Credit cycles and labor market slacks: predictive evidence from Markov-switching models

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Credit cycles and labor market slacks: predictive evidence from Markov-switching models

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Abstract

We model unemployment and credit cycle dynamics as a Markov-switching process with two states to identify labor market slacks i.e., periods of unemployment above its natural rate. Our results for the US economy between 1955 and 2015 show that credit contractions improve the identification of high unemployment states. Moreover, we find that credit cycles have a sizable out-of-sample predictive power on labor market slacks. This implies that the evolution of credit can be used as a leading indicator for economic policies.

JEL classification: C32, E24, E32, E51

Keywords: credit cycle, unemployment, forecast, Markov-switching

1. Introduction

Joblessness in the US has been one of the greatest concerns since the beginning of the 2007-08 global financial crisis, peaking at 10% in October 2009, and a burgeoning of studies have revealed its strong association with credit (see, e.g., Chodorow-Reich, 2014; Bentolila, Jansen, and Jiménez, 2018; Borsi, 2018). Moreover, a growing body of works have confirmed that financial factors, such as the evolution of credit, play an important role in shaping the real economy (see, among others, Drehmann, Borio, and Tsatsaronis, 2012; Schularick and Taylor, 2012; Jorda, Schularick, and Taylor, 2013; López-Salido, Stein, and Zakrajsek, 2017). However, Gadea Rivas and Pérez-Quirós (2015) find that

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this relation has little, if any, power as a policy tool, since credit does not enable to anticipate business cycle turning points, including the onset of economic recessions. Surprisingly, no empirical works have yet exploited the predictive power of the evolution of credit on unemployment fluctuations.

In this paper we contribute to the literature by showing that cyclical variations in private credit are capable of forecasting labor market slacks, i.e., periods of unemployment above its natural rate. First, we study the in-sample relation between credit cycles and unemployment dynamics. Next, we evaluate the out-of-sample predictive power of credit to make inferences about the future. To this end, we employ a Markov-switching (MS) approach (Hamilton, 1989) that allows us to identify expansionary and contractionary episodes of credit as well as high and low unemployment states. We find that credit contractions anticipate labor market slacks, and the inclusion of a credit cycle measure improves the out-of-sample predictive power of the model for unemployment. Thus, private credit contains valuable information to predict future unemployment problems, useful for policymakers going forward.

2. Data and methodology

The study makes use of credit and unemployment series for the US spanning from 1955Q1 to 2015Q3. Credit refers to domestic bank credit to the non-financial private sector, obtained from the Bank of International Settlements database. Harmonized unemployment rate and long-term Natural rate of unemployment (NAIRU) are from the US Bureau of Labor Statistics and the US Congressional Budget Office[4], respectively. Private credit is converted into real terms using the consumer price index from the US Bureau of Labor Statistics. Finally, labor market slack can be defined in several different ways. From a macroeconomic perspective, it is understood as the gap between the

[4] U.S. Congressional Budget Office, Natural Rate of Unemployment (Long-Term) [NROU], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NROU.

conventional unemployment rate and the natural rate of unemployment (NAIRU). We define a binary variable that indicates the state of unemployment at period *t*, taking the value 1 if the rate of joblessness is above the NAIRU (labor market slack), and zero otherwise.

Following the business cycle literature that focuses on output fluctuations, we model unemployment and credit dynamics using a MS process with two regimes. Specifically,

$$u_t = \mu_{S_t^u} + \varepsilon_t^u, \tag{1}$$

where u_t is the unemployment rate in period *t*, $\mu_{S_t^u}$ is a vector of state-dependent intercepts that varies as a function of an unobservable state variable (S_t^u) and follows a two-state Markov process, and $\varepsilon_t^u \sim N(0, \sigma_{S_t^u})$ is the error term. The MS intercepts $\mu_{S_t^u}$ here depend on the rate of joblessness, being in the high ($S_t^u = 1$) or low ($S_t^u = 2$) unemployment state.

Similarly, we consider the following process to describe the evolution of credit,

$$c_t = \mu_{S_t^c} + \varepsilon_t^c, \tag{2}$$

where c_t is the growth rate of real private credit in each period *t*, $\mu_{S_t^c}$ is a vector of MS intercepts, and $\varepsilon_t^c \sim N(0, \sigma_{S_t^c})$ is the error term. Along the credit cycle, $\mu_{S_t^c}$ is associated with credit contractions ($S_t^c = 1$) and credit expansions ($S_t^c = 2$). Finally, credit cycles (cc_t) are constructed using the estimated smoothed probabilities,

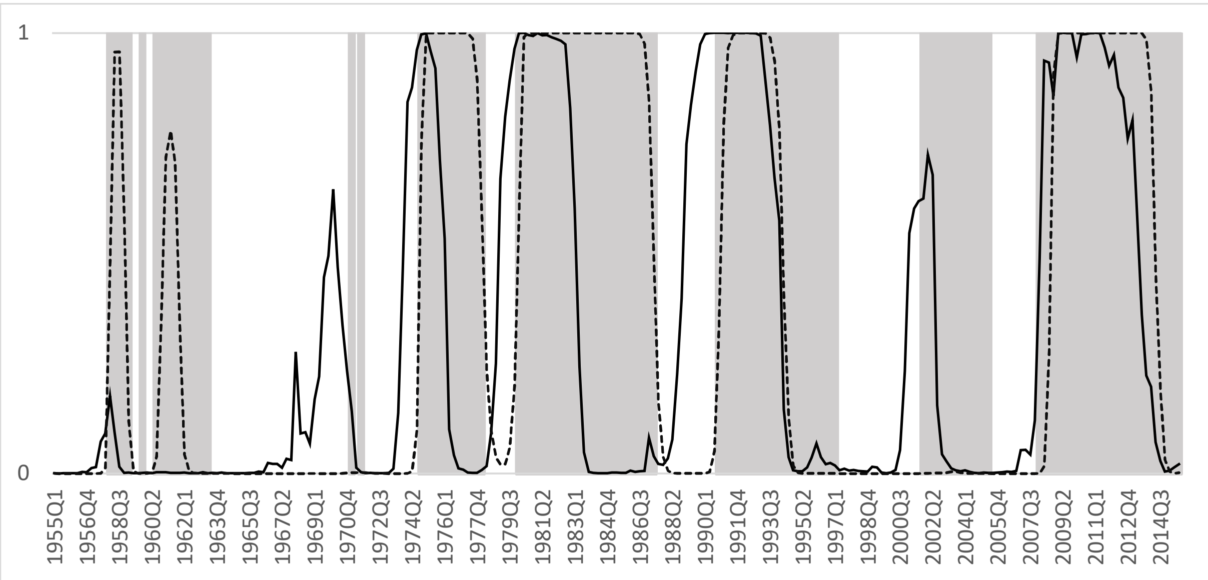
$$cc_t = Prob(S_t^c = 1), \tag{3}$$

with a cc_t equal to 1 corresponding to the highest probability of entering a credit contraction at period *t*.

3. In-sample analysis

Figure 1 displays labor market slack periods in the US together with the smoothed probabilities of unemployment and credit, estimated using the MS models in Equations (1) and (2). By and large, the probabilities of high unemployment states match the periods of slack reflected by the data. A few exceptions include the high rates of joblessness during 1970-71 and 2001-2005, where the MS specification (Equation 1) fails to identify high unemployment states. A visual inspection of Figure 1 further reveals that the beginning of contractionary credit episodes captured by the MS model in Equation (2) typically precedes labor market slacks, i.e., periods when the unemployment rate rises above the NAIRU. Even more, the estimated probabilities of credit contractions increase ahead of the probabilities of high unemployment states.

Figure 1. Labor market slacks and the MS smoothed probabilities of private credit and unemployment



Note: The shaded areas correspond to labor market slacks defined as periods of unemployment above the NAIRU. The solid and dashed lines indicate the Markov-switching smoothed probabilities of private credit and unemployment, respectively.

In light of these findings, we put forward the hypothesis that credit cycles provide useful information to predict labor market slacks. This leads us to test the following extended MS model for unemployment, in which credit cycle is included as an explanatory variable,

$$u_t = \mu_{S_t^u} + \beta_{S_t^u} cc_t + \varepsilon_t^u, \tag{4}$$

where u_t, $\mu_{S_t^u}$, and $\varepsilon_t^u \sim N(0, \sigma_{S_t^u})$ are defined as in our baseline model in Equation (1), and cc_t is the credit cycle measure from Expression (3).

The results show a significantly positive relationship between credit cycles (cc_t) and unemployment rates (u_t) considering both unemployment states (Table 1). In other words, higher probabilities of credit contractions are associated with higher unemployment. Moreover, in high unemployment states this relation is stronger.

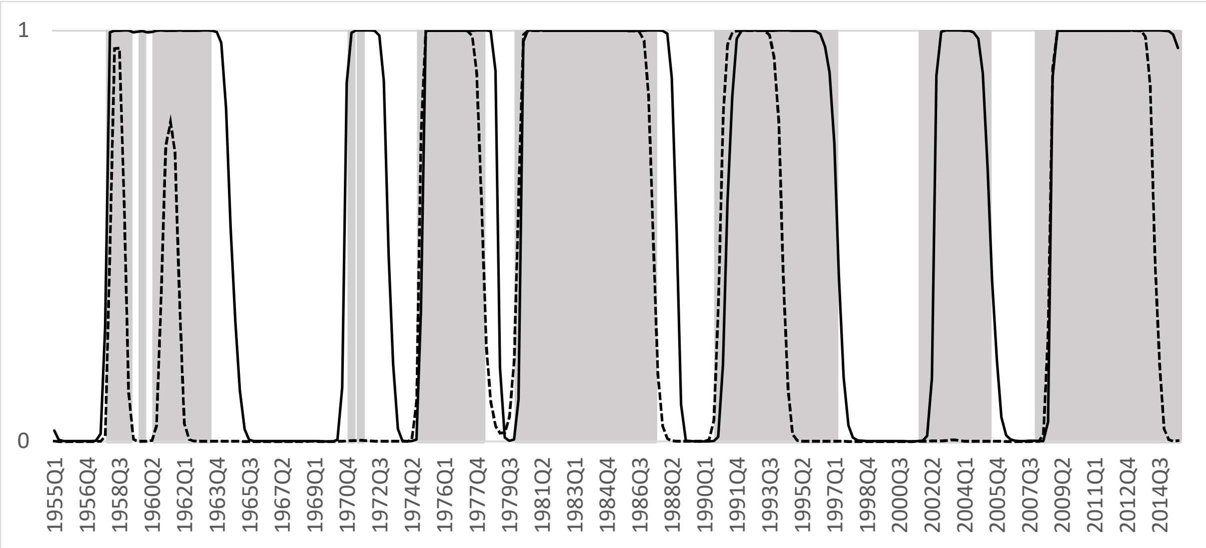
Table 1. Estimation results

High unemployment			Low unemployment		
μ	$\boldsymbol{\beta}$	*log(σ)*	μ	$\boldsymbol{\beta}$	*log(σ)*
6.114	2.270	-0.026	4.230	1.452	-0.610
(0.112)	(0.212)	(0.061)	(0.097)	(0.195)	(0.095)

Note: Estimated coefficients of the Markov-switching model including credit cycle for high and low unemployment states. The dependent variable is unemployment rate. Standard errors in parentheses.

Confirming our conjecture, the estimated smoothed probabilities from Equation (4) considerably improve the identification of labor market slacks, once we include the credit cycle variable in the MS model. Figure 2 illustrates the estimated probabilities of unemployment, both including and excluding credit cycle as a regressor. Remarkably, the extended model estimated using Equation (4) does a better job in capturing labor market slacks in periods including 1956-1963, 1970-71, 1991-1997, and 2002-2005.

Figure 2. Labor market slacks and the MS smoothed probabilities of unemployment, including and excluding credit as an explanatory variable



Note: The shaded areas correspond to labor market slacks defined as periods of unemployment above the NAIRU. The solid and dashed lines indicate the Markov-switching smoothed probabilities of unemployment, including and excluding the credit cycle as an explanatory variable, respectively.

In what follows, we further assess the degree of improvement of our extended model, by computing the corresponding quadratic probability scores (QPS). Following Diebold and Rudebusch (1990), QPS is defined here as the mean square distances between the MS smoothed unemployment probabilities and the values of the binary variable of labor market slack. QPS ranges from 0 to 1, with a score of 0 corresponding to perfect accuracy in terms of matching the periods of slack. As shown in Table 2, the inclusion of the credit cycle measure significantly improves our model, with a QPS of 0.193 vs. 0.127, for the baseline vs. the extended model. It is worth noting that private credit *per se* does not help to explain unemployment dynamics. Namely, if we replace the credit cycle variable in Equation (4) by the growth rate of private credit, the QPS of the model does not improve with respect to that of the baseline specification. Therefore, the probability of entering a phase of credit contraction is what matters for labor market disruptions, and not the rate of credit growth.

Table 2. Quadratic probability scores (QPS)

In-sample specification		Out-of-sample specification	
Baseline model	Extended model	Baseline model	Extended model
0.193	0.127	0.295	0.200

Note: Quadratic probability scores (QPS) of the in-sample and out-of-sample Markov-switching specifications of unemployment, with (extended model) and without (baseline model) credit cycle as an explanatory variable.

4. Out-of-sample analysis

Finally, we study the ability of credit cycles to predict unemployment dynamics in real time for the last 20 years of our sample (1995Q3-2015Q3). The procedure can be summarized in four steps. With information up to 1995Q2, we first estimate the credit cycle using a MS specification for credit as in Equation (2). Second, from this estimation we take the credit cycle variable (cc_t) and include it as a regressor in the MS specification for unemployment as in Equation (4). Third, following Gadea Rivas and Pérez-Quirós (2015), we predict the one-period-ahead probability of high unemployment for 1995Q3,

$$P_{t+1} = (p_{11,t})P_t + (1 - p_{22,t})(1 - P_t), \tag{5}$$

where P_t is the conditional probability of entering a high unemployment state at time t, and $p_{11,t}/p_{22,t}$ represent transition probabilities, i.e., the probability of being in a period of high/low unemployment and staying in the same state. Forth, we iterate the above process using one additional observation at a time until the last sample period.

We examine the predictive efficacy of the out-of-sample MS specification by comparing the QPS of the extended model with that of the baseline model, which excludes credit, and the results are summarized in Table 2. The inclusion of credit cycle as an explanatory variable reduces the QPS from 0.295 to 0.200, thereby improving the accuracy of our model. The 32.2% decrease in the QPS is comparable with the improvement observed in the in-sample analysis, after including the credit measure as a regressor.

5. Concluding remarks

We provide empirical evidence that the unemployment rate is significantly related to the cyclical variations in private credit. Specifically, by analyzing the US economy, we show that credit cycles have a relevant out-of-sample predictive power on labor market slacks. This implies that private credit fluctuations can be used by policymakers in order to anticipate disruptions in the labor markets.

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