Relative Unemployment Rates**

**Net migration (% labour force); UK – Ireland unemployment differential (%), 1960-2015**




*Sources:* AMECO; own workings.

Traditionally, there has been a close connection between the two economies' labour markets (Barrett, 2005; FitzGerald and Kearney, 1999; Krugman, 1997; O' Grada and Walsh, 1994). Obviously, not all outward migration flows from Ireland are to the UK market, but the relationship is a useful one for understanding how relative labour market differences (even if proxied by just one key market) can lead to sizeable migration flows when compared against the economy's total existing labour inputs. Such flows can have important consequences for the economy's potential growth rate, given the importance of labour as an input to the economy's total level of production.

Furthermore, we might seek to recognise the regional nature of Ireland's economy – in particular, the importance of sizeable labour market flows into and out of Ireland. Flows such as these can impact the procyclicality of potential output estimates when modelled in a production function approach, for example. Most importantly, it can mean that potential supply can be very elastic, making it harder to distinguish between trend and cyclical developments.

Another factor worth noting in this context is monetary policy. As a member of the Euro Area, monetary policy for Ireland is set by the European Central Bank, though there is a role for adjustments in macroprudential regulation. This feature can lead to amplified cycles (making it harder to separate trend and cycle), as well as high capital market openness. Crowley and Lee (2008) explore the impact that inappropriate monetary policy can have in terms of amplifying the business cycle for economies such as Ireland. Low interest rates are cited as one contributing factor in the lead-up to Ireland's financial crisis in the late 2000s (Honohan, 2010), though others suggest that the weight of blame is better placed on Irish domestic fiscal and regulatory policy (Whelan, 2013).

### 3.5 Implications for Output Gap Estimates

The issues described above pose significant challenges and it is unlikely that any single solution will adequately address all of these.

One useful solution for many of the distortions caused by the foreign-owned multinational-dominated sectors is to focus on measures of output that distinguish between these sectors and the rest of the economy. The motivation for this kind of approach is even greater if we are interested in an output gap that is relevant for Irish fiscal policy. This is due to the evidence that the relationship between tax receipts and aggregate activity (e.g., GDP and GNP) is weaker than that for domestic measures. By contrast, the relationship between revenues and output from the foreign-owned multinational-dominated sectors tends to be insignificant (IMF, 2015).

The regressions in Table 1 estimate the association between total general government revenue and different measures of nominal aggregate output. The CSO provides a split of Gross Value Added

(GVA) into that of sectors that are dominated by foreign-owned multinational enterprises (GVA of MNEs) and the rest of the economy (Domestic GVA). Regressions (3) and (4) show that changes in GNI* and Domestic GVA explain more of the variation in revenue growth than changes in headline measures such as GDP (1) and GNP (2). By contrast, regression (5) indicates that changes in the gross value added of sectors dominated by MNEs are estimated to have no statistically significant impact on revenues.

**Table 1: Output and General Government Revenue**

Dependent Variable $\Delta Revenue_t/Revenue_{t-1}$ (Sample: 1990–2016)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\Delta GDP_t/GDP_{t-1}$ | 0.6888*** (0.1898) | | | | |
| $\Delta GNP_t/GNP_{t-1}$ | | 0.9665*** (0.2064) | | | |
| $\Delta GNI^*_t/GNI^*_{t-1}$ | | | 0.8439*** (0.1026) | | |
| ΔDomestic $GVA_t$/Domestic $GVA_{t-1}$ | | | | 1.6280*** (0.2290) | |
| ΔGVA of $MNEs_t$/GVA of $MNEs_{t-1}$ | | | | | 0.0244 (0.0327) |
| Constant | 2.4273 (1.4941) | 1.4678 (1.3974) | 0.4217 (0.9789) | 0.0065 (1.1533) | 5.8601 (1.4162) |
| Observations | 27 | 27 | 27 | 27 | 27 |
| R-squared | 0.34 | 0.47 | 0.73 | 0.67 | 0.02 |
| Root Mean Squared Error | 5.18 | 4.67 | 3.32 | 3.68 | 6.33 |

*Sources*: CSO; own workings.

*Notes*: Robust standard errors in parentheses (*** p<0.01; **p<0.05; *p<0.1). Revenue refers to total General Government Revenue. Domestic GVA is total GVA less sectors dominated by foreign-owned multinational enterprises (GVA of MNEs). GNI* is an aggregate that is designed to more accurately capture national income of Irish residents compared to GDP, given that GDP is prone to distortions from foreign-owned multinational enterprises. GNI* differs from actual GNI in that it excludes (i) the depreciation of foreign-owned, but Irish-resident, capital assets (specifically, intellectual property and aircraft leasing assets) and (ii) the undistributed profits of firms that have re-domiciled to Ireland. For years where GNI* data are unavailable (1990-1994), we use extend the GNI* series using the unadjusted GNI series growth rates.

Distinguishing between sectors dominated by foreign-owned multinational enterprises and other ("domestic") sectors enable us to focus on producing output gap estimates that are more relevant for fiscal policy. It also helps us to overcome distortions caused by large shifts in activity attributable to multinational enterprises. However, the distinction between domestic and non-domestic may not be perfect. Another alternative approach we explore is to use additional economic indicators that might provide information more closely linked to domestic cyclical developments (in a Cyclical Indicators approach).

## Section 4: Methodology and Data

This section details the methodologies and data we use to estimate Ireland's output gap.

### 4.1 Methodology

#### Statistical Filters

A range of statistical filters may be applied to individual measures of economic activity (e.g., real GDP) to obtain a smoothed trend series, which may then be considered the economy's level of potential output.[10] For this paper, we consider two of the most common tools, the Hodrick-Prescott (HP) and the Kalman Filter. The output gap is then defined as the difference between trend and actual output levels (expressed as a percentage of the trend level).

**The HP-filter** is a simple smoothing method which obtains time-varying trend estimates by minimising:

$$\sum_{t=1}^{N}[(Y_t - Y_t^*)^2 + \lambda(\Delta Y_t^* - \Delta Y_{t-1}^*)] \tag{1}$$

where $Y_t$ is the output variable of interest (such as real GDP) and $Y_t^*$ is the unobserved trend estimate that we wish to identify. The method (i) minimises the sum of the squared deviations between output and its trend $(Y_t - Y_t^*)$, while (ii) minimising the change in the trend growth rate from one period to another. The lambda $(\lambda)$ parameter allows some flexibility in relation to the smoothness of the extracted trend with the potential output estimates approaching a linear trend for larger values. It is at the discretion of the user how smooth this parameter is set to be, but typically 100 or 6.25 are assumed when identifying trend estimates for the business cycle with annual data.[11] We explore both in the case of the output measures we consider.

**The Kalman Filter** is a variant of state-space models – a general class of linear time series models that combine observable variables $(\mathrm{X_t})$

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[10] See Cerra and Saxena (2000) for an overview.

[11] The choice of smoothing parameter is widely debated and often tends towards what are considered "de facto industry standards" (Maravell and del Rio, 2001). Hodrick and Prescott (1997) themselves suggested a lambda of 100 for annual data and 1600 for quarterly data. Ravn and Uhlig (2002) recommend either (i) varying lambda according to the frequency of the data such that it varies by the fourth power of the frequency observation ratio (e.g., 1600 for quarterly data and $1600/4^4 = 6.25$ for annual data) or (ii) a time domain approach that determines lambda using the ratio of the variance of cyclical components to the variance of the second difference of the trend component so as to allow for idiosyncrasies in the data. In practice estimates will be sensitive to the choice of smoothing parameter. For annual data, the standard Hodrick and Prescott (1997) lambda of 100 implies a cycle of 19.8 years, while the lambda of 6.25 is consistent with a 10-year cycle.

and unobservable ($S_t$) variables. They can be described by two equations.

The first "state" or "transition" equation describes how a set of unobservable state variables, $S_t$ , evolve over time:

$$S_t = FS_{t-1} + u_t \tag{2}$$

The second "measurement" or "signal" equation relates a set of observable signal variables, $X_t$ , to the unobservable state variables:

$$X_t = HS_t + v_t \tag{3}$$

The error terms $u_t$ and $v_t$ are serially independent and may include errors that are normally-distributed or can rely on other distributional assumptions.

The intuition behind state-space models is straightforward. Not being able to observe $S_t$, we make do with an observable, unbiased estimate based on information available up to time t−1. This estimate, called $S_{t|t-1}$ (the estimate of $S_t$ conditioned on information from preceding periods) is equivalent to the left-hand side of equation (2), and its errors can be assumed to be, for example, normally distributed. Substituting this into equation (3), we can describe the observed variables as:

$$X_t = HS_{t|t-1} + v_t + H\left(S_t - S_{t|t-1}\right) \tag{4}$$

Since $S_{t|t-1}$ is observable and we assume that the unobservable elements ($v_t$ and $(S_t - S_{t|t-1})$) are normally distributed, the model can be estimated via maximum-likelihood methods. Given initial estimates of the first-period unobservable state $S_{1|0}$, the combined likelihood for all subsequent data observed is the product of all the period-by-period likelihoods.

The iterative method used to produce the unbiased estimate of our unobservable variable based on information available up to time t–1 (i.e., $S_{t|t-1}$) can be understood as follows. First, given the observed signal variables and some initial assumptions about state mean and variance values, the Kalman filter calculates one-step-ahead estimates of state values and variances. This gives an initial projection of the state variable. Second, the observable data for the next period is used to update the projections from step 1, giving more weight to components with lower variances. In step 2, the error covariance is also corrected with the same weight as the prior estimate of the state variable (Harvey, 1989).

As a starting point, we use the following state-space system representation to model the stochastic process for output:

$$y_t = OG_t + y_t^* \tag{5}$$

$$OG_t = \beta_1 OG_{t-1} + \beta_2 x_{t-k} + \omega_t \tag{6}$$

$$y_t^* = y_{t-1}^* + \varepsilon_t \tag{7}$$

where $y_t$ is the log-level of actual output; $y_t^*$ is the log-level of potential output; and $OG_t$ is the output gap all as measured for the current year $t$. The variable $x_{t-k}$ is an optional vector of economic variables that can enter the equation in the multivariate setting. For our core univariate model, this is set as equal to zero.

The system above assumes the following relationships. First, our actual output variable (e.g., real GDP) is set as equal to potential output plus the output gap. Second, the output gap is modelled as a stochastic process that evolves with an autoregressive component, and with white noise and normally distributed shocks given by $\omega_t$. The shocks in the output gap equation can be thought of as cyclical or transient demand shocks. Third, potential output is assumed to evolve with an autoregressive component also, and, again, with white noise and normally distributed shocks $\varepsilon_t$. The shocks in the latter potential output equation may be deemed as level shocks to potential output.[12]

In an extension of the above, we include a time-varying drift term $\delta_t$ (which, itself, is a random walk also) to our third equation (7) so that we have:

$$y_t^* = y_{t-1}^* + \delta_t + \varepsilon_t \tag{8}$$

To estimate, first we specify that the parameters are normally distributed and initialise the model with the prior that variances are given by a simple HP-filter of historical data. Second, we employ the Kalman filter to estimate the likelihood of the system. Thus, we maximise the posterior density function with respect to our parameters. This can be viewed as a conventional Bayesian approach

[12] Another possibility to explore in this framework would be the inclusion of a fourth equation capturing trend growth $G_t$ and the possibility of shocks to this. As in Blagrave *et al* (2015), this could be modelled in the fashion:
$G_t = \theta G^{SS} + (1-\theta)\, G_{t-1} + \varepsilon_t^G$
This approach would see trend growth $G_t$ as being subject to trend growth rate shocks $\varepsilon_t^G$, the impact of which can fade over time according to the persistence parameter $\theta$ (with smaller values giving more persistent trend growth shocks). The trend (or potential) output equation would be modified to include this trend growth term $G_t$ so that we have: $y_t^* = y_{t-1}^* + G_t + \varepsilon_t$

to estimating parameter values and the variances of shock terms.[13]

The above equations form the core of our state-space system representation. To this, we can then include additional signal variables in a multivariate representation.

### Multivariate Statistical Filters

A useful extension of the state-space representation outlined above is to include a number of additional exogenous and observable economic variables. The idea is to complement our output aggregates with additional economic information about the cycle.

In this context, we examine a number of possible indicators to include in the vector $x_{t-k}$. We examine both contemporaneous interactions and one-year lags. As we introduce the economic indicators assessed via the output gap equation, we are effectively only allowing them to have an indirect impact on potential output. This approach means that such variables are assumed to only contain information about the cyclical or transitory components of output. Of course, many shocks (e.g., financial sector crises) could be argued to have permanent negative impacts on potential output. This possibility is allowed for in an indirect sense under our specification of the output gap equation. As in Borio *et al.,* (2013), this constrains potential output to be proportional to actual output, so that any permanent effects, if relevant, will ultimately be reflected in potential output too

Following the literature, we examine the following economic variables for inclusion. As in Borio *et al.,* (2013), we examine a measure of private sector credit growth, residential property prices and the real interest rate. These are intended to help capture the interactions between financing constraints, collateral values and wealth effects. We also consider the real effective exchange rate and a modified version of the current account balance.[14] Several transformations of each of these variables are examined: mean adjustments on the basis of simple arithmetic averages; mean adjustments on the basis of Cesàro averaging; and gaps produced under a univariate application of the HP-filter.

[13] As noted in McGrayne (2012), though Kalman vehemently denied that Bayes' theorem had anything to do with his invention, Masanao Aoki proved mathematically in 1967 that it can be derived directly from Baye's rule. For a general discussion of how the Kalman filter is used to obtain estimates of the unobservable variables, see Hamilton (1994).

[14] Various measures of inflation (including CPI, core CPI, and some measures of services inflation) and the unemployment rate were also considered but ultimately were left out of the final analysis.

Following Borio *et al.,* (2013), we estimate the inclusion of each variable, one at a time. This sequential approach allows us to assess the effect that each variable introduced in isolation has on our output gap estimates.

### Cyclical Indicators

The cyclical indicators approach is another useful approach for identifying the cycle. It exploits information from a range of variables that might be expected to reflect cyclical developments and is typically applied to survey indicators rather than aggregates like GDP. Measures include various high frequency indicators such as those provided in surveys of consumer and business conditions, labour market indicators and financial indicators.

To combine the cyclical indicators used, we use Principal Components Analysis (PCA) – a statistical technique that attempts to identify the common determinant of a number of variables and to account for as much variability in the data as possible. It assigns weights to each of the variables according to the underlying properties of the dataset, rather than according to prior information like sectoral shares. The correlated variables are then converted into a set of orthogonal, linearly uncorrelated variables called principal components.

Cyclical indicators need to be combined and weighted to produce an aggregate output gap estimate. We therefore transform series into comparable units of measurement before deriving weights for these to produce an output gap estimate. The various cyclical indicators selected are standardised prior to estimation, i.e., they are expressed as a number of standard deviations from the mean of the series. For any given variable $x$, the standardised value of that variable ($\hat{x}$) is given by the expression:

$$\hat{x} = \frac{x - \bar{x}}{\sigma_x} \tag{9}$$

where $\bar{x}$ denotes the sample mean of the series and $\sigma_x$ denotes the standard deviation.

In each case we need to specify the sample period to calculate an appropriate mean and standard deviation of each series. This may not correspond to the entire time series: for indicators with a relatively short time span it may not be appropriate to use the whole sample if the starting point is during a period of elevated or depressed economic activity, as this may introduce a cyclical bias in the long-term average.

One criterion for the period used to calculate the “normal” level of an indicator is whether the series is symmetrically distributed over that period. As such we assess the distribution for symmetry during the period over which an average is taken.

### Testing Results

Tests to establish the success of estimates of potential output and the output gap are made difficult by virtue of the fact that neither variable is observable. As output gap estimates cannot therefore be compared with actual results, a number of other criteria have emerged to assess desirable attributes.

Turner *et al.,* (2016) suggest that in addition to targeting low real-time revisions, other criteria used to judge potential output estimates/methods might also include the ability to explain inflation; applicability across many countries; and a plausibility or “smell” test.

In this spirit, we perform stability tests like those favoured in McMorrow *et al.,* (2015) and elsewhere, but we also extend our tests in two important ways. First, we examine the ability of our output gap estimates to explain inflation. Second, we propose a means of assessing the complexity of estimation procedures. This is an attempt to account for the trade-off between obtaining more appropriate measures at the cost of these becoming more opaque. Greater difficulty in interrogating the methodologies applied and reproducing estimates are major drawbacks of approaches as they become more complex.

## 4.2 Data

As is standard in the literature, we are primarily interested in using appropriate macroeconomic aggregates for discerning the cyclical position of the economy. Recognising the challenges posed in Section 3, we focus on Domestic GVA as the main aggregate of interest. As the economic output attributable to the foreign-owned multinational dominated sector still forms a large and important part of the economy, notwithstanding the weak relationship with revenues, we express our output gap estimates as a share of potential domestic GVA plus actual GVA of multinational enterprises. This is consistent with the approach availed of in IMF (2015), which corresponds to the view that the multinational sector is always operating at full potential with the gap between potential output and actual output one driven primarily by domestic developments.[15]

We also explore the inclusion of a number of additional observable variables in a multivariate setting. This approach is intended to provide further information about the cyclical component of output. By complementing actual economic aggregates (e.g., real GDP or real domestic GVA) with additional information that could help to determine unobservable estimates of the output gap, we can improve the chances that appropriate estimates are identified. The additional variables can be construed as additional signal variables in a multivariate setting, which are intended to augment the signal provided by our actual economic activity measure.

The additional observable variables we examine as complementary to our aggregate measures of economic activity include: a modified measure of the current account balance; the real effective exchange rate; house price growth; real credit growth; and real interest rates. The inclusion of financial variables (real interest rates, house price growth, real credit growth) is intended to capture the influence of the financial cycle and in particular the influence that developments such as asset price booms, or credit expansions may have in determining cyclical developments and budgetary outcomes.

For an alternative cyclical indicators approach, we investigate a battery of additional survey indicators that could serve to identify the cyclical position of the economy. Typically, these approaches focus on survey measures of spare capacity and recruitment difficulties along with official data on variables that signal overheating through the price/wage channel (Pybus, 2011; Murray, 2014).

On the inflation front, we choose variables that might be more closely aligned with domestic price pressures. Previous research for Ireland has shown strong predictive power for components of domestic services inflation using short-run unemployment gaps as a proxy for domestic spare capacity (Bermingham *et al.*, 2012). In this spirit, we focus on components of services inflation that may be said to represent the non-traded element of domestic inflation or the more sheltered sectors of the economy. We include annual price

[15] Rather than using GNI*, we use Domestic GVA. This choice is largely motivated by (i) the lack of inflation-adjusted data for the new GNI* measure; (ii) the fact that domestic GVA provides a clearer separation of sectors dominated by foreign-owned multinational enterprises. The implied assumption is that there is no output gap for sectors dominated by foreign-owned multinational enterprises. This approach would be consistent with the view that the sector faces limited resource constraints over time, can draw on a wider labour pool, and has no capital or efficiency gap.

inflation for restaurants and hotels; recreation and culture; transport services; and private rents.

### Table 2: Summary of Variables Assessed

| | Unit | Source |
|---|---|---|
| **Aggregate Macroeconomic Measure** | | |
| Domestic GVA | Log of level in €m (2015 prices) | CSO |
| **Additional Signal Variables for Multivariate Filters** | | |
| Adjusted Current Account Balance [1] | % GNI* | CSO |
| House Prices | % change y/y | BIS |
| Private Sector Credit growth | % change y/y | CBI |
| Short-Term Real Interest Rates (1yr; CPI inflation) | % | Thomson Reuters |
| Real Effective Exchange Rate (CPI-based, 67 trading partners) | % change y/y | Bruegel |
| **Variables for Cyclical Indicators Approach** | | |
| Exchange Rate: USD-EUR | $/€ | Thomson Reuters |
| Restaurants & Hotels Inflation | % change y/y | CSO |
| Recreation and Culture Inflation | % change y/y | CSO |
| Transport Services Inflation | % change y/y | CSO |
| Domestic Services and Household Services Inflation | % change y/y | CSO |
| Private Rent Inflation | % change y/y | CSO |
| Construction Sector PMI | Index | Markit |
| Services Sector PMI | Index | Markit |
| Annualised Housing Completions Minus Long-Run Average | (4-Qtr moving sum) – (LR avg) [2] | CSO |
| New Vehicle Registrations | % change y/y | CSO |
| Unemployment Rate | % labour force | CSO |

*Notes*: CBI = Central Bank of Ireland; CSO = Central Statistics Office; BIS = Bank for International Settlements;
[1] The modified current account balance is the balance of payments current account balance less the impact of re-domiciled PLCs, depreciation of intellectual property and leased aircraft, research and development imports, net purchases of intellectual property products, and investment into intellectual property assets and aircraft leasing.
[2] The long-run average used here is set as the annual average for the period 1975-2015 (which approximates as 25,000 units), excluding 2003-2009 to account for the bubble period.

## 5. Estimation Results

We focus our investigation on Domestic GVA as a valid measure for determining an output gap relevant for fiscal policy.

### 5.1 Statistical Filters (including Multivariate Filters)

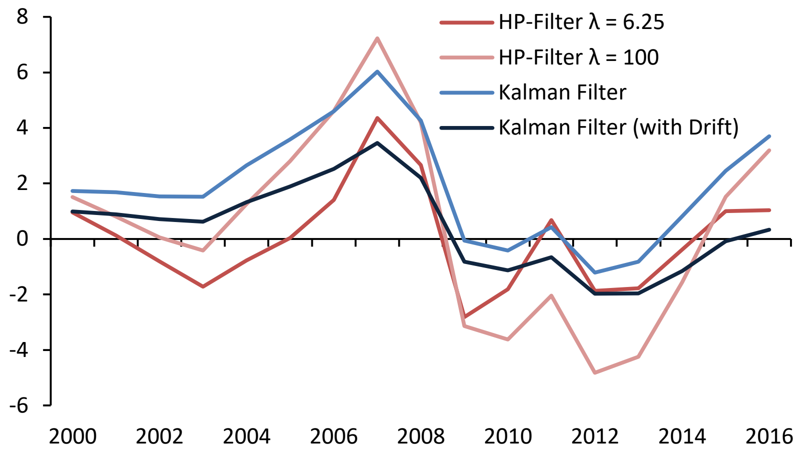
The results of the estimations using statistical filters are shown in Figure 6 (for univariate filter estimates) and Figure 7 (for multivariate filter estimates).

In each case, we filter data on Domestic GVA from 1970–2016.[16] We do not use forecasts in the estimations shown, though forecasts could be used to alleviate end-point bias.[17] Output gap estimates are expressed as actual Domestic GVA as a share of potential Domestic GVA + actual GVA of sectors dominated by multinational enterprises.

Of the variables we examine for inclusion in the multivariate approach, we find house prices and the adjusted current account balance to be significant at the 10 per cent level. All other variables are found to be insignificant. The other specifications explored in Borio *et al.,* (2013), which include credit and real interest rate indicators for example, prove less useful given that the variables are all found to be insignificant at the 10 per cent level. In part, this may reflect data availability considerations and the approaches could yet prove useful in time.

**Figure 6: Univariate Filter Estimates of the Output Gap**

**% potential (based on Domestic GVA)**




*Sources:* CSO data; own workings.
*Notes*: Output gap estimates are expressed as actual Domestic GVA as a share of potential Domestic GVA + actual GVA of sectors dominated by multinational enterprises.

Starting with the univariate filter estimates shown in Figure 6, we see that the results suggest somewhat similar narratives. Results provided by the HP filter with a lambda of 100 and the Kalman filter estimates (both with and without a drift term) suggest an output gap that is positive for most of the early 2000s, then turning negative after the financial crisis begins in 2009 and only turning consistently positive

[16] We extend the outturn Domestic GVA data available for 1995–2016 backwards by linking its growth rates to growth rates for real GNP, with which there tends to be a high correlation. We do this by estimating the typical relationship between the two variables econometrically over the period 1995–2016 based on the relationship (with variables in log-levels): $\Delta GNP_t = \alpha + \beta \Delta Domestic\_GVA_t + \varepsilon_t$

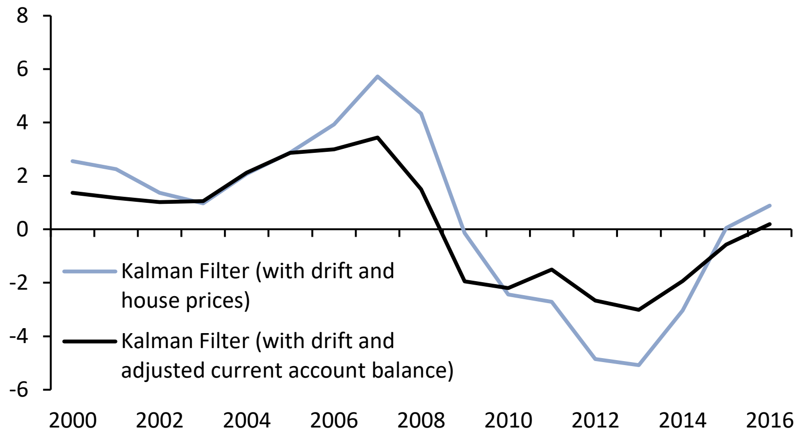
[17] Though forecasts are not typically available for Domestic GVA, they are available for variables such as GNP, which estimates tend to be highly correlated with. This offers one exploitable solution when trying to alleviate end-point bias.

from either 2014 or 2015 onwards. An exception is the HP filter approach that uses a lambda smoothing parameter of 6.25 (consistent with a cycle of 10 years). Results for this approach give a pattern largely different to the other three. In particular, it produces implausible negative estimates from 2002–2004, and an estimate that is more positive than any other method for 2011 despite the widespread downturn in the economy.

In terms of magnitude, there is some notable variation between the methods applied. The HP filter with a lambda of 100 displays wider swings than other methods, with a peak of +7.2 per cent in 2007 and a trough of -4.8 per cent in 2012. By contrast, the estimates produced using the Kalman filter give estimates that are much shallower. The Kalman filter (without a drift term) gives estimates that are quite close to zero for the period 2009–2013, which is at odds with evidence of spare capacity in the economy during this period including the large increases in unemployment.

**Figure 7: Multivariate Filter Estimates of the Output Gap**

% potential (based on Domestic GVA)




*Sources:* CSO data; own workings.
*Notes*: Output gap estimates are expressed as actual Domestic GVA as a share of potential Domestic GVA + actual GVA of sectors dominated by multinational enterprises.

Looking at the multivariate filter estimates shown in Figure 7, both the results including house prices and the adjusted current account balance point to a positive output gap sustained over the 2000s. This positive output gap widens from 2003 as the housing bubble takes hold, with associated negative impacts on the current account balance and rising house prices.[18] The subsequent reversal in the output gap estimates produced under both methods coincides with the collapse of the bubble in 2009. The estimates that control for

[18] Both Whelan (2013) and Honohan (2010) show evidence that the period 2002–2003 marked the onset of the bubble period leading to Ireland's subsequent crisis.

house prices produce a much deeper negative output gap in the period 2010–2014 compared to the estimates that incorporate the adjusted current account balance. This might be expected, given the relatively greater deviation from long-run levels observed in house prices, compared to deviation observed for the current account balance. The former yields estimates that hit a trough at close to 5 per cent, while the latter bottom out at a negative output gap of 3 per cent. Both sets of estimates show a return to modest positive gaps in 2016 of between 0.2 per cent and 0.9 per cent.

## 5.2 Cyclical Indicators

Variables chosen for the construction of principal components estimates should reflect whether the series is symmetrically distributed over the full sample period. As in Bulmer (1979), we take skewness measures of between −½ and +½ for indicator distributions as being approximately symmetric. Excluding indicators whose distributions show skewness greater than 0.5 means we drop the following variables as indicators for consideration in the principal components analysis: Recreation and Culture Inflation; the Unemployment Rate; and Domestic Services and Household Services Inflation (Figures A1 and A2).

**Table 3: Principal Component Variables and Weights**

Sample period: Q1 1996 – Q4 2015[1]

| Variable | Weight [2] |
|---|---|
| Annualised Housing Completions Minus Long-Run Average [3] | 0.90 |
| Restaurants & Hotels Inflation | 0.38 |
| Construction Sector PMI | 0.13 |
| Exchange Rate: USD-EUR | 0.11 |
| Current Account Balance (adjusted for re-domiciled PLCs) | -0.09 |
| Private Rent Inflation | 0.09 |
| Services Sector PMI | 0.08 |
| Traditional Sector Industrial Production | 0.05 |
| Transport Services Inflation | 0.05 |
| Manufacturing Sector PMI | 0.03 |
| New Vehicle Registrations | 0.02 |

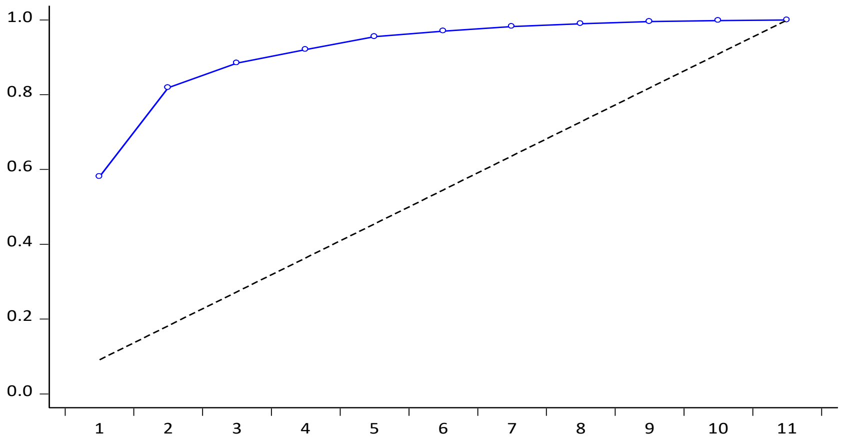
[1] This is the period over which the weights are estimated.
[2] Weights are the loading factors estimated for the first principal component and are consistent with those used to construct the PCA Output Gap Estimates. The square of the weights sum to one.
[3] The long-run average used here is set as the annual average for the period 1975-2015 (which approximates as 25,000 units), excluding 2003-2009 to account for the bubble period.

Table 3 sets out the variables used in the final principal component estimates, along with the derived weights on each indicator. The variables are standardised prior to the computation of the weights, with the mean and standard deviation based on the sample period Q1 1996 – Q4 2002. This period is chosen to reflect a period when (i) the property/credit bubble had not yet begun to cause severe distortions in data and when the effects of a delayed convergence were sufficiently borne out; (ii) when the economy could be said to have been broadly in equilibrium with a balanced current account and relatively low and stable inflation rates; and, of course, (iii) data availability considerations.

The "cumulative proportion" plot, Figure 8, highlights the extent to which each subsequent principal component captures the total variance common to each indicator over and above preceding principal components. The total variation accounted for by the first component is 60 per cent and by the first two components is 79 per cent.

**Figure 8: Eigenvalue Cumulative Proportion**

Cumulative % total variance (Y-axis) by principal component

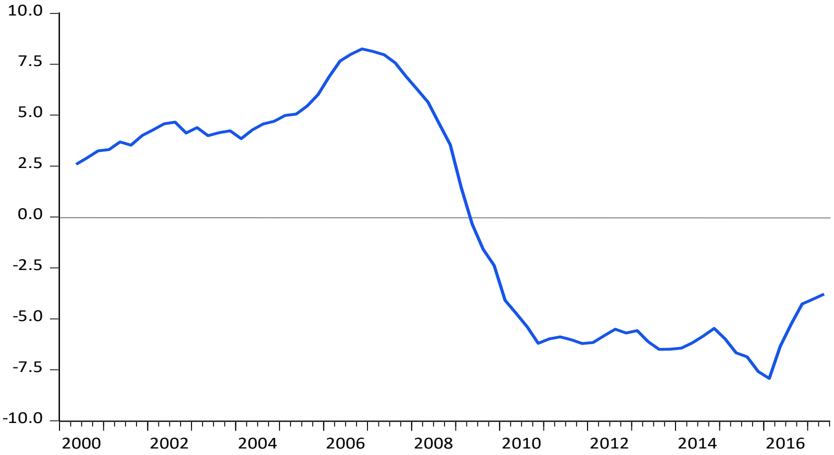



*Note:* The diagonal reference line offers a means of evaluating the size of the eigenvalues. We can compare the slope of the reference line against the slope of the cumulative proportion. The steepness as compared to the reference line gives a sense of eigenvalues that exceed the mean in terms of their capacity to explain total variance.

Taking the first principal component, we find that this produces a reasonable representation of how the output gap might be seen to have evolved over the past two decades (Figure 9). A modest positive output gap estimate of around 2 per cent is recorded in the early 2000s. We then see a gradually widening of the output gap in subsequent years, which accelerates in the 2005-2007 period, consistent with the peak of the property-credit bubble. As the bubble collapse, the output gap turns sharply negative before hitting a trough in 2009-2010. Following a prolonged stagnation, a gradual recovery begins to take place after 2015, with an output gap of -3.8 per cent as of mid-2017. The persistent and deep negative output gap is far more negative than that shown by other measures. In part, this reflects the moderating influence that falling unemployment rates might have (excluded from the estimation process), while sluggish housing completions are likely to have a large negative bearing on the estimates.

**Figure 9: Cyclical Indicators Output Gap Estimates**

Sample period: Q1 1996 – Q2 2017




*Sources:* Own workings.

### 5.3 A Suite of Models Approach

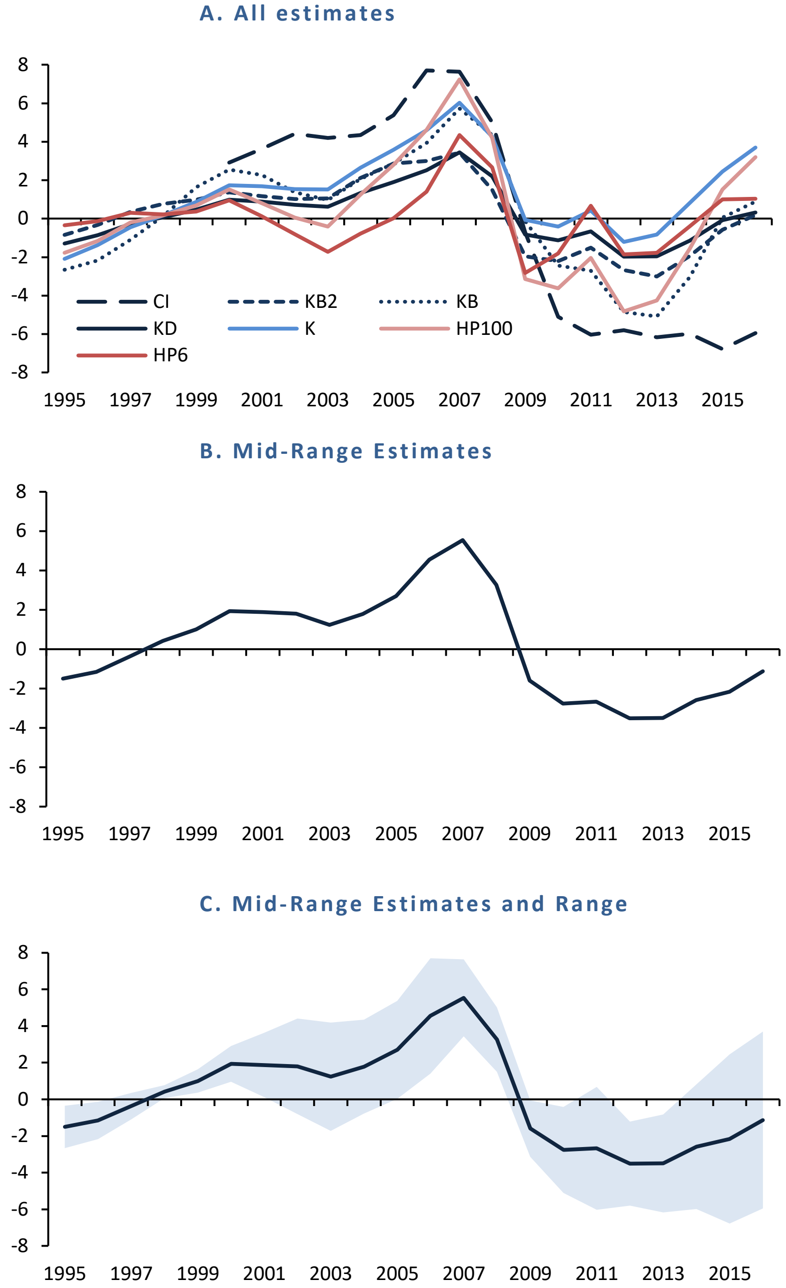
Following the suite of models approach, we examine a set of estimates that combines the information from alternative methods we propose in this section (i.e., the univariate and multivariate filters, and the Cyclical Indicators approach).

There are a number of approaches that could be adopted in terms of model averaging (e.g., simple arithmetic average; information criterion model averaging; Bayesian model averaging, etc.). Here, we employ a relatively simple approach, which is to take the mid-point of the full-range of estimates from the models we have identified. The "Mid-Range" estimates are computed as the year-wise averages of the maxima and minima of estimates produced under each method. For example, in 2010, the Mid-Range estimate is simply the average of the maximum and minimum estimate produced for that year based on all of the methods employed. Figure 10 shows the estimates produced under this approach: first, we show all estimates produced under the suite of models approach; second, we show the mid-range estimates based on these; third, we show the mid-range overlaid on the range itself.

The approach is useful for several reasons: (i) it is not unduly influenced by methods that we use several times, despite these being functionally quite similar (e.g., various modifications of the Kalman filter); (ii) it is simple to calculate; and (iii) it presents an intuitive interpretation in the context of a range of estimates. It has a number of drawbacks, most notably that it does not incorporate model selection criteria that may be relevant (e.g., selection on the basis of stability, ability to explain inflation, etc.). However, as a starting point, it serves as a useful basis for testing.

**Figure 10: Mid-Range Output Gap Estimates**

% potential




*Sources:* Own workings.

*Note:* Mid-Range estimates are computed as the series of averages of the maxima and minima of estimates produced under each method in each period. "HP6" refers to the HP-Filter Domestic GVA estimates ($\lambda$=6.25); "HP100" refers to same with different smoothing parameter ($\lambda$=100); "K" refers to the Kalman Filter Domestic GVA estimates; "KD" refers to the Kalman Filter of Domestic GVA with a drift term; "KB" refers to Kalman Filter of Domestic GVA with drift term and house prices; "KB2" refers to the Kalman Filter of Domestic GVA with a drift term and the adjusted current account balance. "CI" refers to the Cyclical Indicators estimates of the output gap; "Mid-Range" refers to the average of the maxima and minima of each of the preceding methods for each period; while "CAM" refers to the European Commission estimates of the Irish output gap using the Commonly Agreed Methodology.

## Section 6: Testing the Results

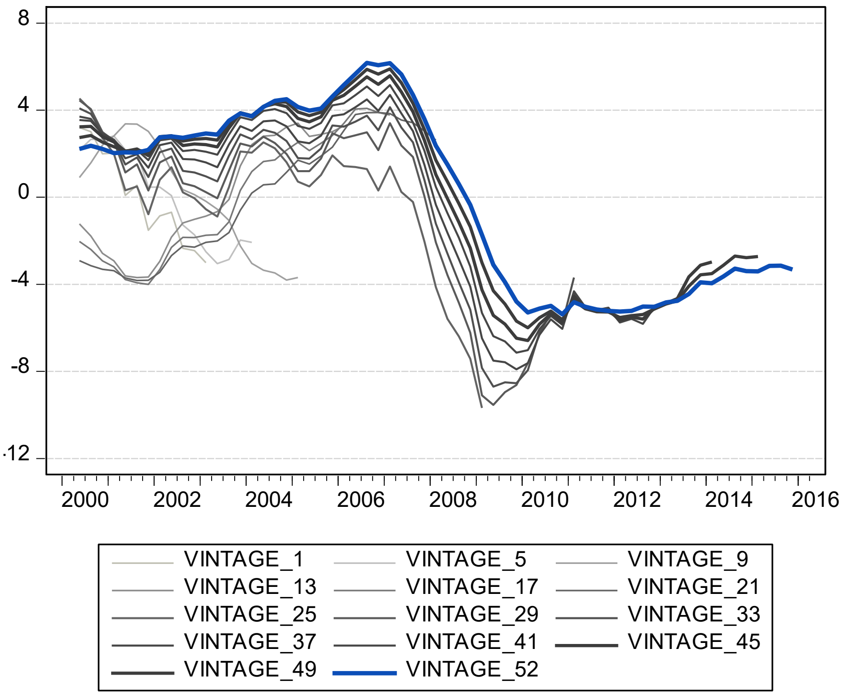
Given the output gaps we construct, we next examine a number of tests to discern the quality of these estimates on the basis of some features which may be desirable or undesirable: (1) stability; (2) how informative real-time estimates are; (3) the ability to explain inflation; and (4) complexity.

### 6.1 Test 1: Stability of Output Gap Estimates

Stability tests involve an examination of how stable the estimates are over time as new vintages of data/forecasts are produced. Figure 11 gives an example of this for the Cyclical Indicators estimates, the idea being to compare repeated iterations of the same methodology over time. We repeat this test for each of the methods explored and using real-time data where relevant (e.g., for Domestic GVA and the for the current account balance). Therefore, the revisions are either the result of (i) revisions to real-time data or (ii) the re-estimation of the model for each period.

**Figure 11: Cyclical Indicators Output Gap Vintages**

Vintages of output gap estimates (% potential) using expanding estimation windows




*Sources:* CSO; Department of Finance; and internal IFAC calculations.
*Note:* Estimates are produced over an expanding sample period, starting with Q1 1996 to Q1 2003 (i.e., Vintage 1 is estimated over the sample period running from Q1 1996 to Q1 2003, while Vintage 5 runs from Q1 1996 to Q1 2004). Estimates show the principal component estimated for the standardised variables identified in Table 3 over the sample period.

As the Domestic GVA series were first published in 2013, and hence real-time estimates only started to be collected from that point onwards, we create a pseudo real-time series. We construct these estimates by exploiting the close historical association between real GNP and Domestic GVA.[19]

To test stability, we examine three measures: (i) the Mean Absolute Revision (MAR); (ii) the max revision; and (iii) the number of sign changes observed. We calculate revisions in two ways: first in terms of year-to-year revisions of estimates (e.g., the revision to the 2000 output gap estimate as estimated in 2006 relative to 2005, then in 2007 relative to 2006, and so on). In this case, the MAR is computed as:

$$MAR_t = \frac{1}{n}\sum_{i=1}^{n}\left|x_{t,i} - x_{t,i-1}\right| \tag{10}$$

where $x_i$ is the $i^{\text{th}}$ output gap estimate for a given year $t$. A summary measure is then obtained by averaging across all of the MAR estimates for each $t$ year.

Second, we can calculate revisions in terms of the final estimate less the initial estimate (e.g., the 2000 output gap estimate as finally estimated in 2016 minus its initial estimate using data up to 2000). The MAR for a given year's output gap estimate is therefore the average of all absolute revisions for each $t$ year where the latter are calculated as:

$$Absolute\ Revisions = \left|x_{t,final} - x_{t,initial}\right| \tag{11}$$

"Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one vintage to the next (or from the initial to final estimates), i.e., from positive to negative or vice versa.

Table 4 shows the summary results of our stability tests for each output gap methodology as would be estimated in real-time. We also include, for reasons of comparison, the real-time estimates produced under the EU commonly agreed methodology for Ireland (full results are presented in Appendix B).[20]

[19] A simple regression of Domestic GVA on a constant and real GNP (traditionally a better measure for the domestic economy in Ireland) – and both in log-differences – can be shown to explain historical variation quite well. We assume that this relationship (estimated over the full sample period 1995 – 2016) holds to create a fitted real-time series of Domestic GVA based on a real-time series for real GNP.
[20] Note that since we use the real-time output gap estimates published by the European Commission (CIRCABC Database) under the EU commonly agreed methodology, these reflect methodological changes that took place over the same period of time.

### Table 4: Revisions to Output Gap Estimates

Full Sample (1999-2015)

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| **Year-to-Year Revisions** | | | | | | | | | |
| MAR | 0.5 | 0.8 | 0.6 | 0.3 | 0.4 | 0.5 | 1.2 | 0.5 | 0.7 |
| Max Revision | 5.5 | 6.9 | 3.0 | 1.8 | 3.2 | 2.3 | 7.1 | 3.4 | 4.2 |
| Sign Changes | 5 | 9 | 3 | 2 | 2 | 6 | 14 | 1 | 17 |
| **Initial-Final Revision** | | | | | | | | | |
| MAR | 2.7 | 4.6 | 2.9 | 1.1 | 2.5 | 1.1 | 4.4 | 1.7 | 2.3 |
| Max Revision | 6.5 | 8.6 | 6.4 | 2.1 | 5.7 | 2.2 | 8.9 | 3.4 | 5.4 |
| Sign Changes | 5 | 4 | 4 | 0 | 2 | 0 | 4 | 1 | 5 |

Recent Sample (2010-2015)

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| **Year-to-Year Revisions** | | | | | | | | | |
| MAR | 1.6 | 2.1 | 1.0 | 0.5 | 0.9 | 0.7 | 0.5 | 0.6 | 0.7 |
| Max Revision | 5.5 | 6.9 | 3.0 | 1.8 | 2.6 | 2.3 | 0.8 | 3.4 | 2.0 |
| Sign Changes | 3 | 1 | 3 | 0 | 1 | 0 | 0 | 1 | 0 |
| **Initial-Final Revision** | | | | | | | | | |
| MAR | 4.0 | 4.9 | 2.7 | 1.3 | 2.6 | 1.2 | 1.6 | 1.9 | 1.8 |
| Max Revision | 6.5 | 7.6 | 3.6 | 2.1 | 4.0 | 2.1 | 3.8 | 3.4 | 4.2 |
| Sign Changes | 3 | 1 | 4 | 0 | 1 | 0 | 0 | 1 | 0 |

*Sources:* Own workings.
*Note:* "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa). "HP6" refers to the HP-Filter Domestic GVA estimates (λ=6.25); "HP100" refers to same with different smoothing parameter (λ=100); "K" refers to the Kalman Filter Domestic GVA estimates; "KD" refers to the Kalman Filter of Domestic GVA with a drift term; "KB" refers to Kalman Filter of Domestic GVA with drift term and house prices; "KB2" refers to the Kalman Filter of Domestic GVA with a drift term and the adjusted current account balance. "CI" refers to the Cyclical Indicators estimates of the output gap; "Mid-Range" refers to the average of the maxima and minima of each of the preceding methods for each period; while "CAM" refers to the European Commission estimates of the Irish output gap using the Commonly Agreed Methodology.

The results in Table 4 based on the full sample suggest that the estimates produced under the Kalman filter with drift (KD) and the Kalman filter with drift and the adjusted current account balance (KB2) have the lowest revisions. In terms of year-to-year revisions, the KD has a mean absolute revision of 0.3 percentage points, while the same measure for the Kalman filter with drift and house prices (KB) is 0.4 percentage points. For the KB2 method, the revisions are marginally higher at 0.5 percentage points. If we consider the revisions in terms of initial minus final estimates, we see that the KD and KB2 methodologies show the lowest revisions on average, at 1.1 percentage points. By comparison, this is less than half of that observed for the CAM.

The largest revisions tend to be observed for the HP filter with a lambda of 100 and for the Cyclical Indicators approach. However, the latter partly reflects the shorter time period over which the estimates are able to arrive at a stable set of results (i.e., the first estimation window is for Q1 1996 to Q1 2003). The estimates for a smaller more recent sample period (2010 to 2015) reveal smaller revisions relative to the CAM and other methods, both on a year-to-year and initial-to-final basis.

A striking number of sign changes is evident for some of the methods. Most notably, the CAM – over the full sample period – shows as many as 17 sign changes on a year-to-year basis. Closest to that is the Cyclical Indicators approach (with 14 sign changes) and the HP filter with a lambda of 100 (9 sign changes). Looking at just the initial-to-final revisions, we see that the CAM also displays a large number of sign changes (5 over the full sample period). This makes it joint highest with the HP filter with a lambda of 6.25 ("HP6"). By comparison, the Kalman filter estimates show very few – if any – sign changes over time, both in terms of the year-to-year and initial-to-final revisions.

Looking at the mid-range estimates, this approach produces results that are – as may be expected – relatively stable. In all cases, its revisions are typically only higher than those produced for two or three other methods; they are lower than those produced under the CAM; and only one sign is evident over time in terms of both year-to-year and initial-to-final revisions.

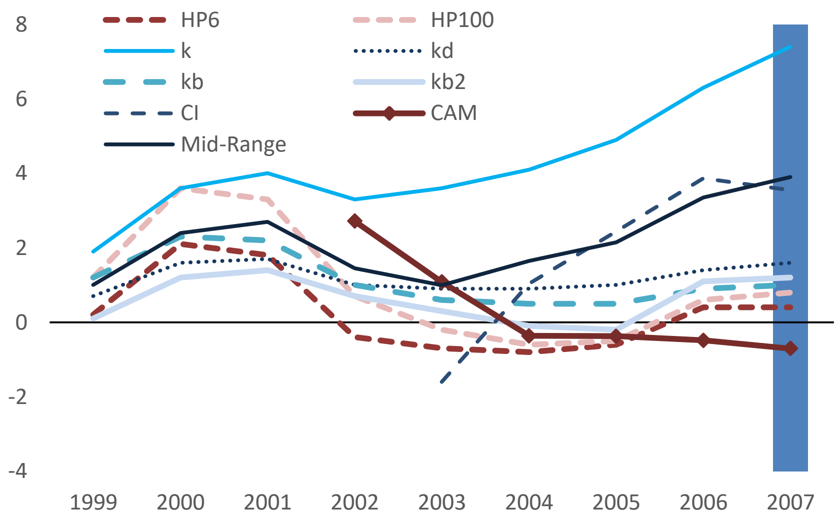
### 6.2 Test 2: How Informative Real-Time Estimates Are

Another test related to the real-time performance of various methods is their informational value at key turning points. An obvious vintage to examine in this regard is the first estimates produced as of 2007 (that is the estimate produced immediately after official 2007 national accounts data become available in June 2008). To be of use to those assessing economic policy, initial output gap estimates should give a fairly clear sense of possible demand excesses or shortfalls. At the very least, they should communicate a sign of the output gap that is in keeping with concurrent economic developments.

Figure 12 shows the first 2007 outturn vintage of output gap estimates produced under each methodology. Aside from the CAM-based estimate for 2007 (-0.7 per cent), all of the methods indicate a positive output gap. Given that this was the peak of the credit/housing bubble, a large positive output gap would be expected. By comparison, the mid-range estimate is 3.9 per cent and lies mid-way between the univariate Kalman filter estimate of 7.4 per cent and the HP filter estimate with $\lambda$ = 6.25. Though positive, the HP filter-based estimates have relatively small magnitudes considering the scale of the demand excess that might have been expected for 2007, as do the Kalman filter estimates that control for house prices (1 per cent) and the adjusted current account balance (1.2 per cent).

**Figure 12: Comparison of the 2007 Vintage of Estimates**

Vintages of output gap estimates produced on a real-time basis as of 2007 (% potential)




*Sources:* Own workings.

*Note*: "HP6" refers to the HP-Filter Domestic GVA estimates (λ=6.25); "HP100" refers to same with different smoothing parameter (λ=100); "K" refers to the Kalman Filter Domestic GVA estimates; "KD" refers to the Kalman Filter of Domestic GVA with a drift term; "KB" refers to Kalman Filter of Domestic GVA with drift term and house prices; "KB2" refers to the Kalman Filter of Domestic GVA with a drift term and the adjusted current account balance. "CI" refers to the Cyclical Indicators estimates of the output gap; "Mid-Range" refers to the average of the maxima and minima of each of the preceding methods for each period; while "CAM" refers to the European Commission estimates of the Irish output gap using the Commonly Agreed Methodology.

## 6.3 Test 3: Output Gap Estimates Ability to Explain Inflation

Another way to examine the plausibility of the output gap estimates produced under different methods is to test their ability to explain inflation. This forms the basis of our third set of tests.

An important consideration in such tests is whether the models already explicitly or tacitly include inflation indicators. In effect, we may simply be forcing output gaps to explain inflation by explicitly including the Phillips curve in our models. Such approaches could introduce large biases and may represent an overly restrictive way of incorporating economic information into statistical methods (Borio *et al.*, 2013). With the exception of the cyclical indicators approach, the estimates of domestic output gaps we produce do not incorporate inflation measures. However, the estimates that incorporate house prices will, of course, have some endogeneity to general price inflation.

To test our output gap estimates ability to explain inflation in the current year t ($\pi_t$), we first estimate a simple Phillips curve equation:

$$\pi_t = \beta_1 \pi_{t-1} + \beta_2 (Output\ gap) \tag{12}$$

before, second, exploring a more complex Phillips curve approach that incorporates inflation-expectations and inflation targeting by a central bank:

$$\pi_t = \beta_1 {\pi^e}_{t+1} + \beta_2 (Output\ gap) \tag{13}$$

where inflation expectations for the next year (${\pi^e}_{t+1}$) are given by:

$${\pi^e}_{t+1} = \beta_3 \pi_t + (1 - \beta_3) \pi^{target} \tag{14}$$

with $\beta_3$ assumed to lie between zero and one, and the inflation target is given by $\pi^{target}$, which we assume to be 2 per cent (consistent with the ECB's mandate). This implies that individuals expect next period's inflation to be a weighted average of officially targeted inflation and past inflation.

The results for each approach and each output gap estimation method are outlined in Tables 5 and 6. For inflation, we consider both headline CPI inflation and core CPI inflation (i.e., excluding energy and unprocessed food). The results suggest that the alternative estimates we produce do not have as strong an explanatory power with regard to price inflation in  a simple Phillips curve setting, however they perform broadly as well as the CAM when using wage inflation and when considering inflation expectations and inflation-targeting.

### Table 5: Output Gaps and Inflation (Simple Phillips Curve Approach)

(Samples: 1990–2016; 2000–2016 for wage inflation)

Dependent variable: CPI inflation

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| $\pi_{t-1}$ | 0.69*** | 0.68*** | 0.68*** | 0.69*** | 0.69*** | 0.67*** | 0.54** | 0.66*** | 0.63*** |
| | (0.12) | (0.13) | (0.13) | (0.13) | (0.13) | (0.13) | (0.22) | (0.13) | (0.11) |
| Output Gap | 0.65** | 0.22 | 0.20 | 0.36 | 0.13 | 0.36 | 0.14 | 0.25 | 0.42*** |
| | (0.24) | (0.14) | (0.16) | (0.27) | (0.15) | (0.22) | (0.13) | (0.17) | (0.14) |
| Observations | 27 | 27 | 27 | 27 | 27 | 27 | 17 | 27 | 27 |
| R-squared | 0.28 | 0.15 | 0.12 | 0.13 | 0.10 | 0.16 | 0.15 | 0.14 | 0.32 |

Dependent variable: Core CPI inflation

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| $\pi_{t-1}$ | 0.73*** | 0.72*** | 0.73*** | 0.74*** | 0.74*** | 0.72*** | 0.60** | 0.71*** | 0.66*** |
| | (0.11) | (0.12) | (0.12) | (0.12) | (0.13) | (0.12) | (0.21) | (0.12) | (0.10) |
| Output Gap | 0.67** | 0.23* | 0.18 | 0.32 | 0.12 | 0.32 | 0.12 | 0.22 | 0.44*** |
| | (0.22) | (0.13) | (0.15) | (0.26) | (0.14) | (0.21) | (0.13) | (0.16) | (0.13) |
| Observations | 27 | 27 | 27 | 27 | 27 | 27 | 17 | 27 | 27 |
| R-squared | 0.39 | 0.25 | 0.21 | 0.21 | 0.19 | 0.24 | 0.21 | 0.22 | 0.44 |

Dependent variable: wage inflation (Compensation per employee hour worked)

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| $\pi_{t-1}$ | 0.84*** | 0.79*** | 0.66*** | 0.73*** | 0.77*** | 0.75*** | 0.81*** | 0.77*** | 0.73*** |
| | (0.09) | (0.10) | (0.13) | (0.12) | (0.12) | (0.11) | (0.13) | (0.12) | (0.09) |
| Output Gap | 0.60** | 0.28* | 0.51* | 0.67* | 0.24 | 0.48* | 0.07 | 0.26 | 0.46** |
| | (0.26) | (0.16) | (0.25) | (0.39) | (0.20) | (0.28) | (0.12) | (0.22) | (0.16) |
| Observations | 27 | 27 | 27 | 27 | 27 | 27 | 17 | 27 | 17 |
| R-squared | 0.69 | 0.65 | 0.67 | 0.65 | 0.62 | 0.65 | 0.59 | 0.62 | 0.72 |

*Sources*: CSO; own workings.
*Notes*: Robust standard errors in parentheses (*** p<0.01; **p<0.05; *p<0.1). "HP6" refers to the HP-Filter Domestic GVA estimates (λ=6.25); "HP100" refers to same with different smoothing parameter (λ=100); "K" refers to the Kalman Filter Domestic GVA estimates; "KD" refers to the Kalman Filter of Domestic GVA with a drift term; "KB" refers to Kalman Filter of Domestic GVA with drift term and house prices; "KB2" refers to the Kalman Filter of Domestic GVA with a drift term and the adjusted current account balance. "CI" refers to the Cyclical Indicators estimates of the output gap; "Mid-Range" refers to the average of the maxima and minima of each of the preceding methods for each period; while "CAM" refers to the European Commission estimates of the Irish output gap using the Commonly Agreed Methodology.

### Table 6: Output Gaps and Inflation (Phillips Curve Approach Incorporating Inflation Expectations and Inflation-Targeting)

(Sample: 1990–2016)

Dependent variable: CPI inflation

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| $\pi^{exp}_{t+1}$ | 1.20*** (0.07) | 1.21*** (0.07) | 1.23*** (0.09) | 1.22*** (0.08) | 1.23*** (0.08) | 1.21*** (0.07) | 1.22*** (0.12) | 1.20*** (0.07) | 1.15*** (0.07) |
| Output Gap | 0.38*** (0.11) | 0.20*** (0.06) | 0.09 (0.08) | 0.33** (0.12) | 0.17** (0.06) | 0.32*** (0.09) | 0.13** (0.05) | 0.25*** (0.07) | 0.25*** (0.07) |
| Observations | 26 | 26 | 26 | 26 | 26 | 26 | 16 | 26 | 26 |
| R-squared | 0.85 | 0.84 | 0.78 | 0.83 | 0.83 | 0.85 | 0.85 | 0.86 | 0.86 |

Dependent Variable: Core CPI inflation

| | HP6 | HP100 | K | KD | KB | KB2 | CI | Mid-Range | CAM |
|---|---|---|---|---|---|---|---|---|---|
| $\pi^{exp}_{t+1}$ | 1.19*** (0.06) | 1.20*** (0.07) | 1.23*** (0.07) | 1.22*** (0.06) | 1.21*** (0.06) | 1.20*** (0.06) | 1.19*** (0.10) | 1.19*** (0.06) | 1.14*** (0.06) |
| Output Gap | 0.32*** (0.10) | 0.17*** (0.05) | 0.05 (0.07) | 0.25** (0.10) | 0.14** (0.05) | 0.25*** (0.08) | 0.11** (0.05) | 0.20*** (0.06) | 0.22*** (0.06) |
| Observations | 26 | 26 | 26 | 26 | 26 | 26 | 16 | 26 | 26 |
| R-squared | 0.89 | 0.89 | 0.85 | 0.87 | 0.88 | 0.89 | 0.89 | 0.89 | 0.90 |

*Sources*: CSO; own workings.

*Notes*: Robust standard errors in parentheses (*** p<0.01; **p<0.05; *p<0.1). "HP6" refers to the HP-Filter Domestic GVA estimates (λ=6.25); "HP100" refers to same with different smoothing parameter (λ=100); "K" refers to the Kalman Filter Domestic GVA estimates; "KD" refers to the Kalman Filter of Domestic GVA with a drift term; "KB" refers to Kalman Filter of Domestic GVA with drift term and house prices; "KB2" refers to the Kalman Filter of Domestic GVA with a drift term and the adjusted current account balance. "CI" refers to the Cyclical Indicators estimates of the output gap; "Mid-Range" refers to the average of the maxima and minima of each of the preceding methods for each period; while "CAM" refers to the European Commission estimates of the Irish output gap using the Commonly Agreed Methodology.

## 6.4 Test 4: Complexity of the Estimation Process Involved

Testing the complexity of an estimation process is also desirable. It can have implications for how informative estimates are in terms of their drivers. Complexity can also be a useful predictor of the likelihood of defects occurring. However, measuring the complexity of estimation code is not a straightforward task. We could examine the length of time it takes to undertake the procedure but this can differ across iterations, with variations in processing power, human error, and differences in user experience and knowledge factors that would need to be controlled for. Also, some methods may require several programming tools to run and so the actual run time or length of code may be less well-defined.

In the field of computer science, one useful approach to testing the complexity of an algorithm involves examining the number of statistical operations required. This is relatively easy for us to investigate, given that we code all of the models in the same software package so that the operations employed are comparable.[21] We count statistical operations as any operational commands used (e.g., sample selection, arithmetic, comparisons, accessing array's elements, assignment, etc.).

**Table 7: Complexity of Estimation Methods**

| Method | Number of Input Series | Number of Statistical Operations Involved |
|---|---|---|
| HP Filter | 2 | 10 |
| Kalman Filter (KF) | 2 | 28 |
| KF with drift | 2 | 31 |
| KF with House Prices | 3 | 34 |
| KF with Current Account | 3 | 34 |
| Cyclical Indicators | 11 | 24 |
| CAM * | 14 | 160+ |

Source: Own workings.
Notes: Statistical operations refer to all operational commands (arithmetic, comparisons, accessing array's elements, assignment, etc.). * The production of CAM-based estimates involves in excess of 160 operations when run through EViews for Ireland (excluding various "if" statements related to country selection). The total operations involved are likely closer to 200 given that we did not replicate two parts of the code: (i) that related to the NAWRU estimation procedure and (ii) that related to detrending of the Solow Residual.

Table 7 summarises the complexity of the estimation methods. In terms of input series the CAM requires the most (14 inputs) as compared to 11 for the cyclical indicators approach and less than 3 inputs for all other approaches.

In terms of statistical operations, the CAM far exceeds the complexity of any other method with over 160 operations involved and likely closer to 200 operations if parts of the estimation process that are conducted in other software were to be included (i.e., macro-enabled Microsoft Excel spreadsheets). This compares to between 10 and 34 operations being required for all of the other methods.

The number of operations involved in CAM estimation by comparison to other methods lends itself to greater risks of defects occurring. This risk is aggravated by the fact that changes to the code are frequent and – though available to general users through code

[21] All of the models are coded in EViews 9.5, with the exception of two sections of the CAM code, which depend crucially on bespoke user interfaces designed to be used within Microsoft Excel. Those sections that we were not able to reproduce in EViews 9.5 are the parts that are designed to: (i) obtain estimates of Trend Factor Productivity by filtering the Solow Residual, and (ii) obtain estimates of the NAWRU based on a new Keynesian Phillips curve approach (Havik *et al.*, 2014).

provided on the European Commission’s Circa website – can often be difficult to ascertain in a timely manner.

### 6.5 Illustrative Comparison with GDP-Based Estimates

Given our focus on domestic measures of economic activity up to now, it is worthwhile comparing the performance under each of these tests for an equivalent GDP-based measure. In Appendix C ,we apply the same approach to GDP as we used for Domestic GVA in the case of the Kalman filter that includes a drift term and the adjusted current account balance.

In terms of the four tests above, the results suggest that GDP-based estimates when compared against Domestic GVA-based estimates are far less stable. However, they perform only marginally worse or about the same when assessed on the basis of informational value as judged by the 2007 vintage of estimates; explanatory power for inflation; and in terms of complexity.

In terms of stability, GDP based estimates show a MAR of 0.9 for year-to-year revisions and 1.6 for initial - final as compared to 0.5 and 1.1, respectively for the Domestic GVA-based estimates. Looking at the 2007 vintages, we see that both the GDP- and domestic GVA-based estimates indicate a positive output gap in 2007 of just over 1 per cent (1.1 per cent and 1.2 per cent, respectively). Inflation, domestic GVA-based measure performs marginally better in terms of explanatory power for each inflation measure and specification.

## Section 7: Conclusions

This paper attempts to identify plausible estimates of Ireland's output gap that are relevant for fiscal policy. In particular, we seek to identify alternative approaches to the EU commonly agreed (production function) methodology.

A number of challenges face us: Ireland's small, open nature; the presence of large foreign-owned multinational enterprises; and a tendency for Ireland to demonstrate characteristics more like that of a regional economy. Recognising these challenges, we prioritise measures that focus on domestic activity – an approach warranted given its relatively more tax-rich nature. In addition, we use a suite of models approach, thus availing of a range of alternative estimation techniques rather than relying on any single approach.

Examining and testing methods based on univariate and multivariate statistical filters and principal components analysis, we find that the results produce more plausible estimates than the commonly agreed methodology's estimates. The alternative estimates also tend to be as stable as CAM-based estimates and are far less complex to estimate. Although their ability to explain price inflation in a standard Phillips curve setting is weaker than that for the CAM, the estimates have a similar explanatory power when incorporating price expectations and inflation-targeting or when considering wage inflation instead of price inflation.

Yet we do not see these alternative estimates as a panacea to identifying cyclical developments and imbalances in the economy. Every cycle is different and keeping analysis simple and with a clear narrative is problematic in a complex world. Designing a "least bad" solution among a host of mediocre choices might be the only realistic goal for the problem of estimating potential output (Blagrave *et al.*, 2015). In particular, it would be worthwhile developing alternative estimates of the output gap and potential output in the context of a full (semi-) structural model approach. This would ensure a more robust foundation for any estimates produced.

Moreover, the concept of potential output might not correspond well with the concept of "sustainable" output. Estimates like those produced here need to be supplemented with a careful scrutiny of economic imbalances to discern whether developments could lead to subsequent painful corrections in the economy. Future research could expand on IFAC's "modular approach", which examines a range of economic indicators for signs of economic imbalances. Modules may focus on areas such as the labour market; housing and investment; credit; and external balances.

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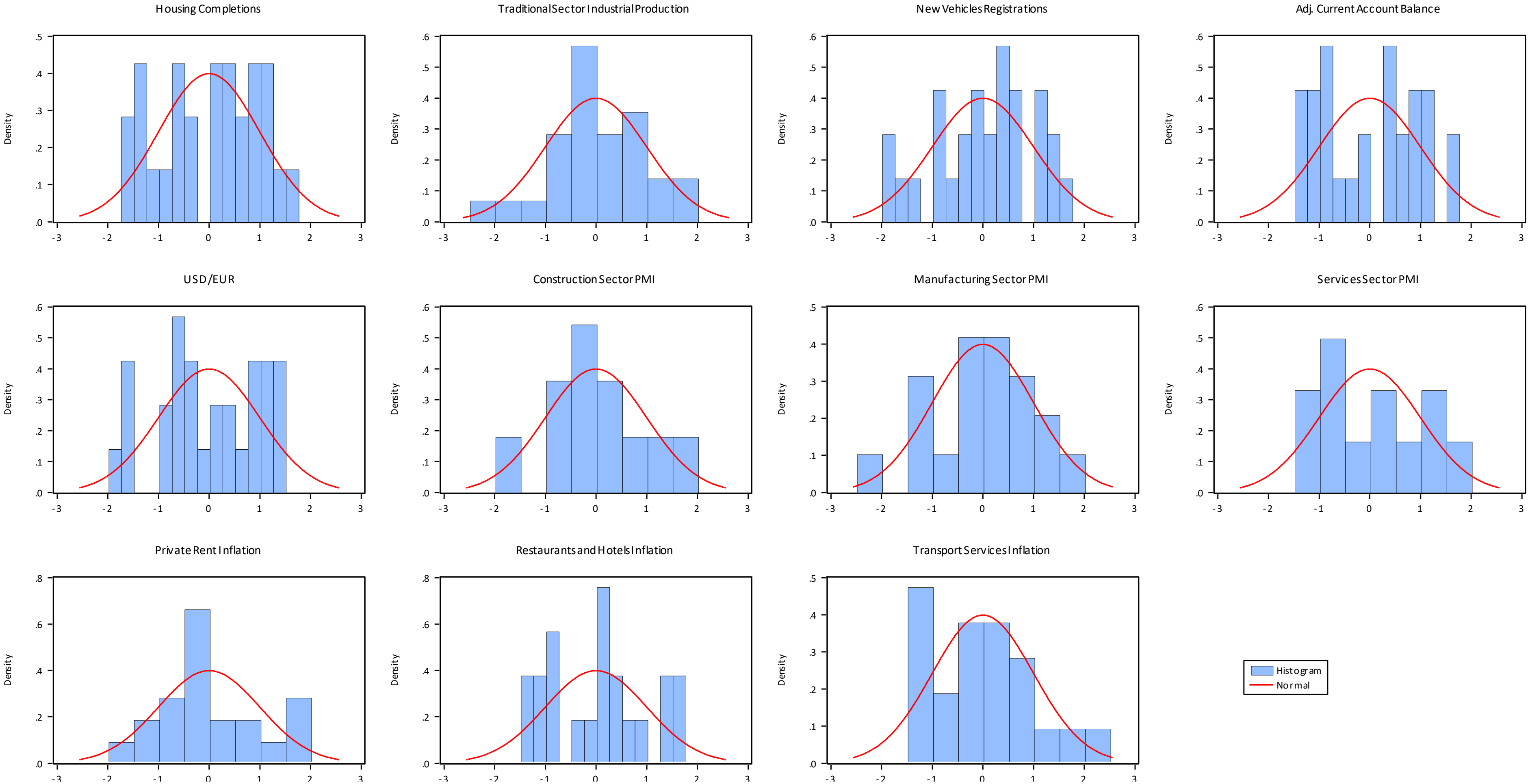
# Appendix A

## Figure A1: Distributions of Cyclical Indicator Series Included

**Variables are standardised over the period Q1 1996 – Q4 2002**




*Sources:* Variable information and sources are detailed in Table 2.

**Figure A2: Distributions of Cyclical Indicator Series Excluded**

Variables are standardised over the period Q1 1996 – Q4 2002

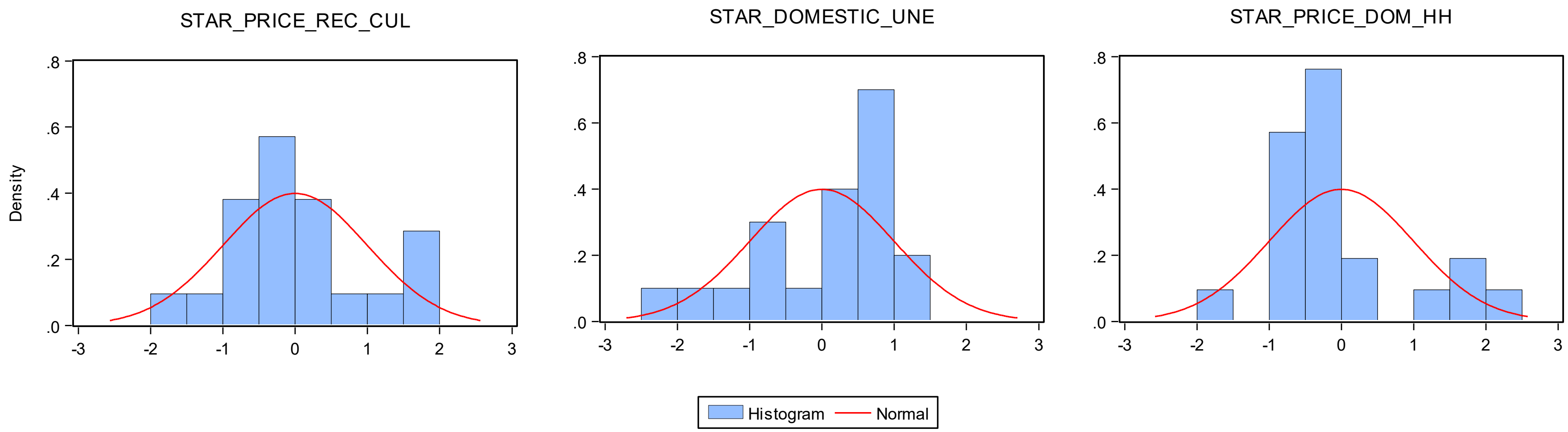
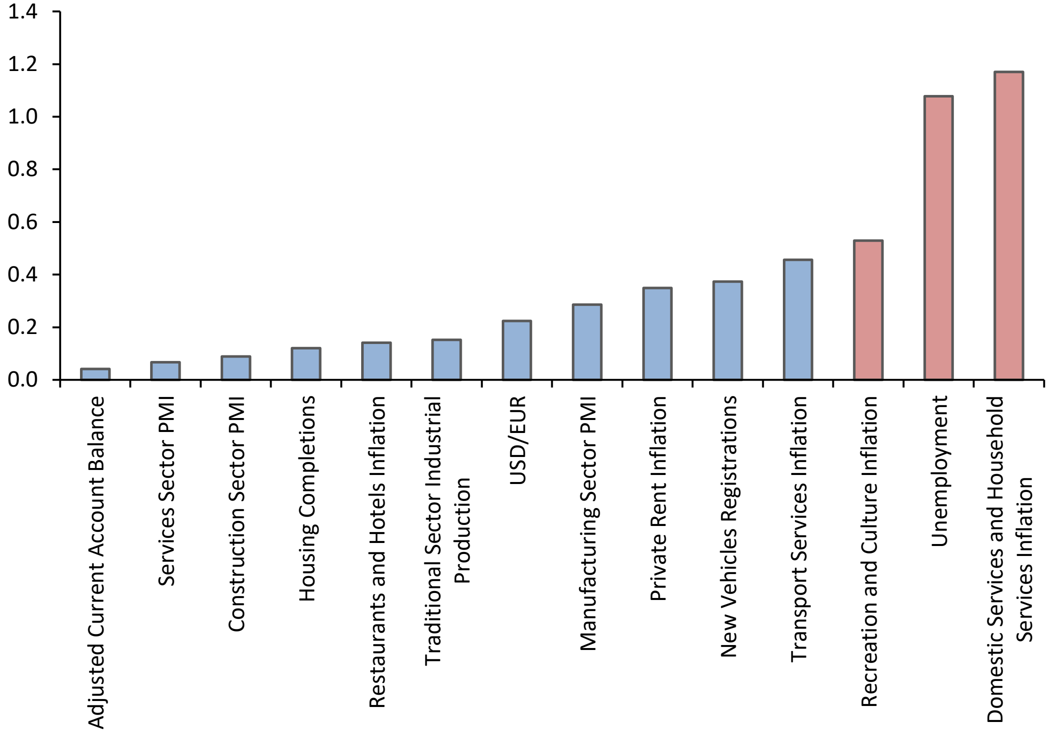


**Figure A3: Skewness of Distributions of All Standardised Variables Considered**

**Skewness measures (absolute values); variables standardised over the period Q1 1996 – Q4 2002**




*Sources:* Own workings. Variables are as detailed in Table 2.

*Note:* Skewness is a measure of asymmetry of the distribution of the series around its mean and is computed as $Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^3$ where where $\hat{\sigma}$ is an estimator for the standard deviation based on the biased estimator for the variance. Variables dropped due to excess skewness are marked in red. The threshold for excess skewness is set at +/- 0.8 in absolute terms. As a robustness check, this threshold was lowered to values of +/- 0.5, and results for the final estimates of the output gap are relatively unchanged.

# Appendix B

**Figure B1: HP Filter of Domestic GVA (λ=6.25)**

Vintages of Output Gap Estimates

Specific Year of Interest (i.e., year Output Gap estimates apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | -0.1 | | | | | | | | | | | | | | | | | | |
| V 2000 | -0.5 | 0.6 | | | | | | | | | | | | | | | | | |
| V 2001 | -0.3 | 1.3 | 0.4 | | | | | | | | | | | | | | | | |
| V 2002 | 0.1 | 2.3 | 2.0 | -2.1 | | | | | | | | | | | | | | | |
| V 2003 | 0.0 | 2.4 | 2.5 | 0.0 | -2.0 | | | | | | | | | | | | | | |
| V 2004 | 0.1 | 2.0 | 1.8 | -0.2 | -0.6 | -0.6 | | | | | | | | | | | | | |
| V 2005 | 0.1 | 2.0 | 1.7 | -0.3 | -0.6 | -0.5 | 0.0 | | | | | | | | | | | | |
| V 2006 | 0.1 | 2.0 | 1.8 | -0.2 | -0.4 | -0.6 | -0.7 | 0.6 | | | | | | | | | | | |
| V 2007 | 0.2 | 2.1 | 1.8 | -0.4 | -0.7 | -0.8 | -0.6 | 0.4 | 0.4 | | | | | | | | | | |
| V 2008 | 0.1 | 2.0 | 1.7 | -0.5 | -0.9 | -0.9 | -0.5 | 1.0 | 2.0 | -1.7 | | | | | | | | | |
| V 2009 | 0.1 | 1.9 | 1.4 | -0.9 | -1.5 | -1.6 | -0.8 | 1.7 | 4.5 | 2.8 | -5.6 | | | | | | | | |
| V 2010 | 0.1 | 1.8 | 1.3 | -1.1 | -1.7 | -1.9 | -1.0 | 1.6 | 4.4 | 3.9 | -2.2 | -3.8 | | | | | | | |
| V 2011 | 0.1 | 1.9 | 1.4 | -1.0 | -1.6 | -1.9 | -1.1 | 1.2 | 3.8 | 3.7 | -1.4 | -2.1 | -1.4 | | | | | | |
| V 2012 | 0.1 | 1.9 | 1.4 | -1.0 | -1.7 | -1.9 | -1.1 | 1.3 | 4.1 | 4.0 | -1.6 | -2.9 | -1.7 | 0.7 | | | | | |
| V 2013 | 0.1 | 1.8 | 1.4 | -1.0 | -1.6 | -1.8 | -1.0 | 1.4 | 4.1 | 4.0 | -1.8 | -3.0 | -2.0 | -1.0 | 1.8 | | | | |
| V 2014 | 0.1 | 1.8 | 1.4 | -1.0 | -1.6 | -1.7 | -0.9 | 1.6 | 4.4 | 4.2 | -1.7 | -2.8 | -2.3 | -2.4 | -0.6 | 3.1 | | | |
| V 2015 | 0.1 | 1.8 | 1.3 | -1.0 | -1.7 | -1.8 | -1.0 | 1.6 | 4.6 | 4.7 | -0.6 | -1.0 | -1.9 | -4.3 | -4.5 | -2.0 | 6.6 | | |
| V 2016 | 0.2 | 2.2 | 1.2 | -1.5 | -2.6 | -1.6 | -0.1 | 2.4 | 5.1 | 4.1 | -1.5 | -1.6 | -1.1 | -2.9 | -3.9 | -3.4 | 1.1 | 4.3 | |
| **MAR** | 0.1 | 0.2 | 0.3 | 0.3 | 0.3 | 0.2 | 0.2 | 0.3 | 0.7 | 0.9 | 1.0 | 0.9 | 0.4 | 1.6 | 2.3 | 3.3 | 5.5 | | 0.5 |
| **Max Revision** | 0.4 | 1.0 | 1.6 | 2.1 | 1.4 | 0.7 | 0.9 | 0.8 | 2.5 | 4.5 | 3.4 | 1.8 | 0.8 | 1.9 | 3.9 | 5.1 | 5.5 | | 5.5 |
| **# Sign Changes** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | | 5 |

*Sources:* Own workings.

*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., "V 2016" refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

**Figure B2: HP Filter of Domestic GVA (λ=100)**

Vintages of Output Gap Estimates

Specific Year of Interest (i.e., year Output Gap estimates apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | 5.7 | | | | | | | | | | | | | | | | | | |
| V 2000 | 3.0 | 5.7 | | | | | | | | | | | | | | | | | |
| V 2001 | 1.2 | 4.5 | 5.1 | | | | | | | | | | | | | | | | |
| V 2002 | 1.3 | 4.5 | 4.5 | 0.3 | | | | | | | | | | | | | | | |
| V 2003 | 1.5 | 4.6 | 4.7 | 1.5 | -1.4 | | | | | | | | | | | | | | |
| V 2004 | 1.3 | 3.9 | 3.8 | 1.3 | 0.2 | -0.5 | | | | | | | | | | | | | |
| V 2005 | 1.3 | 3.9 | 3.8 | 1.2 | 0.4 | -0.2 | -0.2 | | | | | | | | | | | | |
| V 2006 | 1.2 | 3.8 | 3.7 | 1.3 | 0.5 | -0.2 | -0.7 | 0.4 | | | | | | | | | | | |
| V 2007 | 1.2 | 3.6 | 3.3 | 0.7 | -0.2 | -0.6 | -0.5 | 0.6 | 0.8 | | | | | | | | | | |
| V 2008 | 1.1 | 3.6 | 3.4 | 0.9 | 0.1 | -0.2 | 0.0 | 1.3 | 2.0 | -2.4 | | | | | | | | | |
| V 2009 | 0.5 | 3.1 | 3.1 | 0.9 | 0.4 | 0.5 | 1.6 | 3.9 | 5.6 | 1.6 | -9.4 | | | | | | | | |
| V 2010 | 0.0 | 2.6 | 2.7 | 0.7 | 0.5 | 1.0 | 2.6 | 5.5 | 7.6 | 4.7 | -4.8 | -9.9 | | | | | | | |
| V 2011 | -0.2 | 2.3 | 2.4 | 0.3 | 0.2 | 0.7 | 2.3 | 5.4 | 7.9 | 6.2 | -1.6 | -5.3 | -7.6 | | | | | | |
| V 2012 | -0.5 | 2.0 | 2.1 | 0.1 | 0.0 | 0.7 | 2.5 | 5.9 | 8.7 | 7.5 | -0.5 | -4.3 | -5.5 | -5.5 | | | | | |
| V 2013 | -0.5 | 2.0 | 2.1 | 0.0 | -0.1 | 0.6 | 2.4 | 5.6 | 8.5 | 7.2 | -0.6 | -3.7 | -4.2 | -4.2 | -2.2 | | | | |
| V 2014 | -0.4 | 2.2 | 2.2 | 0.2 | 0.1 | 0.7 | 2.4 | 5.6 | 8.3 | 6.8 | -1.2 | -4.2 | -4.8 | -4.9 | -2.5 | 2.5 | | | |
| V 2015 | -0.4 | 2.3 | 2.4 | 0.4 | 0.4 | 1.1 | 2.9 | 6.2 | 9.0 | 7.5 | -0.5 | -3.5 | -6.2 | -8.9 | -7.7 | -2.2 | 10.7 | | |
| V 2016 | 0.3 | 3.1 | 2.6 | 0.2 | -0.2 | 1.8 | 4.3 | 7.4 | 9.4 | 6.0 | -2.7 | -5.7 | -7.1 | -9.2 | -8.7 | -5.1 | 3.8 | 12.0 | |
| **MAR** | 0.4 | 0.3 | 0.3 | 0.3 | 0.4 | 0.3 | 0.6 | 0.8 | 1.0 | 1.6 | 1.8 | 1.6 | 1.3 | 1.6 | 2.2 | 3.8 | 6.9 | | 0.8 |
| **Max Revision** | 2.7 | 1.2 | 0.9 | 1.2 | 1.6 | 0.7 | 1.6 | 2.6 | 3.6 | 4.0 | 4.6 | 4.6 | 2.1 | 4.0 | 5.2 | 4.7 | 6.9 | | 6.9 |
| **# Sign Changes** | 1 | 0 | 0 | 0 | 5 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | | 9 |

*Sources:* Own workings.

*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., "V 2016" refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

## Figure B3: Kalman Filter of Domestic GVA

Vintages of Output Gap Estimates

Specific Year of Interest (i.e., year Output Gap estimates apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | 8.1 | | | | | | | | | | | | | | | | | | |
| V 2000 | 6.2 | 8.6 | | | | | | | | | | | | | | | | | |
| V 2001 | 4.4 | 6.9 | 8.4 | | | | | | | | | | | | | | | | |
| V 2002 | 3.7 | 5.9 | 7.0 | 6.2 | | | | | | | | | | | | | | | |
| V 2003 | 3.4 | 5.5 | 6.4 | 5.9 | 6.0 | | | | | | | | | | | | | | |
| V 2004 | 3.1 | 5.1 | 5.9 | 5.5 | 6.2 | 7.1 | | | | | | | | | | | | | |
| V 2005 | 2.7 | 4.6 | 5.3 | 4.8 | 5.3 | 6.1 | 7.1 | | | | | | | | | | | | |
| V 2006 | 2.4 | 4.2 | 4.7 | 4.2 | 4.6 | 5.1 | 5.7 | 7.3 | | | | | | | | | | | |
| V 2007 | 1.9 | 3.6 | 4.0 | 3.3 | 3.6 | 4.1 | 4.9 | 6.3 | 7.4 | | | | | | | | | | |
| V 2008 | 1.8 | 3.5 | 4.0 | 3.2 | 3.4 | 3.9 | 4.5 | 5.9 | 6.9 | 5.9 | | | | | | | | | |
| V 2009 | 2.0 | 3.7 | 4.2 | 3.5 | 3.8 | 4.3 | 5.1 | 6.7 | 8.1 | 7.0 | 2.5 | | | | | | | | |
| V 2010 | 2.4 | 4.3 | 5.0 | 4.5 | 4.9 | 5.5 | 6.5 | 8.1 | 9.2 | 8.3 | 4.2 | 2.2 | | | | | | | |
| V 2011 | 2.3 | 4.2 | 4.8 | 4.2 | 4.6 | 5.2 | 6.1 | 7.6 | 8.7 | 8.1 | 4.6 | 3.1 | 2.2 | | | | | | |
| V 2012 | 2.3 | 4.1 | 4.7 | 4.1 | 4.5 | 5.0 | 5.9 | 7.4 | 8.6 | 8.0 | 4.2 | 2.3 | 1.6 | 1.6 | | | | | |
| V 2013 | 2.0 | 3.8 | 4.3 | 3.6 | 3.9 | 4.4 | 5.2 | 6.6 | 7.7 | 7.0 | 3.3 | 1.6 | 1.2 | 1.1 | 1.9 | | | | |
| V 2014 | 1.8 | 3.5 | 3.9 | 3.2 | 3.4 | 3.8 | 4.6 | 5.9 | 6.9 | 6.1 | 2.2 | 0.7 | 0.2 | 0.0 | 1.0 | 3.1 | | | |
| V 2015 | 1.8 | 3.5 | 4.0 | 3.2 | 3.4 | 3.8 | 4.6 | 5.9 | 6.8 | 6.0 | 2.0 | 0.4 | -1.0 | -2.4 | -2.0 | 0.3 | 4.8 | | |
| V 2016 | 1.7 | 3.5 | 3.7 | 2.9 | 2.9 | 3.9 | 4.9 | 6.1 | 6.7 | 5.0 | 0.9 | -0.6 | -1.2 | -2.0 | -1.5 | 0.5 | 4.2 | 7.8 | |
| **MAR** | 0.4 | 0.4 | 0.5 | 0.4 | 0.5 | 0.6 | 0.6 | 0.6 | 0.6 | 0.7 | 0.8 | 0.8 | 0.7 | 1.1 | 1.5 | 1.5 | 0.6 | | 4.3 |
| **Max Revision** | 1.9 | 1.7 | 1.4 | 1.0 | 1.1 | 1.2 | 1.4 | 1.4 | 1.2 | 1.3 | 1.7 | 1.0 | 1.2 | 2.4 | 3.0 | 2.8 | 0.6 | | 3.0 |
| **# Sign Changes** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | | 3 |

*Sources:* Own workings.

*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., “V 2016” refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). “MAR” refers to the Mean Absolute Revision from one vintage to the next over all available estimates. “Sign changes” refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

## Figure B4: Kalman Filter of Domestic GVA (with Drift)

### Vintages of Output Gap Estimates

Specific Year of Interest (i.e., year Output Gap estimates apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | 2.7 | | | | | | | | | | | | | | | | | | |
| V 2000 | 1.8 | 2.9 | | | | | | | | | | | | | | | | | |
| V 2001 | 1.1 | 2.3 | 2.8 | | | | | | | | | | | | | | | | |
| V 2002 | 1.2 | 2.3 | 2.6 | 1.6 | | | | | | | | | | | | | | | |
| V 2003 | 1.2 | 2.3 | 2.5 | 1.8 | 1.3 | | | | | | | | | | | | | | |
| V 2004 | 1.0 | 2.1 | 2.2 | 1.6 | 1.6 | 1.6 | | | | | | | | | | | | | |
| V 2005 | 0.9 | 2.0 | 2.1 | 1.4 | 1.4 | 1.4 | 1.5 | | | | | | | | | | | | |
| V 2006 | 0.8 | 1.8 | 1.9 | 1.3 | 1.2 | 1.1 | 1.1 | 1.6 | | | | | | | | | | | |
| V 2007 | 0.7 | 1.6 | 1.7 | 1.0 | 0.9 | 0.9 | 1.0 | 1.4 | 1.6 | | | | | | | | | | |
| V 2008 | 0.8 | 1.7 | 1.8 | 1.2 | 1.0 | 1.0 | 1.2 | 1.7 | 2.0 | 0.7 | | | | | | | | | |
| V 2009 | 0.9 | 2.0 | 2.1 | 1.5 | 1.5 | 1.6 | 2.0 | 2.8 | 3.4 | 2.3 | -1.2 | | | | | | | | |
| V 2010 | 1.1 | 2.2 | 2.5 | 2.0 | 2.1 | 2.3 | 2.7 | 3.6 | 4.1 | 3.2 | 0.2 | -1.5 | | | | | | | |
| V 2011 | 1.1 | 2.2 | 2.5 | 2.0 | 2.0 | 2.3 | 2.7 | 3.5 | 4.0 | 3.4 | 0.8 | -0.5 | -1.4 | | | | | | |
| V 2012 | 1.1 | 2.3 | 2.5 | 2.0 | 2.1 | 2.3 | 2.8 | 3.7 | 4.3 | 3.7 | 1.0 | -0.5 | -1.1 | -1.5 | | | | | |
| V 2013 | 1.1 | 2.1 | 2.4 | 1.8 | 1.9 | 2.1 | 2.5 | 3.4 | 4.0 | 3.4 | 0.8 | -0.5 | -0.9 | -1.3 | -1.2 | | | | |
| V 2014 | 1.0 | 2.0 | 2.2 | 1.6 | 1.7 | 1.8 | 2.3 | 3.1 | 3.7 | 3.1 | 0.4 | -0.8 | -1.2 | -1.6 | -1.3 | -0.3 | | | |
| V 2015 | 1.0 | 2.1 | 2.3 | 1.7 | 1.7 | 1.9 | 2.3 | 3.2 | 3.7 | 3.1 | 0.3 | -0.8 | -1.9 | -3.1 | -3.1 | -2.0 | 1.0 | | |
| V 2016 | 0.9 | 2.1 | 2.1 | 1.4 | 1.3 | 1.9 | 2.5 | 3.1 | 3.4 | 2.2 | -0.7 | -1.8 | -2.4 | -3.2 | -3.3 | -2.3 | 0.1 | 2.0 | |
| **MAR** | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.3 | 0.4 | 0.4 | 0.6 | 0.6 | 0.4 | 0.4 | 0.5 | 0.7 | 1.0 | 0.9 | | 1.4 |
| **Max Revision** | 0.9 | 0.6 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 1.1 | 1.4 | 1.6 | 1.4 | 1.0 | 0.7 | 1.5 | 1.8 | 1.7 | 0.9 | | 1.8 |
| **# Sign Changes** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | | 2 |

*Sources:* Own workings.
*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., "V 2016" refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

### Figure B5: Multivariate Kalman Filter (with Adjusted Current Account Balance)

Vintages of Output Gap Estimates

Specific Year of Interest (i.e., year Output Gap estimates apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | 2.1 | | | | | | | | | | | | | | | | | | |
| V 2000 | 1.6 | 2.5 | | | | | | | | | | | | | | | | | |
| V 2001 | 1.2 | 2.4 | 2.5 | | | | | | | | | | | | | | | | |
| V 2002 | 1.5 | 2.7 | 2.8 | 1.3 | | | | | | | | | | | | | | | |
| V 2003 | 1.5 | 2.7 | 2.7 | 1.5 | 0.6 | | | | | | | | | | | | | | |
| V 2004 | 1.4 | 2.5 | 2.5 | 1.4 | 0.9 | 0.9 | | | | | | | | | | | | | |
| V 2005 | 1.4 | 2.5 | 2.4 | 1.3 | 0.9 | 0.8 | 0.7 | | | | | | | | | | | | |
| V 2006 | 1.3 | 2.4 | 2.3 | 1.2 | 0.8 | 0.6 | 0.3 | 0.6 | | | | | | | | | | | |
| V 2007 | 1.2 | 2.3 | 2.2 | 1.0 | 0.6 | 0.5 | 0.5 | 0.9 | 1.0 | | | | | | | | | | |
| V 2008 | 1.3 | 2.4 | 2.4 | 1.2 | 0.9 | 0.9 | 1.0 | 1.6 | 2.2 | 0.6 | | | | | | | | | |
| V 2009 | 1.8 | 3.1 | 3.0 | 1.7 | 1.3 | 1.7 | 2.2 | 3.4 | 4.8 | 3.8 | -0.8 | | | | | | | | |
| V 2010 | 2.1 | 3.6 | 3.6 | 2.2 | 1.8 | 2.3 | 2.9 | 4.2 | 5.8 | 5.0 | 0.7 | -2.7 | | | | | | | |
| V 2011 | 2.0 | 3.4 | 3.4 | 2.1 | 1.8 | 2.3 | 2.9 | 4.1 | 5.6 | 5.1 | 1.5 | -1.4 | -2.5 | | | | | | |
| V 2012 | 2.2 | 3.7 | 3.7 | 2.2 | 1.9 | 2.4 | 3.1 | 4.4 | 6.1 | 5.6 | 1.6 | -1.7 | -2.7 | -3.4 | | | | | |
| V 2013 | 2.3 | 3.7 | 3.7 | 2.2 | 1.9 | 2.4 | 3.1 | 4.4 | 6.0 | 5.4 | 1.1 | -2.3 | -3.3 | -4.4 | -4.2 | | | | |
| V 2014 | 2.3 | 3.8 | 3.7 | 2.3 | 1.9 | 2.5 | 3.1 | 4.4 | 5.9 | 5.1 | 0.7 | -2.7 | -4.0 | -5.4 | -5.4 | -3.0 | | | |
| V 2015 | 2.7 | 4.4 | 4.3 | 2.7 | 2.2 | 3.0 | 3.7 | 5.2 | 7.0 | 6.2 | 1.2 | -3.0 | -5.1 | -7.6 | -8.0 | -5.1 | 0.8 | | |
| V 2016 | 2.5 | 4.3 | 4.1 | 2.4 | 1.9 | 2.9 | 3.9 | 5.2 | 6.7 | 5.4 | 0.5 | -3.4 | -5.2 | -7.4 | -8.1 | -5.7 | -0.6 | 1.9 | |
| **MAR** | **0.2** | **0.2** | **0.2** | **0.2** | **0.2** | **0.3** | **0.4** | **0.5** | **0.8** | **0.9** | **0.6** | **0.6** | **0.5** | **1.1** | **1.3** | **1.4** | **1.4** | | **1.5** |
| **Max Revision** | 0.5 | 0.7 | 0.6 | 0.5 | 0.5 | 0.8 | 1.2 | 1.8 | 2.6 | 3.2 | 1.5 | 1.3 | 1.1 | 2.2 | 2.6 | 2.1 | 1.4 | | **3.2** |
| **# Sign Changes** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 0 | 0 | 0 | 0 | **1** | | **2** |

*Sources:* Own workings.

*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., "V 2016" refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

**Figure B6: Multivariate Kalman Filter (with House Prices)**

Vintages of Output Gap Estimates

Specific Year of Interest (i.e., year Output Gap estimates apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | 2.2 | | | | | | | | | | | | | | | | | | |
| V 2000 | 1.2 | 2.7 | | | | | | | | | | | | | | | | | |
| V 2001 | 0.0 | 1.6 | 2.8 | | | | | | | | | | | | | | | | |
| V 2002 | 0.2 | 1.8 | 2.7 | 2.1 | | | | | | | | | | | | | | | |
| V 2003 | 0.2 | 1.6 | 2.1 | 1.6 | 1.3 | | | | | | | | | | | | | | |
| V 2004 | 0.0 | 1.4 | 1.9 | 1.6 | 1.6 | 1.5 | | | | | | | | | | | | | |
| V 2005 | 0.1 | 1.3 | 1.7 | 1.1 | 1.0 | 0.7 | 1.0 | | | | | | | | | | | | |
| V 2006 | 0.1 | 1.3 | 1.6 | 0.9 | 0.7 | 0.2 | 0.1 | 1.7 | | | | | | | | | | | |
| V 2007 | 0.1 | 1.2 | 1.4 | 0.7 | 0.3 | -0.1 | -0.2 | 1.1 | 1.2 | | | | | | | | | | |
| V 2008 | 0.5 | 1.6 | 1.7 | 1.0 | 0.8 | 0.6 | 0.6 | 1.5 | 1.8 | 0.9 | | | | | | | | | |
| V 2009 | 1.2 | 2.2 | 2.2 | 1.6 | 1.7 | 2.0 | 2.4 | 2.7 | 3.3 | 1.7 | -2.1 | | | | | | | | |
| V 2010 | 1.3 | 2.3 | 2.6 | 2.1 | 2.2 | 2.5 | 2.9 | 3.6 | 4.0 | 2.9 | -0.3 | -1.8 | | | | | | | |
| V 2011 | 1.1 | 2.2 | 2.4 | 1.9 | 2.0 | 2.2 | 2.6 | 3.5 | 4.0 | 3.5 | 1.0 | -0.4 | -1.3 | | | | | | |
| V 2012 | 1.3 | 2.4 | 2.6 | 2.1 | 2.2 | 2.5 | 3.0 | 3.7 | 4.2 | 3.4 | 0.5 | -0.9 | -1.4 | -1.7 | | | | | |
| V 2013 | 1.2 | 2.2 | 2.5 | 1.9 | 2.0 | 2.2 | 2.7 | 3.4 | 4.0 | 3.2 | 0.4 | -0.8 | -1.1 | -1.4 | -1.2 | | | | |
| V 2014 | 1.2 | 2.2 | 2.4 | 1.9 | 2.0 | 2.3 | 2.7 | 3.3 | 3.6 | 2.6 | -0.3 | -1.4 | -1.7 | -1.9 | -1.7 | -0.5 | | | |
| V 2015 | 1.4 | 2.4 | 2.7 | 2.3 | 2.6 | 3.0 | 3.5 | 3.7 | 3.6 | 2.1 | -1.1 | -2.2 | -2.8 | -3.7 | -4.0 | -2.4 | 0.9 | | |
| V 2016 | 0.9 | 2.1 | 2.1 | 1.4 | 1.3 | 1.9 | 2.5 | 3.1 | 3.4 | 2.2 | -0.7 | -1.8 | -2.4 | -3.2 | -3.3 | -2.3 | 0.1 | 2.0 | |
| **MAR** | **0.3** | **0.3** | **0.3** | **0.3** | **0.5** | **0.6** | **0.6** | **0.5** | **0.4** | **0.5** | **0.8** | **0.6** | **0.5** | **0.8** | **1.2** | **1.0** | **0.8** | | **1.2** |
| **Max Revision** | 1.2 | 1.1 | 0.6 | 0.9 | 1.3 | 1.4 | 1.8 | 1.2 | 1.5 | 1.2 | 1.8 | 1.4 | 1.1 | 1.8 | 2.3 | 1.9 | 0.8 | | **2.3** |
| **Sign Changes** | 0 | 0 | 0 | 0 | 0 | **2** | **2** | 0 | 0 | 0 | **2** | 0 | 0 | 0 | 0 | 0 | 0 | | **6** |

*Sources:* Own workings.

*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., "V 2016" refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

## Figure B7: Cyclical Indicators Estimates

### Vintages of Output Gap Estimates

Specific Year of Interest (i.e., Year Output Gap Estimates Apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | - | | | | | | | | | | | | | | | | | | |
| V 2000 | - | - | | | | | | | | | | | | | | | | | |
| V 2001 | - | - | - | | | | | | | | | | | | | | | | |
| V 2002 | - | - | - | - | | | | | | | | | | | | | | | |
| V 2003 | - | - | - | - | -2.7 | | | | | | | | | | | | | | |
| V 2004 | - | - | - | - | -1.3 | -3.9 | | | | | | | | | | | | | |
| V 2005 | - | - | - | - | 0.0 | -3.2 | -3.7 | | | | | | | | | | | | |
| V 2006 | - | - | - | - | -1.0 | 2.1 | 3.2 | 4.0 | | | | | | | | | | | |
| V 2007 | - | - | - | - | -1.6 | 1.0 | 2.4 | 3.9 | 3.6 | | | | | | | | | | |
| V 2008 | - | - | - | - | 1.9 | -0.1 | -1.8 | -3.2 | -3.5 | -3.2 | | | | | | | | | |
| V 2009 | - | - | - | - | 0.9 | 1.4 | 1.3 | 2.0 | 1.0 | -3.7 | -9.0 | | | | | | | | |
| V 2010 | - | - | - | - | 1.5 | 1.8 | 2.1 | 3.6 | 3.0 | -1.4 | -7.9 | -9.1 | | | | | | | |
| V 2011 | - | - | - | - | 2.2 | 2.5 | 3.0 | 4.7 | 4.2 | 0.1 | -6.5 | -8.7 | -8.8 | | | | | | |
| V 2012 | - | - | - | - | 2.8 | 3.2 | 3.8 | 5.5 | 4.9 | 1.2 | -5.4 | -8.0 | -8.3 | -8.1 | | | | | |
| V 2013 | - | - | - | - | 3.3 | 3.7 | 4.3 | 6.1 | 5.7 | 2.1 | -4.4 | -7.4 | -7.9 | -7.7 | -6.9 | | | | |
| V 2014 | - | - | - | - | 3.6 | 3.9 | 4.7 | 6.6 | 6.3 | 2.9 | -3.4 | -6.8 | -7.5 | -7.3 | -6.8 | -6.0 | | | |
| V 2015 | - | - | - | - | 3.9 | 4.1 | 5.0 | 7.2 | 7.0 | 3.9 | -2.2 | -6.1 | -6.9 | -6.7 | -6.6 | -6.1 | -6.5 | | |
| V 2016 | - | - | - | - | 4.1 | 4.3 | 5.3 | 7.6 | 7.5 | 4.8 | -1.0 | -5.3 | -6.2 | -6.0 | -6.3 | -6.1 | -6.8 | | |
| **MAR** | - | - | - | - | **0.9** | **1.0** | **1.7** | **1.8** | **2.0** | **1.1** | **1.1** | **0.6** | **0.5** | **0.5** | **0.2** | **0.1** | **0.3** | | **1.2** |
| **Max Revision** | - | - | - | - | 3.5 | 5.3 | 6.8 | 7.1 | 7.0 | 2.3 | 1.4 | 0.8 | 0.7 | 0.7 | 0.3 | 0.1 | 0.3 | | **7.1** |
| **Sign Changes** | - | - | - | - | **3** | **3** | **3** | **2** | **2** | **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | **14** |

*Sources:* Own workings.
*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., "V 2016" refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

## Figure B8: CAM Estimates

Vintages of Output Gap Estimates

Specific Year of Interest (i.e., Year Output Gap Estimates Apply to)

Vintage of Data (by initial year)

| | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| V 1999 | - | | | | | | | | | | | | | | | | | | |
| V 2000 | - | - | | | | | | | | | | | | | | | | | |
| V 2001 | - | - | - | | | | | | | | | | | | | | | | |
| V 2002 | - | - | - | 0.8 | | | | | | | | | | | | | | | |
| V 2003 | - | - | - | 5.0 | 0.3 | | | | | | | | | | | | | | |
| V 2004 | - | - | - | 2.9 | 0.2 | -0.8 | | | | | | | | | | | | | |
| V 2005 | - | - | - | 3.1 | 1.4 | 0.1 | -1.6 | | | | | | | | | | | | |
| V 2006 | - | - | - | 3.5 | 1.7 | 0.1 | -0.5 | -1.4 | | | | | | | | | | | |
| V 2007 | - | - | - | 2.7 | 1.1 | -0.4 | -0.4 | -0.5 | -0.7 | | | | | | | | | | |
| V 2008 | - | - | - | 2.5 | 1.3 | 0.5 | 1.3 | 1.7 | 2.9 | -1.4 | | | | | | | | | |
| V 2009 | - | - | - | 3.0 | 1.8 | 1.2 | 2.1 | 2.7 | 4.9 | -0.1 | -7.2 | | | | | | | | |
| V 2010 | - | - | - | 1.2 | -0.3 | -0.8 | 0.5 | 1.7 | 4.3 | -0.1 | -6.4 | -5.2 | | | | | | | |
| V 2011 | - | - | - | 2.2 | 0.8 | 0.3 | 0.8 | 1.8 | 3.7 | -0.3 | -5.8 | -5.0 | -3.1 | | | | | | |
| V 2012 | - | - | - | 2.0 | 0.3 | -0.4 | 0.4 | 1.5 | 3.6 | 0.3 | -4.1 | -4.4 | -2.8 | -1.5 | | | | | |
| V 2013 | - | - | - | 2.0 | 0.3 | -0.4 | 0.4 | 1.5 | 3.6 | 0.3 | -4.1 | -4.4 | -2.8 | -1.5 | -0.5 | | | | |
| V 2014 | - | - | - | 1.7 | -0.3 | -0.2 | 1.2 | 2.8 | 4.7 | 1.0 | -4.6 | -4.1 | -1.3 | -1.8 | -2.6 | -0.2 | | | |
| V 2015 | - | - | - | 2.0 | 0.3 | -0.2 | 1.2 | 2.9 | 4.7 | 0.9 | -4.5 | -4.1 | -2.2 | -3.0 | -3.3 | -1.1 | 1.2 | | |
| V 2016 | - | - | - | 1.4 | -0.5 | 1.0 | 2.0 | 3.8 | 4.6 | -0.7 | -4.5 | -2.1 | -2.2 | -4.0 | -4.7 | -0.1 | 1.4 | 1.7 | |
| **MAR** | - | - | - | **0.9** | **0.7** | **0.7** | **0.7** | **0.8** | **0.9** | **0.6** | **0.5** | **0.5** | **0.5** | **0.6** | **1.4** | **0.9** | **0.1** | | **0.7** |
| **Max Revision** | - | - | - | 4.2 | 2.2 | 2.0 | 1.7 | 2.2 | 3.6 | 1.6 | 1.7 | 2.0 | 1.5 | 1.2 | 2.0 | 1.0 | 0.1 | | **4.2** |
| **Sign Changes** | - | - | - | 0 | **5** | **7** | **1** | **1** | **1** | **2** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | **17** |

*Sources:* Own workings.

*Notes:* Vertical (left) axis gives vintage of data used and is ordered by year for which preliminary data were first available (e.g., “V 2016” refers to the vintage of historical data available as of June 2016). Horizontal (top) axis gives the year of interest (i.e., the year for which we have various estimates of the output gap for, running from top to bottom). “MAR” refers to the Mean Absolute Revision from one vintage to the next over all available estimates. “Sign changes” refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

## Appendix C: Illustrative GDP-Based Output Gap Estimates

### Table C1: Revisions to GDP-based Kalman Filter Output Gap Estimates

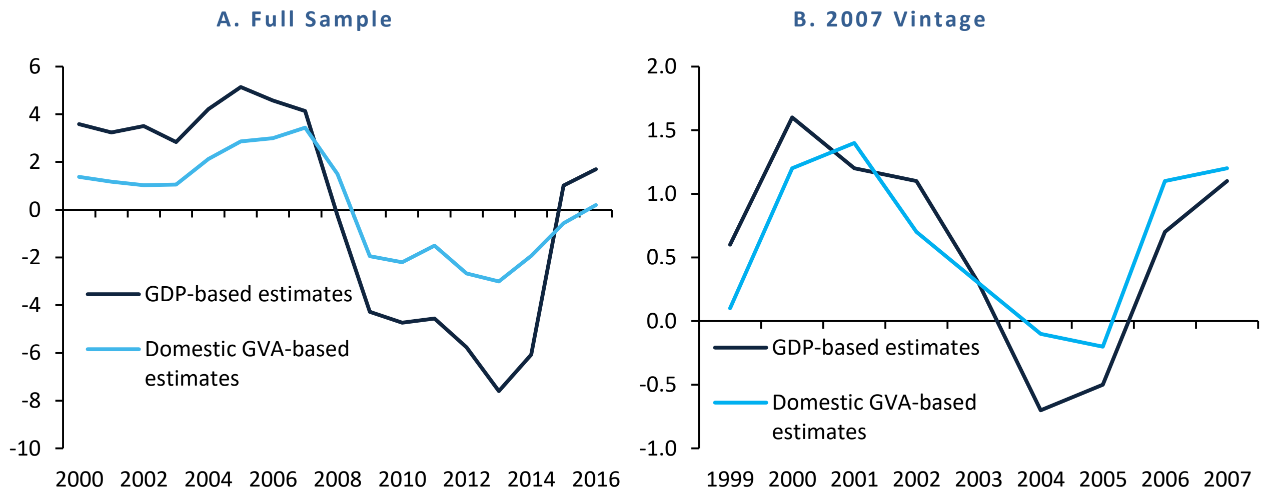
Full Sample (1999-2015)

| | | Full Sample (1999-2015) | Recent Sample (2010-2015) |
|---|---|---|---|
| Year-to-Year Revisions | MAR | 0.9 | 1.4 |
| | Max Revision | 4.3 | 4.3 |
| | Sign Changes | 6 | 0 |
| Initial – Final Revision | MAR | 1.6 | 1.6 |
| | Max Revision | 3.0 | 3.0 |
| | Sign Changes | 1 | 0 |

*Sources:* Own workings.
*Note:* "MAR" refers to the Mean Absolute Revision from one vintage to the next over all available estimates. "Sign changes" refer to a simple count of the number of changes of the sign on the output gap from one year to the next (i.e., from positive to negative or vice versa).

### Figure C1: Kalman Filter estimates with drift term and adjusted current account balance

% of potential




*Sources:* Own workings.

### Table C2: GDP-based Kalman Filter Output Gap Estimates (incorporating a drift term and the adjusted current account balance) and Inflation measures

(Samples: 1990–2016; 2000–2016 for wage inflation)

| Dependent variable: | CPI | Core CPI | Wages | CPI[1] | Core CPI[1] |
|---|---|---|---|---|---|
| $\pi_{t-1}$ | 0.68*** (0.13) | 0.72*** (0.12) | 0.78*** (0.11) | | |
| $\pi^{exp}_{t+1}$ | | | | 1.22*** (0.07) | 1.20*** (0.06) |
| Output Gap | 0.16 (0.11) | 0.15 (0.10) | 0.18 (0.13) | 0.16*** (0.05) | 0.13*** (0.04) |
| Observations | 27 | 27 | 17 | 26 | 26 |
| R-squared | 0.14 | 0.23 | 0.62 | 0.85 | 0.89 |
| RMSE | | | | | |

*Sources*: CSO; own workings.
*Notes*: Robust standard errors in parentheses (*** p<0.01; **p<0.05; *p<0.1).
[1] The second set of CPI and Core CPI measures refers to the specification which includes inflation expectations and inflation targeting.