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# USING CREDIT VARIABLES TO DATE BUSINESS CYCLE AND TO ESTIMATE THE PROBABILITIES OF RECESSION IN REAL TIME*

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Following the debate on the relationship between business and financial cycle rekindled in the last decade since the global financial crisis, we assess the ability of some financial indicators to track the Italian business cycle. We mostly use credit variables to detect the turning points and to estimate the probability of recession in real time. A dynamic factor model with Markov-switching regimes is used to handle a large data set and to cope with the nonlinear evolution of the business cycle. The in-sample results strongly support the capacity of credit variables to estimate the probability of recessions and the implied coincident indicator proves their ability to fit the business cycle. Also in real time the contribution of credit is not negligible compared to that of the industrial production, currently used for the conjunctural analysis.

## 1 Introduction

Detecting the turning points of the economy and catching the short-term evolution of GDP in real time has always been a crucial task for the policy maker. The global financial crisis has reignited the long-standing debate over the relationship between business and financial cycle. Much attention is particularly devoted to credit, whose role in driving macroeconomic variables is being increasingly emphasized. A number of seminal papers investigated credit as a force that amplifies and propagates the shocks hitting the real economy. In the light of the recent economic turmoil, it becomes reasonable wondering whether credit could even herald economic collapses.

In this paper, we carry out a real-time analysis to inspect the ability of some credit variables to track the Italian business cycle, and in particular bank loans, as they are the principal source of financing for small- and

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medium-sized firms in Italy. Credit variables are suitable for the conjunctural analysis because they are released a few days after the reference month and they are not affected by huge historical revisions as the official estimates of many macroeconomic aggregates, notoriously. The real-time perspective helps to overcome the criticism by Gadea Rivas and Perez-Quiros (2015), who claim that all the research on the role of credit to predict macroeconomic fluctuations *does not take into account that recession dating is uncertain in real time*. The authors find that the contribution of credit to forecast turning points is distorted by the Great Recession, which explains most of the covariance between credit and economic aggregates.

We select 20 out of 100 series compiled among bank loans to nonfinancial corporations and households, interests rates on deposits and loans in the interval January 1998–December 2016; we use the quarterly growth rate of the GDP (at monthly frequency) as the target variable. As in Kim and Nelson (1998), we set up a factor model cast in state-space form with Markov switching to cope with the nonlinear evolution of the business cycle. The model is estimated by a multimove Gibbs sampling, which makes approximation-free inference for non-Gaussian and nonlinear state-space models feasible. As a benchmark, we take a model including only the industrial production index.

The in-sample results definitely bolster the coincident relationship between GDP and credit. The probabilities of recession obtained are consistent with GDP's dynamics and they are comparable to those estimated by the benchmark model. Also the composite coincident index fits well the cyclical phases of the Italian economy.

The real-time upshots are encouraging. The credit model fairly assigns the probability of being in a recession phase during the financial crisis and it works better than the benchmark on average. Most importantly, credit variables are more sensitive than the industrial production index to signal the negative turning points. The credit model struggles in the first part of the sovereign-debt crisis; since the end of 2012 credit variables track the economic activity swings as well as the industrial production index. In the last period, it works better than the benchmark to signal the recovery.

The paper is structured as follows. Section 2 reviews the long-standing debate over the relationship between credit and business cycle, going through the most seminal papers. Section 3 describes the information set. Section 4 presents the model. Section 5 reports the results and Section 6 concludes.

## 2 Literature Review

The interplay between financial and business cycles has been long debated in the economic literature. Gertler (1988) surveys the milestones of the academic research from the 'money view' endorsed by Friedman and Schwartz (1963), who emphasize the role of money supply to explain the macroeconomic fluctuations, to the 'credit view', reignited in the seminal papers by Mishkin (1978) and Bernanke (1983), according to which the credit supply is a crucial force moving the economic aggregates and the financial disruption may dramatically affect the depth and the persistence of the recession. Bernanke and Gertler (1995) and Bernanke *et al.* (1999) investigate how frictions in credit markets may influence the monetary policy transmission by amplifying and propagating the conventional interest rate effect. Particular attention was devoted to the capacity of credit of sparking and prolonging economic recessions. In Kiyotaki and Moore (1997), endogenous credit constraints help to understand how relatively small and temporary shocks to technology or income distribution may trigger large and persistent fluctuations in output and how sector-specific shocks may spill over into the entire economy.

In the light of the last decade turmoils in the financial sector, this strand of literature addressing the relationship between credit and business cycle has been elaborated further. Adrian *et al.* (2012) document different stylized facts based on the evidence of the financial crisis 2007–09. They highlight that although bank lending to firms declines during the crisis, the increase of bond financing closes much of the gap. Then, in their model, real activity is affected more by risk premiums rather than from contraction in the total quantity of credit. Several authors argue that credit spread can be used as leading indicator of the business cycle (Stock and Watson, 1989). Guha and Hiris (2002) show that turning points of the long-term credit spread can anticipate those of the business cycle. Gilchrist *et al.* (2009) show that shocks to corporate credit spreads account for a significant fraction of the variance in U.S. economic activity.

Schularick and Taylor (2012) use a very large dataset on 14 countries over 140 years to figure out whether credit booms could herald financial crisis; based on the same information set, Jordá *et al.* (2011) pin down the credit trend as a better predictor of financial instability than external imbalances. Dell'Ariccia and Garibaldi (2005) argue that a persistent credit contraction may have delayed the recovery after 1991 crisis; this point is also underlined in Reinhart and Rogoff (2009), who find that bank crisis materially affect the severity of employment and output decline. In Claessens *et al.* (2012) and Mendoza and Terrones (2008) credit crunches and house prices burst emerge as determinants of the severity and duration of recessions.

A number of paper stress the crucial role of household debt to shape the business cycle. Jordá *et al.* (2015, 2016) show that loose monetary conditions boosts the real estate lending and this may cause house prices bubbles and enhances the risk of financial crises, deeper recessions and slower recoveries. Furthermore, as shown by Mian *et al.* (2013, 2017), the negative relationship between the change of households debt and GDP growth depends on both the level and the distribution of debt: the output decline is larger for higher levels of household debt, particularly in presence of tighter monetary constraints; shocks to the wealth of heterogeneous families, with different marginal propensity to consume out of housing wealth, can amplify aggregate dynamics.

Gadea Rivas and Perez-Quiros (2015) doubt the ability of credit variables to track the turning points of the economy effectively, being the relationship between business and credit cycle mostly affected by the Great Recession. We propose a real-time exercise to overcome this criticism.

The role of the bank credit in macroeconomy is a particularly sensitive issue in Italy, because it is the main financing resource for business. De Bonis and Silvestrini (2014) propose an historical description of the Italian financial cycle over 150 years. Bartoletto *et al.* (2017) introduce a joint dating of both business and financial cycles, using a dating algorithm à la Bry and Boschan (1971). In the same strand, Bulligan *et al.* (2019) employ univariate and multivariate trend-cycle decomposition based on unobserved component models to study the relationship between business and financial cycle. Our paper adds to this strand of literature by inspecting the relationship between business and financial cycles in 'normal' times other than during economic turmoils.

As stated in Burns and Mitchell (1946), the business cycle is characterized by both the comovement among a number of macroeconomic variables and a nonlinear dynamics, depending on the states of the economy. However, these two features were usually addressed separately. It is worth mentioning the numerous contributions by Stock and Watson (1989, 1991, 1993), where the authors stress the first characteristic of the business cycle, by collapsing the information carried by a large data set into few common factors. On the other side, Hamilton (1989) estimate a univariate model with regime-switching to take into account how the evolution of the business cycle depends on whether the economy is in an expansionary or contraction phase. Diebold and Rudebusch (1996) is one of the first attempt to model both comovement and nonlinearity jointly. They estimate a dynamic factor model with regime-switching by approximated maximum likelihood. An approximation-free inference is proposed by Kim and Nelson (1998), who run a multimove Gibbs sampling algorithm to estimate the model.

## 3 Data

We have scanned more than 100 monthly time series on bank credit, regarding both quantities and prices of loans to households (HHs, onward) and non-financial corporations (NFCs, onward). These variables come from two flows of data produced by the Bank of Italy for the ECB: the monetary and financial institutions interest rates and information on banks' balance sheets. We have selected $n = 20$ time series in the interval January 1998–December 2016 (see Table 1 for a detailed description) on the basis of a descriptive inspection. These series constitute the information set of our

TABLE 1
INFORMATION SET

| *Description* | *Treat* |
|---|---|
| Italy, Financial transactions, Loans, Households | out SA |
| Italy, Financial transactions, Loans, Non financial corporations | — |
| Italy, Outstanding amounts, Loans, Households | Δ out |
| Italy, Outstanding amounts, Lending for house purchase, Households | Δ out |
| Italy, Outstanding amounts, Credit consumption and other lending, Households | Δ out |
| Italy, Outstanding amounts, Deposit liabilities, Households | Δ out SA |
| Italy, Spread between 3-5y gross yield at issuance | — |
| Italy, Interest rate on stock, Revolving loans, overdrafts, credit cards, Households | Δ out SA |
| Italy, Interest rate on stock, Revolving loans, overdrafts, credit cards, Non financial corporations | Δ |
| Italy, Interest rate on stock, Total deposits, Households and Non financial corporations | Δ |
| Italy, Interest rate on stock, Overnight deposits, Households | Δ |
| Italy, Interest rate on stock, Overnight deposits, Non financial corporations | Δ |
| Italy, Interest rate on stock, Loans, Households | Δ |
| Italy, Interest rate on stock, Loans, Non financial corporations | Δ |
| Italy, Interest rate on stock, Lending for house purchase, Households | Δ |
| Italy, Interest rate on new business, Loans, Non financial corporations | Δ |
| Italy, Interest rate on new business, Lending for house purchase, Households corporations | Δ |

SA = Seasonal adjustment; Δ = First difference; out = Outlier management.

'credit' model; they are available 15 days after the reference period, far earlier than the official statistics on the main macroeconomic aggregates (the preliminary estimate of the GDP is released 30 days after the reference quarter; the first official estimate is published 60 days later than the end of the quarter[1]), and they provide a very reliable signal in real time. From Fig. 1 we appreciate the strong relationship among bank interest rates and the quarterly growth rate of the GDP (q-o-q GDP), which is the target variable of the model; even before the global financial crisis they comove closely. Figure 2 shows as new financial transactions to households and firms—the flows of loans calculated by adjusting the changes in the stocks to take account of exchange rate fluctuations, value adjustments, reclassifications and all other variations that do not originate from financial transactions—seem to anticipate the drop of GDP in the run-up to the global financial collapse. Some series underwent seasonal adjustment, using seasonal dummies. It is the case of the new financial transactions to households and of the annualized agreed rate[2] on loans to households. Credit variables are often

[1]Before May 2018, the preliminary estimate of the GDP were issued 45 days later than the end of the quarter, while now it is published 30 days later.
[2]The annualized agreed rate is a measure of the interest rates which does not include commissions and other burdens.

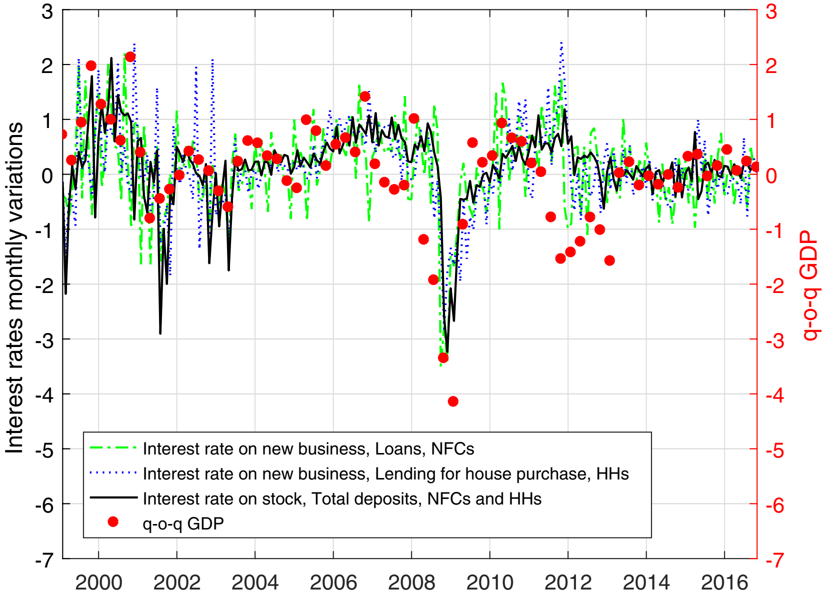


FIG. 1. Interest rates and GDP

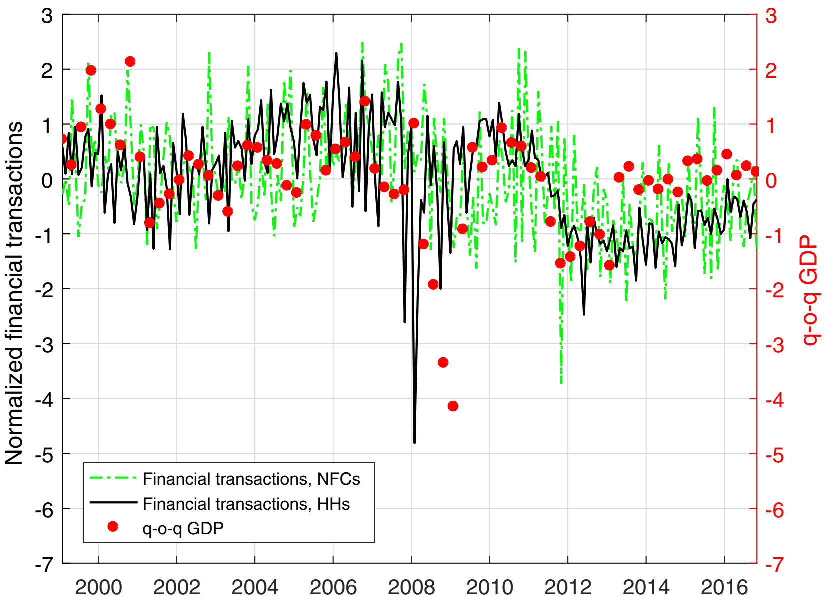


FIG. 2. Financial transactions and GDP

characterized by outliers, which can been pinned down straightfowardly because they are mainly caused by some technical or administrative innovations,[3] like the reorganization of leading banking groups. We identify the outliers as those observations (centered with respect to the historical mean) greater than, at least, 1.5 the standard deviation, and they are replaced by the average of the neighboring observations. Also using the series on the new financial transactions, instead of the stocks, helps us to smooth some of the numerous outliers recorded throughout the sample considered in the analysis.

The quarterly GDP is disaggregated at monthly frequencies by applying the Chow-Lin filter, based on the manufacturing Purchasing Manager Index (PMI) as regressor.[4]

## 4 The Model

We employ the dynamic factor model with Markov switching phases proposed by Kim and Nelson (1998). A large-scale multivariate model meets our scope of inspecting the ability of a number of credit variables to tracking the business cycle without impairing the efficiency of the estimates. Within our factor model, all the information is collapsed in one factor, which represents the business cycle.[5] More formally, the growth rate of the $n$ observable indicators included in the model, $\Delta Y_{it}$ for $i = 1, \dots n$ and $t = 1, \dots T$, is driven by an individual component, $D_i + e_{it}$ (where $D_i$ represents the intercept), and by a common component $\Delta C_t$. The latter can be interpreted as the cyclical component of the economic activity according to the definition of business cycle by Burns and Mitchell (1946). $\Delta C_t$ is a stationary and strongly autocorrelated process, which can be correctly fitted by an AR(1) model with a long-term average split into two components: $\delta$, which is constant over time, and $\mu_{S_t}$, which varies depending on the state of the economy, $S_t$.

$$\Delta Y_{it} = \lambda_i(L)\Delta C_t + D_i + e_{it} \tag{1}$$

$$\Phi(L)(\Delta C_t - \mu_{S_t} - \delta) = v_t, \quad v_t \sim iidN(0,1) \tag{2}$$

$$\Psi_i(L)e_{it} = \epsilon_{it}, \quad \epsilon_{it} \sim iidN(0,\sigma_i^2) \tag{3}$$

[3]See the technical notes in the Statistical Report on Banks and Money, published monthly by the Bank of Italy https://www.bancaditalia.it/pubblicazioni/moneta-banche/2017-moneta/en_BAM_note-met.pdf?language_id=1.

[4]The Purchasing Manager Indexes are issued by Markit (markit.com).

[5]When we handle macroeconomic data, the first factor is likely to represent the business cycle because it explains a significant portion of the covariance among the original variables.

where

$$\mu_{S_t} = \mu_0 + \mu_1 S_t, \quad \mu_1 > 1, \quad S_t = \begin{cases} 0, & \text{if recession} \\ 1, & \text{if expansion} \end{cases} \tag{4}$$

The Markov process is appropriate to shape the nonlinear evolution of the business cycle, characterized by expansionary and recessionary phases:

$$\begin{aligned} Pr\left[S_t = 1 | S_{t-1} = 1\right] &= p \\ Pr\left[S_t = 0 | S_{t-1} = 0\right] &= q \end{aligned} \tag{5}$$

Due to nonlinearity, the estimation of the model is performed using a Markov chain Monte Carlo algorithm (MCMC onward). After setting up some priors about the starting values of the processes $\Delta C_t$ and $S_t$ as well as the parameters, we first generate the entire process of the cyclical component $\Delta C_t$. Based on this estimate, we generate the regimes $S_t$ and finally the parameters. More specifically, we use a multi-move Gibbs sampling introduced by Carter and Kohn (1994).[6] The sampler takes just 1000 replications to converge (see Fig. A1 in the Appendix). The first 20 per cent draws are discarded to obtain stable estimates. Finally, we construct a composite coincident index, which fits the cyclical phases of the Italian economy.[7]

## 5 Results

Our credit model is compared with a benchmark model including only GDP as target and the industrial production index as exogenous variable (IP model, onward). The latter is one of the most important indicator currently used in the real-time assessment of the economic activity, especially in Italy, which is the second manufacturing engine of euro area.

We carried out an in-sample analysis, on the time interval from January 1998 to December 2016, to figure out how well credit variables fit the business cycle. We also simulated an out-of-sample estimation of the model to investigate to what extent the criticism by Gadea Rivas and Perez-Quiros (2015) could be overcome. We used an expanding window and the first estimation sample spans 7 years, from January 1998 to January 2006 while the last sample goes up to December 2016. The last available vintage of data is

[6]The Gibbs sampling is an MCMC algorithm used to approximate the joint distributions by sampling from the conditional distributions and then sparing cumbersome calculations. The multimove Gibbs sampler generates the whole vectors $\tilde{\Delta C}_T = [\Delta C_1, \ldots, \Delta C_T]$ and $\tilde{S}_T = [S_1, \ldots, S_T]$, gaining in computational efficiency and faster convergence than the single-move algorithm, which generates one element at time.

[7]See the Appendix for all the technical details.

TABLE 2
BAYESIAN PRIOR AND POSTERIOR DISTRIBUTIONS

| | *Prior Distribution* | | *Posterior Distribution* | | | | |
|---|---|---|---|---|---|---|---|
| *Parameter* | *Mean* | *SD* | *Mean* | *SD* | *Median* | *5%* | *95%* |
| $p$ | 0.5 | 0.289 | 0.716 | 0.230 | 0.832 | 0.207 | 0.912 |
| $q$ | 0.5 | 0.289 | 0.706 | 0.091 | 0.702 | 0.559 | 0.868 |
| $\phi_1$ | 0.0 | 1.000 | 0.916 | 0.007 | 0.917 | 0.904 | 0.928 |
| $\mu_0$ | 0.0 | 1.000 | −0.797 | 1.037 | −0.713 | −2.602 | 0.867 |
| $\mu_1$ | 0.0 | 1.000 | 1.299 | 0.639 | 1.280 | 0.217 | 2.407 |

cut month-by-month, being careful to replace the pattern of missing values at the end of the sample.[8]

Table 2 reports the prior and the posterior distributions of a selection of parameters from the in-sample exercise.[9] We use noninformative priors for $p$ and $q$ (both set to 0.5), which imply a duration of expansions and recessions equal to two months.[10] $\mu_0$ and $\mu_1$ turn out to be significantly different from zero and this result bolsters the definition by Burns and Mitchell (1946) of the business cycle as characterized by two different phases.

Results from in-sample exercise are clear-cut in favor of the role of credit variables to tracking the business cycle. Figure 3 shows the probabilities of recession (gray bars) estimated by the credit model for each month compared with the monthly growth rate of the GDP. Our model correctly assigns high probability to the event 'recession' when the economy actually undergoes a downturn. Credit turns out to be a good competitor of IP to pin down the contraction of activity as displayed in Fig. 4. This also shows the recessionary phases (shadowed areas) to prove the reliability of our results compared to the chronology of the business cycle.[11] In the run-up to all the economic turmoils depicted in the figure, credit seems to be more sensitive than IP to herald the decline of the GDP. In 2001.Q2, the credit model assigned probability 0.91 in June to the contraction of the GDP instead of 0.80 estimated by the IP model; in 2003.Q1, based on credit we would have bet

[8]As a matter of fact, only GDP and IP have missing values at the end of the sample because they are released 30 days and 45 days later than the reference period unlike the credit variables, which are available just 15 days belatedly. GDP (after being converted in monthly frequency by Chow-Lin based on the manufacturing PMI) and IP are projected up to the nowcasting date by an autoregressive model.

[9]For the sake of simplicity, we do not report the statistics relative to the autoregressive polynomial $\Psi_i(L)$, for $i = 1, \ldots, n$. They are available upon request.

[10]Let $p$ be the probability of being in expansion between $t-1$ and $t$, the expected duration of the positive cyclical phase is given by $\frac{1}{1-p}$.

[11]The official dating provided by the National Institute of Statistics in the Annual Report issued in 2010 was reviewed to take into account the historical revisions of GDP estimates occurred in the meanwhile. Furthermore, we also considered the technical recessions, defined as two straight quarters of negative growth.

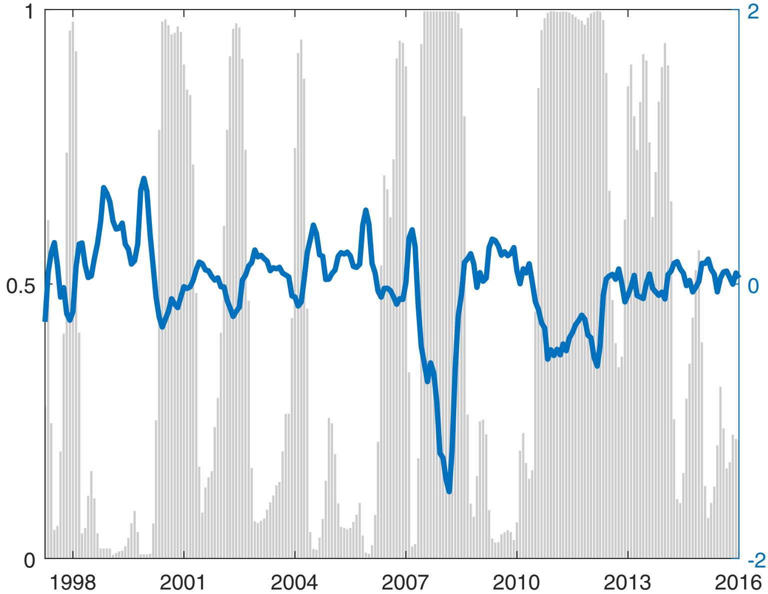


FIG. 3. Probability of recession (grey bars; left side axis) and monthly GDP growth (blue line; right side axis)

0.77 on the decline of the GDP, while the IP model indicated 0.59. The other way round, credit model corrected downward the probability of recession more quickly than the IP model on October and November 2003, when the Italian economy started recovering. Credit variables did better than IP in signaling the storm looming on the economy in the run-up to the financial crisis. Credit model also estimated a 50 per cent lower probability of recession between July 2009 and June 2011, when the headwinds faded. In the summer 2011, credit model assigned a higher probability to recession than the benchmark model, when Italian GDP slowed down markedly. In the wake of the sovereign-debt crisis, credit variables were more effective than IP to depict the recovery: between January 2015 and December 2016, credit model assigned on average 30 per cent lower probability to the event 'recession' than IP model.

The coincident composite index (see Fig. 5) is consistent with the cyclical phases of the Italian economy.

In real time, the results are generally still encouraging. Credit variables are more responsive than IP to signaling the start of the global financial crisis. In the two months, April-May of 2007 (the starting date of the negative turning point), credit model assigned to recession a probability of 0.71 against 0.54 estimated by IP model (see Fig. 6). Credit model struggles to

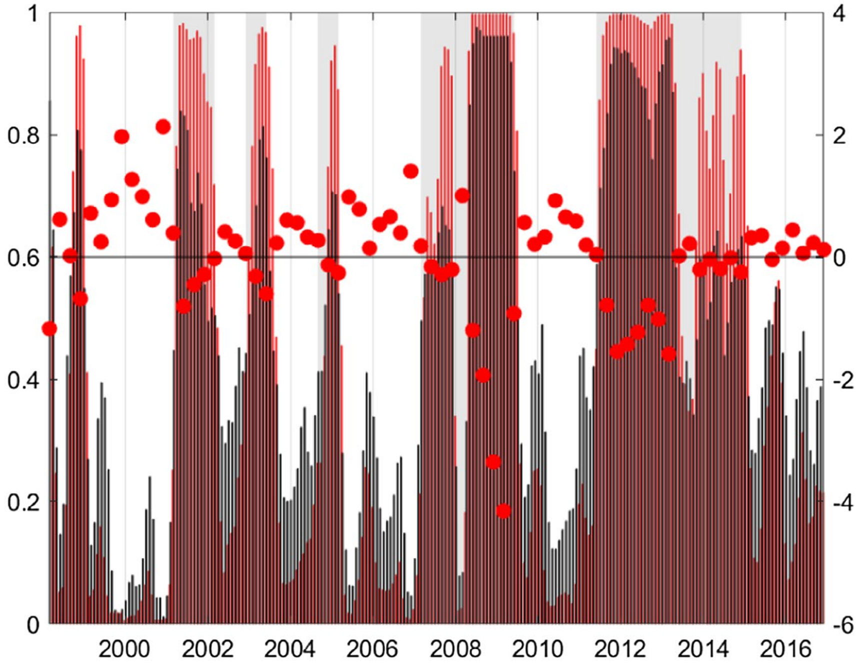


FIG. 4. Probability of recession estimated by credit (red bars) and by IP (black bars) on the left side axis; monthly GDP growth (red dots; right side axis); recession phases (shadowed area)

track the sovereign-debt crisis, in particular during the first phase of the downturn while IP model gives a more stable signal of recession. Starting from the end of 2012, credit model catches up with IP one throughout the European crisis (see Fig. 7). In the first quarter of 2015, credit model on average beats benchmark to signal the recovery. If we exclude the third quarter, when GDP actually stagnated and credit model correctly signaled a higher risk of recession than IP model, credit variables did better than IP to track the positive path of the economy since January 2015 up to the end of the sample (December 2016) as shown in Fig. 8. These results, notably during the financial crisis, answer the criticism by Gadea Rivas and Perez-Quiros (2015). The real-time simulation shows that the credit variables do not need to take advantage of the entire span of information to track the business cycle but as news pile up month by month, they grasp an approaching turning point correctly.

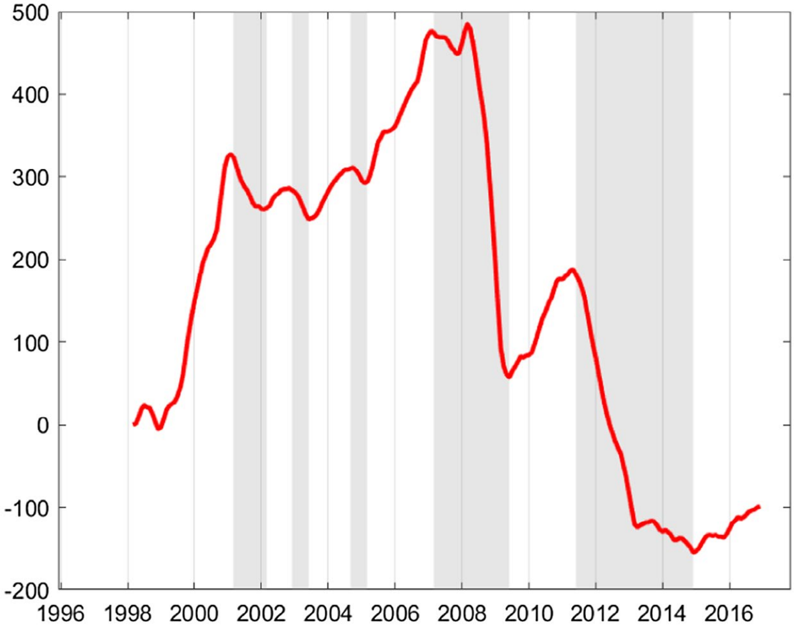


FIG. 5. Composite Coincident Indicator (red line); recession phases (shadowed area)

In Table 3, we present the relative Brier score (BS onward) of the two competing models.[12] In-sample results show that the credit model outperforms the IP model throughout all the cyclical phases of the Italian economy, showing a 34 per cent lower BS. The credit variables are 30 per cent better than IP to catch the negative quarterly variation of GDP, irrespective of whether the latter reflects a recession or a temporary halt. The credit model performs 56 per cent better than the IP model to estimating the probability of recession during the sovereign-debt crisis and it works better also during the following recovery. In real time, overall credit model is still well performing during financial crisis and the most recent recovery while it turns out to be less reliable than IP to track the sovereign-debt crisis and the downturns of GDP.[13]

[12]The relative BS is the ratio between BS of the credit model and BS of the IP model. Therefore, the closer to 0 the relative BS is, the better the credit model performs.

[13]The real-time simulation starts from January 2006, therefore, it is not possible to calculate BS for the cyclical phases and the BS corresponding to negative GDP growth does not cover the same period of the in-sample simulation.

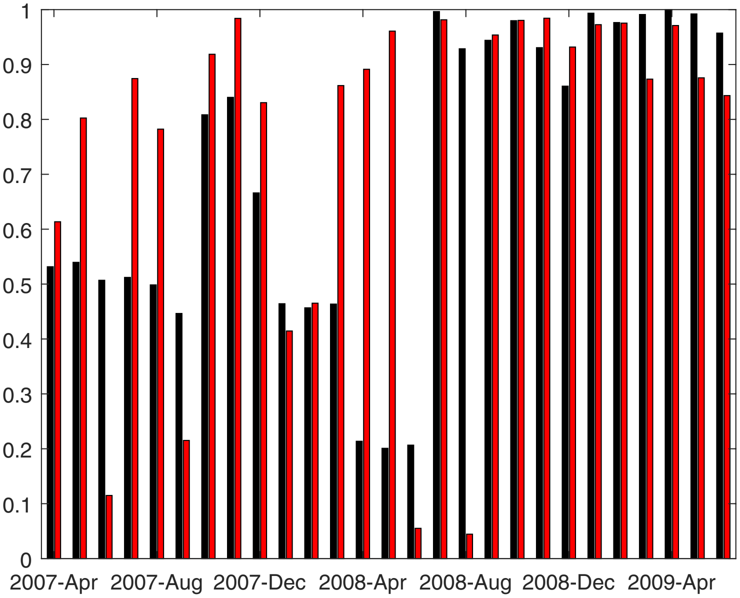


FIG. 6. Probability of Recession Estimated by Credit (Red Bars) and by IP (Black Bars): Global Financial Crisis

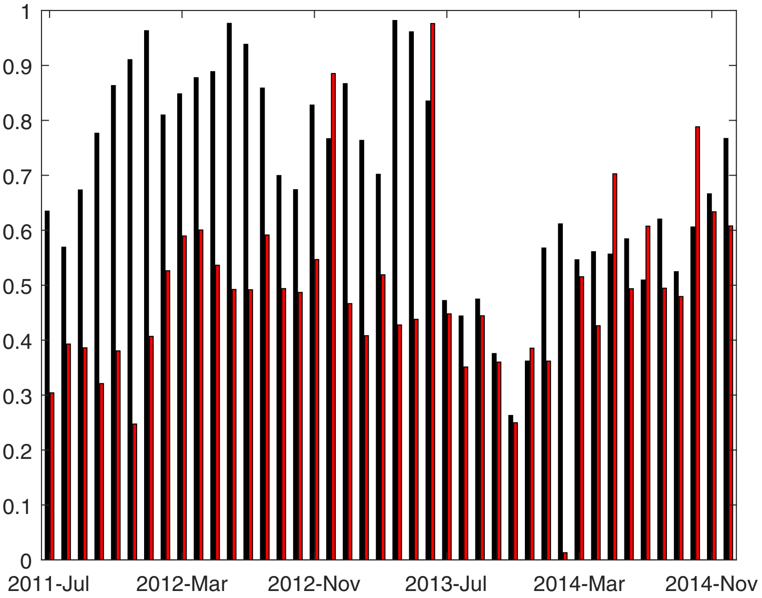


FIG. 7. Probability of Recession Estimated by Credit (Red Bars) and by IP (Black Bars): Sovereign Debt Crisis

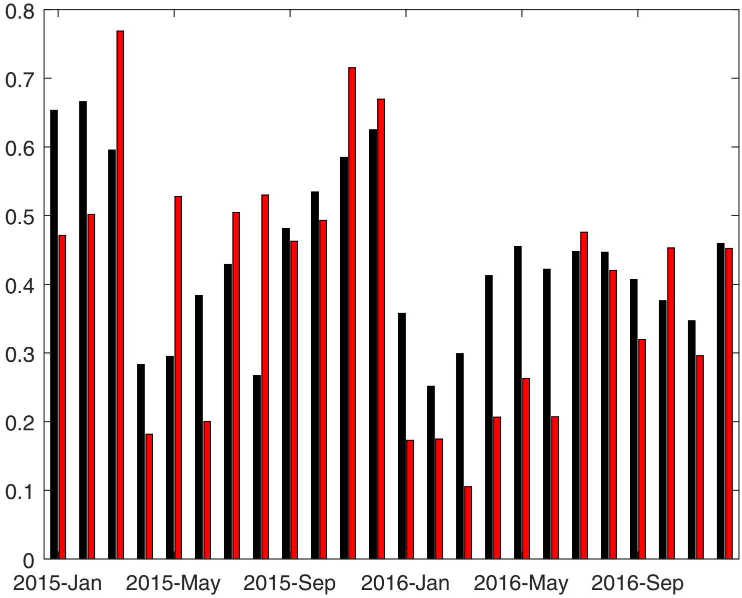


FIG. 8. Probability of Recession Estimated by Credit (Red Bars) and by IP (Black Bars): Recovery

TABLE 3
RELATIVE BRIER SCORE

| | Credit model/IP model | |
|---|---|---|
| | *In-sample* | *Real-time* |
| Cyclical phases | 0.66 | — |
| Negative q-o-q GDP | 0.70 | 1.43 |
| Financial crisis | 0.88 | 0.95 |
| Sovereign-debt crisis | 0.44 | 2.32 |
| Recovery since January 2016 | 0.75 | 0.93 |

## 6 CONCLUSIONS

We compiled many credit variables from banks' balance sheet and from the flow of data on monetary and financial institutions interest rates, including (various measures of) loans to the private sector and interest rates on loans. Then we set up a large-scale dynamic factor model cast in state-space form with Markov switching governing the transition between expansion and recession.

Based on our analysis, bank credit helps tracking the business cycle in Italy. In-sample estimates provide strong evidence of the ability of credit variables to detect the turning points and to correctly estimate the probability of recession. Their performance is comparable to that of IP, which is one of the most important indicators for the real-time analysis of the state of the economy. As a matter of fact, credit seems to be more sensitive than IP to signal whether the economy is approaching a turning point. In the run-up to the economic crisis in the last decade credit model put on average an higher probability on the event 'recession' than the IP model and it signaled fairly better the following recoveries. We implicitly obtained a composite coincident index that fits well the Italian cyclical phases.

Also in real-time results are encouraging. Credit model performs well during the global financial turmoil but fails to track the sovereign debt crisis especially in the first phase of the economic downturn while since the end of 2012 credit catches up with IP in signaling the contraction of GDP. In the aftermath of the most recent crisis, credit variables outperform IP by assigning on average lower probabilities to the downturn.

These results are consistent with the central role of bank credit in the financing of the private sector (both firms and households) for the Italian economy. Our results may have relevant implications for conjuctural analysis, as information on loans and interest rates is available with a short delay and are subject to small revisions unlike the most part of the macroeconomic indicators.

These encouraging results pave the way to an extension of the analysis to euro area and its major countries. There is room to improve the real-time upshots by investigating which credit variables weaken the overall performance of the credit model during the sovereign debt crisis.

## Appendix A

### *A.1. Model Setting*

For identification purposes, all the variables are expressed as deviation from mean, i.e. $\Delta y_{it} = Y_{it} - \Delta \bar{Y}_i$ and $\Delta c_t = \Delta C_t - \delta$. The suitable transformation $\Psi_i(L)\Delta y_{it} = \Delta y^*_{it} = \lambda_i(L)\Psi_i(L)\Delta c_t + \epsilon_{it}$ is adopted to simplify the calculations; both the common and the idiosyncratic components are assumed to follow an AR(1) process and $\lambda_i(L) = \lambda_i$. The model is cast in state-space form:

$$\Delta y^*_t = \begin{bmatrix} \lambda_1 & -\lambda_1\psi_{11} \\ \vdots & \vdots \\ \lambda_n & -\lambda_n\psi_{n1} \end{bmatrix} \cdot \begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{nt} \end{bmatrix} \tag{A1}$$

$$\begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \end{bmatrix} = \begin{bmatrix} \Phi(L)\mu_{S_t} \\ 0 \end{bmatrix} + \begin{bmatrix} \phi_1 & 0 \\ 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} \Delta c_{t-1} \\ \Delta c_{t-2} \end{bmatrix} + \begin{bmatrix} v_t \\ 0 \end{bmatrix} \tag{A2}$$

### *A2. Gibbs Sampling*

Nonlinearity due to unobservable states in the transition equation (A2) impedes the application of the Gaussian Kalman filter for the estimation.

Therefore, we run the multimove Gibbs sampling algorithm introduced by Carter and Kohn (1994).[14]

Let us illustrate the notation. The subscript $t|t$ indicates the estimate made at time $t$ by using the information up to time $t$ while $x_{t|t,x_{t+1}}$ indicates that the estimate of $x_t$ has been updated by combining the information contained in $x_{t|t}$ and that contained in the generated $x_{t+1}$.

*A.2.1. Generation of the Cyclical Component.* We generate the path of the cyclical component $\Delta\tilde{c}_T = [\Delta c_1, \dots, \Delta c_T]$ from its posterior distribution:

$$p(\Delta\tilde{c}_T|\Delta\tilde{y}_T^*) = p(\Delta c_T|\Delta\tilde{y}_T^*)\prod_{t=1}^{T-1} p(\Delta c_t|\Delta\tilde{y}_t^*,\Delta c_{t+1}) \tag{A3}$$

with

$$\Delta c_T|\Delta\tilde{y}_T^* \sim N(\Delta c_{T|T},P_{T|T}) \tag{A4}$$

$$\Delta c_t|\Delta\tilde{y}_t^*,\Delta c_{t+1} \sim N(\Delta c_{t|t,\Delta c_{t+1}},P_{t|t,\Delta c_{t+1}}), \quad t = T-1,\dots,1 \tag{A5}$$

where $\Delta c_{T|T} = E(\Delta c_T|\tilde{y}_T^*)$, $P_{T|T} = Cov(\Delta c_T|\tilde{y}_T^*)$, $\Delta c_{t|t,\Delta c_{t+1}} = E(\Delta c_t|\Delta c_{t|t}, \Delta c_{t+1})$ and $P_{t|t,\Delta c_{t+1}} = Cov(\Delta c_t|\Delta c_{t|t}, \Delta c_{t+1})$. These objects are obtained by the Kalman recursions. The updating equation of the Kalman filter produces $\Delta c_{t|t}$ and $P_{t|t}$ for $t = 1, \dots, T$ and we use the last iteration to generate $\Delta c_T$ from equation (A4). For $T = T-1,\dots,1$ it is straightforward to generate $\Delta c_t$ from equation (A5) given

$$\Delta c_{t|t,\Delta c_{t+1}} = \Delta c_{t|t} + P_{t|t}[\phi_1 \quad 0]\eta_t/R_t$$

$$P_{t|t,\Delta c_{t+1}} = P_{t|t} - P_{t|t}[\phi_1 \quad 0]'[\phi_1 \quad 0]P_{t|t}/R_t$$

where $\eta_{t+1|t} = \Delta c_{t+1} - \Phi(L)\mu_{S_{t+1}} - [\phi_1 \quad 0]\Delta c_{t|t}$ and $R_t = [\phi_1 \quad 0]P_{t|t}[\phi_1 \quad 0]' + var(v_t)$.

*A.2.2. Generation of the Regimes.* Once $\Delta\tilde{c}_T$ has been obtained, we generate the path of the Markow switching indicators $\tilde{S}_T = [S_1, \dots, S_T]$ from the following posterior distribution:

$$p(\tilde{S}_T|\Delta\tilde{c}_T) = p(S_T|\Delta\tilde{c}_T)\prod_{t=1}^{T-1} p(S_t|\Delta\tilde{c}_t,S_{t+1}) \tag{A6}$$

The Hamilton (1989) filter produces $p(S_t|\Delta\tilde{c}_t)$ for $t = 1,\dots,T$. The last iteration of the filter is used to sample $S_T$. The result

[14]As for $\psi_i$ plotted in Fig. A1, it corresponds to the GDP.

$$p(S_t|\Delta\tilde{c}_t, S_{t+1}) = \frac{p(S_{t+1}|S_t)p(S_t|\Delta\tilde{c}_t)}{p(S_{t+1}|\Delta\tilde{c}_t)}$$

is used to generate $S_t$ for $T = T-1, \ldots, 1$. We firstly calculate $p(S_t = 1|\Delta\tilde{c}_t, S_{t+1})$ and then we compare it with a random number $\alpha$ from a uniform distribution on the interval [0, 1]. If the latter is less than or equal to the former, then we set $S_t = 1$ and viceversa.

*A.2.3. Generation of the Parameters.* Within the Bayesian framework the parameters are treated as random variables. Then, we draw them from their posterior distributions. The parameters $\lambda_i$ for $i = 1, \ldots, n$, which load the common cyclical component in the state equation (A1), are sampled from

$$\lambda_i \sim N\big((A_i^{-1} + \sigma_i^{-2}\Delta\tilde{C}^{*\prime}\Delta\tilde{C}^*)^{-1}(A_i^{-1}a_i + \sigma_i^{-2}\Delta\tilde{C}^{*\prime}\Delta\tilde{y}_i^{*\prime}),\\ (A_i^{-1} + \sigma_i^{-2}\Delta\tilde{C}^{*\prime}\Delta\tilde{C}^*)^{-1}\big)$$

with prior $\lambda_i \sim N(a_i, A_i)$ and

$$\begin{aligned}\Delta\tilde{C}^* &= \psi_i(L)[\Delta c_t]_{t=1,\ldots,T}\\ \Delta\tilde{y}_i^* &= \psi_i(L)[\Delta y_{it}]_{t=1,\ldots,T}\end{aligned}$$

The parameters $\tilde{\psi}_i = \psi_{i1}$, associated with the AR(1) process of the idiosyncratic component, are sampled from

$$\tilde{\psi}_i \sim N\big((\Pi_i^{-1} + \sigma_i^{-2}\tilde{X}'\tilde{X})^{-1}(\Pi_i^{-1}\pi_i + \sigma_i^{-2}\tilde{X}'\tilde{Z}),\\ (\Pi_i^{-1} + \sigma_i^{-2}\tilde{X}'\tilde{X})^{-1}\big)$$

with prior $\tilde{\psi}_i \sim N(\pi_i, \Pi_i)$ and

$$\begin{aligned}Z_t &= \Delta y_{it} - \lambda_i\Delta c_t\\ \tilde{Z} &= [Z_t]_{t=1,\ldots,T}\\ \tilde{X} &= [\psi_{i1}Z_{t-1}]_{t=1,\ldots,T, i=1,\ldots n}\end{aligned}$$

The variance of the idiosyncratic component, $\sigma_i^2$, is drawn from the inverted gamma distribution

$$\sigma_i^2 \sim IG\Big(\frac{v_i + T}{2}, \frac{f_i}{2} + \frac{1}{2}(\tilde{Z} - \tilde{X}\tilde{\psi}_i)'(\tilde{Z} - \tilde{X}\tilde{\psi}_i)\Big)$$

with prior $\sigma_i \sim IG(\frac{v_i}{2}, \frac{f_i}{2})$. The parameters $\tilde{\phi} = \phi_1$, associated with the AR(1) process of the common component, are sampled from

$$\tilde{\phi} \sim N\big((A^{-1} + \tilde{Q}'\tilde{Q})^{-1}(A^{-1}\alpha + \tilde{Q}'\tilde{G}),\\ (A^{-1} + \tilde{Q}'\tilde{Q})^{-1}\big)$$

with prior $\tilde{\phi} \sim N(\alpha, A)$ and

$$\tilde{G} = [\Delta c_t - \mu_{S_t}]_{t=1,\dots,T}$$
$$\tilde{Q} = [\phi_1(\Delta c_{t-1} - \mu_{S_{t-1}})]_{t=1,\dots,T}$$

The parameters $\tilde{\mu} = [\mu_0^*, \mu_1]$, which represent the means of the common components depending on the state of the economy, are drawn from

$$\tilde{\mu} \sim N\big((A^{*-1} + \tilde{Q}^{*\prime}\tilde{Q}^*)^{-1}(A^{*-1}\alpha^* + \tilde{Q}^{*\prime}\tilde{G}^*), \\ (A^{*-1} + \tilde{Q}^{*\prime}\tilde{Q}^*)^{-1}\big)_{[I_{\mu_1>0}]}$$

with prior $\tilde{\mu} \sim N(\alpha^*, A^*)_{[I_{\mu_1>0}]}$ and

$$\tilde{G}^* = [\Delta c_t - \phi_1 \Delta c_{t-1}]_{t=1,\dots,T}$$
$$\tilde{Q}^* = [\mu_1(S_t - \phi_1 S_{t-1})]_{t=1,\dots,T}$$
$$\mu_0^* = \mu_0(1-\phi_1)$$

Finally, the transition probabilities, $p$ and $q$, are sampled from the beta distributions

$$q|\tilde{S}_T \sim \beta(u_{00}+n_{00}, u_{01}+n_{01})$$
$$p|\tilde{S}_T \sim \beta(u_{11}+n_{11}, u_{10}+n_{10})$$

where $n_{ij}$ indicates the number of transitions from state $S_{t-1} = i$ to state $S_t = j$, for $i, j = 0,1$ and $u_{00}$, $u_{01}$, $u_{11}$, $u_{10}$ are known (uninformative) priors.

A.2.4. The Composite Coincident Index. It is straightforward calculating the composite coincident index, $C_t$ for $t = 1, \dots, T$, after having set the starting point $C_0$ and the mean of $Y_i$ due to the common component, $\delta$:

$$\delta = E_1'[I_k - (I_k - K^*H)F]^{-1}K^*\Delta\bar{Y} \tag{A7}$$

where $\Delta\bar{Y} = [\Delta\bar{Y}_i \dots \Delta\bar{Y}_n]$, $E_1' = [1 \quad 0 \quad 0 \quad 0 \dots \quad 0]$ is a selection matrix, $K^*$ is the steady-state Kalman gain and $k$ is the dimension of $F$

$$F = \begin{bmatrix} \phi_1 & 0 & \cdots & 0 \\ 0 & \psi_{11} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & \psi_{n1} \end{bmatrix} \tag{A8}$$

The composite coincident index is therefore

$$C_t = \Delta c_t + C_{t-1} + \delta, \quad t = 1, \dots, T \tag{A9}$$

### *A.3. Convergence of the Gibbs Sampling*

As shown in Fig. A1, the sampler converges very quickly as claimed in Carter and Kohn (1994). A burn-in period of 20 per cent is enough to obtain stable estimates.

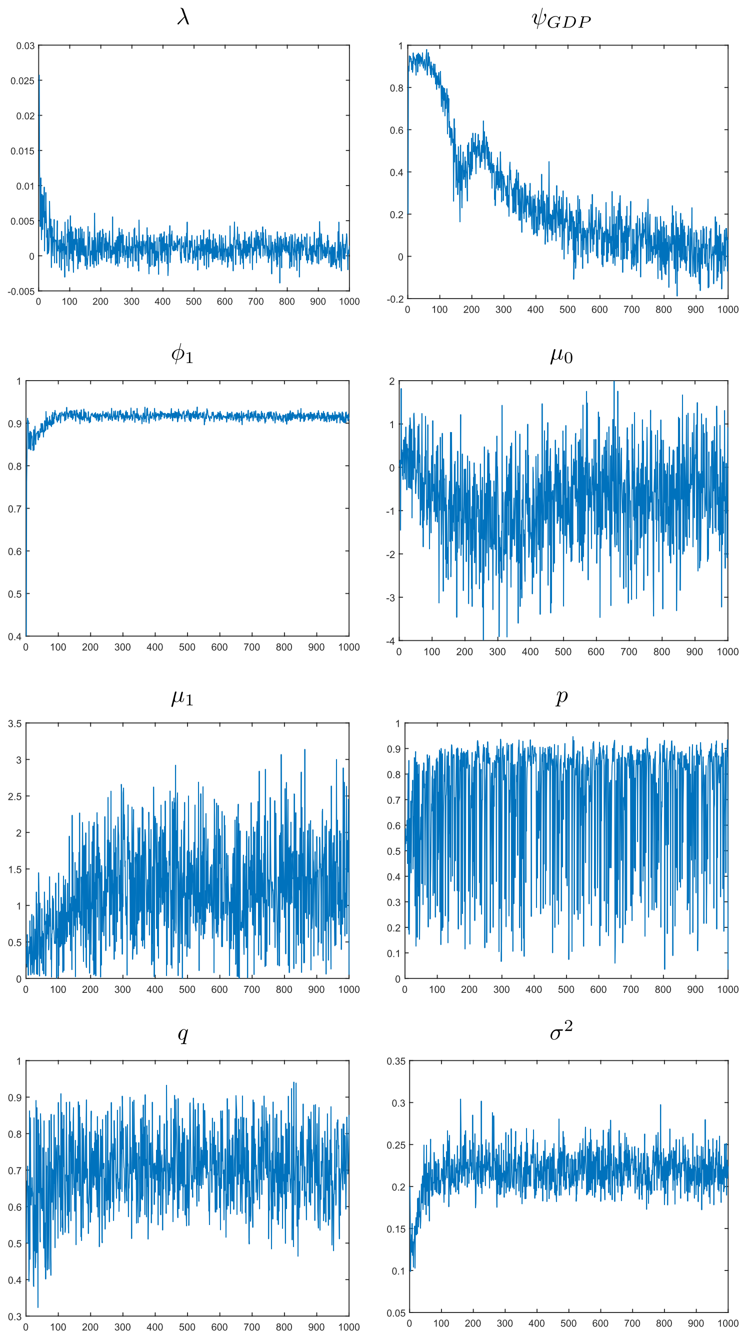


FIG. A3. Sampler Convergence: Generated Values of Parameters

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