Embedding financial cycle information in output gap estimation: A century perspective *

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FIRST VERSION

Abstract

This paper considers the role of financial information in the estimation and dynamics of the US output gap over more than a century. To this end, we employ Borio, Disyatat, and Juselius (2016, 2014)’s parsimonious approach, but extend the methodology to allow for time-varying effects of financial variables. This novel feature significantly improves the real-time estimation of the output gap signaling the peak and trough in economic activity related both to the Great Recession as well as to the Great Depression. Two major insights follow. Credit dynamics are the primary drivers of the observed financial crisis albeit with different conduits over the century: the stock market in 1929 and the housing market in 2008. Accounting for credit growth, US potential growth has been stable at 2% since the beginning of 1980.

JEL codes: C11, C32, E32, O47.

Keywords: Potential Output, Output Gap, Kalman Filter, Real-Financial Cycle, Time-varying parameter

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1 Introduction

Interest in the estimation of the output gap, and the implicit amendments required in policy-making, has witnessed a recent resurgence. Several factors have concurrently contributed to the rebirth of this literature. One has been the debate initiated by Summers (2014) surrounding the structural demand deficiency that has accompanied the post-2008 recovery. The starting point of this argument is the observed decrease in potential output following the recession. Closing of the output gap, measured using CBO’s estimates, is then attributed in equal part both to growth in observed output as well as to the reduction in the level of potential output. It should be noted that the arguments focusing on the level of potential output used by Summers (2014) have as starting point the year 2007. Consider the possibility that the pre-2007 economic exuberance, in retrospect caused by mix of loose lending standards and a bubbly housing market, had been imparting an unwarranted upward trend in potential growth rates. Focusing only the level of potential output from 2007 onwards may induce the reader to consider the potential contraction more severe than warranted, particularly when using the GDP level of 2007 as the original anchor. The estimation of potential GDP becomes therefore one of the focal points of the analysis. Different methods to estimate the output gap can lead to substantially different realities of the state of the economy (see Borio, Disyatat, and Juselius, 2016). Robustness in the estimation of potential output (and its associated output gap) becomes thus an essential feature needed to preserve the validity of any argument built with potential output as an ingredient.

In parallel to the above-mentioned literature, the development of new models of the output gap have been further motivated by the debates around the interaction between the financial and the real cycle. Borio, Disyatat, and Juselius (2016, 2014) (henceforth BDJ) are one of the first studies that develop a simple framework for measuring potential output in which financial factors are allowed to play a central role. Applying to the US data over the 1980-2012 period, BDJ find that information about the financial cycle, particularly credit growth, explains a significant portion of the cyclical movements in output, thus contributing to identify the unobserved potential output. To illustrate, BDJ show that the financial-information-based output gap measure is able to spot the unsustainable expansion in real

1For instance, Claessens, Kose, and Terrones (2012), Schularick and Taylor (2012), Jordà, Schularick, and Taylor (2013), and Aikman, Haldane, and Nelson (2015), among others.
time in the pre-2007 crisis, while the estimates by the OECD, IMF and those based on the HP filter indicated that output was below or at most close to potential.

Our paper contributes to the above-mentioned literature streams in several ways. First, we apply the framework proposed by BDJ to incorporate the financial information, as captured by the behavior of credit as motivated by recent literature on the role of credit on business cycles, in measures of potential output to a century spanning US data set of (Jordà, Schularick, and Taylor, 2017). Nevertheless, given such long-run time series, it is likely that the influence of financial information on cyclical movement of output may not be time-invariant as assumed in the BDJ. In Table 1, we present the correlation between GDP growth rates and credit growth rates over different time frames. The varying correlation suggests that the relationship between financial and business cycles may subject to changes. Therefore, we extend the BDJ framework to allow for the potential changing nature and strength of such a relationship through the use of a time-varying parameter structure. We refer to this extended version as the time-varying parameter BDJ version, which nests the BDJ version as a special case. Second, based on this TVP BDJ framework, we estimate the potential growth the growth in potential output and compare its dynamics with those obtained from popular approaches such as the HP filter and the univariate model. Last but not least, in addition to credit which is used in our baseline, we consider a variety of financial variables and evaluate which variable produces robust real time estimates of output gap, with an emphasis on the two great financial crashes of 1929 and 2007.

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>Δln(GDP), Δln(CRE)</td>
<td>0.47***</td>
<td>-0.14</td>
<td>0.65***</td>
<td>0.87***</td>
<td>0.70**</td>
<td>0.21**</td>
</tr>
</tbody>
</table>

Note: The table shows the correlation between output growth, Δln(GDP), and real credit growth, Δln(CRE). ** p < 1%, *** p < 5%.

As a preview of the results, we indicate the fundamental role that credit growth plays in the determination of potential output and the output gap. The data indicates that real credit growth is more important than any of the other considered financial variables. The relationship is time-varying as highlighted by the fluctuations observed in the parameter capturing the elasticity of the output gap with respect to credit growth. An important observation is
that the channels through which excessive credit overflows into the real economy are different over time. The stock market works as a conduit for the excessive energy emanated by credit in the crash of 1930 leading to the Great Depression. This role is then picked up by the housing market during the recent financial crisis of 2007 causing the Great Recession afterwards. Accounting for credit growth, US potential growth has been stable at 2% since the beginning of 1980.

The remainder of the paper proceeds as follows. Section 2 discusses the model used for analysis. Section 3 presents estimation methodology, prior and posterior distributions of parameters, and the results. Section 4 provides further discussions. Section 5 concludes.

2 The Models

First we describe the parsimonious approach proposed by BDJ (2016; 2014) to embed financial information into estimating output gap. Then we develop a new version of this approach in which the influence of financial variables on output gap is allowed to change over time.

2.1 The Borio, Disyatat, and Juselius Framework

BDJ (2016; 2014) decompose the (log) real GDP ($y_t$) into a trend component $\bar{y}_t$ and its cycle (or output gap) $\hat{y}_t$ as follows:

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

(1)

in which

$$\Delta \bar{y}_{t+1} = \Delta \bar{y}_t + \varepsilon^\alpha_t, \text{ where } \varepsilon^\alpha_t \sim N(0, \sigma^2_{\varepsilon^\alpha})$$

(2)

$$\hat{y}_t = \rho \hat{y}_{t-1} + \gamma f_t + \varepsilon^\beta_t, \text{ where } \varepsilon^\beta_t \sim N(0, \sigma^2_{\varepsilon^\beta})$$

(3)

where $f_t$ is a proxy of financial cycle and $\varepsilon's$ are normally distributed independent white noise processes with zero means.

In this framework, potential growth is assumed to change slowly over time according to a random walk mechanism and subject to a shock $\varepsilon^\alpha_t$. Meanwhile, the output gap in (3) is assumed to follow an autoregressive process and embedded with financial cycle information $f_t$. Therefore, the derived output gap is also known as the finance-neutral measure, indicating

\footnote{For instance, Gordon (2014) argued that labor productivity grew at an average rate 0.8 percent per year faster in the eight decades before 1972 than in the four decades since 1972.}
that output is well above potential during outsize financial booms no matter what the rate of inflation is. By estimating on quarterly US data over the sample 1980Q1-2012Q4 with house price and credit growth, BDJ (2016; 2014) find that the coefficients for financial variables are positive and significant.

BDJ (2016) argue that this approach is not only simple and transparent but also robust in estimating real-time output gaps. These advantages arise from the fact that the BDJ approach does not force the output gap to explain the associated variables; therefore it is less sensitive to potential misspecification in structural relationships. Instead, standard estimators of the parameters in (3) will assign a non-zero (or zero) weight to any information in \( x_t \) that does (does not) help to explain business cycle fluctuations.

It is also worth noting that although financial variables are not allowed to affect directly potential output, the information content that financial factors have for the transitory, cyclical component of output also has a substantial influence on the estimate of potential output because of the constraint in (1). This means that if any permanent effect exists, it will ultimately be reflected in potential output too.

2.2 The Time Varying Parameter BDJ Framework

As motivated in the introduction, the relationship between financial variable, such as real credit growth, and output appears to change over time implying that the information content that financial factors have for output gap is potentially time-varying. For this reason, we improve the BDJ framework by allowing the financial parameter \( \gamma_t \) to be time-varying and name this proposed framework as the TVP-BDJ. With this new feature, the output gap equation in the TVP-BDJ framework is expressed as follows:

\[
\hat{y}_t = \rho \hat{y}_{t-1} + \gamma_t f_t + \varepsilon_t^y, \quad \text{where } \varepsilon_t^y \sim N(0, \sigma^2_{\varepsilon_y}) \tag{4}
\]

where the time-varying parameter \( \gamma_t \) is represented as the driftless random walk process, which has been widely used in TVP models such as Cogley and Sargent (2001), Cogley and Sargent (2005), and Kim and Nelson (2006),

\[
\gamma_{t+1} = \gamma_t + \varepsilon_t^\gamma, \quad \text{where } \varepsilon_t^\gamma \sim N(0, \sigma^2_{\varepsilon^\gamma}) \tag{5}
\]

Other equations, including trend-cycle decomposition (1) and potential output (2), remain as above. It is clear that the BDJ is a special case of the TVP-BDJ model when the variance
of $\varepsilon_t$ is zero.

In what follows, we apply the BDJ framework to the long spanning data set of US economy over nearly 150 years spanning the entire 1880-2013. The data is obtained from the Jordà-Schularick-Taylor Macrohistory Database (Jordà, Schularick, and Taylor, 2017).\(^3\)

3 Estimation

We estimate both two versions, i.e. the BDJ and its TVP version, and let the data decide which one it favors. In each case, the model is written in a state-space representation which allows to estimate the unobserved factors via Kalman filter (see, for instance, Harvey and Todd (1983), Harvey (1985), and Kim and Nelson (1999, Chapter 3) for detailed discussions). Regarding the parameters of the models, we apply the Bayesian approach for analysis in order to downweigh regions of the parameter space that are at odds with observations not contained in the estimation sample. Briefly, in the first step we estimate the mode of the posterior distribution by maximizing the log posterior function, which combines the prior information on the parameters with the likelihood of the data evaluated by Kalman filter. In the second step, we sample from the posterior with a Markov Chain Monte Carlo to obtain the posterior distribution. To generate draws from the posterior distribution of parameters, we apply the Random Walk Metropolis Hastings Algorithm.\(^4,5,6\) This algorithm requires the evaluation of the posterior density, i.e. the product of likelihood function and prior density. Because the prior is relied on well-known densities, the computation of prior density is straightforward. To evaluate the likelihood function of the state-space model, we rely on the Kalman filter.

3.1 The BDJ Model

We start with the BDJ model. As prior distribution, the cyclical component is assumed to be fairly persistent, so the AR(1) parameters $\rho$ is Beta distributed, whose domain is between 0 and 1, with mean 0.8 and standard deviation 0.1. In addition, the key driver of fluctuations in output is cyclical rather than trend shock, so the variance of innovations are

\(^3\)Appendix A contains detailed data definitions and sources.
\(^4\)The Hessian resulting from the optimization procedure was used for defining the transition probability function that generates the new proposed draw.
\(^6\) The Random Walk Metropolis Hastings Algorithm is conducted with 500,000 draws, in which the first half is discarded as burn-in period.
assumed to follow an inverse-gamma-2 distribution with mean of 20 and 1 for cyclical and trend components, respectively, and with standard deviations of their corresponding mean values. On the other hand, we do not put any prior belief on the parameter $\gamma$ which contains the role of financial information on output gap.

According to Borio, Disyatat, and Juselius (2014), credit growth, i.e. the growth of real credit to non-financial private sector, contains significant information and helps generate robust real-time output gap estimates. In the baseline model, we use credit growth as a proxy of financial information $f_t$. The choice of credit is also motivated by the recent literature about the relationship between credit and business cycles, including Jordà, Schularick, and Taylor (2011), Claessens, Kose, and Terrones (2012), Schularick and Taylor (2012), Jordà, Schularick, and Taylor (2013), Borio (2014), and Aikman, Haldane, and Nelson (2015). In section 4.4, we consider a group of different financial variables as a proxy for $f_t$ and compare their real-time performance with the baseline model with credit.

One of the potential problem when using credit growth as a proxy for the financial cycle is that the trend in $f_t$ may pass onto output gap estimates. To avoid this issue, we demean $f_t$ before the estimation. Given the long span of data over more than a century with a variety of economic episodes, we demean the data from its ten-year moving average, which is less restricted than using full-sample mean or Cesàro mean.

### Table 2 – The BDJ Model: Real Credit Growth

<table>
<thead>
<tr>
<th>Domain.</th>
<th>Prior distribution</th>
<th>Posterior Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>(0,1) Beta</td>
<td>0.80 0.10 Mean 0.85 [0.76, 0.94] 1.00</td>
</tr>
<tr>
<td>$\sigma^2_{\varepsilon_y}$</td>
<td>$\mathbb{R}^+$ Inv.Gam.2 1.00 1.00 0.58 [0.25, 1.17] 1.00</td>
<td></td>
</tr>
<tr>
<td>$\sigma^2_{\varepsilon_y}$</td>
<td>$\mathbb{R}^+$ Inv.Gam.2 20.0 20.0 23.9 [18.9, 30.0] 1.00</td>
<td></td>
</tr>
<tr>
<td>$\gamma$</td>
<td>$\mathbb{R}$</td>
<td>0.24 [0.12, 0.37] 1.00</td>
</tr>
</tbody>
</table>

Notes: We do not restrict any prior belief on the parameter $\gamma$. The posterior distribution is obtained by the Metropolis-Hastings algorithm. PSRF- Potential Scale Reduction Factor. Real credit is obtained by deflating the total loans to non-financial private sector by CPI.

The acceptance rate of our draws is 28% which is in the range $20 - 40\%$ as suggested by, for instance, Gelman, Roberts, and Gilks (1996) and Gelman, Carlin, Stern, and Rubin.
(2014, ch.11, p.314) among others.\footnote{High acceptance ratio implies that the jumps are so short that the simulations moves very slowly through the target distribution; whereas low acceptance rate implies that the jumps are nearly all into low-probability areas of the target density, causing the Markov chain to stand still most of the time (Gelman, Roberts, and Gilks, 1996).} In order to check if the chains have converged to the target distribution, we create another sequence of draws and evaluate the potential scale reduction factor ($PSRF$) proposed by Gelman and Rubin (1992). As $PSRF$ is close to 1 - and smaller than 1.2- for all the estimates, the approximate convergence has been reached and the draws are close to the target distribution. As shown in the last column of Table 2, $PSFR$ are nearly one for all the parameters; we, therefore, can make inferences about posterior means and variances.

The mean and the 95\% confidence interval of the posterior distribution of the parameters are shown in Columns 6-7. Overall, the data appear to be quite informative. The cyclical component is estimated to be persistent. Regarding the variance of innovations, we find higher values for cyclical than trend components (23.9 vs. 0.58), implying a larger role for transitory disturbances than permanent ones. Such a result is somewhat expected given our prior specifications, but the differences between prior and posterior means indicate that estimates are substantially affected by the information provided by data. When it comes to the financial parameter $\gamma$, its estimate is 0.24 and statistically significant, which suggests that credit growth plays a certain role in determining the business cycle. Nevertheless, this figure is smaller than the value of 0.4 obtained in Borio, Disyatat, and Juselius (2016, 2014) who use the more recent sample 1980-2012. Such a difference may be driven by the model restriction that the information content that financial factors have for output gap is constant over time, a restriction that is not apparently supported by the data as shown in Section 1.

3.2 The TVP-BDJ Model

The TVP-BDJ model allows the information content that financial factors have for output gap to change over time by modelling the financial parameter $\gamma_t$ as the driftless random walk process. The variance of $\varepsilon_t^y$ is assumed to follow an inverse-gamma-2 distribution with mean of 0.1 and 1 standard deviations, which is a loose prior, in order to guarantee that it is positive. For other parameters $\rho$, $\sigma_{\varepsilon_y}^2$ and $\sigma_{\varepsilon_g}^2$, we use the same priors as in the BDJ model above. Table 3 summarizes the prior distribution of the parameters.
### Table 3 – The TVP-BDJ Model: Real Credit Growth

<table>
<thead>
<tr>
<th>Domain</th>
<th>Distr.</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Mean</th>
<th>[5%, 95%]</th>
<th>PSRF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>Beta</td>
<td>0.80</td>
<td>0.10</td>
<td>0.85</td>
<td>[0.76, 0.93]</td>
<td>1.00</td>
</tr>
<tr>
<td>$\sigma^2_{\varepsilon_y}$</td>
<td>Inv.Gam.2</td>
<td>1.00</td>
<td>1.00</td>
<td>0.56</td>
<td>[0.25, 1.09]</td>
<td>1.00</td>
</tr>
<tr>
<td>$\sigma^2_{\varepsilon_g}$</td>
<td>Inv.Gam.2</td>
<td>20.0</td>
<td>20.0</td>
<td>15.8</td>
<td>[11.9, 20.4]</td>
<td>1.00</td>
</tr>
<tr>
<td>$\sigma^2_{\varepsilon_y}$</td>
<td>Inv.Gam.2</td>
<td>0.10</td>
<td>1.00</td>
<td>0.05</td>
<td>[0.02, 0.10]</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: We do not restrict any prior belief on the parameter $\gamma_t$. The posterior distribution is obtained by the Metropolis-Hastings algorithm. PSRF - Potential Scale Reduction Factor. Real credit is obtained by deflating the total loans to non-financial private sector and house price, respectively, by CPI.

### Figure 1 – Real Credit Growth Time-Varying Parameter (+/- 2 SE)

Note: This figure presents the time-varying influence of real credit growth on output gap $\gamma_t$.

The state-space representation of the TVP-BDJ model is estimated based on the Bayesian approach as mentioned above. The acceptance rates of the draws is about 24 percent. The PSRF of the parameters shown in the last column of Table 3 suggests that the approximate convergence has been reached. Therefore, inferences about posterior means and variances can be made. On the one hand, we find, as in the BDJ model, that the cyclical component is persistent and the transitory disturbances play a larger role than the permanent ones. On the other hand, the variance of cyclical disturbances decreases substantially by more than 30
percent. This suggests that the influence of financial information on output gap is likely more significant in the TVP-BDJ model than the previous one. Figure 1 presents the influence of credit on output gap, suggesting that such an influence has changed over time. It is noted that our model does not focus on the structural interpretation of credit on business cycle, such as the impact of credit structural shock on real economic activity. Instead, we aim to evaluate the contribution of credit information in output gap estimation. For instance, during the World War I and II, \( \gamma \) is small or even has a negative sign during the 1940s, suggesting that credit information is less likely useful to evaluate economic development during those episodes. In contrast, during the 1920s, the influence of credit cycle on output gap has increased and reached the peak in the early 1930, suggesting the potential of credit information as an indicator of the position of business cycle in this period. Since the early 1950s, \( \gamma \) has become relatively stable compared to the preceding periods. For this stability, the BDJ (2016; 2014)’s framework has been relatively successful to capture the credit information into output gap estimation during the post-1980 period.

### 3.3 Model comparison

To evaluate what model the data favors between the standard BDJ and the TVP-BDJ model, we carry out the Bayesian deviance information criterion (DIC). According to Spiegelhalter, Best, Carlin, and Van Der Linde (2002), the DIC is a generalization of the Akaike information criterion, which rewards fit tho the data while penalizing model complexity. The DIC is calculated as

\[
\text{DIC} = \bar{D} + p_D.
\]

The first term \( \bar{D} \) measures goodness of fit as:

\[
\bar{D} = E(-2\log L(\Psi_i)) = \frac{1}{M} \sum_i (-2\log L(\Psi_i)) \text{ where } L(\Psi_i) \text{ is the likelihood evaluated at the } i\text{-th draw of the parameter set } \Psi_i \text{ in the Random Walk Metropolis Hastings Algorithm.}
\]

The second term \( p_D \) is defined as a measure of the number of effective parameters in the model, defined as

\[
p_D = E(-2\log L(\Psi_i)) - E(-2\log L(\Psi_i)) = \frac{1}{M} \sum_i (-2\log L(\Psi_i)) - (\log L(\frac{1}{M} \sum_i \Psi_i)).
\]

Because of priors distributions on the parameters in our model and the presence of latent variables, the number of parameters do not necessarily represent model complexity, as often used in standard AIC and BIC. This problem can be avoided by using the effective number of parameters \( p_D \) in the computation of the DIC. The standard BDJ model’s DIC is 774. In contrast, the TVP-BDJ model has a smaller DIC, which is equal to 761, indicating strong evidence in favor of the model that allows the effect of financial information on output gap.
4 Discussions

4.1 Output gaps

Figure 2 presents the output gap estimates from the TVP-BDJ model using the full sample of data. In general, the estimated gap moves procyclically with the NBER reference cycle. The lowest point in the cycle is related to the Great Depression following the financial crash of 1929; whereas, during the mid-1940s, output expanded far above its potential level. In the pre-2007 crisis, our estimates suggest a large positive deviation of output from its potential level, which can be explained by the sustained run-up in private sector leverage during this period. Meanwhile, in the post-crisis, output gap declined substantially and output was 6 percent below its potential at the end of the sample. This is much higher than the value of negative 2 percent of CBO’s output gap.

Figure 2 – Output Gap Estimates (+/2 SE)

Note: The figure shows the estimates of output gap, which is 100 times natural log deviation of output from its potential level using the TVP-BDJ model. Shaded areas indicate recessions as determined by the National Bureau of Economic Research.
4.2 Real-time Output gaps

It is argued that the estimates of output gap are particularly unreliable in real time, therefore questioning its usefulness for policy-making purposes. According to Orphanides and van Norden (2002), the primary reason that challenges the estimate of potential output in real time arises from the fact that when data in subsequent quarters become available, hindsight may help to clarify our position in the business cycle. Furthermore, the arrival of new data leads to the update/revision of the estimates.

**Figure 3** – Output gap estimates: Real time (Filtered) versus Expost (Smoothed)

Regarding the influence of future information, Figure 3 presents the real-time (filtered) and expost (smoothed) estimates of output gap using the TVP-BDJ model. The filtered series for each time $t$ is based on the sample of data up to that point conditional on the estimated parameters. In contrast, the smoothed series is based on the full sample of data. The real-time OG estimates move well in line with the ex-post estimates in most periods but those in the World War I and II. Most importantly, ahead of the two worst financial crises, the 1929-1930 and 2007-2008, the TVP-BDJ model signaled in real time that output was above its potential level, leading to a substantial positive gap between output and potential during the booms. This result is therefore in line with the credit view argument that financial crises can be seen as “credit boom gone wrong” (see, e.g., Mishkin (1978), Kindleberger (1978))
and others). In a recent paper, Schularick and Taylor (2012) provide empirical evidence to support for this view, documenting that credit growth, or various scalings of credit volume, is the single best predictor of financial stability.

To put a numerical value on the relative real-time performance, we follow Melolinna and Tóth (2016) to calculate the mean of absolute deviation of the full sample output gap estimate from the real time estimates, normalized by the standard deviation of the full sample gap. This provides a measure of standardized average errors (SAE). Table 4 reports the results suggesting that the real-time performance of the TVP-BDJ model is clearly better than the standard BDJ model. In addition, we consider a univariate model by excluding the financial variable $f_t$ from output gap equation and find that its SAE is larger. Furthermore, we calculate the revisions of output gap estimates based on the popular Hodrick-Prescott method. The HP-based real-time estimates are the one-sided HP estimate (see Stock and Watson (1999)).

Table 4 shows that the revisions of HP-based estimates are largest among those considered. This result is thus in line with the argument that the HP filter is notorious for its unusual behavior of cyclical components near the end of the sample (see, e.g., Baxter and King, 1999).

Table 4 – Relative Real-time Performance: Standardized Average Errors (SAE) over 1901-2013

<table>
<thead>
<tr>
<th></th>
<th>TVP-BDJ</th>
<th>BDJ</th>
<th>Univariate</th>
<th>HP</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAE</td>
<td>0.36</td>
<td>0.44</td>
<td>0.53</td>
<td>0.59</td>
</tr>
</tbody>
</table>

Notes: Standardized average errors are calculated as the mean of absolute deviation of the ex post (smoothed) output gap estimate from the real time (filtered) estimates, normalized by the standard deviation of the ex post estimates. War and aftermath periods are excluded (1914-1919 and 1939-1947).

Another issue of real-time estimate is the update of parameters estimates given the arrival of new data. We use 1891-1950 as the initial sample and then estimate the model recursively to the end of the sample, i.e. adding one quarter by one from 1951-2013. Therefore, the model is estimated recursively for 63 times. We retain only the end-point estimates of output gap in each estimation and construct the pseudo real-time series of output gap from 1951-2013. Note that there is a difference between actual real time and pseudo real-time data. The former is the actual data available in real time, while the latter is constructed based on the

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The smoothing parameter is set to 100, a standard value for annual data.
Notes: The pseudo real-time output gap is obtained by recursively estimating the models using 1891-1950 as the initial sample and adding one by one observation from 1951-2013.

4.3 Potential Growth

One important economic notion is the growth of potential output, i.e. the annual increase in the production capacity of the economy. In order to capture possible changes over the sample, the potential growth is modelled in a random walk manner as discussed in section 2. In Figure 5, we present the smoothed estimates of potential growth from several models: the HP, the univariate model, and the TVP-BDJ model. Regarding the HP filter, we first obtain
the trend, i.e. potential output, using a smoothing parameter of 100 and then calculate the corresponding annual growth. We also consider the standard BDJ model and find that the estimate of potential growth from that model is quite similar with the one obtained from the univariate model. Such a result is not surprising given the statistically insignificant estimate of the coefficient relating to the financial factor in the BDJ model. Therefore, we present only the estimates obtained from the univariate model.

**Figure 5 – Potential Growth: Smoothed Series**

![Potential Growth: Smoothed Series](image)

Notes: The figure shows the smoothed estimates of the potential growth of output ($\Delta \eta_t$) from three different models: the HP filter, the univariate model, and the TVP-BDJ model.

Although the estimates of potential growth exhibit different degrees of volatility between the models, with the HP-based estimates being the most volatile, they show a similar pattern. The potential growth decreased considerably in the first thirty years of the century. However, during the next decade, the potential growth increased substantially and reached a peak of 5 percent or above in the early 1940s. Since then, it follows a declining trend, intermitted by the periods of stable or slightly increasing growth. Specifically, in all models, we observe two significant falls: in the second half of the 1940s and in the decade from the mid 1960s to the mid 1970s. During the period 1980-2000, the potential growth fluctuates between 2 and 2.5 percent. When it comes to the post-2000 period, there have been divergences.
Figure 6 – Potential Growth: Filtered Series

Notes: The figure shows the filtered estimates of the potential growth of output ($\Delta y_t$) from three different models: the HP, the univariate model, and the TVP-BDJ model. The filtered estimates are those estimated using the sample of data available up to the point of estimation. For the HP, it is the one-sided HP estimate as in Stock and Watson (1999) with the smoothing parameter being equal to 100.

between the estimates to some extent. Both the HP-based and univariate estimates display that the potential growth has been declining; whereas, the TVP-BDJ model suggests a relatively stable potential growth. Figure 6 presents the un-smoothed (or filtered) post-2000 potential growth, which suggests that the recent financial crash is one of the key factor that contributes to the fall of potential growth in both the HP and univariate model. Specifically, with the HP, its one-sided estimate plummeted by about 3 percent from 2.5 percent in 2007 to -0.5 percent in 2009, then returned to 1 percent by the end of the sample. With the univariate model, the potential growth also decreased from 2.5 percent in 2007 to 1.5 percent by 2009 and has stayed at that level since then. On the other hand, the potential growth in the TVP-BDJ model stay stable at the rate of 2 percent. Such a result has an important implication for the weak recovery in the post-crisis. Specifically, based on the TVP-BDJ model, the weak growth in the post-crisis is less likely caused by the decline of potential growth. Instead, it is a consequence when the financial boom busted, causing a huge and long-lasting economic damage. This is in line with the argument that standard methods for potential output estimation which do not take into account the role of financial information may underestimate the potential output during the credit-driven recession and,
hence, support the “financial cycle drag” interpretation on the weak growth (ECB, 2017; Borio, 2017).

4.4 Alternative Specifications

As in Borio, Disyatat, and Juselius (2016), the baseline model specifies that the real credit growth affects the output gap contemporaneously. We consider two alternative lag specifications in which credit growth is modelled to affect output gap with a lag of one and two years, respectively.\(^9\) We calculate the standardized average errors to evaluate the relative real-time performance as discussed above and present the results in the first row of Table 5, rescaled by the baseline value. As it can be seen, these alternative lag specifications are not as competitive as the baseline model. Meanwhile, the model with a lag of two years performs worst with its SAE being more than twice the one of the baseline.

**Table 5** – Relative Real-time Performance: Standardized Average Errors (SAE) over 1913-2013

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous</th>
<th>First Lag</th>
<th>Second Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Growth</td>
<td>1.00</td>
<td>1.62</td>
<td>2.14</td>
</tr>
<tr>
<td>House Price Growth</td>
<td>1.66</td>
<td>1.62</td>
<td>1.81</td>
</tr>
<tr>
<td>Stock Price Growth</td>
<td>1.46</td>
<td>1.40</td>
<td>1.47</td>
</tr>
<tr>
<td>Narrow Money Growth</td>
<td>1.12</td>
<td>1.31</td>
<td>2.18</td>
</tr>
<tr>
<td>Broad Money Growth</td>
<td>1.61</td>
<td>1.45</td>
<td>1.64</td>
</tr>
<tr>
<td>Interest Rate</td>
<td>1.65</td>
<td>1.97</td>
<td>2.29</td>
</tr>
</tbody>
</table>

Notes: Standardized average errors are calculated as the mean of absolute deviation of the ex-post (smoothed) output gap estimate from the real time (filtered) estimates, normalized by the standard deviation of the ex-post estimates. The table evaluates the SAEs in terms of the financial variable (in real term) used as well as the lag specification, relative to the baseline, i.e. the model with contemporaneous real credit growth. A greater-than-one value implies a larger revision between the real time and ex-post estimates compared to the baseline. The smallest SAE for a given variable (in a row) is underlined. War and aftermath periods are excluded (1914-1919 and 1939-1947).

The preceding discussions have focused on credit, a choice of variable that is motivated by recent literature about the interaction between credit and business cycles. In this section, we investigate the real-time performance of other key financial variables in comparison to credit. This additional set includes house price growth, stock price growth, narrow money growth, narrow money growth,

\(^9\)Most of studies using quarterly data consider up to four lags, so a maximum of two-year lag is appropriate with annual data.
broad money growth, and short-term interest rate. Similar to the case with credit growth, each of these variables, in real term, is used as a proxy of financial information in the TVP-BDJ model. In fact these variables may affect output gap at different time horizons, so we consider several lag specifications in which each variable is allowed to enter with a lag of up to two years. Therefore, with these five variables and three various lag structures, we estimate a total of 15 different specifications using the TVP-BDJ framework and then evaluate the real-time performance based on the standardized average errors relative to the baseline, i.e. the model with contemporaneous real credit growth. The rescaled SAEs of these models are shown in Table 5. First, for a given financial variable, the specification with a lag of two years has the largest revision between the real-time and ex-post estimates, indicating that such a specification is the least helpful in measuring real-time output gap compared to those with contemporaneous or one-year-lag effect. However, the results are not homogeneous. For house price, stock price, and broad money, including its one-year lag benefits the real-time estimate of output gap more than other lag specifications. Meanwhile, for narrow money growth and interest rate, their contemporaneous effects lead to smaller revisions in output gap estimates. Most importantly, our results show that the baseline model, which use the contemporaneous real credit growth as a proxy of financial variable, has the best real-time performance, i.e. a model that produces the smallest revisions among those considered. This result thus affirms the importance of taking credit growth into account when evaluating business cycles.

While the SAE provides a measure to evaluate the magnitude of revision in output gap estimates, it is also crucial to investigate if the output gap estimates are reasonable. For instance, it is known that the Beveridge-Nelson trend-cycle decomposition provides an estimate of output gap with relatively small revision; however, those estimates do not match up well at all with the reference cycle of U.S. expansions and recessions (Kamber, Morley, and Wong, forthcoming). Therefore, the next section is devoted to investigate the qualitative aspect of the output gap estimates using the aforementioned financial variables.

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The data is obtained from the Jordà-Schularick-Taylor Macrohistory Database, see Jordà, Schularick, and Taylor (2017).
4.5 Two Financial Crashes of 1929 and 2007

As discussed above, the parsimonious approach proposed by Borio, Disyatat, and Juselius (2014, 2016) takes into account the relationship between the financial developments and economic activity and yields a finance-neutral measure of output gap. Thus, a positive/negative gap indicates that output is well above/below potential during significant financial booms/bursts. In what follows, we investigate the behavior of output gaps in the window of five years before and after the two probably most devastating financial crashes since the early 1900s: the crash of 1929 and the recent crisis of 2007.

4.5.1 The financial crash of 1929

Figure 7 shows the real-time and ex-post output gap estimates by the TVP-BDJ model for different financial variables for the period 1924-1934. To facilitate the presentation, for each financial variable we present only the model with the lag structure that yields minimum revisions in output gap estimates based on the SAE (those underlined in Table 5). In the running up to the crisis 1929, in most of the cases but the narrow money the real-time measure signals that the economy was well above its potential. Particularly, both the models with credit and stock price moves quite closely with the ex-post measures, which is therefore in line with the view that attributes the great crash of 1929 to a credit-fueled stock market bubble, as argued by Galbraith (1972).

The financial crisis 1929 caused output to fall substantially below its potential level by more than 20 percent in retrospect as shown by the ex-post estimates in Figure 7 regardless the financial variable used. Regarding the real-time performance, our results show that the model with credit captures well this slump. Interestingly, while the model with narrow money does not signal the boom prior the crisis, it characterizes well the substantial reduction of output in the bust, suggesting that monetary policy might have played a certain role causing the slump. This result appears to be in line with Friedman and Schwartz (1963) who show that monetary contraction and errors by the Federal Reserve caused the Great Depression.

In addition, our results show that the model with broad money also captures relatively well the expansion, recession, as well as turning point in real time. Given the stable relationship between credit and broad money throughout the era up to WW2, such a result is somewhat

11The full description with different lag specifications can be found in the online supplementary material.
Figure 7 – Ex-post versus Real-time Output Gap: 1925-1934

(a) Credit
(b) House price
(c) Stock Price

(d) Narrow Money
(e) Broad Money
(f) Interest Rate

Note: The figure shows the real-time (dashed) and ex-post (solid) output gap estimates for the 1925-1934 period using the TVP-BDJ framework with different proxies for financial information.

predictable (see Schularick and Taylor, 2012). When using house price as a proxy of the financial information, the real-time measure also indicates that the economy was overheated in the pre-1929, but does not capture well the slump thereafter.

4.5.2 The financial crisis of 2007

Moving to the recent financial crisis, Figure 8 presents the real-time and ex-post estimates for the 2003-2012 period using the TVP-BDJ framework with different proxies for financial information. To ease the presentation, the model with the lag structure that yields minimum revisions in output gap estimates based on the SAE is presented.\(^{12}\)

Similar to the financial crash of 1929, the model with credit indicates that output was

\(^{12}\)The full description of output gap in the 2003-2012 period with different lag specifications can be found in the online supplementary material.
Figure 8 – Ex-post versus Real-time Output Gap: 2007-2012

(a) Credit  (b) House price  (c) Stock Price

(d) Narrow Money  (e) Broad Money  (f) Interest Rate

Note: The figure shows the real-time (dashed) and ex-post (solid) output gap estimates for the 2003-2012 period using the TVP-BDJ framework with different proxies for financial information.

well above potential during the financial boom of the 2000s. Moreover, it also captures well the reduction of output in the aftermath of the crisis in which there is hardly any difference between the real-time and ex-post results. Nevertheless, there are several different features from the 1930s era. First, the model with stock price misses this boom completely regardless the lag specification set in the model. On the other hand, the inclusion of house price performs quite well, characterizing the expansion, recession, as well as turning point in real time closely with the full sample. Other financial variables appear do not perform well in real-time. These results are in line with Drehmann, Borio, and Tsatsaronis (2012) who study the financial cycle in a sample of seven industrialized countries over the period 1960-2011 and show that the financial cycle, described in terms of the joint fluctuations of credit and property prices, is very closely associated with financial crises. Our results are also similar
to Borio, Disyatat, and Juselius (2016) who consider the US quarterly data over the sample 1980Q1–2012Q4 and document that the proxies for the financial cycle, notably credit growth and possibly combined with house price, help generate economically plausible output gaps with good real-time performance.

5 Conclusion

In this paper, we extend Borio, Disyatat, and Juselius (2016, 2014)’s parsimonious approach to account for financial information in the measure of output gaps. Specifically, the relationship between financial and business cycles are allowed to change over time. Such an extension is favored by the data. More importantly, our results show that this novel feature improves the real-time estimation of the output gap, particularly signaling the peak and trough in economic activity related both to the Great Recession as well as to the Great Depression. Comparing these two financial crashes, we indicate the fundamental role that credit growth plays in the determination of potential output and the output gap. Nevertheless, credit dynamics affect the real activity via different conduits over the century: the stock market in 1929 and the housing market in 2008. Accounting for credit growth, US potential growth has been stable at 2% since the beginning of 1980.
References


Appendix

A.1 State-space Specification: The BDJ model

The state-space form of the BDJ model is written as follows:

\[
Y_t = HX_t \\
X_t = M + FX_{t-1} + W_t \quad W_t \sim iidN(0,Q).
\]

where the observation vector \( Y_t \) is:

\[
Y_t = [y_t]
\]

and the state vector \( X_t \) is:

\[
X_t = \begin{bmatrix}
\bar{y}_t \\
g_t \\
\hat{y}_t
\end{bmatrix}
\]

where \( g_t = \bar{y}_t - \bar{y}_{t-1} \).

The coefficients of matrices are described as follows:

\[
H = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix},
\]

\[
F = \begin{bmatrix} 1 & 1 & 0 \\
0 & 1 & 0 \\
0 & 0 & \rho \end{bmatrix}, \quad W = \begin{bmatrix} 0 \\
\varepsilon_g \\
\bar{\varepsilon}_g \end{bmatrix}, \quad Q = \begin{bmatrix} 0 & 0 & 0 \\
0 & \sigma_{\varepsilon_g}^2 & 0 \\
0 & 0 & \sigma_{\hat{y}_g}^2 \end{bmatrix}, \quad M = \begin{bmatrix} 0 \\
0 \\
\gamma f_t \end{bmatrix}.
\]

The parameters are collected in the vector \( \theta = [\rho, \gamma, \sigma_{\varepsilon_g}^2, \sigma_{\hat{y}_g}^2]' \).

A.2 State-space Specification: The TVP-BDJ model

The state-space form of the time-varying parameter BDJ model is presented as follows:

\[
Y_t = HX_t \\
X_t = M + FX_{t-1} + W_t \quad W_t \sim iidN(0,Q).
\]

where the observation vector \( Y_t \) is:

\[
Y_t = [y_t]
\]
and the state vector $X_t$ is:

$$X_t = \begin{bmatrix} \bar{y}_t \\ y_t \\ \dot{\bar{y}}_t \\ \gamma_{t+1} \end{bmatrix}$$

where $g_t = \bar{y}_t - \bar{y}_{t-1}$. Note that, $\gamma_{t+1}$ is modeled as $\gamma_{t+1} = \gamma_t + \varepsilon_t^\gamma$, so $\gamma_{t+1}$ is revealed conditional on information at time $t$.

The coefficients of matrices are described as follows:

$$H = \begin{bmatrix} 1 & 0 & 1 & 0 \end{bmatrix},$$

$$F = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \rho & f_t \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad W = \begin{bmatrix} 0 \\ \varepsilon_g \\ \varepsilon_{\dot{y}} \\ \varepsilon_{\gamma} \end{bmatrix}, \quad Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \sigma_{\varepsilon_g}^2 & 0 & 0 \\ 0 & 0 & \sigma_{\varepsilon_{\dot{y}}}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\varepsilon_{\gamma}}^2 \end{bmatrix}, \quad M = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}. \quad (12)$$

The parameters are collected in the vector $\theta = [\rho, \gamma, \sigma_{\varepsilon_g}^2, \sigma_{\varepsilon_{\dot{y}}}^2, \sigma_{\varepsilon_{\gamma}}^2]'$.

### A.3 Two Great Crises

We estimate the TVP-BDJ model with different proxies of financial information with respect to the variable and its lag specification. In addition to real credit growth, we consider real house price growth, real stock price growth, real narrow money growth, real broad money growth, and real short term interest rate. Each variable is allowed to enter with a lag of up to two years.

#### A.3.1 The 1930 Crisis
Figure 9 – Model with Real Credit Growth: Ex-post versus Realtime Output Gap between 1925-1934

Figure 10 – Model with Real House Price Growth: Ex-post versus Realtime Output Gap between 1925-1934

Figure 11 – Model with Real Stock Price Growth: Ex-post versus Realtime Output Gap between 1925-1934
Figure 12 – Model with Real Narrow Money Growth: Ex-post versus Realtime Output Gap between 1925-1934

Figure 13 – Model with Real Broad Money Growth: Ex-post versus Realtime Output Gap between 1925-1934

Figure 14 – Model with Real Interest Rate: Ex-post versus Realtime Output Gap between 1925-1934
A.4 The 2007 Crisis
Figure 15 – Model with Real Credit Growth: Ex-post versus Realtime Output Gap between 2003-2012

Figure 16 – Model with Real House Price Growth: Ex-post versus Realtime Output Gap between 2003-2012

Figure 17 – Model with Real Stock Price Growth: Ex-post versus Realtime Output Gap between 2003-2012
Figure 18 – Model with Real Narrow Money Growth: Ex-post versus Realtime Output Gap between 2003-2012

Figure 19 – Model with Real Broad Money Growth: Ex-post versus Realtime Output Gap between 2003-2012

Figure 20 – Model with Real Interest Rate: Ex-post versus Realtime Output Gap between 2003-2012