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Measuring Output Gap: Is It Worth Your Time?

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Measuring Output Gap: Is It Worth Your Time?

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Abstract

We apply a range of models to the U.K. data to obtain estimates of the output gap. A structural VAR with an appropriate identification strategy provides improved estimates of output gap with better real time properties and lower sensitivity to temporary shocks than the usual filtering techniques. It also produces smaller out-of-sample forecast errors for inflation. At the same time, however, our results suggest caution in basing policy decisions on output gap estimates.

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I. INTRODUCTION

The output gap—a deviation of an economy's output from its "potential" level[2]—is a very important concept in macroeconomics. It reflects the position of the economy in the business cycle: a negative output gap indicates a recession or an initial stage of a recovery, while a positive output gap signals a period of economic overheating. The size of the output gap is of particular interest to policymakers. For example, a government's fiscal policy stance is usually assessed in terms of a "structural budget balance", which adjusts the headline balance for the position of the economy in the business cycle. The relationship between the output gap, inflation, and inflation expectations, i.e., the "Phillips Curve", is the foundation of modern monetary policy. Yet, the output gap is not directly observed, because it is a function of potential output, a latent variable itself. As a result, economists and policymakers have to rely on estimates of the output gap.

A commonly shared view is that only supply shocks affect potential output. Thus, one way of estimating the output gap is through a proper identification and aggregation of such shocks in order to obtain a measure of potential output. Examples of this approach are structural vector autoregression models (SVARs) in the spirit of Blanchard and Quah (1989) and Galí (1999), which use long-term restrictions to identify shocks with a permanent effect on output.[3] So far, however, structural models have not gained much popularity for the purpose of output gap estimation. One reason could be that many of these models—often developed with other objectives in mind—are not sophisticated enough. In general, good performance of SVARs in output gap estimation depends on proper identification of supply shocks. In the context of small open economies, this implies not only distinguishing between different domestic shocks, but also considering global factors. Thus, proper shock identification might require expanding considerably the dimension of the SVAR and imposing additional identification restrictions.

Most practitioners have relied on more a-theoretical approaches instead. The so-called filtering methods typically identify potential output by fitting real GDP series to a slow-moving trend.[4] Sometimes variables other than actual output are also included to improve the identification of potential output: these additional variables are informative as long as movements in potential output affect them differently than the cyclical movements in output.

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[2] The concept of potential output (and hence the output gap) can be defined in different ways. From a purely statistical perspective, potential output would be associated with the trend or smooth component of the actual output. From an economic point of view, potential output is often seen as characterizing the sustainable (i.e., consistent with stable inflation) aggregate supply capabilities of the economy. Potential output could also be defined as the level of output attainable when making full use of factors of production.

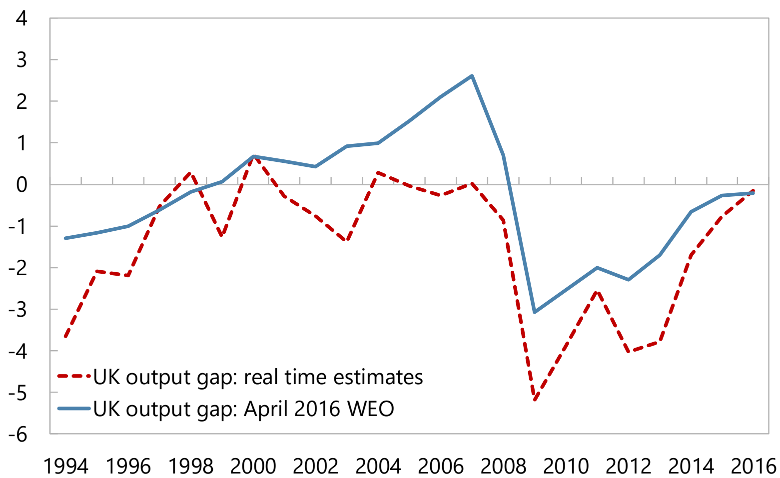
[3] By identifying the shocks with permanent impact on output as supply shocks, one can reconstruct the potential output based on the time series of these shocks. However, Blanchard (2018) notes that there may be supply shocks that do not have a permanent effect on output.

[4] Filtering methods are used e.g., by the Federal Reserve Bank, the International Monetary Fund (IMF), and the Organization for Economic Co-operation and Development (OECD): see Coibion et al. (2018) for details.

For example, motivated by their relationship with the output gap through the Phillips Curve and the Okun's Law, inflation and unemployment are used in Blagrave et al. (2015).

It follows that, to the extent that the output gap is used to assess a country's fiscal stance or to inform monetary policy decisions, biases in the estimates of the output gap could potentially contribute to policy mistakes (Orphanides 2001, 2003). In fact, poor quality of output gap estimates has been well documented for several institutions. For example, Nelson and Nikolov (2003) find that errors in real-time estimates of the output gap have likely contributed to monetary policy mistakes in the U.K. in the 1970s. In their second fiscal risks report, the Office for Budget Responsibility (2019) highlights output gap mismeasurement as a fiscal risk.[5] For the IMF, Kangur et al. (2019) show that real-time output gap estimates exhibit large and negative biases (Figure 1) and are not useful to predict inflation.

Figure 1. World Economic Outlook Estimates of U.K. Output Gap
(In percent of potential output)



Sources: WEO Database.

We contribute to the literature by comparing properties of output gap estimates obtained using different methods, including a two-variable Blanchard and Quah (1989) SVAR and a range of filtering techniques. We also propose a new method based on a SVAR with a mix of short-, long-term-, and sign restrictions, which we think is suitable for identifying permanent shocks in a small open economy. The SVAR draws on Forbes' et al.'s (2018) identification strategy, which distinguishes between *domestic* and *global* demand and supply shocks. Similar to Blanchard and Quah (1989)—Blanchard-Quah hereafter—we identify permanent shocks as those that have long-term effects on output, and assume these shocks drive the potential output, but in our case these shocks can have both domestic and global origins. In general, there are several channels through which a global supply shock might affect the

[5] For instance, initial (real-time) estimates by the HM Treasury in the U.K., IMF and OECD all pointed to an output gap of close to zero just before the 2008 recession, while the average of the latest estimates for the same period is much higher (around 2½ percent). This suggests a downward revision in the estimated size of the structural deficit in that year of around 1.2 percent of nominal GDP.

domestic production frontier. For example, a positive technological shock originating abroad could reduce the costs of imports for the local consumers and producers, as well as raise productivity of the latter. A discovery of new oil and gas reserves would have a similar effect.

We apply the open economy SVAR to the U.K. data, and compare the resulting output gap estimates to those obtained using alternative methods. The open economy SVAR performs better than its comparators along three relevant dimensions. First, it provides output gap series that are less sensitive to (externally estimated) transitory shocks (such as a monetary policy shock). Second, its real-time output gap estimates are associated with smaller ex-post revisions (once new data is added to the end of the sample). Third, it appears to have a stronger predictive power for inflation. Nevertheless, there are limits to this methodology too. For instance, as pointed out in Blanchard (2018), assuming that all supply shocks have permanent effects on output might not be correct. Secondly, even if expanded considerably, the number of shocks and the range of economic dynamics an SVAR can reflect, is limited. Thus, policymakers should look a range of output gap estimates and use their best judgement to assess the cyclical position of the economy.

The rest of the paper is organized as follows. Section II presents a range of methods frequently applied for output gap estimation. Section III introduces the small open economy SVAR and discusses the estimation strategy. In Section IV we compare performance of output gap estimates obtained through methods described in Sections II–III. Section V concludes.

II. Overview of Models For Output Gap Estimation

In this section, we briefly discuss the approach to potential output identification in three types of filtering methods, and in the Blanchard-Quah SVAR. In Section IV we apply these four approaches to estimate output gap series for the U.K., and to compare their performance to the open-economy SVAR presented in Section III.

Hodrick-Prescott (HP) filter. The simplest of the filtering methods identifies potential output by fitting a "smooth" trend $\tau_{t=1}^{T}$ into the actual output series $y_{t=1}^{T}$:

$$\min_{\tau}\left(\sum_{t=1}^{T}(y_t-\tau_t)^2+\lambda\sum_{t=2}^{T-1}[(\tau_{t+1}-\tau_t-(\tau_t-\tau_{t-1})]^2\right)$$

The larger the value of the smoothing parameter λ, the higher is the penalty for variations in the growth rate of the trend component.[6] The key advantage of the HP filter is that it is a simple, transparent method that can be applied to any country where GDP data exist. A

[6] Hodrick and Prescott (1997) suggest a value of λ=1,600 for quarterly data. Ravn and Uhlig (2002) argue instead that λ should vary by the fourth power of the frequency observation ratio, and thus should equal 6.25 for annual and 129,600 for monthly frequency, respectively.

straightforward generalization of the HP filter is the so-called production function approach, where output is typically decomposed (based on an assumed production function) into, for example labor, capital and total factor productivity. The individual components are then separately filtered using different values of the smoothing parameter and the resulting individual trend series are combined to obtain an estimate of potential output.[7]

By construction, the filtering techniques do not distinguish between different types of shocks. For instance, a series of positive demand shocks will increase the trend-based estimate of potential output in a similar way to a one-time positive productivity shock of a comparable magnitude. Coibion et al. (2018) document this fact by showing that potential output estimates made by the U.S. public institutions and by leading international organizations—largely based on filtering methods—respond to both supply and demand shocks.

Another drawback of using filtering methods (for policymaking purposes) in real time is the end-of-sample problem. The statistical approach that is the basis for filtering methods assumes that the average deviation of actual output from its potential level should be zero over the sample period. Thus, when the latest datapoint shows a weakening in GDP, the filter automatically adjusts potential output estimates in the earlier periods downwards—identifying them as times of above-potential output. The downward correction of the past potential output estimates leads to a decline of the estimated output gap in the current period. As Krugman (1998) puts it, the filter-based methods exclude the possibility of protracted recessions. Orphanides and van Norden (2002) and Marcellino and Musso (2011) show that the end-of-sample problem explains a large part of the ex-post revisions of the output gap estimates for the U.S. and for the Eurozone, respectively. Both papers also conclude that multivariate methods making use of additional information from inflation, unemployment, and other variables—described in the next paragraph—do not perform significantly better than simpler univariate models.[8]

Multivariate Kalman (MVK) filter. Multivariate filtering techniques are a generalization of the HP (univariate) filter. In the multivariate filters, variables other than GDP are often included—based on relationships established by economic theory—to improve identification of potential output: Additional variables are informative if movements in potential output affect them differently than the cyclical movements in actual output. At the same time, however, it has to be acknowledged that significance of economic relationship could change over time.

In practice, the Phillips curve and the Okun's law are most frequently used to augment a univariate filter of GDP series:

[7] See also Hamilton (2018) for a detailed discussion of statistical properties of the HP filter.

[8] Additionally, the HP filter has an I(2) component, which can give rise to spurious cycles, whereas most macroeconomic series, such as growth, are generally found to be I(1), see Harvey and Jaeger (1993).

$$\hat{y}_t = y_t - \bar{y}_t,$$

$$\pi_t = \lambda\pi_{t+1} + (1-\lambda)\pi_{t-1} + \beta\hat{y}_t + \varepsilon_t^{\pi},$$

$$\hat{u}_t = \tau_1\hat{u}_{t-1} + \tau_2\hat{y}_t + \varepsilon_t^{u},$$

$$\hat{u}_t = u_t - \bar{u}_t,$$

where y_t, $\bar{y}_t$, and $\hat{y}_t$ denote actual output, potential output, and output gap, respectively; π_t is the inflation rate, and $u_t, \bar{u}_t, \hat{u}_t$ stand for actual unemployment rate, natural unemployment rate, and the difference between the two.[9]

Multivariate Kalman filter with financial variables (MVKfin). In the aftermath of the global financial crisis (GFC) a new strand of literature started looking at the impact of financial variables on the business cycle and on potential growth. Borio et al. (2017) argued that financial imbalances can explain periods of large output gaps but muted inflationary pressures, and that incorporating financial factors into the models of potential output can increase the accuracy of estimates. Borio et al. (2017) augmented a univariate Kalman filter of GDP series with a range of financial variables aimed to capture financial imbalances[10]:

$$\hat{y}_t = \alpha\hat{y}_{t-1} + \gamma_1 r_t + \gamma_2\Delta cr_t + \gamma_3\Delta hp_t,$$

where r_t is the real interest rate, Δcr_t is real credit growth, and Δhp_t is real house price growth.

Blanchard-Quah structural VAR (BQ SVAR). Coibion et al. (2018) argue that structural models, such as the SVARs of Blanchard-Quah, and Gali (1999) produce output gap estimates that outperform filtering techniques in at least some of the desirable properties, such as not responding to the demand shocks.

The underlying idea of the SVAR approach is to estimate supply shocks using identification restrictions and to reconstruct potential output based on these shocks. The SVAR specification, as initially proposed by Blanchard-Quah, consists of GDP growth (Δy_t) and unemployment rate (u_t):

$$\begin{bmatrix} 1 & B_{0,12} \\ B_{0,21} & 1 \end{bmatrix}\begin{bmatrix} \Delta y_t \\ u_t \end{bmatrix} = \begin{bmatrix} A_{0,1} \\ A_{0,2} \end{bmatrix} + \begin{bmatrix} B_{1,11} & B_{1,12} \\ B_{1,21} & B_{1,22} \end{bmatrix}\begin{bmatrix} \Delta y_{t-1} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} B_{2,11} & B_{2,12} \\ B_{2,21} & B_{2,22} \end{bmatrix}\begin{bmatrix} \Delta y_{t-2} \\ u_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^d \end{bmatrix},$$

where A_0 is a vector of constants, and B_j is a *2x2* matrix of coefficients for lags *j=0,1,2.*[11] The structural shocks ε_t^s and ε_t^d are assumed to be uncorrelated, and only the former can have

[9] See Appendix for a full specification of the MVK filter applied to the U.K. data.

[10] See Appendix for a full specification of the MVKfin filter used in this paper.

[11] Blanchard-Quah consider a SVAR with 2 lags.

permanent effects on GDP. This is achieved through a zero restriction on the long-term response of output to (demand) shocks ε_t^d. Potential output path is backed out from the historical decomposition of shocks: it is equal to the sum of the supply shocks over time, i.e., $\bar{y}_t = y_0 + \sum_{i=1}^{t} \varepsilon_{t-i}^s$, where y_0 is the log of real GDP in the initial period.

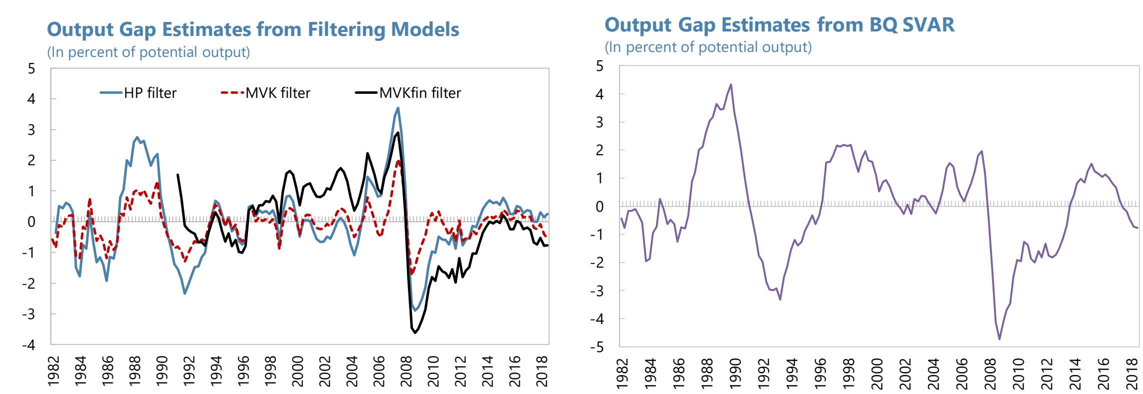
As already mentioned, so far SVARs have not been frequently used to estimate the output gap. One reason could be that they are not sophisticated enough for the purpose. In particular, the benchmark Blanchard-Quah is a highly restrictive model that only allows two types of shocks. Especially in the context of small open economies, this is likely insufficient to properly identify all shocks that affect the economy in distinct ways.

Estimating output gap for the U.K. Figure 2 presents estimates of the U.K. output gap obtained using the four methods described in this section: three filtering techniques and the BQ SVAR. For the HP filter, a smoothing parameter of λ=1,600 was used. Specification and estimation details for the MVK, MVKfin and the BQ SVAR are described in the Appendix.

Although often different in levels, output gap series from the filtering methods present very similar dynamics over time, with a sharp decline during the GFC, and closing of a negative output gap around 2013–2014 (2010–2011 for the MVK). Looking at the years in the run-up to the GFC, for which there is strong consensus that the U.K. economy was operating above its potential, the simple HP filter points to a positive output gap starting already in 2005, while the MVK filter–starting in mid-2006. Instead, the MVKfin filter suggests that the U.K. economy was operating above potential uninterrupted since the late 1990s.

Output gap series estimated using the BQ SVAR show similar dynamics, with the pre-crisis output gap turning positive (but somewhat smaller in absolute terms compared to the filtering techniques) around mid-2006, followed by a return of output to its potential level by 2014, positive output gaps between 2014–2017, and a negative output gap most recently.

Figure 2. Output Gap Estimates for the U.K. (1982–2019)



Source: Haver Analytics, authors' calculations.

Source: Haver Analytics, authors' calculations.

Notes: Figure 2 presents output gap estimates from the four models presented in Section II. The HP filter, BQ SVAR, and MVK filter models were estimated on the sample 1982: Q1–2019: Q1. The MVKfin model was estimated on a shorter sample, 1991: Q1–2019: Q1, due to unavailability of data on credit to private sector for earlier years.

Overall, three out of four methods suggest that U.K. output returned back to its potential level relatively quickly after the GFC: the MVK filter shows a positive output gap briefly around 2010, while the output gaps obtained using the HP filter and the BQ SVAR turn positive around 2014. This is somewhat at odds with the common perception of a prolonged period of output operating below its potential after the GFC—and we will return to this issue in the later sections.

III. SMALL OPEN ECONOMY SVAR

Next, we consider a "small open economy" SVAR. The purpose is to investigate whether a sufficiently rich and properly identified SVAR can overcome the limitations of the benchmark BQ SVAR and yield output gap estimates with better properties. Crucially, in our small open economy SVAR we allow both *domestic* and *global* shocks to have permanent effects on output. Examples of persistent global shocks that can affect domestic potential output include a positive technology shock that reduces costs of imports for local consumers and producers, and raises productivity of the latter; as well as a discovery of new oil and gas reserves abroad. Separately, with mobile capital, changes in relative factor prices abroad can change relative factor intensity, and so production in the domestic economy.

The SVAR we consider includes six variables: U.K. real GDP growth, U.K. CPI inflation at constant tax, the U.K. shadow interest rate, changes in the Sterling exchange rate index, U.K. import price inflation, and changes in foreign export prices (see Appendix Table A.1 for data sources and a description of variables). Following Forbes et al. (2018), the six structural shocks are identified via a combination of zero short-run and long-run restrictions, as well as sign restrictions (Table 1):

- Only domestic supply shocks and persistent global shocks are assumed to affect the level of output in the long run. Persistent global shocks incorporate any foreign shocks with a lasting effect on U.K. output, as well as any (foreign or domestic) demand shocks with a permanent impact on U.K. output (e.g., related to secular stagnation).[12]

- Global shocks are distinguished from domestic shocks by assuming that domestic developments do not affect world export prices neither on impact nor in the long run. On the other hand, global shocks may impact both world export prices and the U.K. economy.

[12] Blanchard et al. (2015) find that recessions triggered by demand shocks are frequently followed by lower output or even lower output growth and can thus have permanent effects. In our identification approach we allow global shocks to have a permanent effect on global output, but do not impose it. As a result, domestic demand shocks with a permanent effect on domestic output are nested in this specification. Separately, as a robustness check we also run a SVAR where we include zero restrictions only (i.e., we do not impose sign restrictions). There, the domestic permanent shock can reflect both domestic supply shocks and domestic demand shocks with permanent impact on domestic output (see Section IV.A for details).

- In addition, we impose several sign restrictions widely applied in the literature (Fry and Pagan, 2011). For example, the domestic supply shock is associated with a negative correlation between GDP and CPI in the first 2 periods. This assumption ensures that the domestic shocks we identify as leading to long-lasting changes in output are in fact supply-driven. Furthermore, we impose a positive correlation between a domestic demand shock and i) GDP, ii) CPI, and iii) exchange rate (i.e., a positive demand shock leads to appreciation of the domestic exchange rate). Monetary policy shocks are identified such that a lower interest rate is associated with a rise in GDP and CPI, and depreciation of the nominal exchange rate. It is also assumed that an exogenous exchange rate appreciation implies a fall in CPI.

The model includes two lags of each variable[13] (following Forbes et al. 2018) and is estimated over 1982: Q1 to 2019: Q1 using Bayesian methods with Minnesota-style priors, as in Binning (2013). The standard errors, percentiles and confidence intervals reported are based on a Gibbs sample procedure, from which we save and use the final 1000 repetitions.

Table 1. Identification Restrictions

	UK supply shock	UK demand shock	UK monetary policy shock	Exo. Ex rate shock	Persistent global shock	Transitory global shock
			Short-run restrictions			
UK GDP growth	+	+	-			
UK CPI	-	+	-	-		
UK interest rate		+	+	-		
UK nominal ERI		+	+	+		
UK import prices						
World (ex-UK) prices	0	0	0	0	+	+
			Long-run restrictions			
UK GDP growth		0	0	0		0
UK CPI						
UK interest rate						
UK nominal ERI						
UK import prices						
World (ex-UK) prices	0	0	0	0		

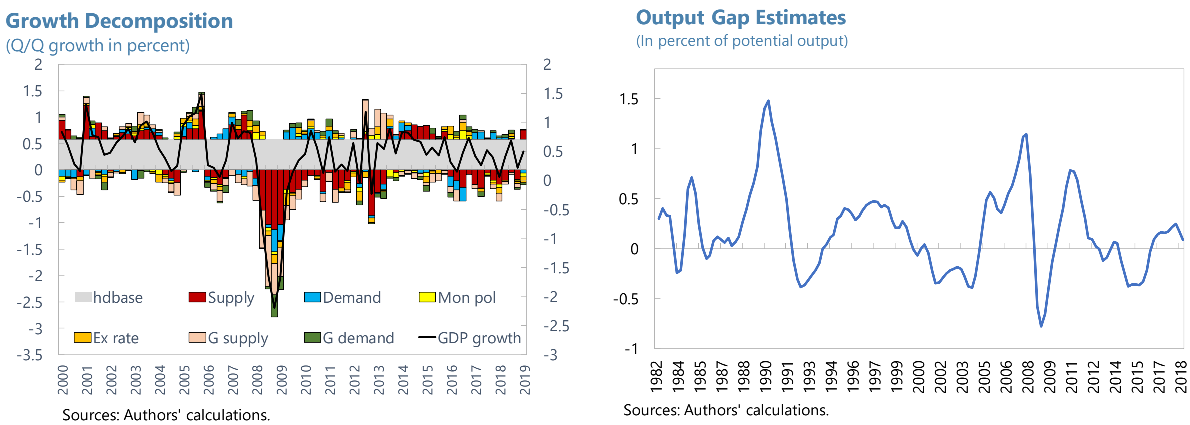
Note: A '+' ('-') sign indicates that the impulse response of the varible in equation is restricted to be positive (negative) in the quarter the shock considered hits and in the following quarter. A '0' denotes that the response of the varaible in question is restrcited to be zero (either on impact or in the long run)

Figure A.1 in the Appendix presents impulse responses to each type of shock. The results are broadly consistent with the literature. A loosening of monetary policy by 100 basis points causes output to fall by about 0.5 percent, consistent with Burgess et al. (2013). An exchange rate shock that leads to sterling appreciation of 1 percent causes import prices to fall by 0.5 percent, in line with findings in Forbes et al. (2018). Moreover, a positive domestic supply shock causes output to increase permanently, while a positive demand shock leads only to a temporary improvement in output. Finally, the price level falls following a positive domestic supply shock. These properties of the impulse responses of domestic variables to domestic supply and demand shocks broadly carry over to persistent and temporary global shocks, respectively.

[13] The estimated output gap remains similar if more lags are used. Results for estimated output gaps with 4, 6 or 8 lags are available upon request.

Figure 3 plots the historical decomposition of GDP growth. It shows that domestic *and* global supply shocks have been key drivers of the sharp decline in growth during the GFC, and that the U.K. economy has been hit with a series of negative domestic supply shocks after the Brexit referendum. Figure 3 also shows time series of the U.K. output gap derived using potential output estimates from the small open economy SVAR. The latter is calculated by accumulating past domestic supply and persistent global shocks. The estimates suggest that the U.K. economy experienced two periods of considerable overheating—in the late 1980s and prior to the GFC—both followed by strong declines in growth.

Figure 3. Small Open Economy SVAR for the U.K.



Notes: Figure 3 presents GDP growth decomposition and output gap estimates from the small open economy SVAR described in Section III.

Interestingly, after 2010 the output gap estimated based on the open economy SVAR displays dynamics somewhat similar to the simple BQ SVAR and the MVK filter. In particular, between 2010: Q2–2012: Q4 the open economy SVAR suggests that the output gap became positive in 2010: Q2, peaked in 2011: Q2, and turned negative in 2013: Q2. The multivariate Kalman filter estimates also suggest output gap turned positive in 2010: Q2, although by less. However, the open economy SVAR indicates a negative output gap between 2014: Q3–2016: Q3, while other methods suggest closed or positive output gaps during the same period. Also, all other methods suggest the output gap to be turning negative after the Brexit referendum in 2016: Q3, but the open economy SVAR points to a moderately positive output gap until only very recently.

What were the macroeconomic conditions like in these two episodes? In between 2010: Q2–2012: Q4, headline growth rebounded strongly from an average of minus 4 percent year-on-year per quarter in 2009 to an average of 2 percent between 2010: Q2 and 2011: Q4. Afterwards, the economy slowed. At the same time, domestic inflation (measured by core services inflation) and wage growth have both accelerated compared to the growth rates in the previous four quarters. While all these indicators point towards a positive output gap in 2010: Q2–2012: Q4, unemployment remained stubbornly high throughout the period, at around 8 percent. Between 2014: Q4–2016: Q3 growth accelerated, reaching an average rate of 2.8 percent. Unemployment declined, and wage growth picked up further. Yet, core services inflation as well as GDP deflator decelerated, which suggests the U.K. economy was experiencing a series of positive supply shocks.

Which method should we believe when assessing the position of the U.K. economy on the business cycle after the GFC? Instead of focusing on the level of the output gap estimates, we next look at the change in the different output gap measures. Intuitively, we expect a positive change in output gap should be associated with an acceleration in inflation or wage growth. As illustrated in Table 2 below, the MVK filter, the BQ SVAR and the open economy SVAR all suggest output gap declined between 2011: Q2–2013: Q3. This is consistent with falling core services inflation and wage growth, but inconsistent with accelerating GDP deflator. Over the period of 2014: Q3–2015: Q3, the three indicators of price pressures change in different directions, making it difficult to infer about output gap dynamics. However, all three inflation indicators suggest an improving output gap between 2016: Q2 and 2018: Q2, which is consistent only with the open economy SVAR.

Overall, none of the methods considered gives an output gap estimate that is consistent with all the post-GFC price dynamics. At the same time, the open economy VAR seems to perform marginally better. In the next section we turn to more formal tests to assess the performance of the output gap measures.

Table 2. Changes in Output Gaps and Inflation
(In percentage points)

Changes in (ppt)	2011Q2-2013Q3	2014Q3-2015Q3	2016Q2-2018Q3
GDP deflator	0.59	-1.36	1.84
Core services inflation	-0.34	-0.09	0.18
Wage growth	-0.95	1.37	1.07
Changes in estimated output gaps			
HP filter	+	unchanged	-
MVK	-	unchanged	-
MVKfin	+	unchanged	-
BQ SVAR	-	unchanged	-
Small open economy SVAR	-	-	+

Source: IMF staff calculations.

IV. Alternative Output Gap Estimates: Which One To Choose?

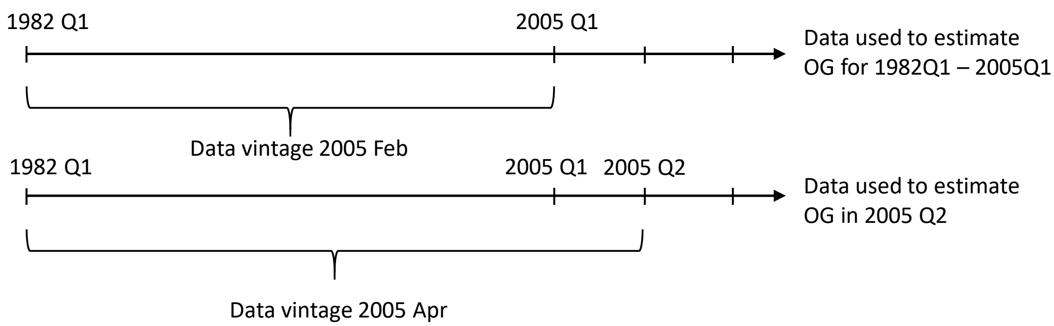
In the last two sections we presented five alternative methods for constructing output gap estimates. In this section we compare their performance using three tests. First, we test the real-time properties of the output gap estimates. Secondly, following Coibion et al (2018), we check how real-time potential output estimates from the five models respond to supply versus demand shocks. Finally, we test which of the five output gaps performs better in forecasting inflation.

A. Real-time Performance

Following Orphanides and van Norden (2002) we check how output gap estimates derived using different methods perform using real-time data. That is, for a given year and quarter in our sample, we estimate each of the five models using only the data available as of that point in time.[14] As seen in Figure 1, ex-post revisions of output gap estimates can be considerable. A desirable feature of an output gap model would be to have minimal ex-post revisions to real-time estimates.

In our exercise, we use Bank of England's "GDP Real Time Database", which contains monthly vintages of key macroeconomic variables published since January 1990 until August 2016 (as of time of writing this paper). Each vintage shows data available on the last working day of that month. We use the real-time GDP series, and—for the small open economy SVAR—also the real-time import price deflator series.

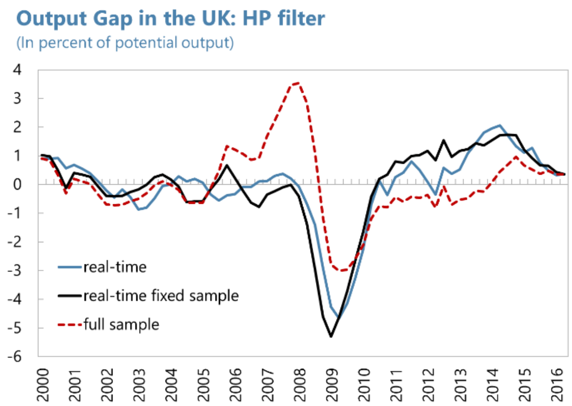
We estimate the real-time output gap series through an iterative procedure. That is, for each quarter between 2005: Q1 and 2016: Q2 we run a separate regression, using only the data from 1982: Q1 up until the given year and quarter, while replacing the GDP series (and the import price deflator) with the real-time GDP (and the import price deflator) series from the Bank of England's database available in the middle month of that quarter. The first iteration is based on data from 1982: Q1 to 2005: Q1 (in order to have sufficiently many observations in regressions).



Figures 4–5 plot, for each of the models described in Sections II-III, the real-time output gap estimates against the output gap series obtained based on the full sample. Given that our real-time estimates start in 2005 only, we focus on the performance of the five models in predicting positive output gaps before the GFC. As seen in Figure 4, the three filtering-based methods fail to signal, in real time, an overheating of the U.K. economy in that period.

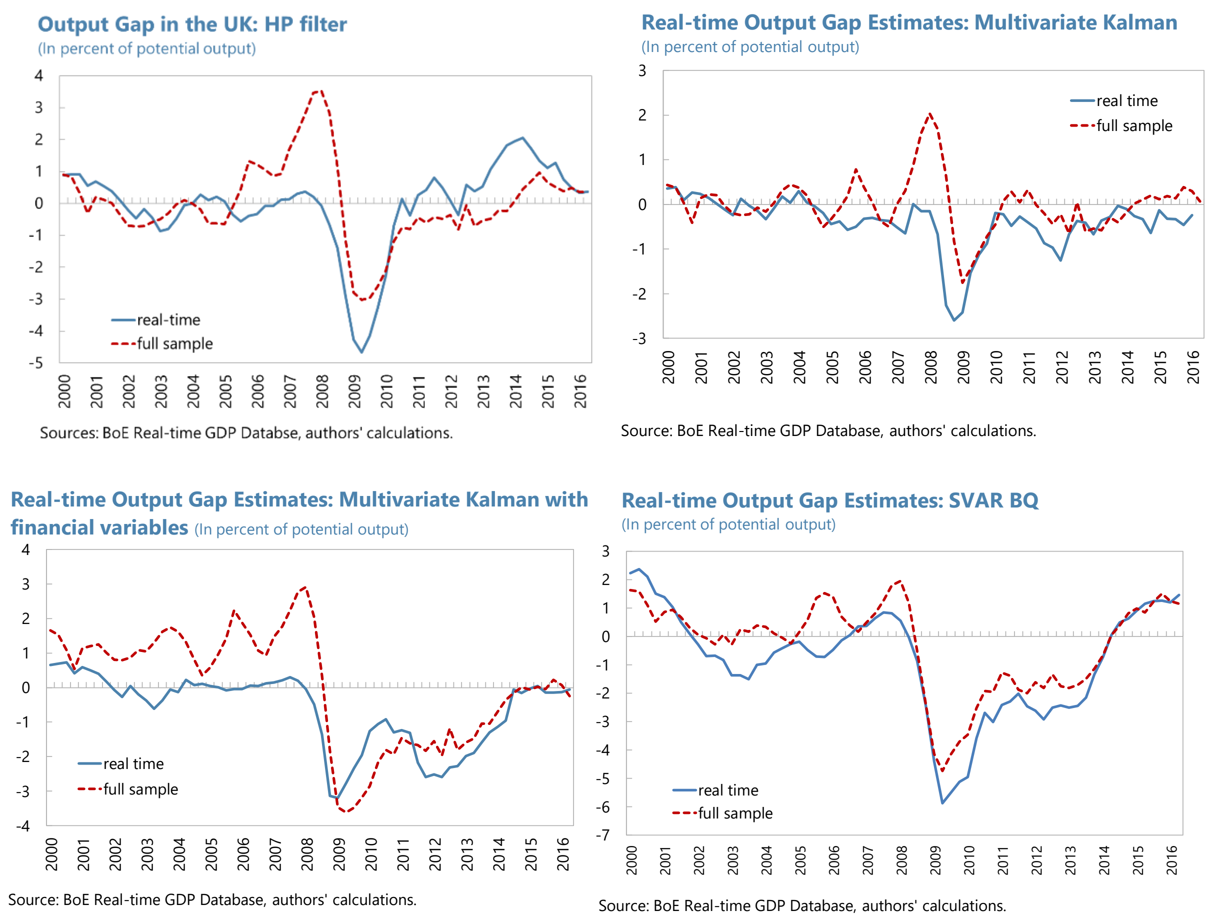
[14] For HP filter approach, to mitigate the end-of-sample problem, we "extended" the real GDP series by 8 quarters using the last available year-on-year growth rate.

We then run additional regressions to verify whether the ex-post revisions to the output gap estimates are due to the revisions in GDP data before and during the GFC.[15] The results confirm the findings of Orphanides and van Norden (2002) and Marcellino and Musso (2011) that the poor performance of the filtering methods reflects the end-of-sample problem highlighted in Section II rather than consecutive data updates. Instead, the BQ SVAR signals a slightly positive output gap starting in 2006: Q1. At the same time, the real-time estimates suggest a positive and quite large output gap between 2014 and 2016, which is difficult to reconcile with the relatively small size of the positive output gap before the GFC.



Sources: BoE Real-time GDP Database, authors' calculations.

Figure 4. Real-time U.K. Output Gap Estimates from Filter-based and BQ SVAR Models



Notes: Figure 4 presents output gap estimates derived using real-time data (blue lines) and based on the full sample (1982: Q1–2019: Q1, and 1991: Q1–2019: Q1 for the MVKfin; red dashed lines) for each of the models presented in Section II.

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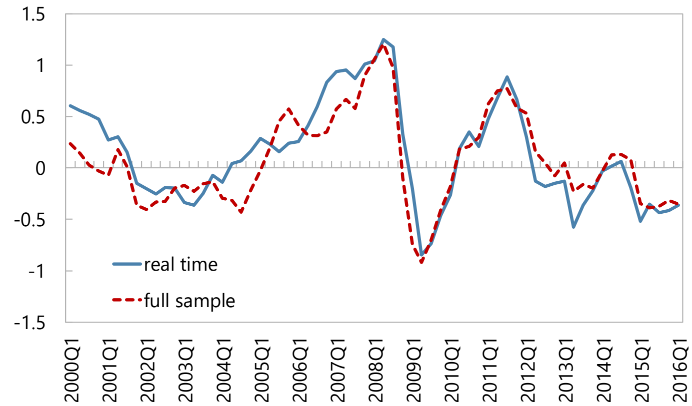
[15] That is, we run the regressions through the iterative process described before but using GDP growth data as available in 2016Q2 instead of the real-time time series.

Moving to the small open economy SVAR (Figure 5), it is easy to notice that the real-time output gap estimates follow the full sample estimates more closely compared to the previous four methods. Additionally, the extended SVAR signals opening of a positive output gap already in 2004: Q1. The real-time output gap reaches 1 percent around 2008: Q1, in line with the full-sample estimate.

Figure 5. Real-time Output Gap Estimates: Extended SVAR
(In percent of potential output)



Source: BoE Real-time GDP Database, authors' calculations.

Notes: Figure 5 presents output gap estimates derived using real-time data (blue lines) and based on the full sample (1982: Q1–2019: Q1, red dashed lines) for the small open economy SVAR model presented in Section III.

B. Responses to Shocks

In the second test, we check how the *real-time* potential output estimates respond to different types of shocks. We follow a similar exercise conducted by Coibion et al (2018), who show that the potential growth estimates of leading international institutions are procyclical, i.e., respond positively to transitory shocks. To conduct the exercise, we rely on time series of shocks that are either drawn from other authors, or computed based on existing literature:

- **Global permanent shocks.** For global technology shocks, we use Beaudry and Portier (2006) U.S. TFP news shocks based on short-run and long-run restrictions, as updated by Valerie Ramey.[16]
- **Global temporary shocks.** We identify U.S. monetary policy shocks using high frequency surprises around policy announcements as external instruments as in Gertler and Karadi (2015). For global fiscal shocks we use the U.S. military spending news shocks of Ramey (2016).
- **Domestic shocks.** We derive domestic fiscal shocks following Blanchard and Perotti (2002) SVAR specification and identification strategy. To obtain U.K. monetary policy shocks we use a VAR with GDP growth, unemployment, inflation and the interest rate (with four lags) and apply a Cholesky decomposition on this ordering. Finally, for productivity shocks we use residuals from a regression of output per worker on its lags.

[16] Available here: https://econweb.ucsd.edu/~vramey/research.html#data

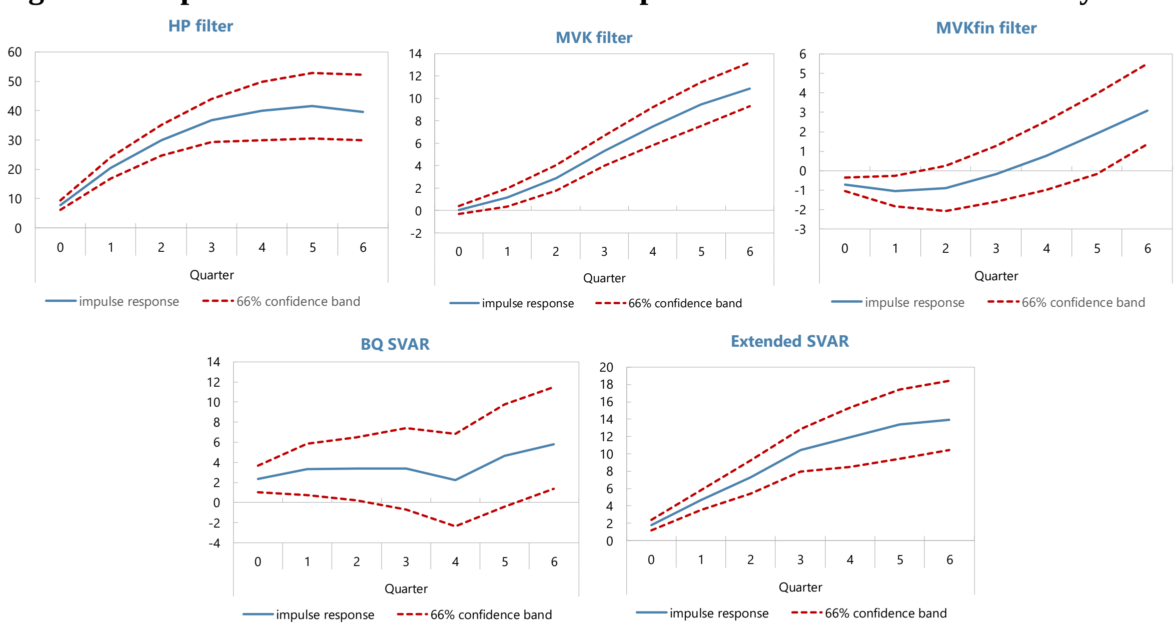
To study effects of these economic shocks on estimates of potential output, for each shock *s*, we regress the current (natural logarithm of) potential growth estimate on current and past values of the shock:

$$\Delta \bar{y}_t = \alpha^s + \sum_{k=0}^{K} \varphi_k^s \varepsilon_{t-k}^s + \zeta_t^s$$

Due to the small number of observations, we limit the specification to 6 lags (K=6), and we consider one shock at a time; we also use Newey-West standard errors. We construct impulse responses (IRFs) of potential output by summing coefficients φ_{t-k}^s up to a given horizon (e.g., φ_0^s for current period, $\varphi_0^s + \varphi_1^s$ for one period after a shock, etc.).

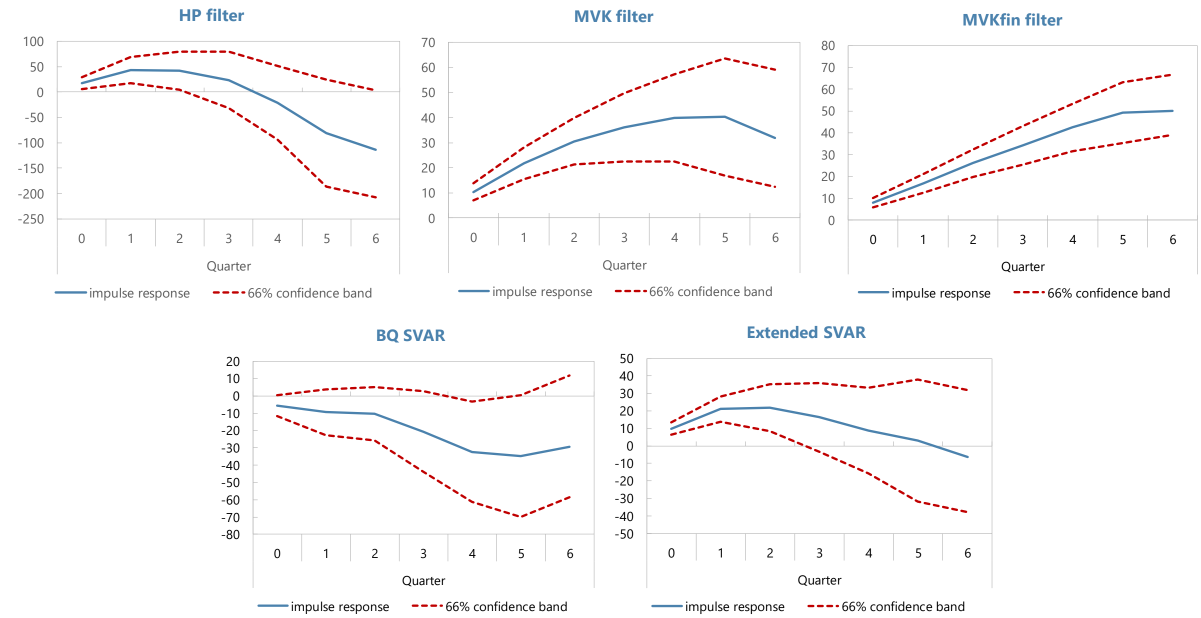
Figures 6 and 7 show the impulse responses of potential output estimates using the five models to a U.S. productivity (Figure 6) and a U.S. fiscal shock (Figure 7). All models yield the expected—positive and significant—response of potential output to a positive global productivity shock. However, for a positive U.S. fiscal shock—an example of a transitory global shock—potential output responds in line with intuition only in the case of the two SVAR models. The two multivariate filters yield a statistically significant increase in potential growth after a U.S. fiscal shock, while for the HP filter the response of potential output is actually negative (and marginally statistically significant) after 6 quarters. Instead, potential output from the small open economy SVAR model initially increases after a positive transitory global shock, but the response ceases to be statistically significant already after 3 quarters.

Figure 6. Responses of Real-time Potential Output Estimates a U.S. Productivity Shock



Source: IMF staff calculations.
Notes: Figure 6 shows impulse responses of potential output estimated using the models from Sections II–III to a one standard deviation positive U.S. productivity shock, obtained using the Beaudry Portier (2006) short-run restrictions. Red dashed lines show 66 percent confidence bands around the estimates.

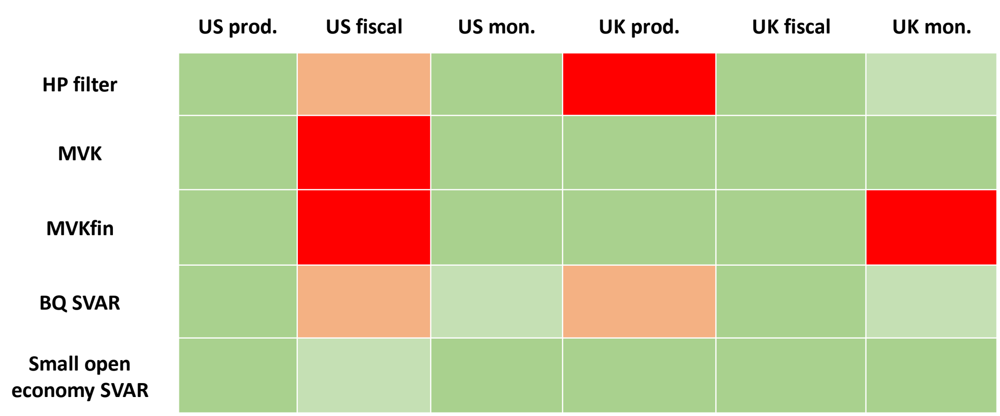
Figure 7. Responses of Real-time Potential Output Estimates a U.S. Fiscal Shock



Source: IMF staff calculations.
Notes: Figure 7 shows impulse responses of potential output estimated using the models from Sections II-III to a one standard deviation positive U.S. fiscal shock identified as in Ramey (2016). Red dashed lines show 66 percent confidence bands around the estimates.

Figure 8 summarizes the qualitative assessment of the IRF properties for the five model and all six types of shocks we consider compared to their “expected properties.” All remaining IRFs are presented in Figures A.2–A.5 in the Appendix. The SVAR-based potential output estimates tend to perform relatively well, although for the BQ SVAR the estimates respond almost significantly to a U.S. fiscal shock and insignificantly to a U.K. productivity shock over the medium run.

Figure 8. Shock Responses of Potential Output Estimates: A Summary



Source: IMF staff calculations.
Notes: Figure 8 summarizes the assessment of the IRF properties of potential output estimates from the five models described in Sections II and III (rows), and six types of shocks (columns). Dark green color marks IRFs that are in line with economic intuition both in the short and in the medium term. Light green color marks the cases where IRFs are in line with intuition only in the medium term. If the IRFs are counterintuitive in the medium term they are marked with dark red color; if the IRFs in the medium term are a boarder-line case, they are marked with bright red.

Filter-based estimates show more counter-intuitive results. In particular, HP filter-based potential output does not seem to respond significantly to a U.K. productivity shock, while potential output from the MVKfin model responds positively to a U.K. monetary policy shock. Overall, potential output estimates from the small open economy VAR have the most intuitive impulse responses to the six shocks considered.

C. Inflation Forecasting

Another desirable feature of a good output gap estimate would be to have a strong explanatory power for predicting inflation. To test this property, we estimate the following Phillips curve based on Blanchard (2016):

$$\pi_t = \theta\hat{y}_t + \lambda\pi_t^e + (1-\lambda)\pi_{t-1}^* + \mu\pi_{m,t} + \varepsilon_t, \qquad (1)$$
$$\pi_t^e = \alpha + \beta\pi_{t-1}^* + \eta_t,$$

where π_t is headline consumer price inflation (defined as quarterly inflation, annualized), $\hat{y}_t$ is the output gap, π_t^e denotes long-term inflation expectations, π_{t-1}^* is the avearge of the last four quarterly inflation rates, and $\pi_{m,t}$ is import price inflation relative to headline inflation.

We perform two tests. First, we check in-sample properties of the five output gap measures from Sections II–III: For this purpose, we estimate the above Phillips curve for the period of 1993: Q1 to 2016: Q2.[17] In the second test, we calculate the squared errors from one-quarter ahead out-of-sample inflation forecast through an iterative procedure. That is, for each quarter between 2006: Q1 and 2016: Q1 we estimate a separate Philips curve, using real time output gap estimates and only the data from 1982: Q1 up until the given year and quarter.

Table 3 shows results of the first test. All five estimated output gaps display the right sign and are statically significant except the MVK filter-based estimate. R-squared values indicate that all models have similar properties in terms of goodness-of-fit, with the small open economy SVAR slightly outperforming other methods. Table 4 compares the sum of squared errors of the projected inflation relative to the realized inflation. The SVAR-based estimates produce the smallest forecast error, although it is very close to the estimates based on the MVK filter. However, it is important to note that a small error term under the MVK approach should be expected by design, as the Phillips curve is embedded in the estimation approach. On net, the output gap estimates from the small open economy SVAR appears to have the smallest error terms in forecasting inflation, although the differences with other methods may not be statistically significant.

[17] The U.K. adapted inflation targeting framework in October 1992, thus we started the estimation from 1993.

Table 3. Estimated Phillips Curve

	CPI inflation (qoq percent change)				
VARIABLES	(1)	(2)	(3)	(4)	(5)
pie (-1)	0.37***	0.36***	0.34***	0.34***	0.20**
	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)
pie (-2)	0.16	0.16	0.15	0.15	0.08
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
pie (-3)	0.191*	0.204**	0.181*	0.201**	0.171*
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
pie (-4)	0.104	0.125	0.0676	0.122	0.131
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
imported pie/ pie	0.0008***	0.0008***	0.0007**	0.0008***	0.0008***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
HP filter	0.05*				
	(0.03)				
MVK		0.10**			
		(0.04)			
MVK fin			0.01		
			(0.03)		
BQ SVAR				0.07**	
				(0.03)	
Small open economy VAR					0.40***
					(0.09)
Constant	0.0006	0.0006	0.001	0.0006	0.001**
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)
Observations	105	105	97	105	105
R-squared	0.56	0.57	0.41	0.57	0.62

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IMF staff calculations.
Notes: Table 3 shows results of regression (1) when using output gap estimates from the five models in Sections II–III as a measure of $\hat{y}_t$ (columns 1–5).

Table 4. Average of Squared Errors of Out-of-Sample Projected Inflation over 2006: Q1–2016: Q2

HP filter	MVK	MVK fin	BQ SVAR	Small open economy SVAR
0.27	0.26	0.28	0.24	0.24

Source: IMF staff calculations.
Notes: Table 4 shows the average of squared error terms for out-of-sample inflation projections (in percentage points) from the five models from Sections II–III, obtained in an iterative procedure described in Section IV.C.

D. Robustness

We run a series of robustness checks to verify whether our results are not driven by a selection of a particular specification of the five methods. To mitigate the end-of-sample problem present in the three filtering approaches, we extend the sample by one year with Consensus forecasts of GDP and—in the case of the MVK and the MVKfin—of inflation. We also test the sensitivity of the MVK output gap estimates to choosing an alternative set of parameter priors (e.g., lower or higher value of the parameter β, different values of the steady state unemployment and potential output growth) and consider a specification with detrended unemployment series. These alternative specifications to not yield results considerably different from the baseline specifications. In the case of the BQ SVAR, the results are robust to using a different measure of unemployment that accounts for underemployment. For the small open economy SVAR, we estimate the model when not imposing any sign restrictions—again, the results are not much affected. Finally, all five methods do not yield considerably different output gap estimates when the estimation sample starts in 1993: Q1, i.e., after a stabilization of inflation at a new, lower level.[18]

V. Conclusions

In this paper we analyze the properties of different output gap models using data for the U.K. We also consider a small open economy SVAR for the purposes of estimating potential output and output gap. This model identifies both domestic and global supply shocks that have a permanent impact on the domestic output, and potential output is calculated as the sum of the past domestic and global supply shocks.

We confirm the finding in Coibion et al (2018) that filtering-based models produce potential output estimates that respond to transitory shocks in a procyclical way. Instead, models that distinguish between different types of shocks (i.e., SVAR-based) yield potential output estimates with better impulse response properties. Overall, we find that the small open economy SVAR performs best among all the models we consider and is characterized by the best real-time properties of output gap estimates.

Coming back to the question posed in the title of this paper "Are output gap estimates worth economists' time?" Our results suggest that the answer is yes. However, proper care needs to be taken when identifying all relevant persistent shocks. It is also crucial to verify a model's performance against a set of established tests, where a good output gap model should be characterized by minimal ex-post revisions to real-time estimates since they matter the most for policy-making. At the same time, it has to be borne it mind that there is no perfect measure of the output gap, and thus looking at a broader range of indicators might be the best strategy for getting a more accurate picture of the cyclical position of the economy.

[18] These results are available upon request.

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Appendix

Data

Table A.1. Data Sources and Variable Definitions

Variable	Source	Comment
real GDP	ONS	
rate of unemployment	ONS	
consumer price index	ONS	At constant tax
interest rate	Haver	Based on shadow rate for 1995:Q1-2019:Q1. Prior to 1995:Q1, the series are based on the Bank rate
nominal exchange rate index	Haver, Bank of England	(narrow) Effective exchange rate
import prices	WEO	U.K. imports of goods and services price deflator
export prices	WEO	World CPI weighted by U.K. export share

Multivariate Kalman Filter: Specification and Estimation

We follow Blagrave et al. (2015), where the following system of equations is used for the filtering exercise ($\hat{x}_t$ denotes deviation of variable x_t from its potential level $\bar{x}_t$)

$$\hat{y}_t = y_t - \bar{y}_t, \qquad \text{(C.1)}$$

$$\bar{y}_t = \bar{y}_{t-1} + g_t + \varepsilon_t^{\bar{y}}, \qquad \text{(C.2)}$$

$$g_t = \theta g^{ss} + (1-\theta)g_{t-1} + \varepsilon_t^{g}, \qquad \text{(C.3)}$$

$$\hat{y}_t = \varphi \hat{y}_{t-1} + \varepsilon_t^{\hat{y}}, \qquad \text{(C.4)}$$

where y_t stands for log real GDP, $\bar{y}_t$ is the log of unobservable potential GDP that grows at a potential growth rate g_t (with g^{ss} denoting growth rate in steady-state). The ε_t terms denote i.i.d, normally distributed errors.

$$\pi_t = \lambda\pi_{t+1} + (1-\lambda)\pi_{t-1} + \beta\hat{y}_t + \varepsilon_t^{\pi}, \quad \text{(C.5)}$$

$$\hat{u}_t = \tau_1\hat{y}_t + \tau_2\hat{u}_{t-1} + \varepsilon_t^{u}, \qquad \text{(C.6)}$$

$$\hat{u}_t = u_t - \bar{u}_t, \qquad \text{(C.7)}$$

$$\bar{u}_t = \tau_4(\bar{u}^{ss} + (1-\tau_4)\bar{u}_{t-1}) + g_t^{u} + \varepsilon_t^{\bar{u}}, \qquad \text{(C.8)}$$

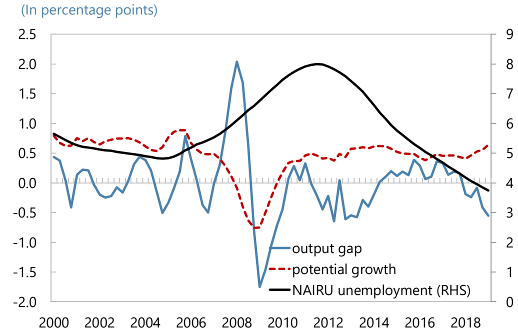
$$g_t^{u} = (1-\tau_3)g_{t-1}^{u} + \varepsilon_t^{g^{u}}, \qquad \text{(C.9)}$$

where π_t is the inflation rate, u_t stands for the unemployment rate, and g_t^u is the trend unemployment rate (this specification allows for persistent deviations of the equilibrium value of the unemployment rate $\bar{u}_t$ from its steady-state value $\bar{u}^{ss}$). Parameter values and the variances of shock terms for these equations are maximum likelihood estimates obtained using Bayesian estimation. In particular, we set the priors at the posteriors estimated for the U.K. in Blagrave et al. (2015). Table below shows the priors and posteriors of the estimated parameters, based on the full sample, i.e., 1982: Q1–2019: Q1.

parameter	prior	posterior
λ	0.25	0.23
β	0.15	0.1
φ	0.7	0.72
θ	0.2	0.1
τ_1	0.4	0.33
τ_2	0.4	0.48
τ_3	0.1	0.09
τ_4	0.1	0.09
g^{ss}	1.6	
$\bar{u}^{ss}$	4.5	

Figure below shows the behavior of the output gap, potential growth rate, and the equilibrium unemployment rate (NAIRU), estimated using the multivariate Kalman filter.

MVK Filter: Full Sample Results
(In percentage points)



Sources: Authors' calculations.

Multivariate Filter with Financial Variables: Specification and Estimation

The MVF model is based on Berger et al. (2015). Potential output is estimated by decomposing observed GDP time series into two unobservable components: the cycle and the trend GDP.

$$y_t = \bar{y}_t + \hat{y}_t$$
$$\Delta^2 \bar{y}_t = \bar{\varepsilon}_t$$
$$\lambda \equiv \frac{Var(\hat{y}_t)}{Var(\bar{\varepsilon}_t\ )}$$

Where y_t and $\bar{y}_t$ represent logs of observed and potential output, respectively, and $\hat{y}_t$ is the cyclical component (i.e., output gap). Similar to the HP filter, the model is estimated with a constraint on the variance ratio λ that is set at 1600 which implies that potential output will capture output movements at frequencies above 8 years. In addition, the model considers a set of observable variables that could be correlated with output gap.

$$y_t - \bar{y}_t = \rho(y_{t-1} - \bar{y}_{t-1}) + \beta x_t + \varepsilon_t^o$$

Where the variance ration $\frac{Var(y_t - \bar{y}_t)}{Var(\Delta^2 \bar{y}_t)}$ is constrained to match the one implied by equations 1-3 and implicitly the frequency characteristic of the HP filter. More specifically, x_t includes real credit growth, real house price inflation, and stock price inflation. The model is estimated using maximum likelihood approach. The table below lists the estimates of key financial variables of interest.

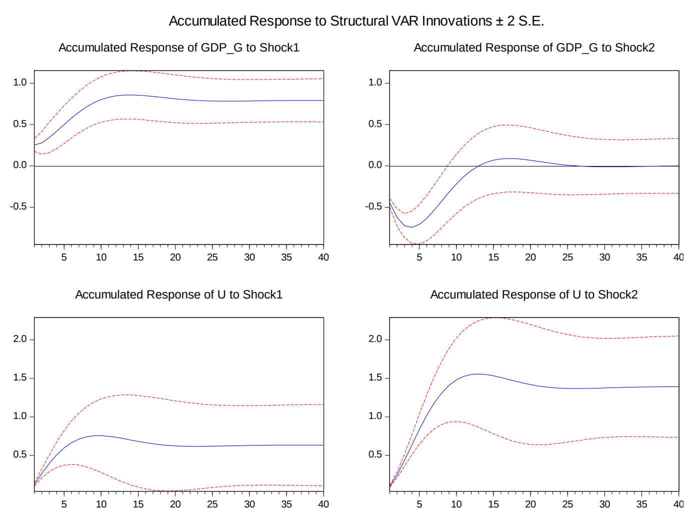
	Estimate	Std. error	p-value
Real HPI growth	0.02	0.007	0.001
Real credit growth	0.008	0.008	0.309
Stock price growth	0.004	0.002	0.038

Blanchard-Quah SVAR: Specification and Estimation

Following Blanchard and Quah (1989), we estimate a 2-equation SVAR (using the maximum likelihood), that includes quarterly real GDP growth and detrended unemployment rate:[19]

$$\begin{bmatrix} 1 & B_{0,12} \\ B_{0,21} & 1 \end{bmatrix} \begin{bmatrix} \Delta y_t \\ u_t \end{bmatrix} = \begin{bmatrix} A_{0,1} \\ A_{0,2} \end{bmatrix} + \begin{bmatrix} B_{1,11} & B_{1,12} \\ B_{1,21} & B_{1,22} \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^d \end{bmatrix}.$$

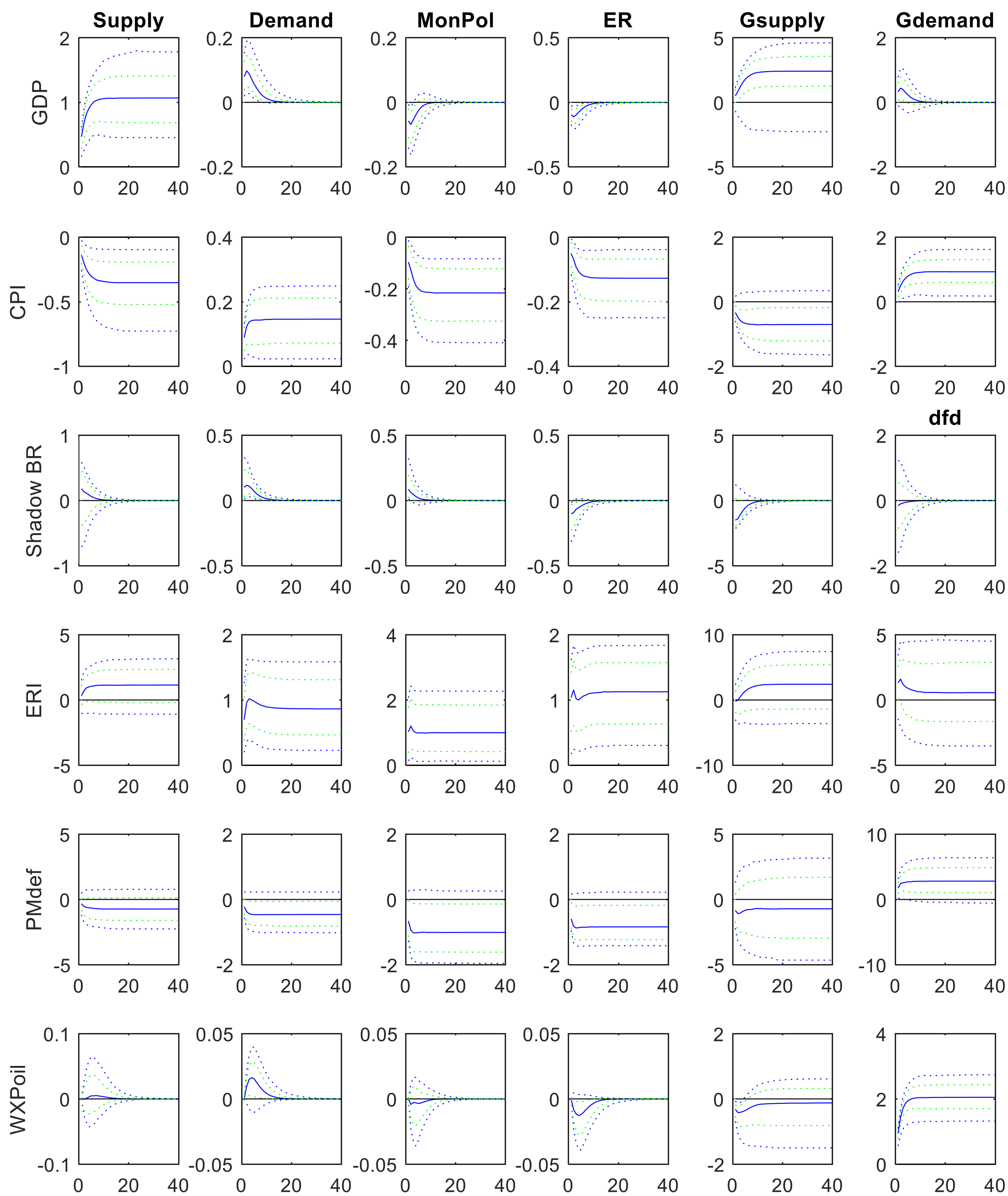
The sample is 1982: Q1–2019: Q1. The SVAR includes 2 lags of each variable—selected based on the AIC criterion—and is identified by imposing a zero long-run impact of demand shocks (ε_t^d) on GDP growth. The chart below shows cumulative impulse responses of real GDP (*GDP_G)* and the unemployment rate (*U*) to a one standard deviation supply (*Shock1*) and a one standard deviation demand shock (*Shock2*).



[19] We use detrended unemployment rate to remove a downward trend observed in data. The 5-quarter moving-average unemployment rate has declined considerably over the recent decades: from over 8 percent in 1980s and early 1990s to around or somewhat below 5 percent before and after the GFC, respectively.

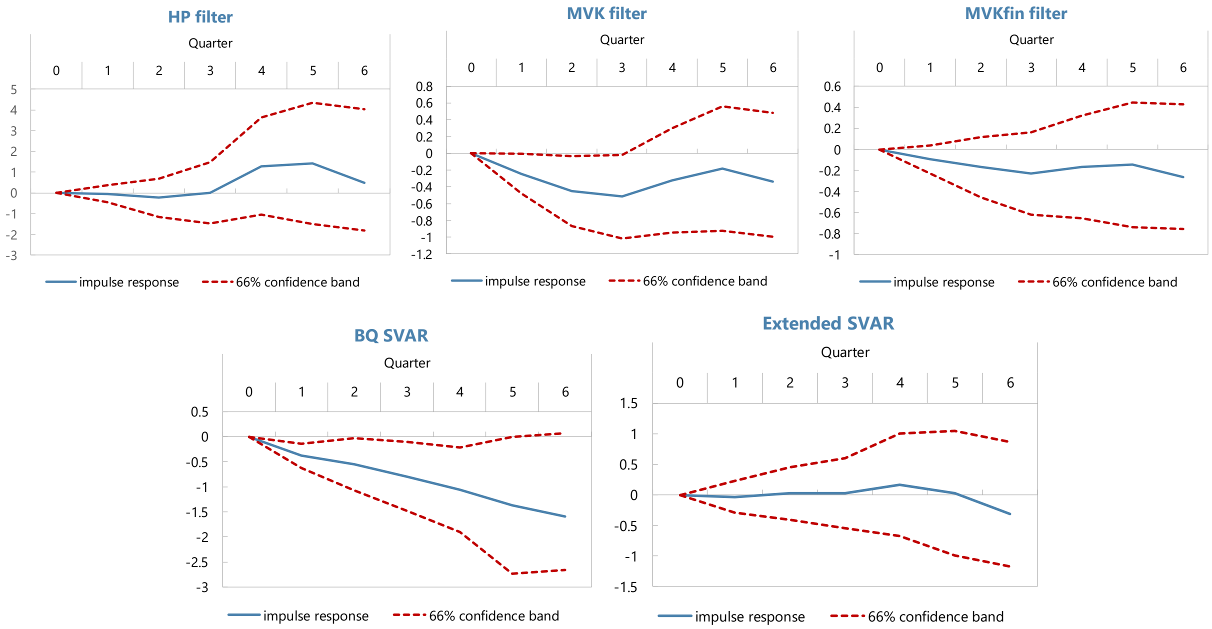
Small Open Economy SVAR

Figure A.1. Small Open Economy SVAR: Impulse Response Functions



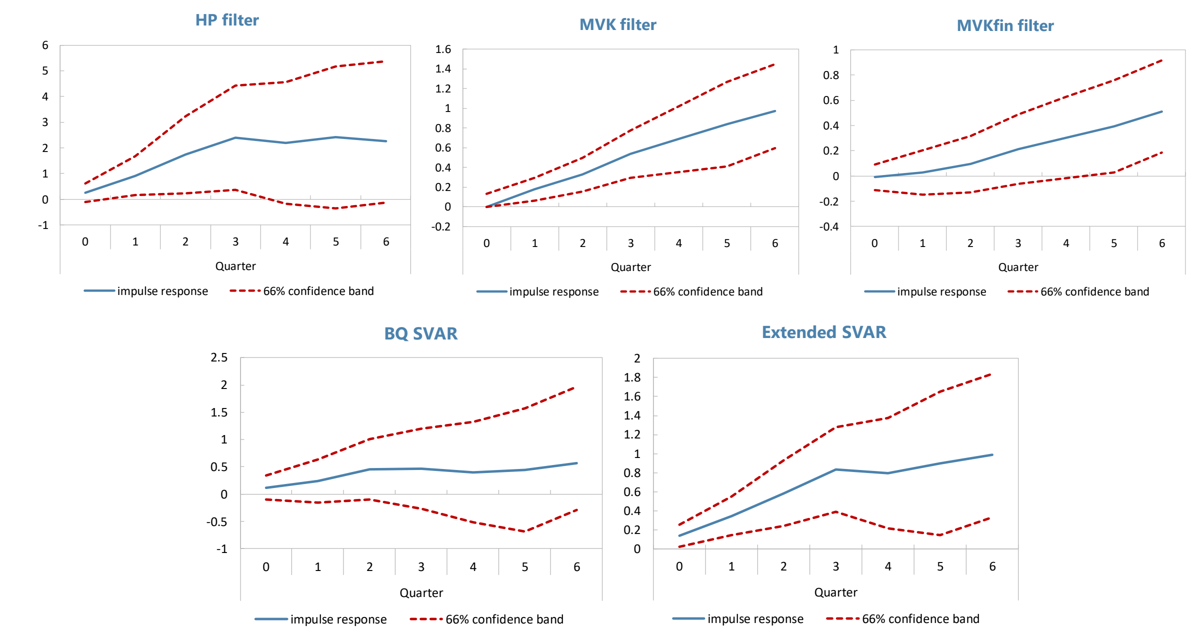
Testing Output Gap Estimates

Figure A2. Responses of Real-time Potential Output Estimates a U.S. Monetary Shock



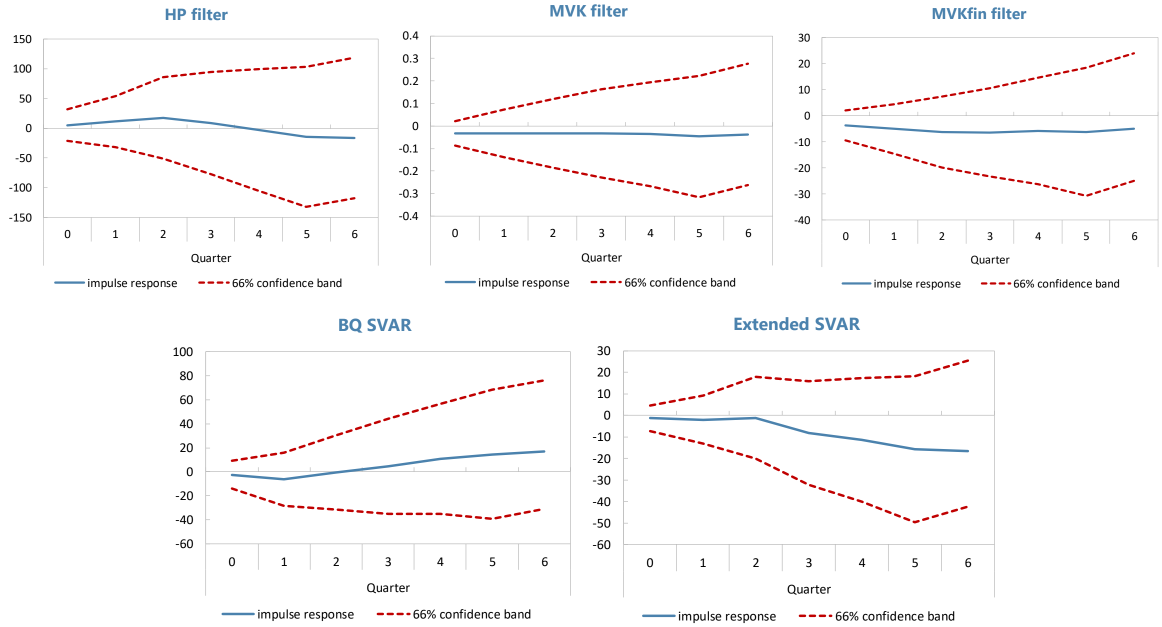
Notes: Figure A2 shows impulse responses of potential output estimated using the models from Sections II–III to a one standard deviation positive U.S. monetary policy shock, obtained following Gertler and Karadi (2015). Red dashed lines show 66 percent confidence bands around the estimates.

Figure A3. Responses of Real-time Potential Output Estimates a U.K. Productivity Shock



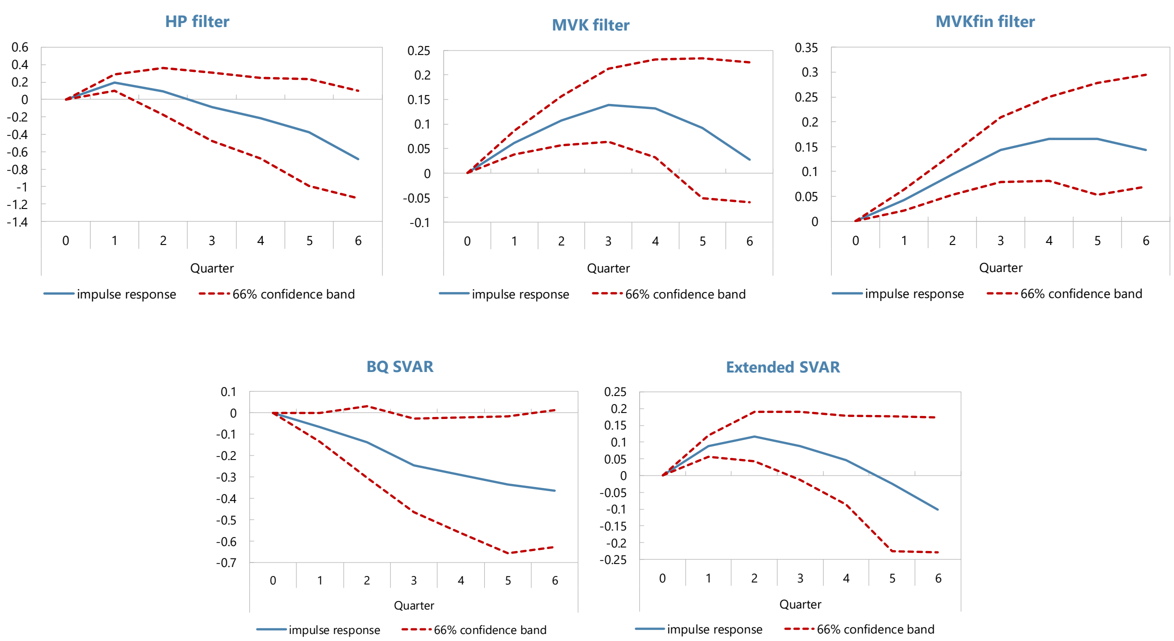
Notes: Figure A3 shows impulse responses of potential output estimated using the models from Sections II–III to a one standard deviation positive U.K. productivity shock, obtained as described in Section IV. Red dashed lines show 66 percent confidence bands around the estimates.

Figure A4. Responses of Real-time Potential Output Estimates a U.K. Fiscal Shock



Notes: Figure A4 shows impulse responses of potential output estimated using the models from Sections II–III to a one standard deviation positive U.K. fiscal shock, obtained as described in Section IV. Red dashed lines show 66 percent confidence bands around the estimates.

Figure A5. Responses of Real-time Potential Output Estimates a U.K. Monetary Shock.



Notes: Figure A5 shows impulse responses of potential output estimated using the models from Sections II–III to a one standard deviation positive U.K. monetary policy shock, obtained as described in Section IV. Red dashed lines show 66 percent confidence bands around the estimates.