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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 extend the parsimonious approach of Borio, Disyatat, and Juselius (2016, 2014) to allow for time-varying effects of financial factors. This novel feature significantly improves real-time estimates of the output gap. It signals the peak and trough in economic activity related to both the Great Recession and 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, the 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

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). The *Secular Stagnation Hypothesis* focuses on the structural demand deficiency and its role in the weak 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 the CBO's estimates, is attributed in equal part to both growth in observed output and 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 a mix of loose lending standards and a bubbly housing market, had been causing an unjustified increase in potential growth rates. Focusing on the level of potential output only from 2007 onwards may induce the reader to consider the ensuing contraction more severe than warranted, particularly when using the GDP level of 2007 as the original anchor.

An alternative hypothesis is offered by Borio (2017)'s *Financial Cycle Drag Hypothesis*. Financial booms and busts, and the associated banking stress, lead to prolonged capital misallocation and lower potential output. This point is reinforced by Jordà, Schularick, and Taylor (2011, 2017) cross-country compilation of 140 years of crises episodes. 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 economic realities (see Borio, Disyatat, and Juselius, 2016). Robustness in the estimation of potential output (and its associated output gap) is an essential feature needed to preserve the validity of any argument built with potential output as an ingredient. A natural reaction may be that understanding which of the above-described mechanisms is prevalent, becomes clear only in retrospect. In real time, little could be said about the sustainability of the observed growth rates. Our work tackles this often-encountered remark by showing the added benefits our methodology delivers in producing real-time estimates of potential output.

The debate around the importance played by the financial-real cycle interaction in conditioning the length and severity of historical crisis episodes, as presented among other by

Claessens, Kose, and Terrones (2012), Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013), has motivated the development of a new class of output gap models. 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 play a central role. Analyzing US data over the 1980-2012 period, BDJ find that information about the financial cycle, particularly the credit growth, explains a significant portion of the cyclical movements in output, thus contributing to identifying the unobserved level of potential output. To illustrate, BDJ show that the financial-information-based output gap measure is able to spot the unsustainable expansion in real time in the pre-2007 crisis period, 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. The wider adoption and use of state-space models Melolinna and Tóth (2016) coupled with the empirical insights afforded by long-run data Jordà, Schularick, and Taylor (2017) are additional elements contributing to the methodological renaissance witnessed in the estimation of output gaps.

Our paper contributes to the above-mentioned literature streams in several ways. First, we assess the ability of output gap models, enhanced with financial factors, to shine a light on historic economic episodes reaching as far as back as the 1929 Great Depression. Nevertheless, given such long-run time span, it is unlikely for financial factors to influence cyclical movements of output in a time-invariant fashion. In Table 1, we present the correlation between the GDP growth rates and credit growth rates over different time frames. The time-varying correlation suggests that the relationship between financial and business cycles may not be stable over time. Therefore, we extend the existing 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 **T**ime-**V**aring **P**arameter **O**utput **G**ap (TVP-OG in short), which nests the BDJ version as a special case. Second, based on the TVP-OG, we estimate the growth in potential output and compare its dynamics with those resulting from the 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 the output gap, with an emphasis on the two great financial crashes of 1929 and 2007.

As a preview of our results, we indicate the important role that credit growth plays in

Table 1 – Output growth and credit growth

Corr	Pre-1930	1931-1950	1951-1970	1971-1990	1990-2013	**Full-sample**
$\Delta ln(GDP), \Delta ln(CRE)$	0.47***	-0.14	0.65***	0.87***	0.70**	**0.21****

Note: Table shows the correlation between output growth, $\Delta ln(GDP)$, and real credit growth, $\Delta ln(CRE)$. $***p < 1\%, **p < 5\%$.

the real-time determination of potential output and the output gap. In this aspect, the data indicates that real credit growth has a better 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, the 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 the 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 the output gap. Then we extend this approach and allow the influence of financial variables on output gap 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:

$$y_t = \bar{y}_t + \hat{y}_t, \tag{1}$$

in which

$$\Delta\bar{y}_t = \Delta\bar{y}_{t-1} + \varepsilon_t^g, \text{ where } \varepsilon_t^g \sim N(0, \sigma^2_{\varepsilon_g}) \tag{2}$$

$$\hat{y}_t = \rho \hat{y}_{t-1} + \gamma f_t + \varepsilon_t^{\hat{y}}, \text{ where } \varepsilon_t^{\hat{y}} \sim N(0, \sigma^2_{\varepsilon_{\hat{y}}}) \tag{3}$$

where f_t is a proxy for the 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 is subject to a shock ε_t^g.[1] Meanwhile, the output gap in (3) is assumed to follow an autoregressive process and is embedded with financial cycle information f_t. Therefore, the derived output gap is also known as the finance-neutral measure, indicating that output is well above its potential during the outsize financial booms no matter what the rate of inflation is. By estimating with the quarterly US data over the sample 1980Q1-2012Q4 with house price and credit growth, BDJ (2016; 2014) find that the coefficient for financial variables is positive and significant.

BDJ (2016) argue 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 of 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 the level of potential output as well.

2.2 The Time Varying Parameter Output Gap 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. Jordà, Schularick, and Taylor (2017) highlight the structural differences in the dynamics of credit pre versus post World War II and their implications for financial stability and growth. We therefore extend

[1] 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.

the BDJ framework by allowing the financial parameter γ_t to be time-varying and name this proposed framework as the **T**ime -**V**aring **P**arameter **O**utput **G**ap (TVP-OG in short) framework. With this new feature, the output gap equation in the TVP-OG framework is expressed as follows:

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

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

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

Other equations, including trend-cycle decomposition (1) and potential output (2), remain as above. It is clear that the BDJ model is a special case of the TVP-OG model when the variance of ε_t^{γ} is zero.

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

3 Estimation

We estimate both the BDJ and the TVP-OG model, 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 the 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 adopt 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.[2,3,4] This algorithm requires the evaluation of the posterior density, i.e. the product of likelihood function and prior density. Because the prior relies 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. Regarding the prior distributions, the cyclical component is assumed to be fairly persistent, so the AR(1) parameters ρ is Beta distributed, whose domain is between 0 and 1, with mean of 0.8 and standard deviation of 0.1. In addition, the key driver of fluctuations in output is cyclical rather than trend shock, so the variances of innovations are 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 γ 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 on 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 performances with the baseline model that using the credit growth as the proxy.

One of the potential problems arising when using credit growth as a proxy for the financial cycle is that the trend in f_t may pass onto the output gap estimate. To prevent this from occurring, we demean f_t before the estimation. Given the long span of data over more than

[2] The Hessian resulting from the optimization procedure was used for defining the transition probability function that generates the new proposed draw.

[3] See Chib and Greenberg (1995) for a detailed exposition of the algorithm.

[4] The Random Walk Metropolis Hastings Algorithm is conducted with 500,000 draws, in which the first half is discarded as burn-in period.

a century with a variety of economic episodes, we demean the data from its ten-year moving average, which is less restrictive than using the full-sample mean or *Cesàro* mean.

Table 2 – The BDJ Model: Real Credit Growth

		Prior distribution			**Posterior Distribution**		
	Domain.	Distr.	Mean	St. Dev.	Mean	$[5\%, 95\%]$	PSRF
ρ	(0,1)	Beta	0.80	0.10	0.85	[0.76, 0.94]	1.00
$\sigma^2_{\varepsilon_g}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	1.00	0.58	[0.25, 1.17]	1.00
$\sigma^2_{\varepsilon_{\hat{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	20.0	20.0	23.9	[18.9, 30.0]	1.00
γ	$\mathbb{R}$				0.24	[0.12, 0.37]	1.00

Notes: We do not impose any prior belief on the parameter γ. 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 of $20 - 40\%$ as suggested by, for instance, Gelman, Roberts, and Gilks (1996) and Gelman, Carlin, Stern, and Rubin (2014, ch.11, p.314) among others.[5] 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, $PSRF$ 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 the 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 the data. When it comes

[5]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).

to the financial parameter γ, 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 of 1980-2012. Such a difference may be driven by the model restriction that the information content that financial factors have for the 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-OG Model

The TVP-OG model improves the estimation of the output gap by incorporating the information content of a financial factor previously identified in the literature, allowing its impact in the determination of the gap to vary over time. The added flexibility comes from modelling the financial parameter γ_t as a driftless random walk process. The variance of ε_t^{γ} is assumed to follow an inverse-gamma-2 distribution with a mean of 0.1 and 1 standard deviations, which is a loose prior, in order to guarantee that it is positive. For parameters ρ, $\sigma^2_{\varepsilon_{\hat{y}}}$ and $\sigma^2_{\varepsilon_g}$, we use the same priors as in the BDJ model above. Table 3 summarizes the prior distribution of the parameters.

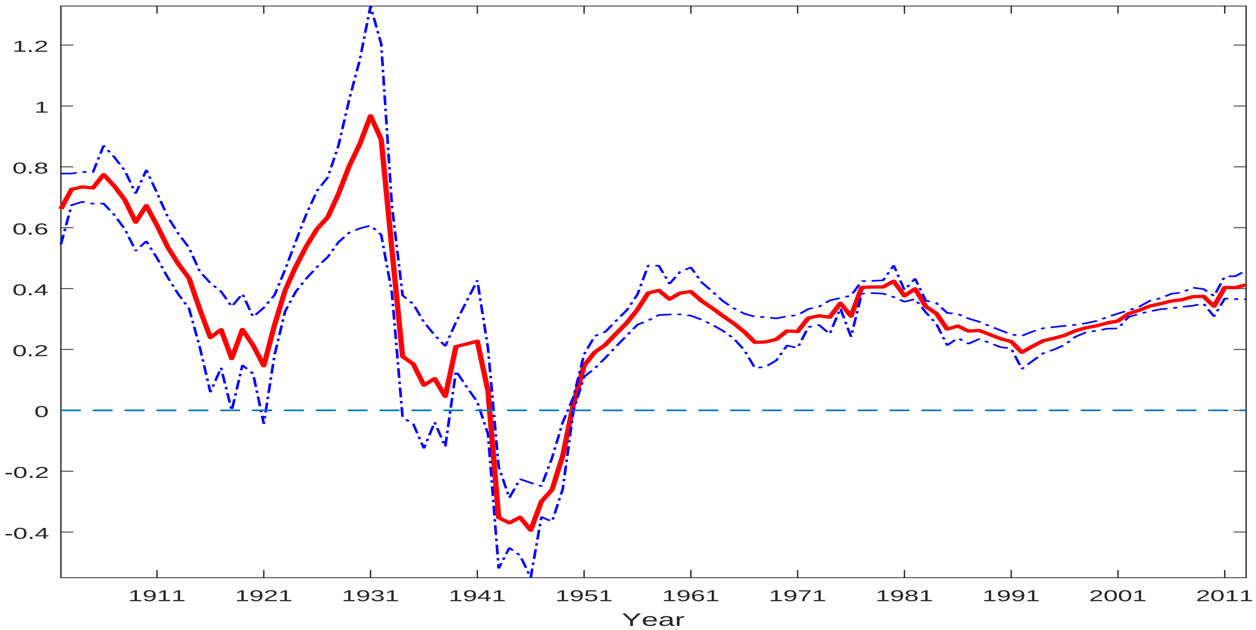
Table 3 – The TVP-OG Model: Real Credit Growth

		Prior distribution			**Posterior Distribution**		
	Domain.	Distr.	Mean	St. Dev.	Mean	$[5\%, 95\%]$	PSRF
ρ	(0,1)	Beta	0.80	0.10	0.85	[0.76, 0.93]	1.00
$\sigma^2_{\varepsilon_g}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	1.00	0.56	[0.25, 1.09]	1.00
$\sigma^2_{\varepsilon_{\hat{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	20.0	20.0	15.8	[11.9, 20.4]	1.00
$\sigma^2_{\varepsilon_{\gamma}}$	$\mathbb{R}^+$	Inv.Gam.2	0.10	1.00	0.05	[0.02, 0.10]	1.00

Notes: 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 state-space representation of the TVP-OG model is estimated based on the Bayesian approach as mentioned above. The acceptance rates of the draws is about 24%. 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

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 γ_t.

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%. This suggests that the influence of financial information on output gap is likely more significant in the TVP-OG model than in the previous specification. Figure 1 presents the influence of credit on output gap, suggesting that such an influence has changed over time. It is worth stressing that our model does not focus on the interpretation of the structural role credit plays in driving the business cycle, such as the impact of structural credit shocks on real economic activity. Instead, we aim to evaluate the contribution of credit information in the estimation of the level and dynamics of the output gap.

A pronounced reduction in γ can be observed in the beginning of the century, with values decreasing from approximately 0.7 in 1900 to about 0.2 towards the end of WW I only to increase very rapidly during the Roaring Twenties. Deviations of credit from its trend are thus estimated to have a lower impact on output gap in the period surrounding WW I.

The flurry of economic activity following the end of WW I, a hallmark of the period 1920-1930, had triggered an episode of rapid urbanisation and with it an increase in land and housing mortgage. A notable increase in the average ratio of nonfarm residential mortgage debt to nonfarm residential wealth is reported in Morton (1956), with the ratio jumping from around 10% in 1920 to a peak of 35% in 1932, followed by a sudden decline that lasted until the end of WW II. The qualitative behavior of this ratio, a proxy of leverage, coincides with the sharp increase in γ to almost 1 in 1930 and its subsequent contraction until the end of WW II.

Since the early 1960s, γ has become relatively less volatile as compared to the preceding periods. Given the observed parameter stability in particular after 1980, the BDJ (2016; 2014)'s estimate of 0.4 over the period 1980 - 2012 closely resembles our TVP-OG estimate over the same period, providing preliminary evidence in favor of our methodology. As indicated in Section 2.2, the BDJ is nested within the TVP-OG specification when the variance of ε_t^γ is zero and as a consequence, the influence of financial information on output gap is considered constant over time.

3.3 Model comparison

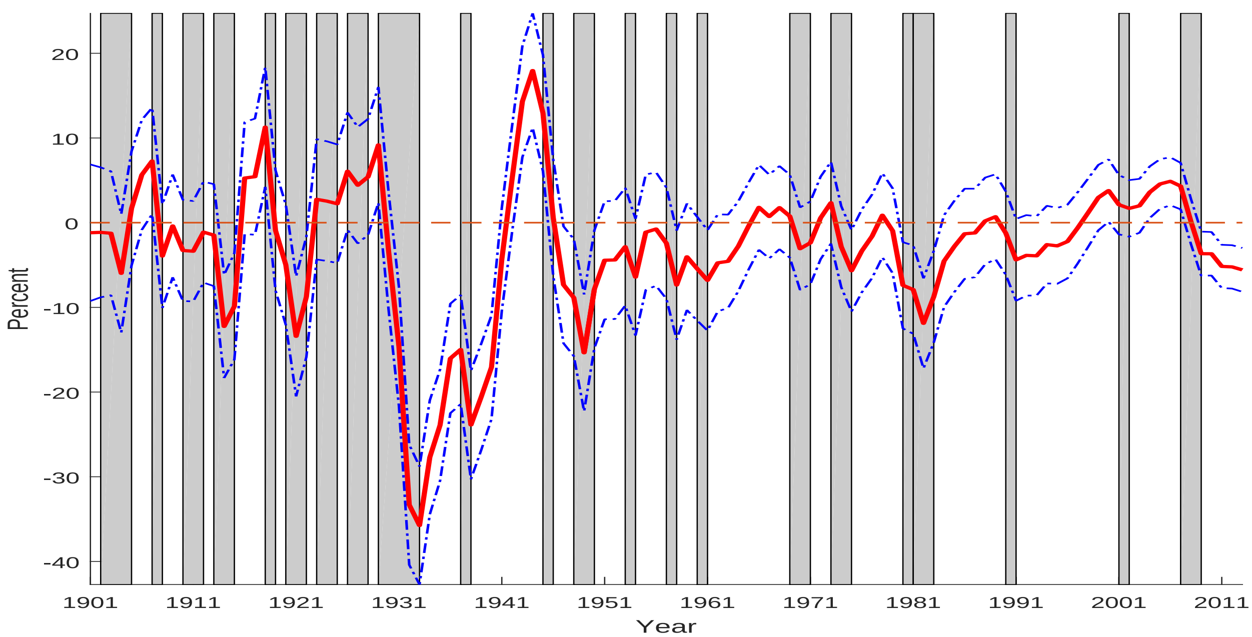
To evaluate what model the data favors between the BDJ and the TVP-OG model, we make use of the Bayesian deviance information criterion (DIC). According to Spiegelhalter, Best, Carlin, and Van Der Linde (2002), the DIC is a generalization of the Akaike information criterion, which rewards fit tho the data while penalizing model complexity. The DIC is calculated as $DIC = \bar{D} + p_D$. The first term $\bar{D}$ measures goodness of fit as: $\bar{D} = E(-2logL(\Psi_i)) = \frac{1}{M}\sum_i(-2logL(\Psi_i))$ where $L(\Psi_i)$ is the likelihood evaluated at the i-th draw of the parameter set Ψ_i 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 $p_D = E(-2logL(\Psi_i))-(-2logL(E(\Psi_i))) = \frac{1}{M}\sum_i(-2logL(\Psi_i))-(-2lnL(\frac{1}{M}\sum_i \Psi_i))$. Because of priors distributions on the parameters in our model and the presence of latent variables, the number of parameters do not necessarily represent the 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 DIC value of TVP-OG model is equal to 761, indicating strong evidence in favor of the model that allows the effect of financial information on output gap to be time-varying.

4 Discussion

4.1 Output Gaps

Figure 2 presents the output gap estimates from the TVP-OG 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 period, 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 period, the output gap declined substantially and output was 6% below its potential at the end of the sample. This is much higher than the value of negative 2% of CBO's output gap.

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

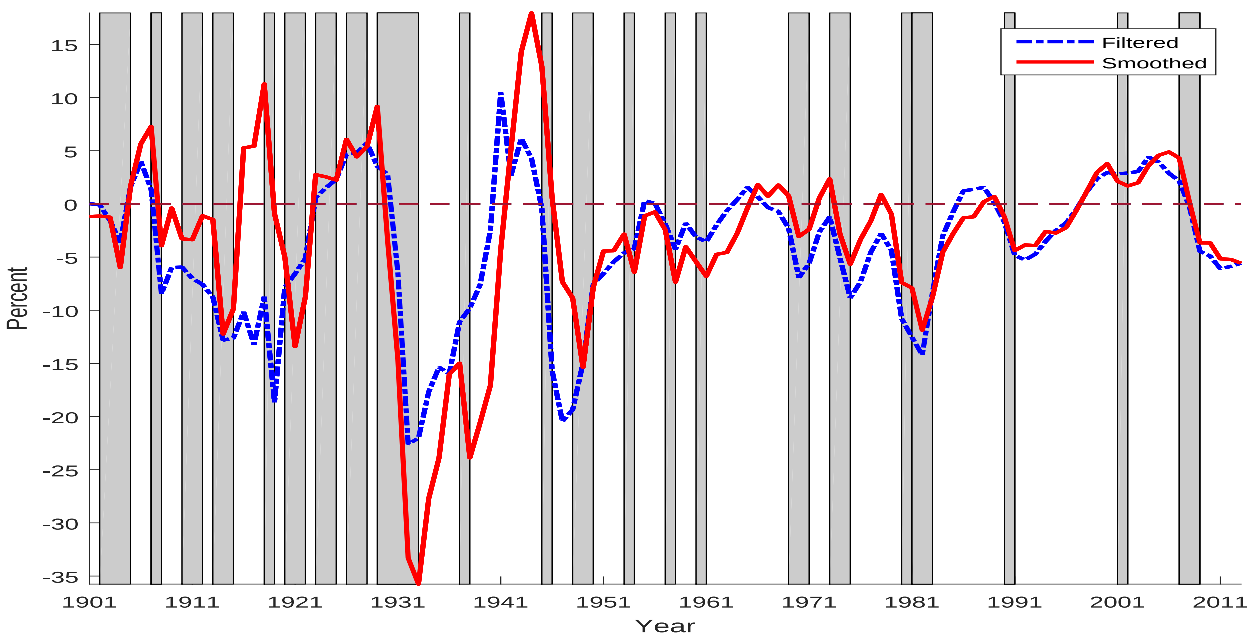


Note: The figure shows the estimates of output gap, which is 100 times natural log deviation of output from its potential level using the TVP-OG model. Shaded areas indicate recessions as determined by the National Bureau of Economic Research.

4.2 Real-time Output Gaps

It is argued that the estimate of output gap is 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 different informational content carried by future data that become available in subsequent quarters. Hindsight helps clarify our position in the business cycle, with the interpretation of the present depending on unknown future data. Furthermore, the arrival of new data leads to the update/revision of the estimates further challenging the estimation of the output gap with traditional methods.

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 ex-post (smoothed) estimates of output gap using the TVP-OG 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 except 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-OP model signals 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 this view, documenting that credit growth, or various scalings of credit volume, is the single best predictor of future financial stability.

To assign 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 estimates from the real time ones, normalized by the standard deviation of the full sample gap. This provides a measure of the standardized average errors (SAE). Table 4 reports the results, suggesting that the real-time performance of the TVP-OG model is better than the standard BDJ model. In addition, we consider a univariate model by excluding the financial variable f_t from the 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)).[6] 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

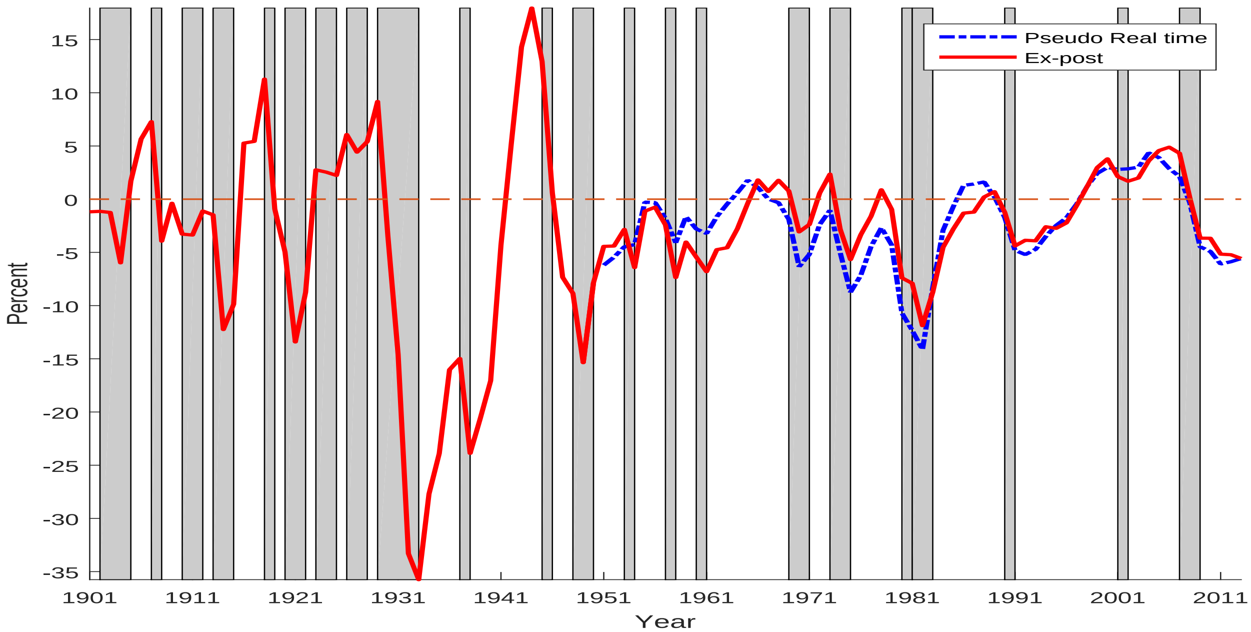
	TVP-OG	BDJ	Univariate	HP
SAE	**0.36**	0.44	0.53	0.59

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 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 onwards. Therefore, the model is estimated recursively 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-

[6]The smoothing parameter is set to 100, a standard value for annual data.

Figure 4 – Output gap estimates: Pseudo Real time versus Expost



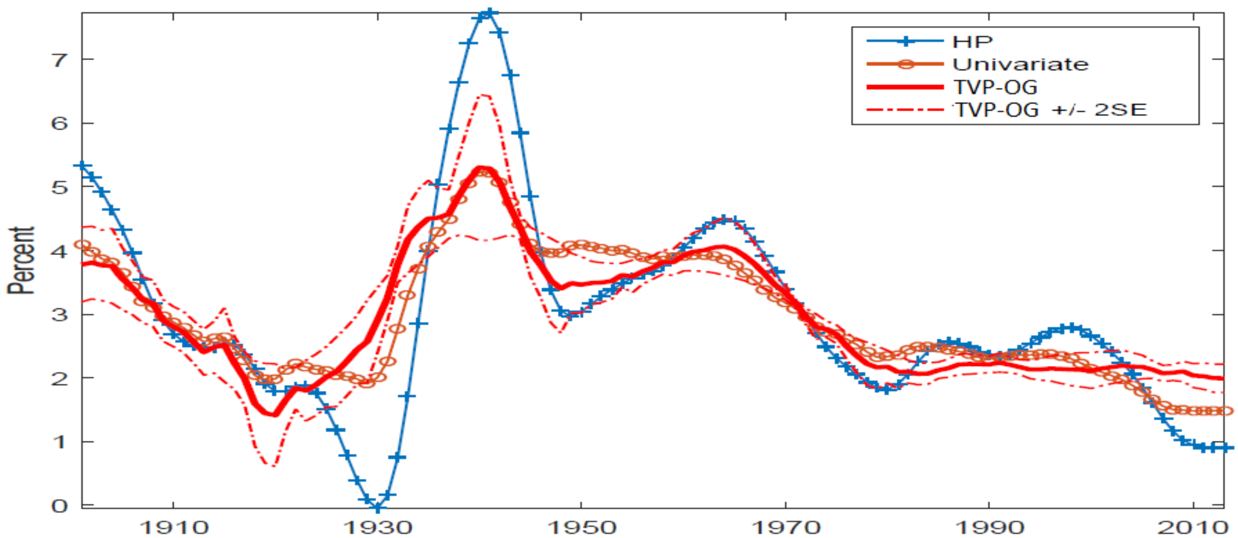
Notes: The pseudo real-time output gap is obtained by recursively estimating the models using 1891-1950 as the initial sample and adding one by one observation from 1951-2013.

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 final vintage and may be subject to revisions. Given the fact that vintage data is not available for the whole sample, we use the pseudo real-time data instead. A consequence of using pseudo real time is that we exclude the issue of data revisions. However, such an exclusion may not be problematic because, according to Orphanides and van Norden (2002), data revisions are not the primary source of revisions on output gaps estimates and, thus, even if the reliability of the underlying real-time data were improved, the improvement of output gaps estimates would not be significant. The pseudo-real time estimates are substantially similar to the filtered real-time series and the findings remain that the TVP-OG model signaled in real time that output was above its potential level prior to the recent financial crisis.

4.3 Potential Growth

One important product of our model is the estimate of growth in potential output. In order to capture possible changes over the sample, 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-OG 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.

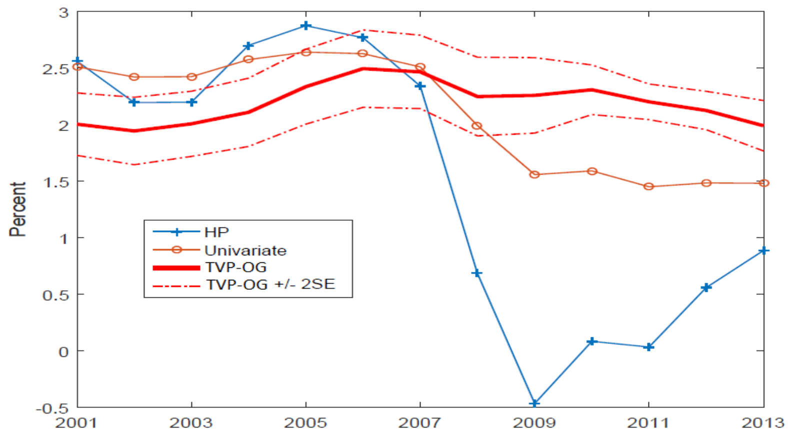
Figure 5 – Potential Growth: Smoothed Series



Notes: The figure shows the smoothed estimates of the potential growth of output ($\Delta\overline{y}_t$) from three different models: the HP filter, the univariate model, and the TVP-OG model.

Although the estimates of potential growth exhibit different degrees of volatility across the models, with the HP-based estimates being the most volatile, they show a similar qualitative pattern. Potential growth decreased considerably in the first thirty years of the century. However, during the next decade, potential growth increased substantially and reached a peak of 5% or above in the early 1940s. Since then, it follows a declining trend, intermitted by periods of stable or slightly increasing growth. Specifically, in all models, we observe two significant decreases in the growth rate: the second half of the 1940s and the decade from the mid 1960s to the mid 1970s. During the period 1980-2000, potential growth fluctuates between 2 and 2.5%. When it comes to the post-2000 period, there have been divergences between the estimates to some extent. Both the HP-based and univariate estimates display that potential growth has been declining, whereas the TVP-OG model suggests a relatively stable level of potential growth.

Figure 6 – Potential Growth: Filtered Series



Notes: The figure shows the filtered estimates of the potential growth of output ($\Delta \overline{y}_t$) from three different models: the HP, the univariate model, and the TVP-OG 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.

Figure 6 presents the un-smoothed (or filtered) post-2000 potential growth, which suggests that the recent financial crash is one of the key factors contributing to the decreases of potential growth in both the HP and univariate models. Specifically, with the HP, its one-sided estimate plummeted by about 3% from 2.5% in 2007 to -0.5% in 2009, then returned to 1% by the end of the sample. With the univariate model, the potential growth also decreased from 2.5% in 2007 to 1.5% by 2009 and has remained at that level since then. On the other hand, potential growth in the TVP-OG model stays stable at the rate of 2%. This result provides an important explanation for the weak recovery in the post-crisis period potentially at odds with the *Secular Stagnation Hypothesis*. Specifically, based on the TVP-OG model, the weak growth in the post-crisis period is less likely caused by the decline of potential growth. Instead, it is the consequence of the financial boom going bust and the ensuing debt overhang, causing persistent economic damage. Standard methods for the estimation of potential output which do not take into account the role of financial information may underestimate the level of potential output during the credit-driven recession and, hence, support the *Financial Cycle Drag Hypothesis* interpretation of 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 the output gap with a lag of one and two years, respectively.[7] 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

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

Notes: Standardized average errors are calculated as the mean of absolute deviation of the expost (smoothed) output gap estimate from the real time (filtered) estimates, normalized by the standard deviation of the expost 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 expost 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 motivated by the recent literature on 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, broad money growth, and short-term interest rate.[8] Similar to the case of credit growth, each of these variables, in real term, is used as a proxy for financial information in the TVP-OG model. In fact, these variables may affect output gap at different time horizons, so we con-

[7] Most of studies using quarterly data consider up to four lags, so a maximum of two-year lag is appropriate with annual data.

[8] The data is obtained from the Jordà-Schularick-Taylor Macrohistory Database, see Jordà, Schularick, and Taylor (2017).

sider 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-OG 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 least helpful in measuring the 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 the 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 uses 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 the 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 the relatively small revision; however, those estimates do not match up well with the reference cycle of U.S. expansions and recessions (Kamber, Morley, and Wong, forthcoming). Therefore, the next section is devoted to investigating the qualitative aspect of output gap estimates using the before-mentioned financial variables.

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 the 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

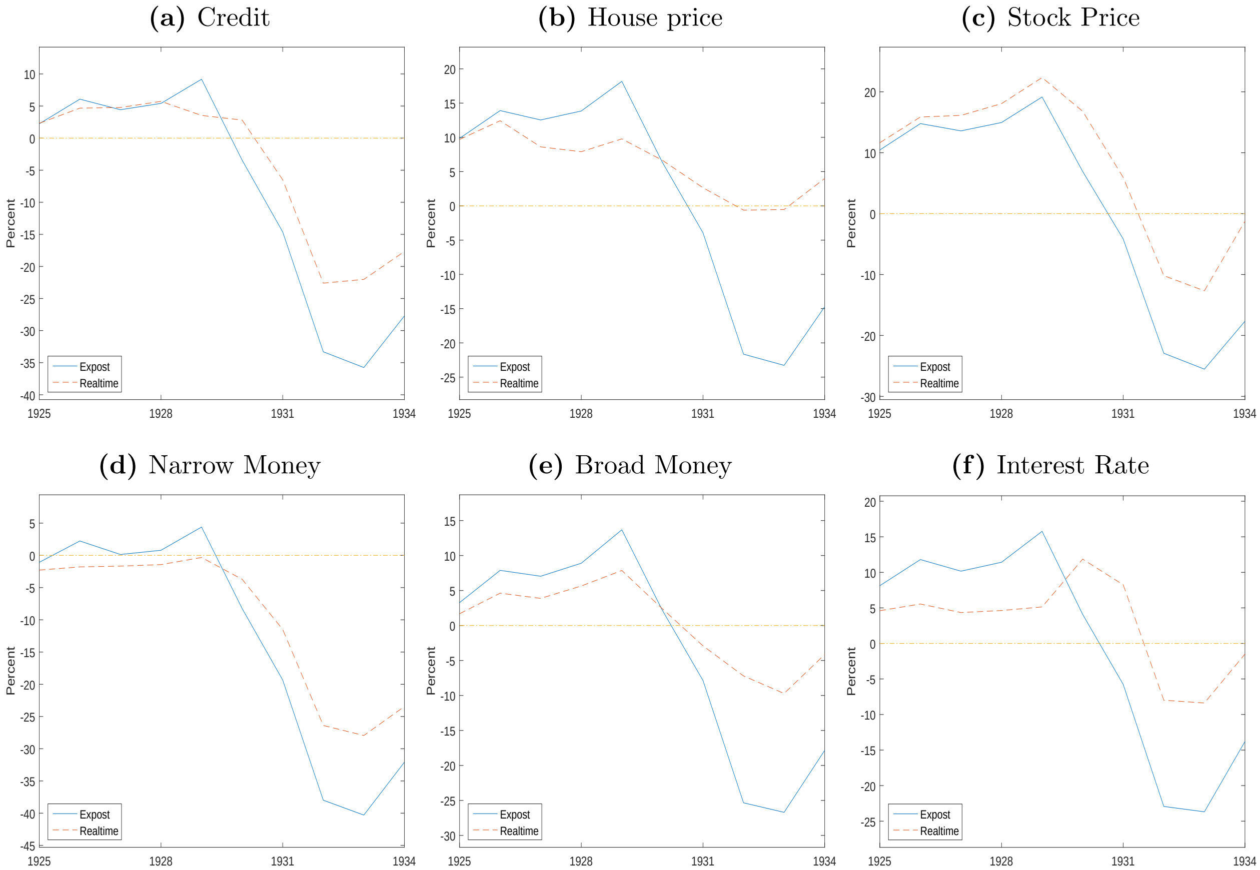
Figure 7 shows the real-time and ex-post output gap estimates by the TVP-OG model for different financial variables for the period of 1924-1934. To facilitate the presentation, for each financial variable we present only the model with the lag structure that yields minimum revisions in output gap estimates based on the SAE (those underlined in Table 5).[9] In the run up to the 1929 crisis, with most variables but narrow money, the real-time measure signals that the economy was above (credit, broad money and interest-rates) or well above (in the case of stock and housing prices) 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 of 1929 caused output to fall substantially below its potential level by more than 20 % in retrospect, as shown by the ex-post estimates in Figure 7 regardless of 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 in causing the slump. This result appears to be in line with Friedman and Schwartz (1963) who show that monetary contraction and potential policy missteps by the Federal Reserve have emboldened some negative effects of the Great Depression. It is worth also emphasising that the decrease in output is estimated at substantially different levels depending on the different financial factor used. The model with narrow money or credit indicate a slump of 40 percent while the model with house prices, equity prices or interest rates indicate a drop of 25 percent. A similar feature is observed for the estimate of output overshoot prior to the crisis.

In addition, our results show that the model with broad money also relatively well captures 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 some-

[9] The 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



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

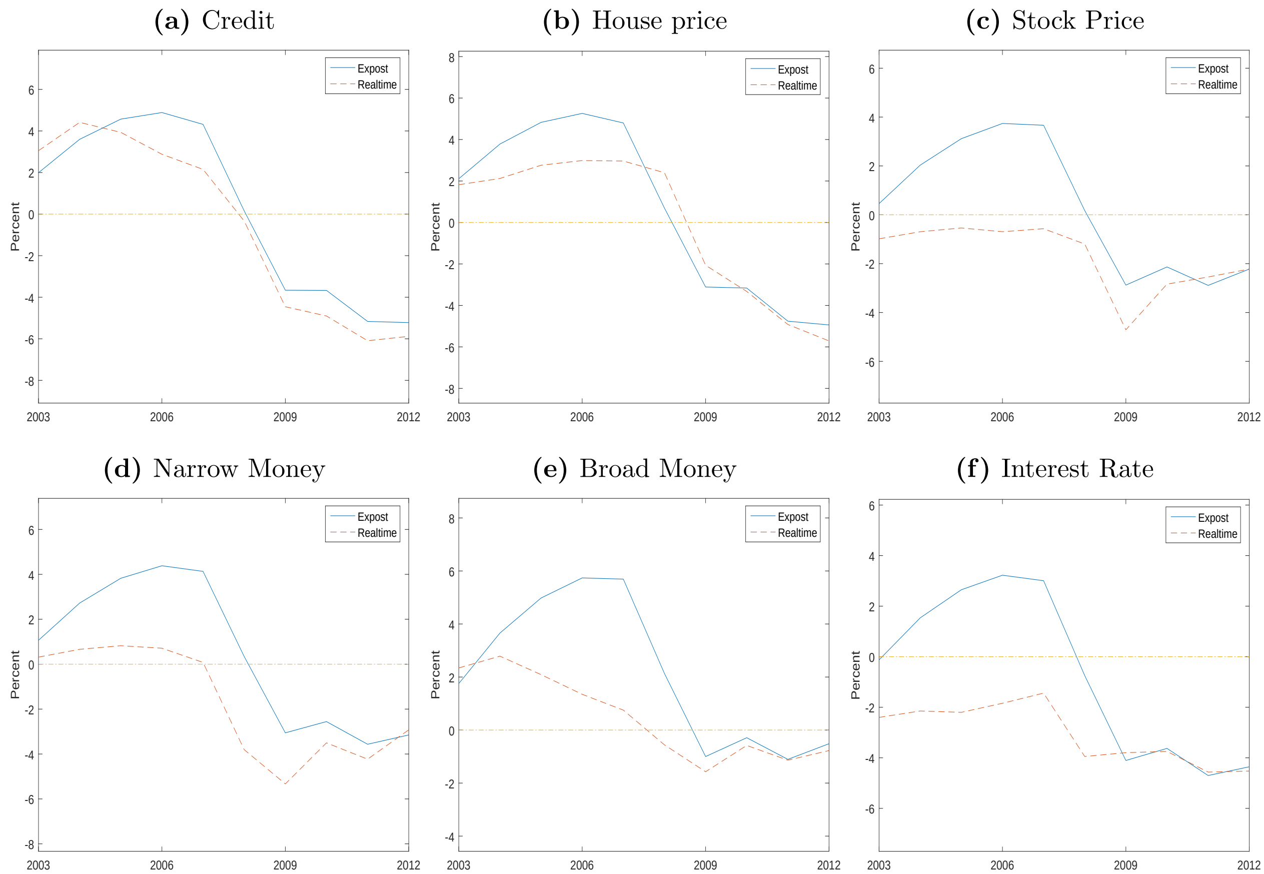
what predictable in light of the findings in (see Schularick and Taylor, 2012). When using house price as a proxy of the financial information, the real-time measure also indicates that the economy was overheated in the pre-1929, but does not capture adequately the slump thereafter.

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-OG framework with different proxies for financial information. To facilitate the presentation of our results, the model with the lag structure that yields minimum revisions in output gap estimates based on the SAE is presented.[10]

[10]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



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

Similar to the financial crash of 1929, the model with credit indicates that output was 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 of 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 the turning point in real time closely with the full sample. Other financial variables, it appears, 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 of 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 the 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 proxies of the financial cycle, notably credit growth and possibly combined with house price, help generate economically plausible output gaps with good real-time performance.

5 Conclusions

In this paper, we extend the parsimonious approach Borio, Disyatat, and Juselius (2016, 2014) 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 indicate the important 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, the US potential growth has been stable at 2% since the beginning of 1980.

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A Appendix

A.1 State-space Specification: The BDJ model

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

$$Y_t = HX_t \tag{6}$$

$$X_t = M + FX_{t-1} + W_t \qquad W_t \sim iidN(0, Q). \tag{7}$$

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:

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

$$F = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \rho \end{bmatrix}, \quad W = \begin{bmatrix} 0 \\ \varepsilon_g \\ \varepsilon_{\hat{y}} \end{bmatrix}, \qquad Q = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon_g} & 0 \\ 0 & 0 & \sigma^2_{\varepsilon_{\hat{y}}} \end{bmatrix}, \quad M = \begin{bmatrix} 0 \\ 0 \\ \gamma f_t \end{bmatrix}. \tag{8}$$

$$\tag{9}$$

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

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

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

$$Y_t = HX_t \tag{10}$$

$$X_t = M + FX_{t-1} + W_t \qquad W_t \sim iidN(0, Q). \tag{11}$$

where the observation vector Y_t is:

$$Y_t = [y_t]$$

and the state vector X_t is:

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

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

The coefficients of matrices are described as follows:

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

$$F = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \rho & f_t \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad W = \begin{bmatrix} 0 \\ \varepsilon_g \\ \varepsilon_{\hat{y}} \\ \varepsilon_{\gamma} \end{bmatrix}, \quad Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon_g} & 0 & 0 \\ 0 & 0 & \sigma^2_{\varepsilon_{\hat{y}}} & 0 \\ 0 & 0 & 0 & \sigma^2_{\varepsilon_{\gamma}} \end{bmatrix}, \quad M = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}. \tag{12}$$

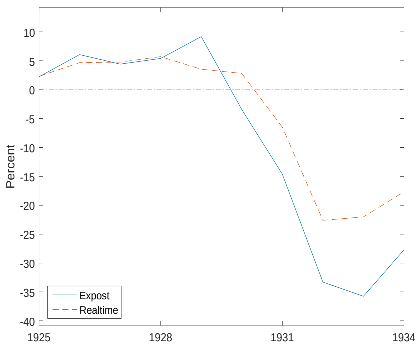
(13)

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

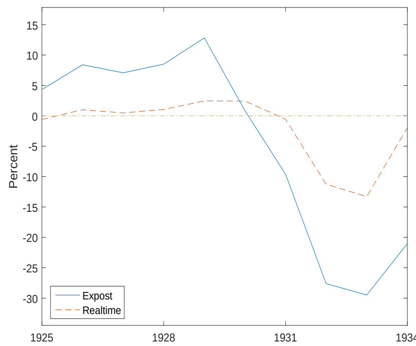
A.3 Two Great Crises

We estimate the TVP-OG 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



(a) Contemporaneous



(b) First Lag

(c) Second Lag

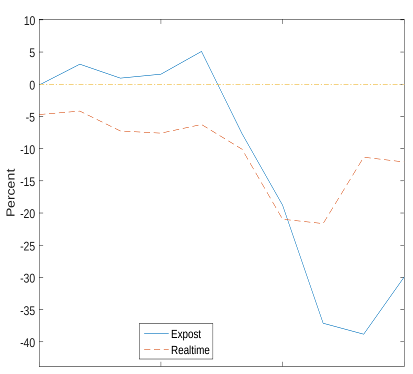
Figure 9 – Model with Real Credit Growth: Ex-post versus Realtime Output Gap between 1925-1934

(a) Contemporaneous

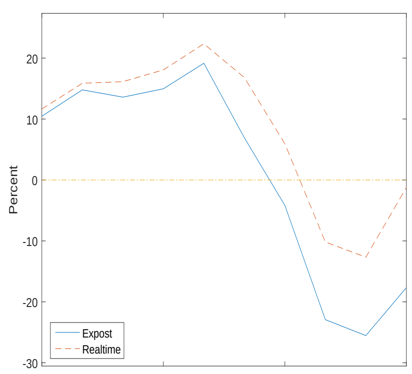
(b) First Lag

(c) Second Lag

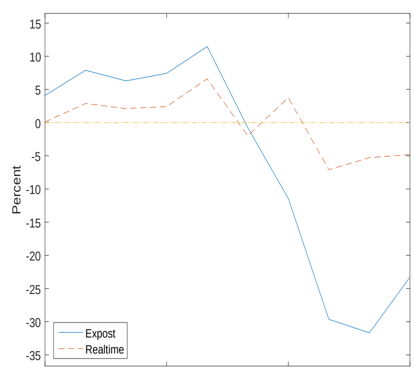
Figure 10 – Model with Real House Price Growth: Ex-post versus Realtime Output Gap between 1925-1934



(a) Contemporaneous



(b) First Lag



(c) Second Lag

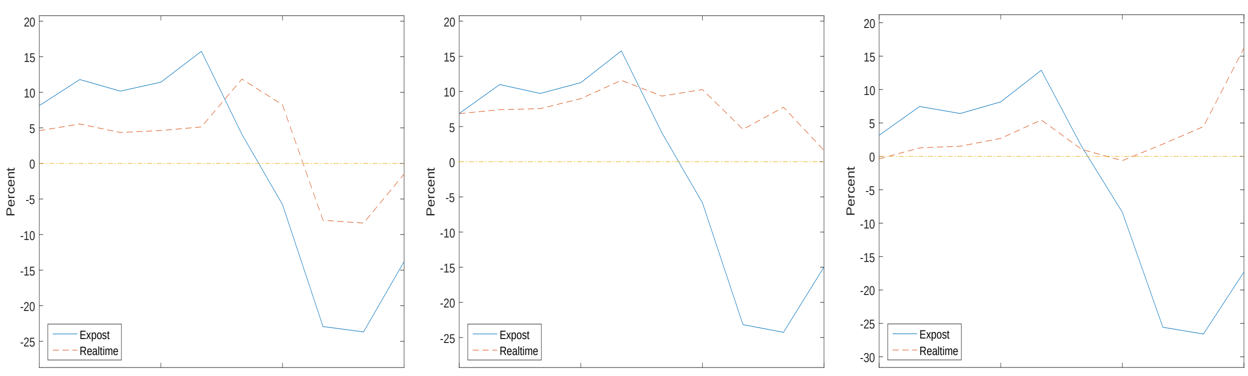
Figure 11 – Model with Real Stock Price Growth: Ex-post versus Realtime Output Gap between 1925-1934

(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

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

(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

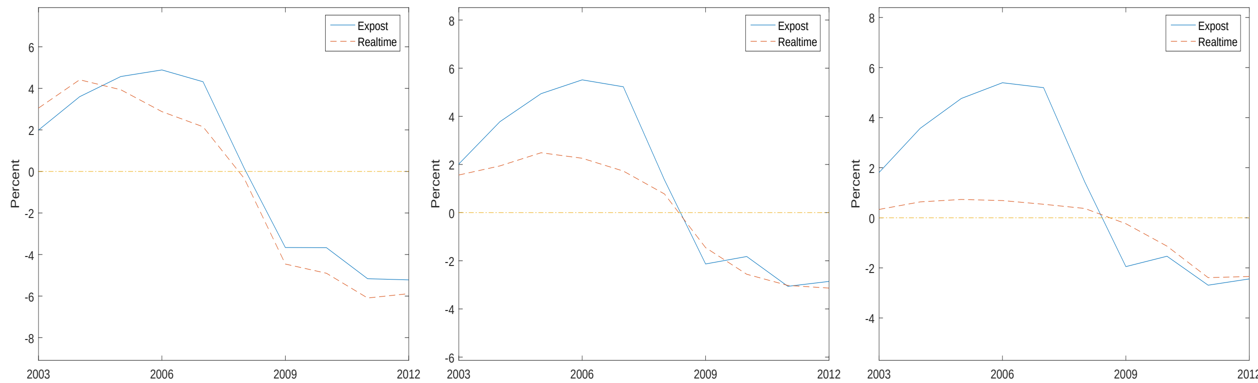
Figure 13 – Model with Real Broad Money Growth: Ex-post versus Realtime Output Gap between 1925-1934



(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

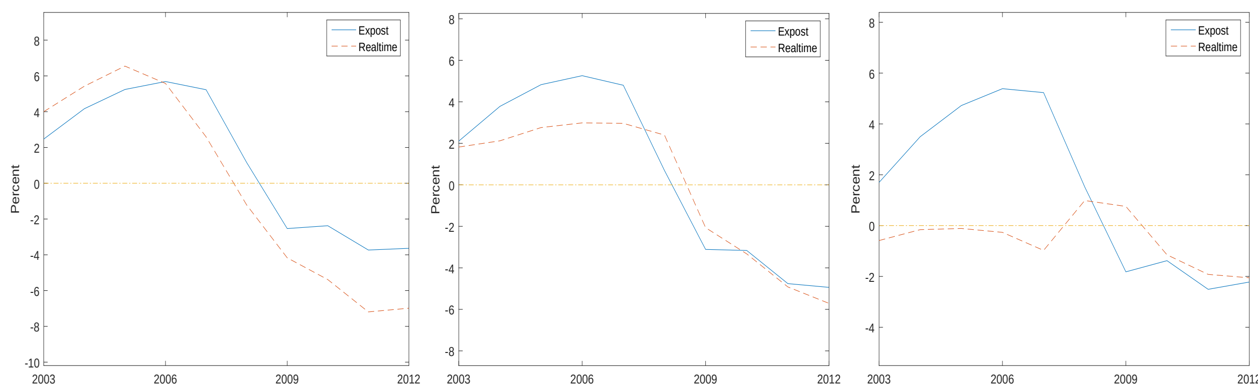
Figure 14 – Model with Real Interest Rate: Ex-post versus Realtime Output Gap between 1925-1934

A.4 The 2007 Crisis



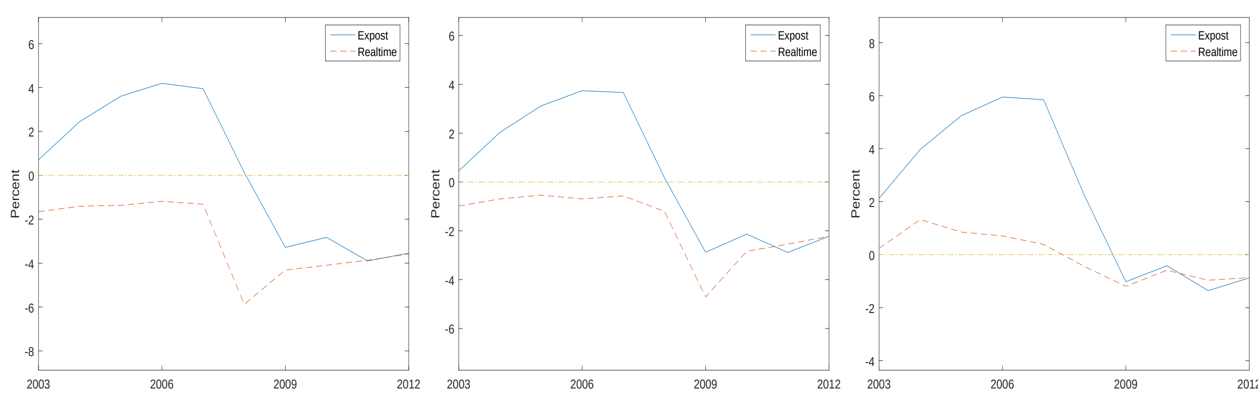
(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

Figure 15 – Model with Real Credit Growth: Ex-post versus Realtime Output Gap between 2003-2012



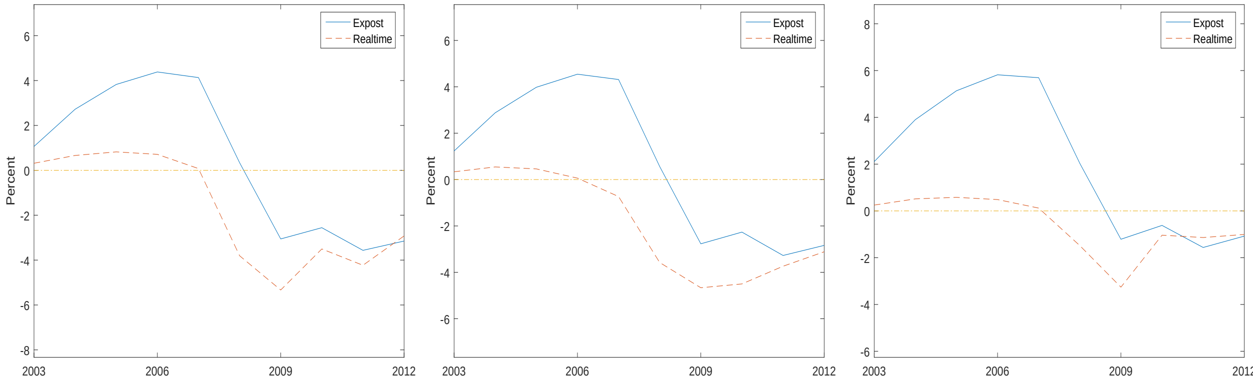
(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

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



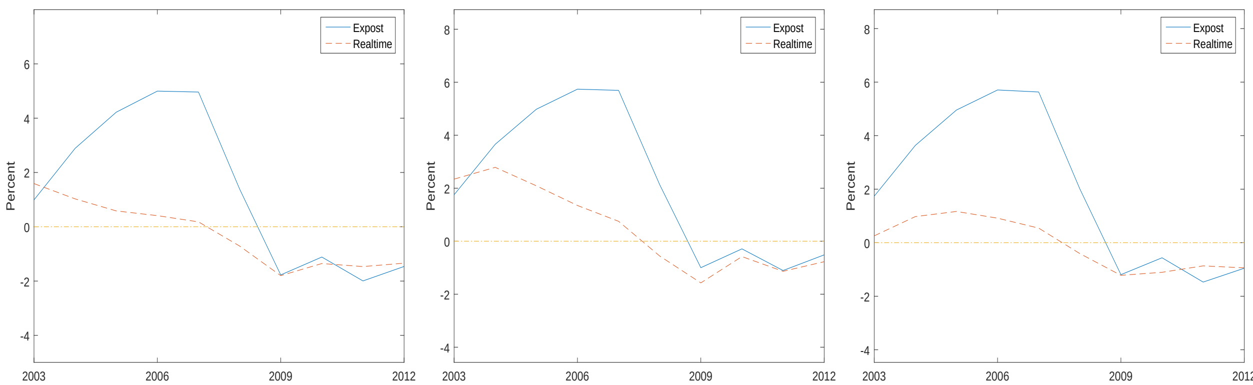
(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

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



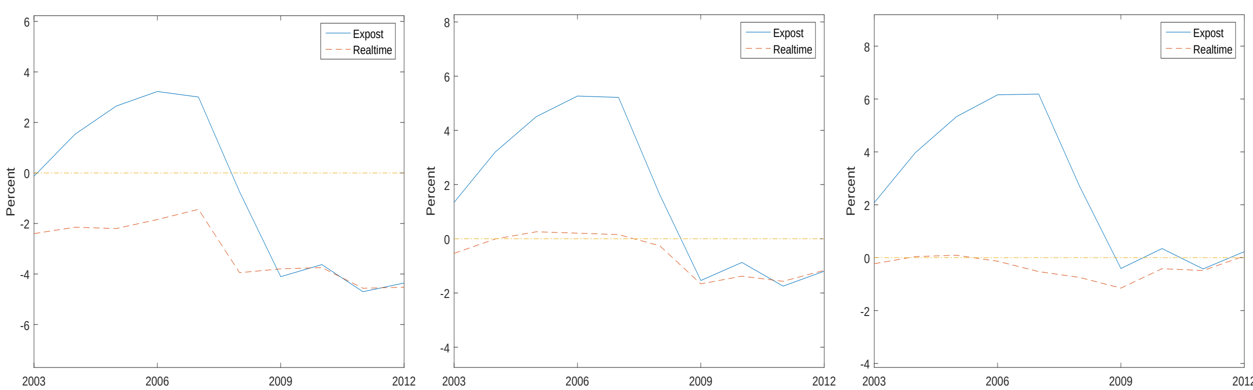
(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

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



(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

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



(a) Contemporaneous **(b)** First Lag **(c)** Second Lag

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