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Multivariate Filter Estimation of Potential Output for the Euro Area and the United States

by Ali Aichi, Olivier Bizimana, Silvia Domit, Emilio Fernandez Corugedo,
Douglas Laxton, Kadir Tanyeri, Hou Wang, and Fan Zhang

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Research Department

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Abstract

Estimates of potential output are an important component of a structured forecasting and policy analysis system. Using information on consensus forecasts, this paper extends the multivariate filter developed by Laxton and Tetlow (1992) and modified by Benes and others (2010) and Blagrove and others (2015). We show that, although still fairly uncertain, the real time estimates from this approach are more accurate relative to those of naïve univariate statistical filters. The paper presents estimates for the euro area and the United States and discusses how the filtered estimates at the end of the sample period can be improved with additional information.

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¹ The estimates of potential output and the output gap presented in this paper are not official IMF estimates. The programs and potential output estimates in this paper can be downloaded from www.douglaslaxton.org. The views expressed in this paper are those of the authors and do not necessarily represent those of the IMF or IMF policy. The authors would like to thank the European Department of the IMF for helpful comments. All errors and omissions are our own.

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I. INTRODUCTION

This paper provides a re-examination of the multivariate filter (MVF) developed by Laxton and Tetlow (1992) and modified by Benes and others (2010) and Blagrove and others (2015). Using the Okun (1962) definition of potential output, estimates of potential output and the output gap (defined as the percent deviation of actual GDP from potential output) are presented for the United States and the euro area. There are several reasons why this technique is useful for analyzing the evolution of potential output and the output gap. First, the estimates of the output gap are economically plausible, with estimated periods of excess supply and demand coinciding closely with the priors of practitioners. Second, the filter includes some very basic economic identification restrictions—specifically the structure of the filter relates the output gap to slack in the labor market and supply-shock adjusted measures of inflationary pressures. Third, the filter produces more accurate real-time estimates of potential and the output gap relative to estimates from the Hodrick-Prescott (HP) filter, though a certain amount of uncertainty in real-time estimates is unavoidable. The multivariate filter performs well in the aftermath of financial crises, which tend to have significant scarring effects on the level of output and/or its growth rate.² Finally, the results can be also adjusted in a transparent manner using information from outside of the model. This is particularly helpful at the end of the sample, given the uncertainty surrounding real-time assessment of economic slack. Still, it is important to note that the filter presented in this paper is designed to be the ‘least bad’ among a host of very mediocre choices—there is no panacea to the problem of estimating potential output and users should feel free to impose their judgment based on additional information not included in the filter. That said, the multivariate filter estimates provide a very useful starting point for any analysis and impose some discipline on the estimation process.

The remainder of the paper begins with a brief review of the concept of potential output (Section II), contrasting it with concepts of ‘sustainable’ output recently discussed in the literature, as well as techniques commonly used to estimate potential. Section III presents the methodology used in this paper; detailed results are presented for the U.S. in Section IV. Section V provides a discussion about other sources of information to consider in assessing the degree of slack in the economy and shows how the estimates can be modified by imposing judgment in particular time periods. Section VI reports the results for the euro area. Section VII presents confidence bands surrounding the estimates of potential output using the multivariate filter, and compares them to those from an HP filter. Section VIII concludes.

² See, for example, Chapter 3 of the April 2009 WEO, which analyses the short-term dynamics of output following financial crises and Abiad and others (2009) who investigate the medium-term dynamics of output following banking crisis.

II. POTENTIAL OUTPUT—BRIEF OVERVIEW OF COMMON ESTIMATION TECHNIQUES

Potential output is generally thought of as the maximum level of output that an economy can sustain without generating inflationary pressure (Okun (1962)). This definition is particularly prevalent among monetary policy makers, as it allows them to communicate their policy stance in the context of the short-run tradeoff between output and inflation.³ It is of critical importance that we be concrete in defining the concept of potential output, as this will shape how potential, and the corresponding output-gap estimates, are used by policy makers.

Although many practitioners approach potential output with the Okun definition in mind, some recent work has focused on expanding or altering this definition to include consideration of macroeconomic imbalances more broadly (see Alberoa, Estrada, and Santabarbara (2013)), as well as financial imbalances in particular (see Borio, Disyatat, and Juselius (2013)). These measures are perhaps best thought of as gauging the *path of sustainable future* output, rather than *current potential* output (in the inflation/output tradeoff sense). More specifically, these sorts of imbalances may signal the risk of a future disorderly adjustment wherein output would be substantially lower for a period of time—both the timing of such an adjustment, and whether one would ultimately occur, is very uncertain. For example, in the case of financial-sector imbalances, a strong increase in credit growth often precedes a financial crisis. However, there is no *a priori* reason why rapid credit growth needs to be unsustainable—this sort of credit expansion could equally well be the product of sound economic fundamentals. Given the difficulty of identifying the drivers of a credit expansion in real time, it would not be wise to counsel policy makers to treat all such expansions as bad; rather, these sorts of expansions should be considered carefully, and treated as increasing the (downside) risks around a given baseline. As such, we view approaches which consider financial-sector and broader macroeconomic imbalances as complements to—rather than substitutes for—the Okun concept of potential output.⁴

One of the more prevalent techniques to estimating potential is the use of univariate statistical filters, such as the HP filter, to smooth out fluctuations in output. The appeal of this approach is that it is simple, transparent, and can be applied to any country where GDP data exist. Unfortunately, the approach's relative simplicity brings with it several notable limitations. Chief among these is that the estimates are better thought of as 'trend' (rather than potential) growth, since these filters do not incorporate any economic structure, and thus are not consistent with an economic concept of potential—univariate filters represent a

³ For an example of how this tradeoff is communicated, see Bank of Canada (2009).

⁴ See, for example, Benes, Laxton, and Kumhof (2014a and 2014b), which assesses vulnerabilities associated with excessive credit expansions and asset price bubbles, and the consequences of different macro-prudential policies or Rabanal and Sanjani (2015), which discusses the role of financial variables in computing the output gap.

purely statistical approach to approximating potential output. In addition, the estimates which come out of these filters will reflect several statistical features which may be undesirable. For example, the estimates of the output gap will be mean zero (over a sufficiently long sample period), and the relative volatility of the cyclical vs. structural component will be determined by the selection or estimation of a smoothing parameter. Finally, univariate filters suffer from a particularly acute ‘end-of-sample’ problem, with estimates towards the end of a given sample period being subject to significant revisions as more data ultimately become available and the sample is extended.

Another common technique to estimating potential output is the production-function approach, in which the inputs of production are considered separately. In its simplest form, this entails specifying a two-factor production function (generally Cobb-Douglas), obtaining data on employment and the capital stock, and then calculating total-factor productivity (TFP) as the residual from the production-function equation. By smoothing the resulting TFP series, and specifying a process for ‘potential’ employment, one arrives at an estimate for potential output by combining these trends with the estimate of the capital stock.⁵ This approach has the benefit of allowing for a more detailed examination of the drivers of potential. However, there are also limitations; in particular, reliable capital-stock data can be hard to obtain, and the estimates of potential arising from this approach are only as good as the filters used to de-trend the TFP and employment components.⁶

Furthermore, a good deal of work has focused on the use of multivariate filters to estimate potential (see Laxton and Tetlow (1992), Kuttner (1994), and more recently Benes and others (2010), among others). This approach adds economic structure to estimates by conditioning them on some basic theoretical relationships (such as a Phillips curve relating the inflation process to the output gap). One strength of this approach is that estimates of the output gap and potential are consistent with the Okun concept of potential. In addition, in its simplest form this technique is relatively easy to implement requiring only a few variables, and it can be augmented where data availability permits (see for example Alich (2015)). Another advantage of the multivariate filter is that the estimates may not deviate too much from actual data, which helps capture shocks that may have lasting effects on the economy and leads to swift revisions of potential output. These features make the multivariate filter particularly useful for measuring potential output in the aftermath of the global financial crisis and the euro area sovereign debt crisis, for example, to the extent that these have had scarring effects on the level of output and/or its growth rate. The shortcomings of the multivariate-filter approach are similar to those facing other methods—there remains an important end-of-

⁵ For an example of how the production-function approach can be implemented, see D’Auria and others (2010).

⁶ As an example, if the employment and TFP series are de-trended using an HP filter, then the resulting estimates of potential output will have almost identical properties to those arising from a direct HP filtration of GDP data.

sample problem, and the estimates of potential and the output gap are only improved relative to a simple statistical filtration if the structural relationships specified in the filter are valid in the economy in question.

Yet another technique which is gaining popularity in recent years is the use of DSGE models to estimate potential and the output gap (see, for example, Vetlov and others (2011)). This approach is theoretically rigorous, and is thus particularly appealing to academic audiences. Unfortunately, this technique is very difficult to implement, requiring extensive modeling expertise and a great deal of time and effort. In addition, estimates of the output gap and potential output derived from these models tend to be particularly sensitive to the specifications of the DSGE model being used, and they are not always intuitive. This is problematic for policy makers who want to use these estimates to formulate policy.⁷

III. METHODOLOGY

The multivariate filter approach specified in this paper is relatively simple, requiring data on just a few observable variables. The three core variables of the model require data on GDP, the CPI, and the unemployment rate. We measure the data at annual frequency to help deal with the noise in higher frequency quarterly data. In addition, we use data from consensus forecasts on near-term annual CPI inflation and longer-term real GDP growth to help better identify supply and demand shocks and if the shocks to potential are affecting the underlying growth rate of potential or just the level. In this section, we present the equations which relate these three observable variables to the latent variables in the model. Parameter values and the variances of shock terms for these equations are estimated using Bayesian estimation techniques and are provided in the appendix.⁸

In the model, the output gap is defined as the deviation of real GDP, in log terms (Y_t), from its potential level (\bar{Y}_t):

$$(1) \quad y_t = Y_t - \bar{Y}_t$$

The stochastic process for output (real GDP) is comprised of three equations, and subject to three types of shocks:

$$(2) \quad \bar{Y}_t = \bar{Y}_{t-1} + G_t + \varepsilon_t^{\bar{Y}}$$

⁷ See Juillard and others (2007) and Vetlov and others (2011) for a discussion of issues related to measuring potential output from DSGE models.

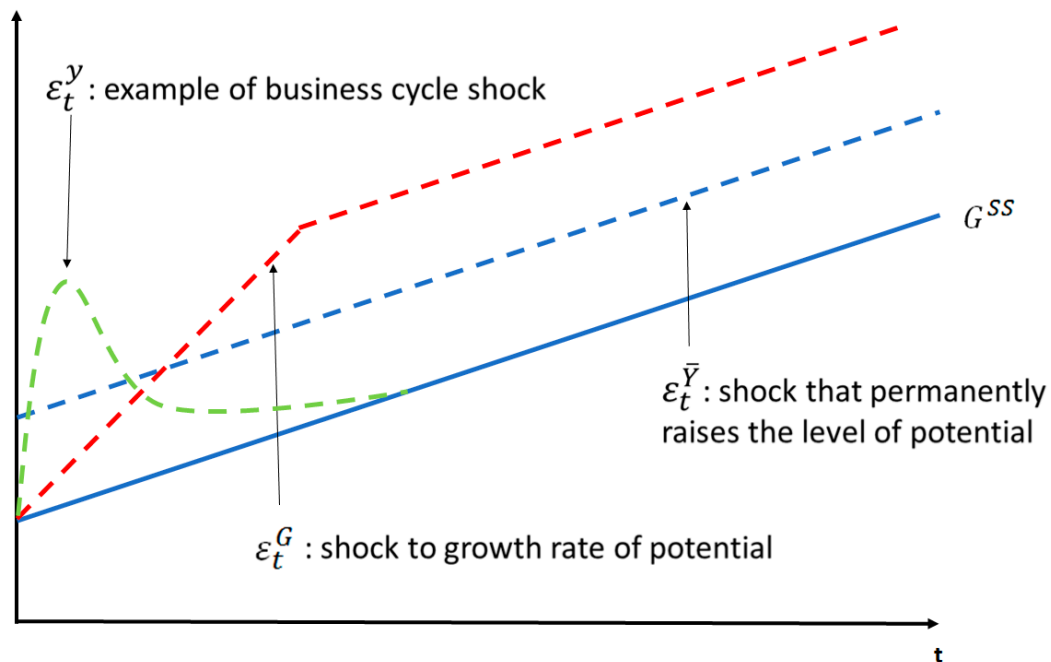
⁸ More specifically, we use regularized maximum likelihood techniques (see Ljung, 1999). Also, see Hamilton (1994) for a general discussion of the Kalman filter, which is used to obtain estimates of the unobservable variables as part of the estimation process.

$$(3) \quad G_t = \theta G^{SS} + (1 - \theta)G_{t-1} + \varepsilon_t^G$$

$$(4) \quad y_t = \phi y_{t-1} + \varepsilon_t^y$$

The level of potential output (\bar{Y}_t) evolves according to potential growth (G_t) and a level-shock term ($\varepsilon_t^{\bar{Y}}$). Potential growth is also subject to shocks (ε_t^G), with their impact fading gradually according to the parameter θ (with lower values entailing a slower adjustment back to the steady-state growth rate following a shock). Finally, the output gap is also subject to shocks (ε_t^y), which are effectively demand shocks. The role of each shock term is expressed graphically in Figure 1:

Figure 1. Shocks to the Level and Growth Rate of Potential Output and the Output Gap



Source: Authors' estimates.

All else equal, output would be expected to follow its steady-state path, which is shown above by the solid blue line (which has a slope of G^{SS}). However, shocks to: the level of potential ($\varepsilon_t^{\bar{Y}}$); the growth rate of potential (ε_t^G); or the output gap (ε_t^y), can cause output to deviate from this initial steady-state path over time. As shown by the dashed blue line, a shock to the level of potential output in any given period will cause output to be permanently higher (or lower) than its initial steady-state path. Similarly, shocks to the growth rate of potential, illustrated by the dashed red line, can cause the growth rate of output to be higher

temporarily, before ultimately slowing back to the steady-state *growth rate* (note that this would still entail a higher *level* of output). And, finally, shocks to the output gap would cause only a temporary deviation of output from potential, as shown by the dashed green line.

In order to help identify the three aforementioned output shock terms, a Phillips Curve equation for inflation is added, which links the evolution of the output gap (an unobservable variable) to observable data on inflation according to the process:⁹

$$(5) \quad \pi_t = \lambda E_t \pi_{t+1} + (1 - \lambda) \pi_{t-1} + \beta y_t + \varepsilon_t^\pi$$

Finally, equations describing the evolution of unemployment are included to provide further identifying information for the estimation of the output gap:

$$(6) \quad \bar{U}_t = (\tau_4 \bar{U}^{ss} + (1 - \tau_4) \bar{U}_{t-1}) + g \bar{U}_t + \varepsilon_t^{\bar{U}}$$

$$(7) \quad g \bar{U}_t = (1 - \tau_3) g \bar{U}_{t-1} + \varepsilon_t^{g \bar{U}}$$

$$(8) \quad u_t = \tau_2 u_{t-1} + \tau_1 y_t + \varepsilon_t^u$$

$$(9) \quad u_t = \bar{U}_t - U_t$$

Here, \bar{U}_t is the equilibrium value of the unemployment rate (the NAIRU), which is time varying, and subject to shocks ($\varepsilon_t^{\bar{U}}$) and also variation in the trend ($g \bar{U}_t$), which is itself also subject to shocks ($\varepsilon_t^{g \bar{U}}$)—this specification allows for persistent deviations of the NAIRU from its steady-state value. Most importantly, we specify an Okun's law relationship wherein the gap between actual unemployment (U_t) and its equilibrium process (given by u_t) is a function of the amount of slack in the economy (y_t).

Equations 1-9 comprise the core of the model for potential output. In addition, data on growth and inflation expectations are added to help identify shocks, and to improve the accuracy of estimates at the end of the sample period:

$$(10) \quad \pi_{t+j}^C = \pi_{t+j} + \varepsilon_{t+j}^{\pi^C}, \quad j = 0, 1$$

⁹ Some recent work suggests that the slope of the Phillips curve relationship (β) has flattened over the past several decades (IMF, 2013), whereas other studies suggest that it may have steepened in some countries in recent years (Riggi and Venditti, 2014). Although the methodology in this paper does not allow for time variation in parameter estimates, modest changes in the estimated value of the parameter β , on its own, do not materially change the estimates of potential output and the output gap.

$$(11) \quad GROWTH_{t+j}^C = GROWTH_{t+j} + \varepsilon_{t+j}^{GROWTH^C}, \quad j = 0, \dots, 5$$

For real GDP growth ($GROWTH$) the model is augmented with forecasts from consensus economics for the five years following the end of the sample period. For inflation, expectations data are added for one year following the end of the sample period. These equations relate the model-consistent forward expectation for growth and inflation (π_{t+j} and $GROWTH_{t+j}$) to observable data on how consensus forecasters expect these variables to evolve over various horizons (one to five years ahead) at any given time ($GROWTH_{t+j}^C$). The ‘strength’ of the relationship between the data on consensus and the model’s forward expectation is determined by the standard deviation of the error terms ($\varepsilon_{t+j}^{\pi^C}$ and $\varepsilon_{t+j}^{GROWTH^C}$). In practice, the estimated variance of these terms allows consensus data to influence, but not completely override, the model’s expectations, particularly at the end of the sample period. In a way, the incorporation of consensus forecasts can be thought as an heuristic approach to blend forecasts from different sources and methods. The resulting impact of this information on the historical estimates of potential and the output gap can be significant, as shown in the following section.

IV. ESTIMATING THE OUTPUT GAP FOR THE U.S.

In order to illustrate the multivariate-filter approach, this section presents detailed results for the United States. The results for the euro area are presented in Section VI. We use the same approach in constructing estimates for these two regions. This version of the multivariate filter uses data on real gross domestic product, CPI inflation, the unemployment rate as well as Consensus Economics multi-year-ahead forecasts for CPI inflation and GDP growth. We will show that the latter data, in particular, are very important for identifying the historical shocks to the output gap, level shocks to potential, as well as the shocks that drive a wedge between underlying growth rate of potential and its steady-state rate. The sources for the data are presented in Appendix A1.

The priors and posterior estimates for the model’s parameters are presented in Appendix A2. The common priors across countries for the parameters are identical to what was used in Blagrove and others (2015) and seem to work well in a very large sample of countries.¹⁰ The parameters for the country-specific steady-state GDP growth rates reported in the appendix are taken from the April 2015 Consensus Economics long-term survey of GDP growth 6-10 years ahead. The parameters for the steady-state unemployment rates were taken from OECD’s long-term (2019) forecast of the NAIRU published in their Economic Outlook

¹⁰ The programs for reproducing the estimates in Blagrove and others (2015) can be found at www.douglaslaxton.org.

database (Version 95) in May . Both of these parameters act as attractors in the system and will determine where GDP growth and unemployment converge to over the medium term.

To shed light on the role of the different components of the model, we present each marginal step in the construction of the estimates by gradually expanding the list of observable variables. In what follows, we show that the simple model specified in this paper offers several noteworthy advantages (namely, the theoretical coherence of output-gap estimates and inflation, the transparency of the estimates, as well as its end-of-sample revision properties and the robustness of real-time estimates). However, it is far from perfect, and should not be used mechanically to obtain estimates (nor should any model).

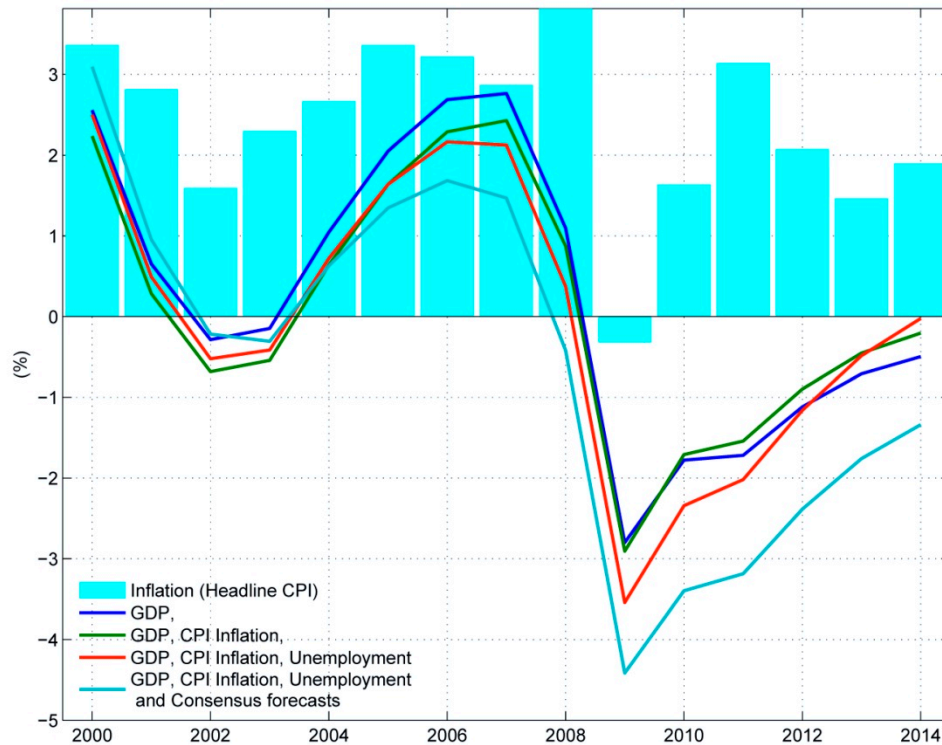
The output gap estimates based on just using information on GDP and equations 1-4 from the preceding section are depicted by the blue line in Figure 2. This effectively is a univariate representation of GDP and potential output. However, unlike the HP filter, which assumes that both the output gap and the second difference of potential are white noise processes, equations 1- 4 provide a more plausible set of stochastic processes.¹¹ Recall, the output gap is assumed to be positively serially correlated. The level of potential is affected by two types of shocks: a shock that can have permanent effects on the level of potential; and a shock that can cause persistent deviations of the growth rate of potential from some long run steady-state growth rate.

The parameters that determine the standard deviations of the shocks are reported in Appendix A3. They have been calibrated so that approximately $\frac{3}{4}$ of the variance in the growth rate of annual GDP growth is driven by variability in the change in the output gap. This calibration would be consistent with the view that shocks to potential output are significant, but not the dominant source of variation in annual GDP growth.¹²

¹¹ Estimates of the HP filter can be obtained by minimizing the following objective function: $\sum_{t=1}^T (Y_t - \bar{Y}_t)^2 + \lambda \sum_{t=1}^{T-2} [(\bar{Y}_{t+2} - \bar{Y}_{t+1}) - (\bar{Y}_{t+1} - \bar{Y}_t)]^2$. They can also be obtained by using the Kalman filter to estimate the unobservable component (\bar{Y}_t) in the following statistical model: $Y_t - \bar{Y}_t \sim N(0, \sigma_y^2)$ and $(\bar{Y}_{t+2} - \bar{Y}_{t+1}) - (\bar{Y}_{t+1} - \bar{Y}_t) \sim N(0, \sigma_{\bar{y}}^2)$. The code and related training material for comparing these two sets of results can be found on www.douglaslaxton.org.

¹² There is a large empirical literature that attempts to estimate the relative contribution of demand and supply shocks. See, for example, Christiano and Eichenbaum (1990), and Cogley (1990). Our conclusion from reading this literature is that it is impossible to reliably estimate these contributions in the class of models that are typically studied and consequently it is necessary to calibrate these parameters rather than try to estimate them. For the purpose of estimating confidence bands we consider alternative estimates where the contribution of output gap shocks represent approximately 95% of the contribution to GDP growth as well as an alternative case where they only represent about a half of the variation in GDP growth. Readers interested in understanding how the basic results depend on these assumptions can download the code at www.douglaslaxton.org and modify them.

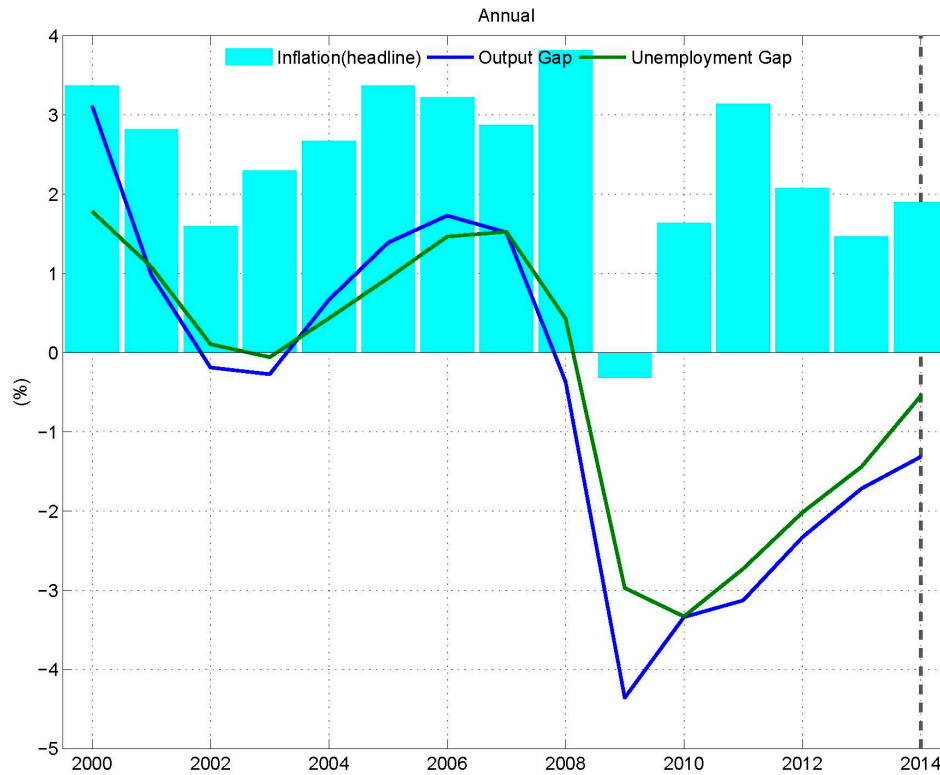
Figure 2. U.S.: Output Gap Decomposition



Source: Authors' estimates.

The addition of inflation to the list of observable variables and the Phillips Curve (equation 5) suggests slightly less excess demand in the pre-crisis period, given that inflation was not very elevated (dark green line). In the post-crisis period, the inclusion of inflation points to less economic slack, which results from the structure of the filter, where observed increases in inflation are associated with a closing output gap, all else equal. Of course, as practitioners we may not agree with this simple mechanical assessment of the filter, which would motivate the addition of judgment to help condition these estimates at the end of the sample.

The additions of model structure for unemployment (equations 6-9) and the unemployment data produce the estimates depicted by the red line. Adding unemployment to the model results in significantly larger estimates of slack following the global financial crisis. This reflects a very tight correlation between the output gap and the unemployment gap (Figure 3) which helps to identify periods of large slack during periods of high unemployment, such as during the period after the global financial crisis.

Figure 3. U.S.: Output Gap, Unemployment Gap, and Inflation

Source: Authors' estimates.

Adding consensus medium-term forecasts for GDP growth and near-term forecasts for CPI inflation as well as equations 10 and 11 produces the teal line. This results in even larger and more persistent negative output gaps after the global financial crisis. This seems to reflect the fact that consensus forecasts were fairly strong for most of the past decade, with the exception of the crisis period, and have slowed only moderately since the crisis—the filter interprets this as evidence that the observed decline in growth during the crisis had an important cyclical element.

The output-gap estimates can also be considered in conjunction with the other measures being used to help identify them. In Figure 3, the estimated output gap (blue line) is shown for the U.S. alongside the estimates of the unemployment gap (green line) and inflation rate (teal bars). The upshot of this analysis is that these pieces of information are consistent.

In particular, the global financial crisis plunged the U.S. economy into a deep recession, opening up significant slack in both labor and goods markets. Overall, the amount of slack in the economy has diminished, but there are still underutilized resources more than 7 years after the global financial crisis, which seems consistent with the current moderate inflation.

V. ASSESSING ADDITIONAL INFORMATION OUTSIDE THE MULTIVARIATE FILTER

Whereas the simplicity of the multivariate filter approach allows for a timely assessment of potential output, it is often beneficial to consider a wider set of evidence in order to refine the estimates provided by the filter. The methodology discussed in Section III is well-suited to incorporate additional information when estimating potential output. In particular, the filtered estimates at the end of the sample period can be improved with additional sources of information, including labor market indicators and other information on the supply side of the economy. This can be done either by explicitly specifying additional economic relationships in the filter or through off-model judgment.

To illustrate how additional information might help inform one's assessment about potential output, and hence the output gap, this section discusses recent work on drivers of potential output and measures of slack. We focus on the U.S. given the extensive body of relevant work and statistics available, which can shed light on issues that are not explicitly captured by the multivariate filter framework and help to fine-tune the potential output estimate. In particular, we discuss issues around data mis-measurement, labor force composition, resource utilization and total factor productivity, although this is by no means an exhaustive account. Figure 4 plots external estimates which illustrate the impact of some of these factors on U.S. labor productivity growth.

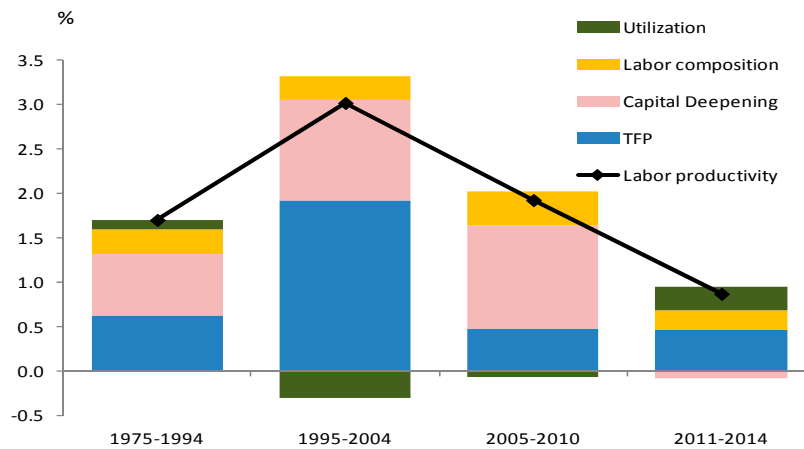
Data mis-measurement can be an important issue when estimating potential output, particularly at the end of the sample where data are relatively new. For example, Higgins (2015) argues that weak initial estimates of labor productivity tend to be revised up three years later. And Byrne and Pinto (2015) argue that difficulties around measuring the price of high-tech equipment have understated reported investment and thus overstated the weakness in capital deepening since 2010. Taken together, these studies suggest that actual potential output in recent years might be higher than suggested by the current vintage of data.

The composition of the labor force can also affect potential output, as labor productivity rises when the labor force becomes more qualified or the structure of the economy moves towards higher skilled occupations. Whereas total educational achievement of a given population might tend to move only gradually, the average quality of workers in the economy might also change within the business cycle. For example, Fernald (2014b) argues that the U.S. labor force became more skilled during the Great Recession, as lower skilled workers

disproportionately lost jobs. The United Kingdom experienced something similar, as discussed in Corder (2015).

Resource utilization, or the intensity with which labor and capital are used in the economy, varies over the business cycle. As such, failing to account for it might lead us to underestimate (overestimate) total factor productivity when utilization is low (high). Measuring utilization is non-trivial. Capacity utilization surveys capture the extent to which manufacturing firms are operating above or below capacity. But they might fail to capture structural shifts which affect the definition of capacity itself. For example, when a product becomes obsolete, capacity utilization in that industry might be reported as very low to the extent that the production lines are unused, when effectively the stock of capital in that industry will not add to potential output until it is readjusted to new production lines. The *degree of labor utilization also matters*. Here we refer to utilization over and above what can be inferred from the gap between unemployment and the NAIRU, which is already captured in the multivariate filter framework. For example, measured labor productivity may vary depending on the effort required of employees per hour of work. Also, it could fall in recessions if firms initially hoarded labor to either avoid firing and hiring costs or to preserve valuable skills in anticipation of higher future demand. Whereas labor utilization is also difficult to measure, Basu, Fernald, and Kimball (2006) argue that measures of hours per worker provide a good proxy. Several studies illustrate the importance of accounting for resource utilization when estimating potential output. Alich (2015) argues that the inclusion of capacity utilization is crucial to obtain a reliable measure of potential output for the U.S., particularly in periods when the labor gap and capacity utilization give opposing steers about the degree of slack in the economy. Fernald (2014a) estimates a comprehensive measure of resource utilization for the U.S. which also captures labor utilization. This measure suggests that the utilization gap was nearly closed in 2013, in contrast to the evidence based solely on simple capacity utilization surveys.

A key driver of potential output is the evolution of *total factor productivity*. Here, the debate about current drivers and long-run prospects is far from settled. Some claim that the slowdown in U.S. TFP growth in recent years is a legacy of the financial crisis, whereas others argue that it started before the crisis. Many have coalesced on explanations relating to the impact of the information technology innovations. For example, Fernald (2014b) attributes the slowdown to the information and communication technology (ICT) revolution having run its course. And Gordon (2012) argues that the ICT revolution temporarily masked a structural decline in U.S. trend growth. In contrast, Cardarelli and Lusinyan (2015) find that the slowdown in TFP in recent years was not concentrated in IT-producing states or in those that use it intensively. Instead, they place more weight on explanations around reduced efficiency in combining innovation and production inputs.

Figure 4. U.S.: Decomposing Labor Productivity Growth

Source: Fernald (2014b) and Robertson (2015).

Note: Labor productivity defined as business sector output per hour worked.

VI. ESTIMATING THE OUTPUT GAP FOR THE EURO AREA

We apply the multivariate filter to estimate potential output and the output gap for the euro area. As in the case of the U.S., the blue line in Figure 5 shows the output-gap estimates associated with the chosen relative incidence of supply/demand shocks.

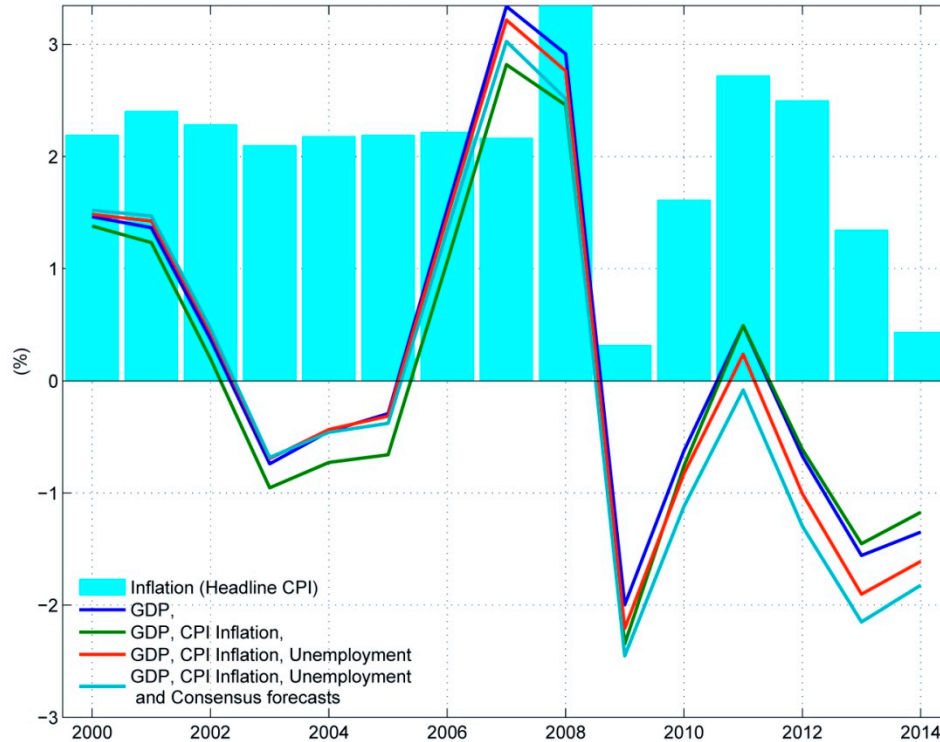
Overall, the results for the euro area are different from the United States. In particular, the addition of economic structure affects the filter's assessment essentially after the euro area sovereign debt crisis.

The green line in the graph above shows the role of additional economic structure (inflation), which results in slightly less excess demand before the global financial crisis, as inflation was stable and close to the ECB's target. The additional information on unemployment (red line) suggests that data on labor-market conditions do not add much identifying information for the output gap in the euro area. Adding information on inflation and growth expectations (teal line) does not alter the filter's assessment of the gap significantly.

During the post-global financial crisis recovery phase, the addition of model structure leads to the same assessment of the gap: the output gap closes rapidly, in line with the rebound in inflation, but widens subsequently on the back of the euro area sovereign debt-crisis. However, adding unemployment leads to a downshift of the output gap since the sovereign debt crisis, as the filter interprets the deterioration in the labor market as cyclical. Moreover, the addition of inflation and growth expectations (teal line) leads to more economic slack,

especially at the end of the sample period, as the filter interprets weak euro area growth as temporary.

Figure 5. Euro Area: Output Gap Decomposition



Source: Authors' estimates.

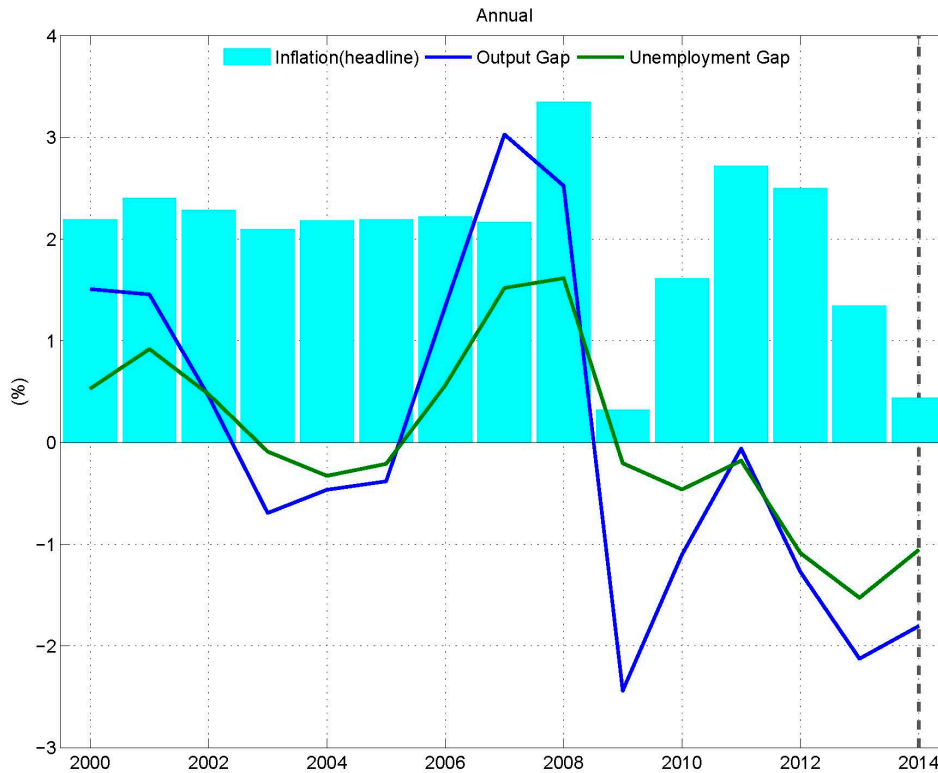
We also consider the output-gap estimates in conjunction with the other measures used to help identify them. Figure 6 shows that the estimated output gap (blue line) is consistent with the estimates of the unemployment gap (green line) and the inflation dynamics in the euro area (teal bars).

Incorporating additional information in the euro area from the production function, and comparison with other institutions

For the euro area, in order to more effectively evaluate the consistency of the results from the multivariate filter, we examine the drivers of potential growth using a growth accounting framework. Data on capital and labor inputs are used to decompose the filter's estimates of potential growth into its component parts using a Cobb Douglas production function approach:

$$\bar{Y}_t = \bar{A}_t K_t^\alpha \bar{L}_t^{(1-\alpha)} \quad (\alpha = 1/3).$$

Figure 6. Euro Area: Output Gap, Unemployment Gap, and Inflation



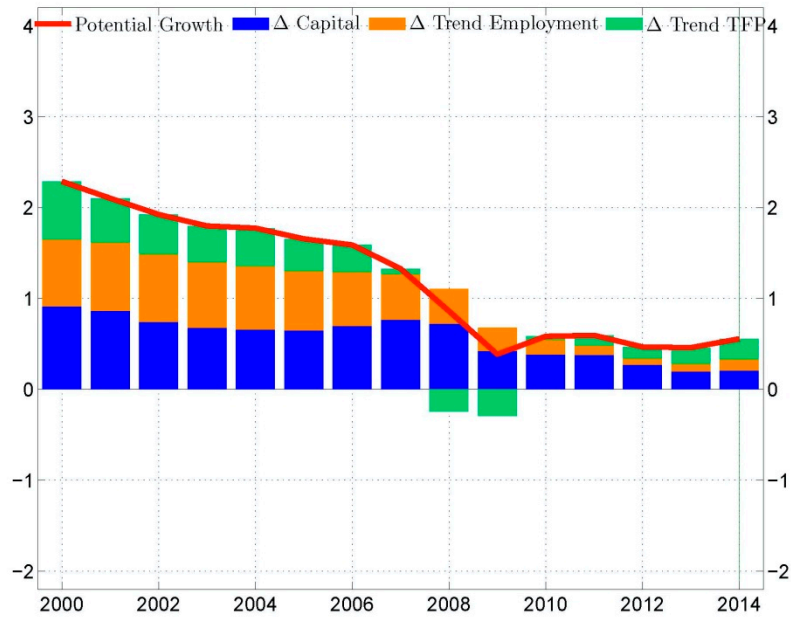
Source: Authors' estimates.

\bar{Y}_t is potential output, K_t the stock of productive capital, \bar{L}_t potential employment, \bar{A}_t potential total factor productivity and α the share of capital in potential output. The decomposed estimates of potential output growth provide information about the plausibility of the estimated path from the multivariate filter, given information on the production-function components (Figure 7).

The estimated path for potential growth in recent years appears plausible. In particular, the drop in potential growth during the global financial crisis in 2007-08 reflects a negative contribution from total factor productivity (green bar) and smaller positive contributions from the capital stock (blue bar) and labor inputs (orange bar) due to the contraction in investment and a rise in the structural unemployment rate. Moreover, the sovereign debt

crisis has dampened further potential growth, with additional declines in investment, while the contribution from employment remains well below the pre-crisis levels. The contribution from TFP growth was small. Given that demographics should continue to make a smaller contribution to potential growth, any acceleration in potential growth will need to be driven by trend TFP and higher investment rates.

Figure 7. Euro Area: Potential Growth Components



Source: Authors' estimates.

Additionally, we compare the results from the multivariate filter with the estimates from other international organizations (see Table 1). The estimates of potential that come out of the filter are broadly comparable with that of other institutions. However, the filter's estimate of potential growth decelerated earlier than that from other institutions at the beginning of the global financial crisis. The estimates of potential growth and the output gap from these institutions have been close to the filter's results subsequently. However, the model shows a slight pick-up in potential growth during the recovery in 2010, followed by a slight deceleration during the euro area sovereign debt crisis. The estimates from other international organizations do not fully capture the uptick in potential growth during the recovery phase.

Table 1. Euro Area: Comparison of Results

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Potential GDP Growth (in %)														
OECD EO	2.4	2.1	1.8	1.6	1.5	1.6	1.7	1.5	0.8	0.8	0.8	0.7	0.7	0.8
EC	2.3	2.0	1.9	1.9	1.8	1.8	1.8	1.4	0.6	0.6	0.7	0.4	0.4	0.6
IMF WEO	2.0	2.0	1.6	1.7	1.6	1.5	1.4	1.1	0.5	0.7	0.7	0.5	0.5	0.8
MVF	2.1	1.9	1.8	1.8	1.7	1.6	1.3	0.9	0.4	0.6	0.6	0.5	0.5	0.6
Output gap (in %)														
OECD EO	2.0	1.0	-0.1	0.2	0.4	2.2	3.6	2.6	-2.9	-1.7	-0.9	-2.3	-3.3	-3.2
EC	2.0	0.9	-0.3	0.1	0.0	1.4	2.7	1.8	-3.4	-2.0	-1.1	-2.2	-3.1	-2.8
IMF WEO	1.3	0.1	-0.9	-0.3	-0.3	1.4	2.9	2.3	-2.9	-1.5	-0.6	-1.9	-2.9	-2.8
MVF	1.5	0.5	-0.7	-0.5	-0.4	1.3	3.0	2.5	-2.5	-1.1	-0.1	-1.3	-2.1	-1.8
Natural Unemployment Rate (in %)														
OECD EO	8.8	8.8	8.9	8.9	8.9	8.9	8.9	8.9	9.1	9.2	9.3	9.5	9.6	9.6
EC*	9.0	8.9	9.0	8.9	8.9	8.9	8.9	9.0	9.3	9.4	9.3	9.6	9.7	9.8
IMF WEO	8.9	8.8	8.7	8.7	8.6	8.5	8.5	8.6	8.8	9.1	9.2	9.4	9.5	9.4
MVF	9.2	9.1	9.0	8.9	8.9	8.9	9.0	9.2	9.4	9.7	10.0	10.3	10.5	10.5
Unemployment Gap (in ppt)														
OECD EO	0.8	0.4	0.0	-0.2	0.0	0.6	1.4	1.4	-0.4	-0.7	-0.7	-1.8	-2.4	-2.0
EC*	0.7	0.3	-0.1	-0.4	-0.2	0.5	1.4	1.4	-0.3	-0.8	-0.9	-1.8	-2.3	-1.8
IMF WEO	0.5	0.1	-0.4	-0.6	-0.5	0.1	1.0	1.1	-0.8	-1.1	-1.0	-2.0	-2.5	-2.2
MVF	0.9	0.5	-0.1	-0.3	-0.2	0.6	1.5	1.6	-0.2	-0.5	-0.2	-1.1	-1.5	-1.1

Source: OECD Economic Outlook (EO) June 2015; EU Commission (EC) May 2015; IMF World Economic Outlook (WEO) Live, July 2015; authors' estimates.

Note: *Nonaccelerating Wage Rate of Unemployment (NAWRU).

VII. UNCERTAINTY IN ESTIMATING THE OUTPUT GAP AND POTENTIAL

Uncertainty in estimating the output gap in the U.S.

Potential output and the output gap are not variables that can be observed—they can only be estimated, and these estimates are subject to varying degrees of imprecision, depending on the technique used and the amount of information available when the estimates are constructed. To assess the robustness of the MVF estimates of potential, we construct confidence bands for the MVF approach specified in this paper and then compare them to confidence bands for a simple HP filtration of GDP. These confidence bands measure the uncertainty inherent in the model's estimates of the latent variables, and are not intended to capture model or parameter uncertainty, which are broader concepts beyond the scope of this exercise.

The objective of this exercise is to compare the performance of the HP filter and the multivariate filter, under various assumptions about the relative importance of supply and demand shocks. To do this, we need benchmark estimates for the parameters of the model. These estimates are obtained from the posterior estimation of the full structural model

described in the paper (equations 1-11). These estimates are summarized in Appendix Tables A2 and A3.

As we have discussed in Section IV, the econometric literature on the uncertainty about the sources of demand and supply shocks provides various calibrations for the relative contribution of supply and demand components to output movements. We take our estimates from the mode of the posterior distribution as the benchmark case, where demand shocks can explain approximately 74% of total output variations. We consider two other alternative cases where the ratio is 93% and 55%, respectively. These two alternative cases use the same equations and parameter estimates as the benchmark case – except, of course, different standard deviations for supply and demand shocks. Table 2 compares the standard deviations of the shocks for all three cases.

Table 2. Standard Deviations of Supply and Demand Shocks

Shocks	Parameters	Benchmark	Alternative (I)	Alternative (II)
Supply Shock	$\sigma(\varepsilon^{\bar{Y}})$	0.2	0.1	0.4
	$\sigma(\varepsilon^G)$	0.2	0.1	0.4
Demand Shock	$\sigma(\varepsilon_t^y)$	0.8	1.0	1.0
Percent of Demand Shock	$\frac{\sigma^2(\Delta y)}{\sigma^2(\Delta Y)}$	≈74%	≈93%	≈55%

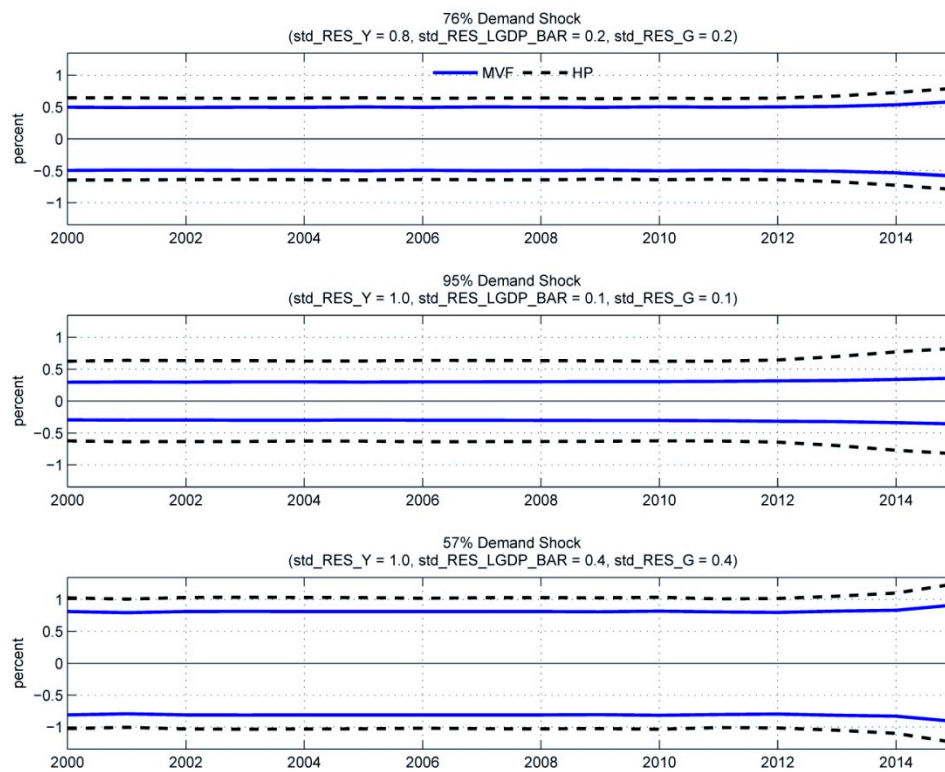
Note: σ represents standard deviation.

Source: Author's calculation.

A Monte Carlo simulation of 1,000 draws of all variables from the full structural model is conducted. We simulate for a sufficiently long period (1000 years). To alleviate the burn-in bias, the first 500 years of simulation are discarded.

The HP filter with a signal-noise ratio (λ) of 6.25 is applied to the GDP observables in each of the 1,000 samples. We compute the deviations of the HP filter estimates of the potential output and output gap from the assumed true paths, and report the 95% confidence bands in Figure 8. Similar steps are implemented for the multivariate filter to allow a fair comparison between the two methods. The multivariate filter is applied to all the observables in each sample, and the 95% confidence bands of the deviations of the estimates of potential output and output gap from their assumed true paths are plotted.

Figure 8. U.S.: 95% Confidence Bands for Estimates of Potential Growth

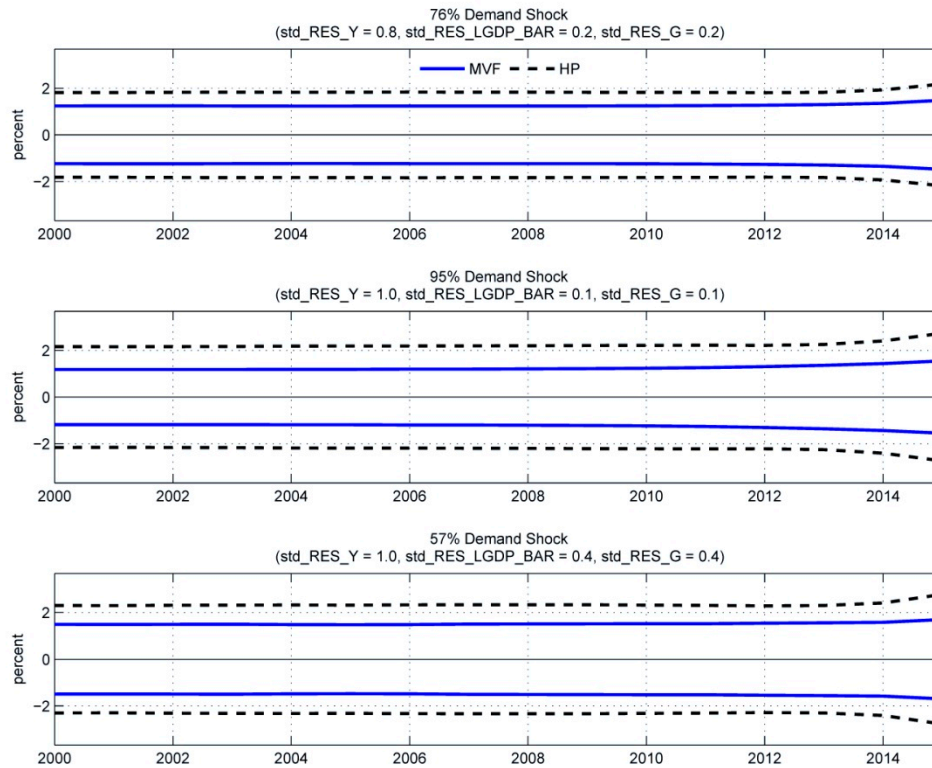


Source: Authors' estimates.

Each panel shows results using three different calibrations for the relative variance of supply and demand shocks. The top one is the baseline calibration of the MVF used in this paper (where demand shocks explain approximately 76% of total output variations), and showing alternative calibrations serves as a robustness check to ensure that the improved fit of the MVF relative to the HP filter is not a function of these relative variances. As shown in the figures, irrespective of the assumed relative incidence of these shocks, the estimates of potential and the output gap coming from the MVF are subject to less uncertainty than are those from an HP filter. This result follows from the fact that more identifying information is used in the MVF than in a simple univariate filter.¹³

¹³ The *degree* to which the MVF estimates outperform those from the simple HP filter does vary by country, and depends on the strength of the relationship between the output gap and inflation/unemployment in a given economy.

Figure 9. U.S.: 95% Confidence Bands for Estimates of Output Gap

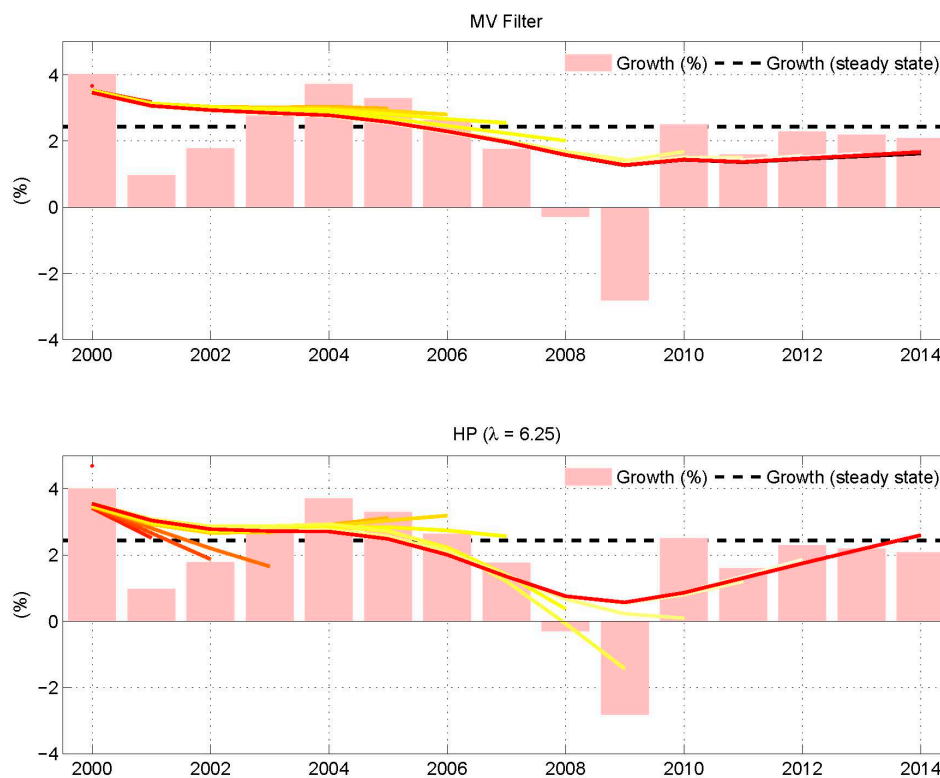


Source: Authors' estimates.

Real-time estimates coming from the MVF are also less prone to revision than are estimates derived from an HP filter. In Figure 10, quasi-real-time¹⁴ estimates of potential output over the past 20 years are plotted.

¹⁴ These estimates are constructed by sequentially estimating potential output in each year, using only the data available as of that date. For example, the quasi-real-time estimates of potential in 2007 (for both HP and MVF) would have used data from the beginning of the sample through 2007 only. The estimates are 'quasi' real-time in the sense that actual vintage data are not used for this exercise (but rather only currently-available data, which have been revised over time).

Figure 10. U.S.: Potential Growth Estimates as the Sample Is Extended



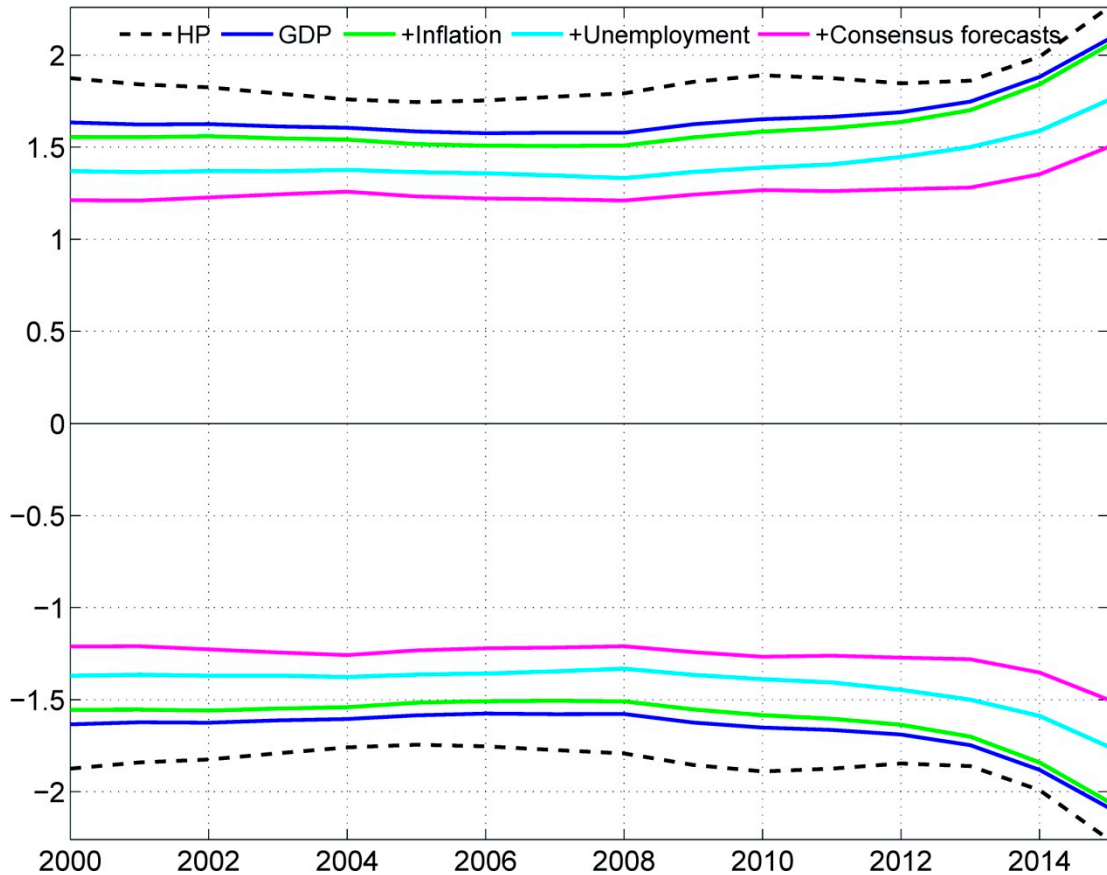
Source: Authors' estimates.

Having established that the MVF estimates of potential output growth are subject to less uncertainty than are those coming from the HP filter, we proceed to investigate how the uncertainty surrounding the MVF estimates of potential output growth change when the model is expanded piece-by-piece, adding each identifying equation one-by-one. Similar to the results shown in the previous exercise, the estimates of potential output growth become more robust as more information is added to the model in the form of additional structure. The results for the U.S. are shown in Figure 11.¹⁵ Relative to the simplest possible formulation of the MVF (with GDP only) shown by the blue line (and using only equations 1-4 from Section III), the addition of model structure which relates estimates of the output gap to inflation (equation 5) improves the performance of potential-growth estimates materially (shown by the green line). From there, adding model structure (equations 6-9) and data on unemployment further improves the robustness of estimates (teal line). Adding

¹⁵ The lines of the chart are presented in deviations from the Kalman smoother's mean estimate.

structure (equation 10-11) and observable data on consensus expectations of inflation and growth yields significantly improves the performance (pink line).

Figure 11. U.S.: 95% Confidence Bands for Estimates of Output Gap (with structure/data added incrementally)



Source: Authors' estimates.

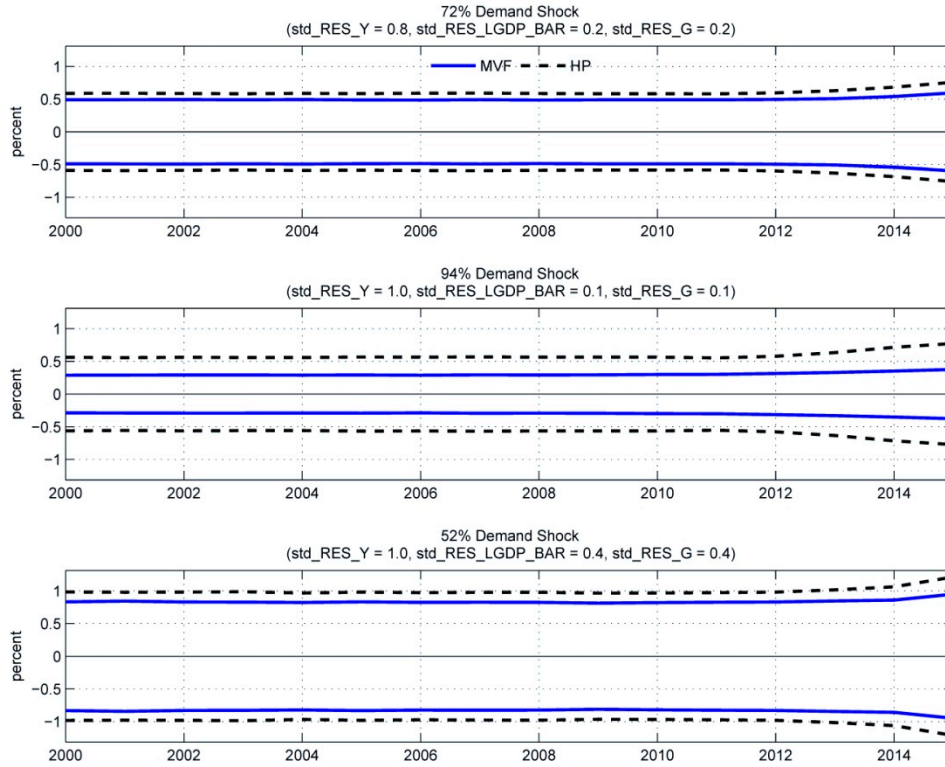
Uncertainty in estimating the output gap in the euro area

We assess the robustness of the MVF estimates of potential and the output gap for the euro area, by constructing confidence bands for the MVF approach specified in this paper and comparing them to confidence bands for a simple HP filtration of GDP (Figure 12 and 13).

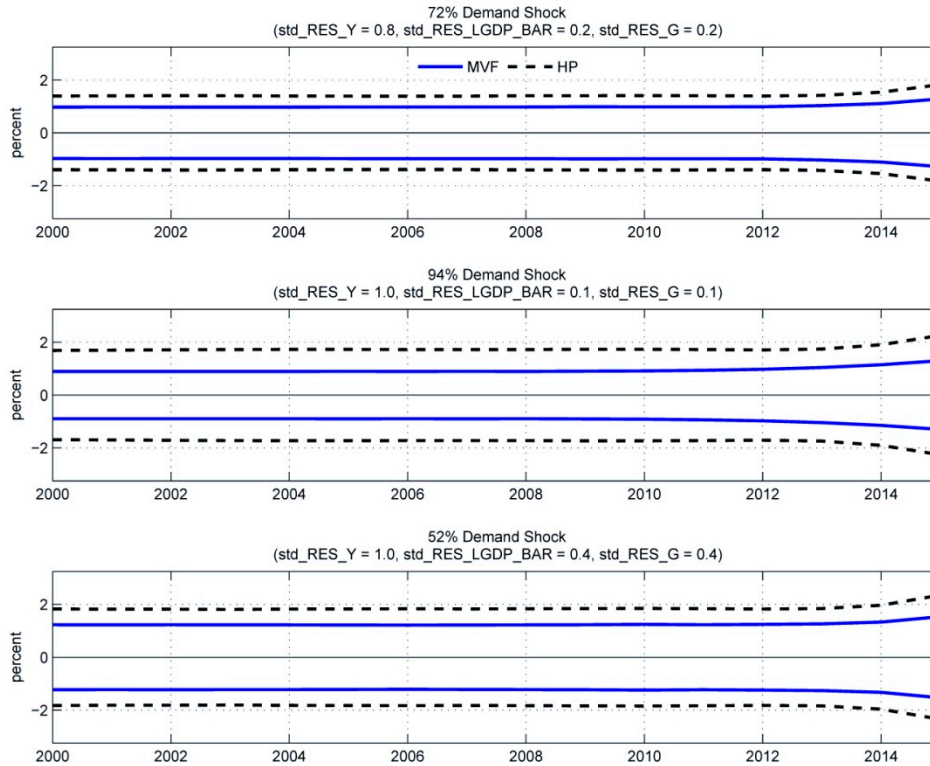
As previously shown for the U.S., each panel shows results using three different calibrations for the relative variance of supply and demand shocks. As shown in the figures, the estimates

of potential and the output gap generated by the MVF are subject to less uncertainty than are those produced by the HP filter.

Figure 12. Euro Area: 95% Confidence Bands for Estimates of Potential Growth



Source: Authors' estimates.

Figure 13. Euro Area: 95% Confidence Bands for Estimates of Output Gap

Source: Authors' estimates.

VIII. CONCLUSION

The methodology presented in this paper draws on previous work applying multivariate filters to the estimation of potential output. By embedding the structural relationship between inflation, unemployment and the output gap, this class of models produces estimates of potential output and economic slack which are intuitive and consistent with basic economic theory. The innovations in this paper are twofold: first, this approach is particularly useful in estimating potential output in the U.S. where the availability of many other sources of information helps to fine-tune the filter's estimate. And, second, data on growth expectations have been added in order to help address (though not completely alleviate) the end-of-sample problem in the U.S. and the euro area. As shown in the preceding section, estimates of potential obtained using this model are more robust than are those resulting from HP-filtering techniques. Still, the end-of-sample problem remains an issue, particularly around turning

points in the business cycle, which motivates the use of additional information taken from outside the model by practitioners when using the results to guide policy.

Future work will focus on extending the methodology to other countries, and experimenting with alternate measures of inflation, such as core inflation or PCE inflation in the case of the United States. In addition, the results will be investigated further to gauge whether there are important commonalities in the evolution of potential output in the pre- and post-crisis periods across countries—this will be done by decomposing the existing results using a production-function approach. The approach could also be extended by explicitly incorporating other sources of information into the multivariate filter, such as the capacity utilization rates and/or measures of capital services.

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APPENDIX

Table A1. Data Sources

Indicator	Source
Inflation Expectations	Consensus Economics
Gross Domestic Product Growth Expectations (Constant Prices)	Consensus Economics
Gross Domestic Product (Constant Prices)	IMF, World Economic Outlook Database
CPI Inflation	IMF, World Economic Outlook Database
Unemployment Rate	IMF, World Economic Outlook Database

Table A2. Estimated Parameters

Parameter	Common Prior Mode	Common Prior Dispersion	Posterior Mode (U.S.)	Posterior Mode (Euro Area)
β	0.25	0.1	0.050	0.167
λ	0.25	0.1	0.317	0.259
ϕ	0.60	0.1	0.711	0.582
θ	0.10	0.1	0.115	0.076
τ_1	0.10	0.1	0.492	0.352
τ_2	0.10	0.1	0.352	0.251

Table A3. Calibrated Parameters

Parameter	Value
$\sigma(\varepsilon_t^y)$	0.8
$\sigma(\varepsilon_t^{\bar{y}})$	0.2
$\sigma(\varepsilon_t^G)$	0.2
$\sigma(\varepsilon_t^u)$	0.5
$\sigma(\varepsilon_t^{\bar{U}})$	0.1
$\sigma(\varepsilon_t^{g\bar{U}})$	0.1
τ_3	0.1
τ_4	0.1
G^{ss}	2.30 (U.S.) 1.40 (Euro Area)
\bar{U}^{ss}	5.92 (U.S.) 9.73 (Euro Area)

Selected Equations

$$\pi_t = \lambda\pi_{t+1} + (1 - \lambda)\pi_{t-1} + \beta y_t + \varepsilon_t^\pi$$

$$y_t = \phi y_{t-1} + \varepsilon_t^y$$

$$G_t = \theta G^{ss} + (1 - \theta)G_{t-1} + \varepsilon_t^G$$

$$u_t = \tau_2 u_{t-1} + \tau_1 y_t + \varepsilon_t^u$$

$$G_t^{\bar{U}} = (1 - \tau_3)G_t^{\bar{U}} + \varepsilon_t^{G^{\bar{U}}}$$

$$\bar{U}_t = (\tau_4 \bar{U}^{ss} + (1 - \tau_4)\bar{U}_{t-1}) + G_t^{\bar{U}} + \varepsilon_t^{\bar{U}}$$

Note: σ represents standard deviation. G^{ss} is taken from Consensus Economics long-term (6-10 years ahead) growth forecast for GDP (April 2015). \bar{U}^{ss} is taken from OCED Economic Outlook No. 95 (May 2014).