Leading Indicators for the Capital Goods Industry[*]

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Abstract

The goal of this paper is to build leading indicators to predict the capital goods business cycle in Brazil. We propose a probit model with autoregressive dynamics consisting of series with predictive power to anticipate contractions in this sector. The model is especially suitable for this sector as it includes information about the characteristics of cycle phases and their duration in the estimation of recession probability, and adapts well to the high volatility of the capital goods business cycle. The results indicate that the dynamic probit model has a better forecasting performance than the simple probit model in several aspects, both within and out of sample and in real time.

Keywords: Leading Indicators, Business Cycles, Probit Model, Bayesian Method.

JEL Codes: C22, E32.

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1. Introduction

The financial crisis that impacted the world economy at the end of 2008 interrupted a five-year period of strong output growth, both in developed and emerging countries.[1] The intensity of this phenomenon sparked new interest in business cycles and in the ability to predict these movements, especially through coincident, leading, and lagging indicators.

The primary goal of this paper is to build leading indicators that can predict business cycle turning points in the Brazilian capital goods industry using a dynamic probit model.[2] The purpose is to combine the autoregressive probit model of Chauvet and Potter (2005) with the autoregressive probit model of Dueker (1997), in which both the latent variable and the binary indicator, which determine the cyclical movements, follow autoregressive processes, respectively. This method allows constructing more accurate forecast probabilities. It is common knowledge that simple probit models generate recession probabilities period-by-period. On the other hand, the method proposed in Chauvet and Potter (2005) allows constructing "first-time" hitting probabilities of a recessionary (or expansionary) period and probabilities that the cycle phase will continue for k periods ahead. These "first-time hitting" probabilities take into account information on the duration of cycle phases, which potentially yield more accurate predictions of recessions and expansions. The introduction of an autoregressive process for the binary indicator, as in Dueker (1997), also allows the use of information about the duration of the business cycle in the generation of forecast probabilities, yielding probabilities with higher signal-to-noise ratio. Therefore, by using the Bayesian estimation method, this paper compares the traditional recession probabilities of the simple probit model with the posterior mean of the initial probabilities of the proposed model, the probability intervals given by the estimated posterior distribution and the first-time hitting probabilities in- and out-of-sample.

The combination of these two probit models is one of the contributions of this paper and, to our knowledge, it has not been proposed in the literature. Another contribution of this paper is the assessment of cyclical characteristics of the capital goods industry, in addition to the construction of leading indicators for this sector.[3] This industrial sector is one of the most dynamic and contains macroeconomic inferences of characteristics related to investment and to potential GDP, which makes it very sensitive to changes in the economic scenario.

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[1]See Bajari et al. (2008), IMF (2008) and Kose et al. (2008).

[2]Turning points refer to the beginning and end of business cycle phases: peaks represent the beginning of recession periods while troughs represent their end.

[3]According to IBGE, the capital goods industry includes the production of several items in the following segments: metal products; computer equipment, electronic and optical devices; electrical machines, devices and materials; machinery and equipment; motor vehicles, trailers and bodies; other transportation equipment; furniture; miscellaneous products. According to PIA/IBGE data for 2008, the value-added of industrial transformation of this aggregate amounts to 16.3% of the total of the Brazilian industry.

This paper extends Chauvet and Silva (2004) and Chauvet and Morais (2008). Chauvet and Silva (2004) use a simple probit model to predict business cycles at the aggregate level for the Brazilian economy whereas Chauvet and Morais (2008) build leading indicators for the Brazilian GDP using an autoregressive probit model with recurrent structural changes, as proposed in Chauvet and Potter (2005).

Monitoring the economic activity through coincident and leading indicators is a traditional and successful method in the USA since the seminal work of Burns and Mitchell (1946). Economic indicators became popular in most OECD countries in the 1970s and 1980s and, with the growing global economic integration, they have disseminated further all over the world.

The interest in studying business cycles in Brazil is still recent, but there exists an ever-increasing applied literature.[4] Nevertheless, there is a gap in the literature applied to Brazil in this area, especially with respect to sectoral analysis. Among the main motivations of this paper, we have: the analysis of business cycles of an important economic sector for the aggregate economic dynamics, such as that of the capital goods industry, and the investigation of how their cyclical movements are related to that of the economy as a whole.

Since no business cycle dating procedure is available for the industrial production series under the capital goods category, we used the method of Bry and Boschan (1971) in this reference series.[5] The results indicate that, between January 1991 and June 2009, the capital goods industry had five recession periods with mean duration of 51 months from peak to peak and 45 from trough to trough. The longest recession occurred between the fourth quarter of 1997 and the third quarter of 1999. Moreover, the business cycle in this segment and that of the aggregate economy share some similarity, as dated by the Business Cycle Dating Committee (CODACE) for the Brazilian GDP.[6] However, recessions in the capital goods industry were longer and more pronounced.

In what follows, we use the simple and proposed dynamic probit model, linear regressions and analysis of turning points to organize and select the most important leading indicators of recession from a set of over 200 economic series. We select indicators that predict the behavior of capital goods production, classified into short-, medium- and long-term.

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[4]Worth mentioning are Chauvet and Potter (2001), Chauvet (2002), Ellery Jr et al. (2002), Picchetti and Toledo (2002), Chauvet and Silva (2004), Duarte et al. (2004), Chauvet et al. (2006), Lima et al. (2006), Morais and Portugal (2007, 2008), Araújo et al. (2008), and Chauvet and Morais (2008).

[5]This paper uses Haywood's (1973) extension. This extension includes an additional criterion, which takes into account the length of the cycles.

[6]The Business Cycle Dating Committee (CODACE) was set up by the Brazilian Institute of Economics (IBRE) with the aim of identifying the peaks and troughs of the Brazilian economy. This committee consists of a panel of seven independent economists and is similar to the NBER's business cycle dating committee.

After the selection of the relevant indicators, the next step was to predict recession phases. In order to accomplish that, leading variables are combined in the proposed dynamic probit model and the results are compared with those of the simple probit model and of the probit model proposed in Chauvet and Potter (2005), both out-of-sample and in real time. The models are estimated using Bayesian methods.

Given the uncertainty with respect to the beginning and end of recessions, this analysis shows the importance of constructing leading indicators, which yield effective signals of business cycle turning points. The results indicate that the models provide different insights about the probability of future recessions, predicting them 1 to 14 months ahead. It is interesting to notice that the recession probabilities of the simple probit model show large uncertainty over their values, hindering a conclusion about the end of the 2008-2009 recession. The real-time recession probabilities of the autoregressive probit model, on the other hand, indicate that the last recession period in the capital goods sector ended in the first half of 2009. The probability that it could have ended in July 2009 (based on data up to December 2008) is relatively high, and this prediction is much less uncertain than the one obtained from the simple probit model.[7] The proposed model also displays less uncertainty about this prediction when compared to the prediction from the probit model of Chauvet and Potter (2005).

In summary, the recession signals obtained from the simple probit models within- and out-of-sample show large uncertainty over their values, which makes it difficult to draw more conclusive interpretation of their turning point prediction. On the other hand, the recession probabilities of the proposed autoregressive probit model improve the signal-to-noise ratio compared to the simple probit model and to Chauvet and Potter's model (2005). In addition, the resulting predictions are a lot less uncertain.

The present paper is organized as follows. Section 2 reviews the related literature on business cycles and leading indicators. Section 3 describes the models used and the first-time hitting probabilities of the cycle phases. Section 4 presents the business cycle dating procedure for the capital goods industrial production. Section 5 describes the process used to classify and select the best leading indicators. Section 6 discusses the forecast results and Section 7 concludes.

2. Review of the Literature

The first studies on cycles in the international literature were related to climatic events and focused on their conceptualization and characterization. Application to economic cycles began with the seminal work of Burns and Mitchell (1946), with contributions and later extensions of Moore (1983), and Zarnowitz (1992), among many others. Bry and Boschan (1971) proposed a method for obtaining turning

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[7]The first version of this paper was written in July 2009, when no information on the end of this recession was available.

points in series using an algorithm that formalizes the ideas of Burns and Mitchell (1946). More recently, intensification of research in the area has encouraged the inclusion of more rigorous statistical techniques to measure several stylized facts about business cycles. Stock and Watson (1989, 1991, 1993) propose the use of dynamic factor models to obtain coincident indicators. Hamilton (1989, 1990) proposes univariate Markov regime switching models to capture business cycle phases, taking into consideration several important characteristics such as asymmetry, duration, and intensity of cycles. More recently, Chauvet (1998) proposed the use of a combination of multivariate dynamic factor models with Markov regime switching in order to obtain economic indicators for the United States, and Chauvet (2001b) to obtain a coincident indicator of the Brazilian economy.

In the literature, univariate or multivariate Markov switching models are often used to characterize cycle phases and to inform the state of the economy with coincident indicators, whereas probit models are used to predict their turning points. Multivariate Markov models can also be useful for building leading indicators and forecasting recessions, as in Chauvet (2001a), but this requires that the included leading series have synchronized cyclical movements, which restricts the number of possible variables. For this reason, Chauvet and Silva (2004), Chauvet and Morais (2008) and the present paper use probit models to build leading indicators for Brazil.

In the analysis of business cycles, peaks represent the end of an expansionary period and troughs indicate the end of a recessionary period, called turning points.[8] This definition contrasts with the most popular one, which assumes that recession is a sequence of decreases in the rate of growth of economic activity. However, from the perspective of the economy as a whole, there may be a contraction in a sector (e.g., industry), but the cycle phases may be different in other economic sectors. Thus, an economic recession not only involves the behavior of a single variable or sector, but also the joint behavior of indicators that are representative of the aggregate economic activity.

The interest in investigating business cycle in Brazil is still recent, but there exists a growing literature that applies different estimation techniques. Barros (1993) uses the principal component method to model sectoral comovements. Engle and Issler (1993) use autoregressive vectors to capture short- and long-term comovements of GDP per capita in Argentina, Brazil, and Mexico in the postwar period. Chauvet (2001b) uses nonlinear dynamic factor models to build a composite indicator of the Brazilian GDP and Chauvet (2002) utilizes Markov switching models and alternative *ad-hoc* methods to characterize and date periods of recession and expansion in Brazil. Duarte et al. (2004) compare three alternative indices for economic activity in Brazil using the canonical method. Ellery Jr et al. (2002) study the cyclical characteristics of production in Brazil using a general equilib-

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[8]See Zarnowitz (1992) for a discussion on business cycle and Milas et al. (2006) for several applications.

rium approach. Araújo et al. (2008) propose a method for constructing a secular series for the Brazilian GDP, which was also useful for characterizing changes in the historical output volatility.[9] Hollauer et al. (2009) use the Conference Board method, linear dynamic factor models and the approach of Mariano-Murasawa to build coincident indicators of Brazilian industrial activity.

In addition to these studies, there are some others that focus on sectoral or regional analyses. For instance, Picchetti and Toledo (2002) use a linear dynamic factor model to extract a common stochastic component in industrial production. Morais and Portugal (2007) build a composite indicator for the industrial activity of the State of Rio Grande do Sul; Morais and Portugal (2008) apply the Markov regime switching model to identify stylized facts of industrial production cycles in the main Brazilian states; and Morais and Frainer (2005) investigate economic cycles in the industry of Bahia. More recently, Chauvet (2012) studies business cycles in Minas Gerais, establishing a chronology of recessions and constructing coincident and leading indicators for the economy of this Brazilian state.

Notwithstanding these studies on cycles, estimates of their turning points and construction of aggregate coincident indicators for Brazil, there is still a gap in the literature concerning the investigation of leading indicators, particularly for sectoral data. The works of Chauvet and Morais (2008), Campelo Júnior (2008), and Chauvet (2012) are some of the few which focus on leading indicators for sectoral analysis. Campelo Júnior (2008) uses the traditional NBER method, causality tests, and linear regressions to build leading indicators for the Brazilian industry.

For aggregate data, however, there are the papers of Chauvet (2001a), who builds real-time leading indicators of the Brazilian inflation; Contador and Ferraz (2001), who use traditional nonparametric methods for the construction of leading indicators for economic activity; Chauvet and Silva (2004), who use simple probit models to identify leading variables for the Brazilian business cycle; Lima et al. (2006), who use the principal component method applied to a large dataset to build leading and coincident indicators for the Brazilian economy. There are some other related articles, which do not aim to predict business cycle turning points, but to temporally project the aggregate activity instead. For example, Ferreira et al. (2005) use diffuse linear and nonlinear indicators to predict the rate of growth of the Brazilian GDP, and Chauvet et al. (2006) compare the forecast ability for GDP growth in Brazil using several specifications of Markov regime switching models.

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[9]The chronology of recessions found by the authors is similar to the one obtained in Chauvet and Potter (2001), Chauvet (2002).

3. Probit Model

3.1 Simple probit model

Suppose a latent variable, Y_t^*, for which there is a binary realization of an indicator Y_t that represents the occurrence or not of an event. In the present paper, it is assumed that the variable Y_t^* represents the business cycle phases of the capital goods sector, recession or expansion, given by:

$$Y_t = \begin{cases} 0 & \text{if} \quad Y^* < 0 \\ 1 & \text{if} \quad Y_t^* \geq 0 \end{cases} \tag{1}$$

It is assumed that a business cycle n begins one month after the end of a recession and goes on up to the month in which a trough is observed. Therefore, if t_{n-1} is the end date of business cycle $n-1$ then the dates of business cycles n are given by $t \in \{t_{n-1}+1, \ldots, t_n - 1, t_n\}$, which leads us to associate the set of expansionary cycles with $E = \cup E_n$ and the set of recessionary cycles with $R = \cup R_n$. In the analysis of leading indicators, the main goal is to predict Y_t^*, i.e., the turning points of the cycles. In the case of the probit model, this can be obtained from:

$$Y_t^* = \beta_0 + \beta_m S_{t-k} + \varepsilon_t \qquad \varepsilon_t \overset{IID}{\sim} N(0,1) \tag{2}$$

where S_{t-k} is the set of leading series, k is the forecasting horizon in months and β_m, with $m = 1, \ldots, M$, are the regression coefficients.

The traditional recession forecasts are obtained from the conditional probability of occurrence of a recession $(Y_t^* \geq 0)k$ periods ahead, based on a simple normal cumulative distribution function, $\Phi(.)$:

$$P\left(Y_t^* \geq 0 | S_{t-k}, \beta\right) = \Phi\left[\beta_0 + \beta_m S_{t-k}\right] \tag{3}$$

where $\beta = [\beta_0, \beta_m]'$.

First-time Hitting Probability and Recession Forecast

An alternative method for building probabilities takes into account the first time a recession occurs or its complement, such as the probability to remain in an expansion (Chauvet and Potter, 2005). This type of probability includes more information to forecast business cycles, since it takes into account the duration of business cycle phases. Let the first occurrence of a recession be:

$$H_R(t) = \left\{ H : Y_{t+H}^* > 0, Y_{t+H-1}^* < 0, \cdots, Y_{t+1}^* < 0 \right\}$$

with associated first-time hitting probability of a recession given by:

$$\pi_R(k,t) = P\left[H_R(t) = k\right] P\left[Y_{t+k}^* > 0 / Y_{t+k-1}^* < 0, \cdots, Y_{t+1}^* < 0\right] (1 - \pi_R(k-1,t))$$

where $\pi_R(0, t) = 0$ and $k = 1, 2, \ldots, K$. Therefore, $\pi_R(k, t)$ is the probability that a recession $H_R(t)$ will take place for the first time in month k of forecasting horizon K. This derivation is based on the hypothesis that the state of the business cycle is known at t, yielding K forecasting periods. These expressions, conditional on the sequence of values of the selected leading indicators $S_{t-K}^k = \{S_{t-K+1}, S_{t-K+2}, \ldots, S_{t-K+k}\}$, give:

$$\pi_R(k, t) = \Phi\left[\beta_0 + \beta_m S_{t-K+k}\right] \Pi_{s=1}^{k-1} \left\{1 - \Phi\left[\beta_0 + \beta_m S_{t-K+s}\right]\right\} \tag{4}$$

In the simple probit model, $\pi_R(k, t)$ represents a constant conditional probability of recession, which is closely related to the likelihood function of the observed data:

$$L\left(Y^T / S^{T-K}, \beta\right) = \prod_{t \in R} \Phi\left[\beta_0 + \beta_m S_{t-K}\right] \prod_{t \in E} \left\{1 - \Phi\left[\beta_0 + \beta_m S_{t-K}\right]\right\} \tag{5}$$

Another tool suggested by Chauvet and Potter (2005) consists of the real-time forecast of the probability of a continuing expansion for k additional months. For the simple probit model, this forecast is obtained from the equation:

$$\prod_{s=1}^{k} \left\{1 - \Phi\left[\hat{\beta}_0 + \hat{\beta}_m S_{T+k-s}\right]\right\} \tag{6}$$

where, by construction, the forecast converges to 0 when k increases.

3.2 Dynamic autoregressive probit model

In this paper, we propose a combination of the probit models of Chauvet and Potter (2005) and of Dueker (1997). Chauvet and Potter's (2005) model generalizes the simple probit model by introducing dynamics into the latent variable Y_t^*, such that it follows a first-order autoregressive process, implying different first-time hitting probabilities. Thus, equation (2) includes the dynamics of the latent variable:

$$Y_t^* = \beta_0 + \beta_m S_{t-k} \theta Y_{t-1}^* + \varepsilon_t \tag{7}$$

assuming that the autoregressive coefficient $|\theta| < 1$ and the initial business cycle is partially observed beginning at $t = K + 1 (t_1 = K)$ This model is combined with Dueker's (1997), which proposes a probit model with an autoregressive process for the binary indicator Y_t:

$$Y_t^* = \beta_0 + \beta_m S_{t-k} + \theta Y_{t-1}^* + \phi Y_{t-1} + \varepsilon_t \tag{8}$$

An important economic aspect is that, because of the potential presence of outliers or structural breaks in several series, the determination of business cycles

can differ over time. This can occur even if the same methodology is applied to the same series. Note that the impact of structural breaks on the frequency, duration and probabilities of recession can be especially significant, as shown by Chauvet and Potter (2001, 2005, 2010). In this paper, we also consider a version of the probit model with recurrent structural breaks proposed by Chauvet and Potter (2005). In this case, it is assumed that the parameters of the model can be different in each one of the business cycle. Thus, equation (7) is modified, allowing the variance of the residuals to vary across business cycles:

$$Y_t^* = \beta_0 + \beta_m S_{t-k} + \theta Y_{t-1}^* + \phi Y_{t-1} + \sigma(t)\varepsilon_t \tag{9}$$

Assuming that, $|\theta| < 1, \sigma_n = \sigma(t)$ if $t_{n-1} < t \le t_n$ with $n = 1, \ldots, N$. Therefore, $\Phi_n[\beta_0 + \beta_m S_t] = \Phi[\beta_0 + \beta_m S_t)/\sigma_n]$, and the model allows for different parameters in each cycle, with $\beta_{n0} = \frac{\beta_0}{\sigma_n}$ and $\beta_{n1} = \frac{\beta_m}{\sigma_n}$.

First-time Hitting Probability and Recession Forecast

The estimation of the probit model in the presence of an autoregressive component for the latent variable using a classical likelihood method is complex and requires the calculation of multiple integrals over the unknown value of the lagged latent variable. This procedure increases the complexity of the estimation.

As in Chauvet and Potter (2005), this paper uses Bayesian methods to estimate the models with the Gibbs sampler. The Bayesian method solves this problem in a relatively simple way compared to the classical likelihood method. One of its advantages is that it utilizes distributions of the predicted probabilities, which contain information on the uncertainty of the parameter and on the most recent values of the latent variable.

In order to find the probability of recession at time t of the dynamic probit model, it is necessary to integrate all the values of the latent state variable. For instance, if the economy is in a period of expansion at time t and cycle n, then the first-time hitting probability, previously given in the simple model by (4), is modified to:

$$\pi_R(t, 1) = \int_{y_t < 0} \Phi_n \left(\beta_0 + \beta_m S_{t-K+1} + \theta y_t^* + \phi y_t \right) f \left(y_t^* / S^t \right) dy_t^* \tag{10}$$

This way, the probabilities k periods ahead are given from multiple integration of $\{Y_{t+s}^* : s = 0, \ldots, k-1\}$:

$$\pi_R(t, k) = \int_{\dot{y}_t < 0} \cdots \int_{\dot{y}_{t+k-1} < 0} \Phi_n \left[\beta_0 + \beta_m S_{t-K+k} + \theta y_{t+k-1}^* + \phi y_{t+k-1} \right]$$
$$\prod_{s=0}^{k-1} \left\{ 1 - \Phi_n \left[\beta_0 + \beta_m S_{t-K+s} + \theta y_{t+s}^* + \phi y_{t+s} \right] \right\}$$

$$f\left(y_{t+k-1}^*, \cdots, y_t^*/S^t\right) dy_{t+k-1}^* \cdots dy_t^* \tag{11}$$

Hence, the likelihood function, instead of being given by (5), can be written as the product of $\pi_R(t,k)$ and $\pi_E(t,k)$:

$$L\left(Y^T/S^{T-K}, \beta, \{\sigma_n\}, \theta, \phi\right) = \pi_E\left(t_{N-1}, T - t_{N-1}\right)$$
$$\prod_{n=2}^{N-1} \left\{\pi_R\left(n-1+1, t_n - t_{n-1} - r_n + 1\right) \Pi_E\left(t_n - r_n, r_n\right)\right\} \tag{12}$$

In (12), the term $\pi_E(t_{N-1}, T-t_{N-1})$ represents the probability associated with a continued expansion. That is, the probability of not observing a recession in the latest $T - t_{n-1}$ periods of the sample.

One of the differences in the forecasting analysis when the Bayesian method is used is that the cumulative distribution function is evaluated at each draw of the Gibbs sampling, instead of using a maximum likelihood estimator. Thus, the collection of forecasts can then be averaged to yield an estimate of the posterior mean of the recession probability. For the simple probit model, the forecasts are:

$$\hat{P}\left(Y_{T+K}^* \geq 0/S_T, S^{T-K}, \psi, Y_T\right) = \frac{1}{I} \sum_{i=1}^{1} \Psi\left[\beta_m^{\{i\}} S_T\right] \tag{13}$$

where ψ represents the hyperparameters of the prior distributions and the hypothesis of the initial conditions of the latent variable and of the leading variables. The posterior predictive distribution can be analyzed directly in order to obtain confidence intervals for the recession probabilities.

The second difference is concerned with the estimation of the autoregressive component for the latent variable in the proposed model and forming forecasts. The forecasts for the unknown values of the lagged latent variable are obtained from the numerical integration in each step of the Gibbs sampler, generating a draw of Y_T^*, θ and σ. In what follows, these values can be used to simulate J time series realizations of $\{Y_{T+s}^*; s = 1, 2, \ldots, k\}$ using values of the observed leading variables from $T - K + 1$ to $T - 1$. The average of these J draws is given by:

$$\hat{P}\left(Y_{T+K}^* \geq 0/S_T, S^{T-K}, \psi, Y_T^{*\{i\}}, Y_T^{\{i\}}, \xi^{\{i\}}\right) = \frac{1}{J} \sum_{j=1}^{J} \Phi$$
$$\left[\left[\left(\beta_0^{\{i\}} + \beta_m^{\{i\}} S_t + \theta^{\{i\}} Y_{T+k-1}^{*\{j\}} + \phi^{\{i\}} Y_{T+k-1}^{\{j\}}\right) / \sigma_N^{\{i\}}\right] \tag{14}$$

where $\xi^{\{i\}}$ represents the set of draws of parameters in the i-th iteration. An estimate of the posterior mean of the recession probabilities can be obtained from averaging the estimated probabilities over the draws. The collection of draws

yields an estimate of the posterior distribution, improving the accuracy of real-time turning point forecasts.

The main goal of the analysis of the relationship between leading indicators and turning points of business cycles is to build better forecasts of these turning points. In this paper, we use these tools to obtain real-time recession forecasts for the industrial production of capital goods in Brazil. In particular, we use the posterior mean of the initial probabilities, the probability intervals given by the estimated posterior distribution, and the cumulative product of individual probabilities (first-time hitting probabilities), in addition to information from the simple recession probabilities of the probit model. Detailed information about the estimation method can be found in Chauvet and Potter (2005).

4. Business Cycles Chronology for the Capital Goods Industry

In order to analyze the forecasting performance of leading series in indicating the beginning and end of business cycle phases, it is necessary to first determine the chronology of these cycles. These recession reference dates are the forecasting objects that the leading indicators must predict.

There are several methods (parametric and nonparametric) proposed in the international literature for dating business cycles (see, for instance, Harding and Pagan (2003) for a discussion). In this paper, we use the method of Bry and Boschan (1971), extended by Haywood (1973), to assess the cyclical variations in the capital goods industry.[10] Note that this method follows the traditional definition of business cycles, in which the peak-to-peak or trough-to-trough periods should have at least 15 months whereas the duration of an expansion or of a recession cannot be shorter than 5 months.

The dating process of this methodology also follows some specific rules. For instance, no turning point is considered within a six-month interval before the sample end or after its beginning. This is an important issue, as the turning points closest to the end of the sample period will be eliminated in the estimation. In addition, the method also involves elimination of extreme local minima and maxima values, and the use of moving averages with frequency of three to six months, depending on the monthly cyclical dominance.

The goods capital industrial production, obtained from the Brazilian Institute of Geography and Statistics (IBGE),[11] is the reference series used for Brazil. Figure 1 shows its behavior and the dating of its cycles (shaded area). In the period analyzed, with data from January 1991 to April 2009, the capital goods industry had five recessions. Notice that up to 2003, the series oscillated within a stationary interval. This is a curious dynamic, as with the price stability attained by

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[10]Special thanks to Mark Watson for providing the GAUSS routine used to implement the method of Bry and Boschan (1971). The statistical results were omitted due to space consideration and are available from the authors upon request.

[11]The index number was seasonally adjusted by the X-12 method.

the Real Plan, one would expect improvement of the economic environment and of the forecast of economic agents with positive impact on investments. However, it took around 10 years for production to return to the same level reached before the Real Plan. Moreover, three recessionary cycles were experienced by this sector during this period. The most severe recession occurred in the first years of the Real Plan, possibly indicating the strong sensitivity of this industry to exchange rate, as it was also the case in the fourth cycle, from July 2001 to March 2003. Nevertheless, from 2003 on, the production of capital goods grew strongly, which was only interrupted more recently by the world financial crisis in 2008.

Figure 1
Production of Capital Goods and Dating of Business Cycles
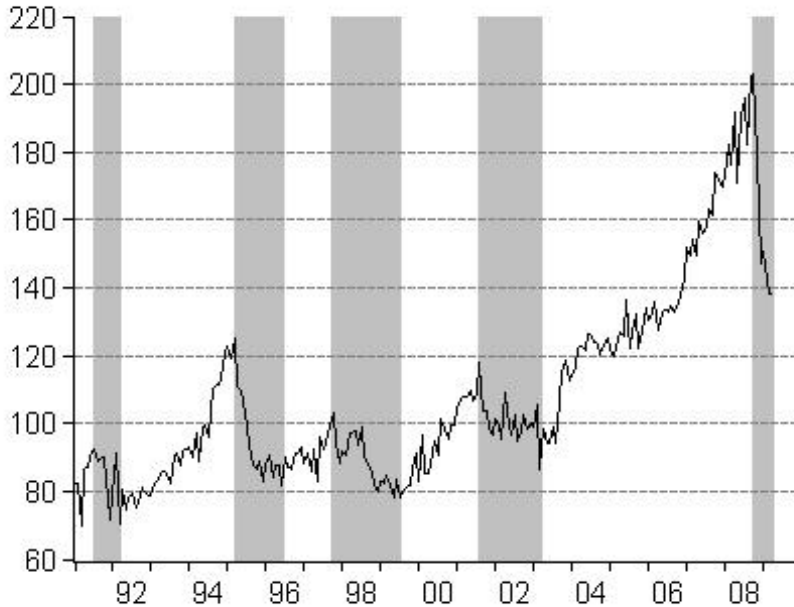
Source of raw data: IBGE.

The dating of the business cycle for the production of capital goods, as well as those established by CODACE for aggregate economic activity in Brazil (herein represented by the GDP), are shown in Table 1. In order to make this comparison, the index number of the industrial series was converted into quarterly frequency. As it can be observed, the dates are similar, especially with respect to the beginning of recessions (peak). Nonetheless, the aggregate economic activity had six recessions in the analyzed period, one more than the capital goods industry. This

is due to two mild and very short recessions that affected the Brazilian aggregate economy between 2001 and 2003, which correspond to one longer recession in the capital goods production sector. Therefore, the estimates indicate that this recession had one less peak and trough than the Brazilian business cycle.

In the first version of this paper, written in July 2009, the analysis did not allow inferring that the last recession ended in 2009, both for the Brazilian economy and for the industrial production series. This occurs because the method used for this estimation needs six observations at the end of the series to find a turning point. Since the last piece of information available for the industrial production series was that of April 2009, there were not enough data to determine the end of recession. However, the trough was predicted by leading indicators in real time, as it will be discussed in the next section. In the present version of the paper, the method applied to more recent data indicates that the end of recession in the capital goods sector occurred in May 2009.

Figure 2 shows the GDP series for Brazil (index number), the capital goods production series and the respective business cycles dating. The lighter shaded area corresponds to the business cycle dating for the Brazilian economy according to CODACE. The area marked by vertical lines corresponds to the dating of capital goods industrial cycles. Finally, the darker shaded area shows the periods in which there is a recession in the capital goods sector, but an expansion in the Brazilian aggregate economic activity.

As observed, the recessionary periods in the capital goods industry are longer than those of the Brazilian economy. In general, they last three months to one year more than recessions in the aggregate economic activity. While the mean duration of recessions in Brazil is three quarters in the analyzed period, the mean duration of recessions in the capital goods sector is five quarters.

Persistence of a recession for a longer period can be explained by the intrinsic characteristics of the industry in this category, as well as by the sequential movements often observed in the production chain of each sector. When the economy is recovering, indicating the end of a recession, there is an initial increase in the consumption of final goods and in the production of intermediate goods. Some variables such as hours worked and wages paid to workers also increase. Only after the first signs of robustness of this economic recovery, captured by the aggregate GDP, will the confidence of entrepreneurs be restored. Naturally, after continuing economic recovery signs, there will be a recovery in the investment level, with an impact on the production of capital goods.

Note also that the cycles of capital goods production oscillate more than those of the GDP. This result is expected, since the aggregate activity includes several productive segments and the service sector that display milder cycles. In any case, a more pronounced cycle in the capital goods industry indicates large uncertainty surrounding this productive segment.

Table 1
Dating of business cycles

GDP – CODACE (1)		Capital goods production sector (2)	
Peak	Trough	Peak	Trough
2nd quarter of 1989	1st quarter of 1992	3rd quarter of 1991 (July)	1st quarter of 1992 (March)
1st quarter of 1995	3rd quarter of 1995	1st quarter of 1995 (March)	2nd quarter of 1996 (June)
4th quarter of 1997	1st quarter of 1999	4th quarter of 1997 (October)	3rd quarter of 1999 (July)
1st quarter of 2001	4th quarter of 2001	3rd quarter of 2001 (August)	1st quarter of 2003 (March)
4th quarter of 2002	2nd quarter of 2003		
3rd quarter of 2008	1st quarter of 2009	4th quarter of 2008 (October)	**2nd quarter of 2009 (May)***

(1) Business Cycle Dating Committee – CODACE – IBRE/FGV.

(2) Dating procedure obtained in the present paper using the method of Bry-Boschan.

(*) This dating was not available in the first version of the paper, written in July 2009.

Figure 2

Production of Capital Goods, Brazilian GDP, and Business Cycle Dating
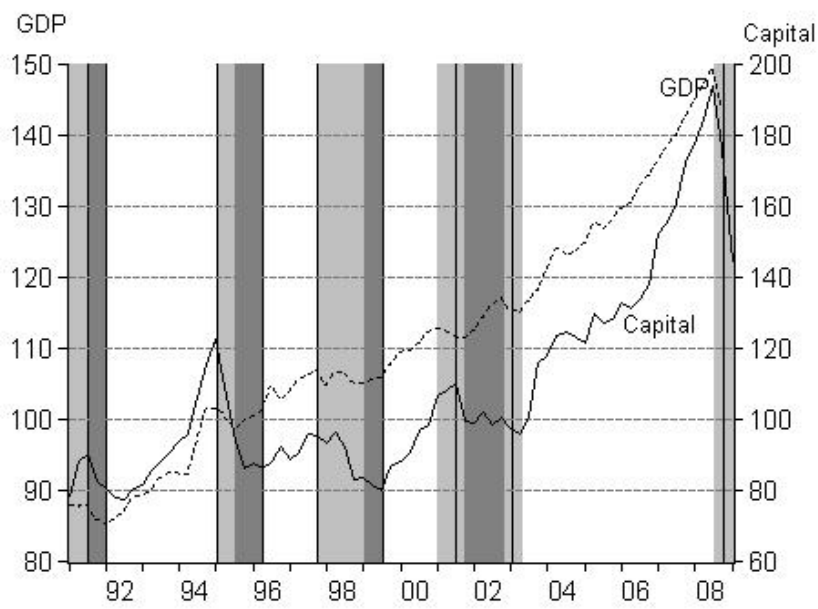
Source of raw data: IBGE. Dating of the Brazilian Business Cycle: CODACE.

5. Selection of Leading Indicators

The construction of cyclical indicators requires a statistical investigation of a broad array of candidate series. The first step is the determination of the reference series, which will represent the business cycle of a country or sector of economic activity for which one seeks to predict turning points. This was done in the previous section for the capital goods industrial production series.

The second step, to be implemented in this section, is the selection of leading indicators. Based on a large set of data series, categorized by related areas, the series are pre-selected based on two criteria. The first one contains practical information on the quality and reliability of the data, such as: the candidate series should not be subjected to frequent methodological revisions; the data should be available for timely consultation and should be long enough to represent several cycles. In addition, for real-time monitoring of the economy, the data must be available at the highest frequency possible, which for this sector implies that the candidate series should have monthly periodicity. The second criterion concerns the economic significance of the data – i.e., there must be an economic reason to regard a series as a leading variable, as is the case, for example, of:

(i) measures of the initial stages of the production process (inputs, intermediate products, energy, etc.);

(ii) variables that represent supply and demand pressures, or that can contribute towards economic fluctuations such as those that reflect fiscal and monetary policies;

(iii) series that indicate changes in expectations of the private sector, such as confidence indices and financial market indices and;

(iv) variables more sensitive to economic fluctuations (e.g., hours worked, measures of stock, etc.).

As the goal of the article is to forecast cycles, the trends of all series were removed according to the results of unit root and structural break tests, and all series were tested for stochastic trend (unit root) with structural breaks or deterministic trend with structural breaks. The augmented Dickey and Fuller (1979) and Phillips-Perron's (1998) tests were used to test for unit roots. In addition, Perron's (1989) test was used with the null hypothesis of integration with structural breaks against the alternative of deterministic trend in the presence of structural breaks. Based on the result of these tests, the series were transformed into log first differences if unit root tests (with potential structural breaks) indicated stochastic trends, or transformed into stationary ones through regressions if the tests indicated deterministic trends (with potential structural breaks).

The third step consists of statistical evaluation of the indicators. As with the reference series, the turning points for the candidate series are determined so that

they can be compared with the reference ones. The cross correlation between the reference cycle and the cycle of each of the leading series allows identifying their average prediction lead.[12] This correlation is complemented with cross-spectral analysis,[13] causality tests, and dynamic factor analysis. The use of factor models allows extracting a common component for each indicator which, compared with the cross correlation with the common component of the reference series, helps with their classification into leading, coincident or lagging indicators (see, for instance Zarnowitz, 1992, Chauvet, 2001a).

Leading indicators were also classified according to their forecasting performance of recessions within- and out-of-sample. Probit models using the dating of the reference series as the dummy variable and with each of the leading indicators as explanatory variables were estimated to classify the best candidates and the best forecast horizon, using Hannan-Quinn, Akaike information (AIC) and Schwarz information (SIC) criteria, the maximum likelihood ratio test, and McFadden's R-squared.

First, around 200 series were studied and classified according to their forecasting power within- and out-of-sample. We give weight both to the ability of the data to predict turning points in the capital goods production sector as well as to the predictive power for aggregate economic cycles. Among the best leading indicators, several of them measure the initial stages of production (e.g. inputs) or measure domestic and foreign demand.

The indicators are classified into two types: those that predict the economy within a relatively short period, from one to five months (short lead models) and those that precede recessions with a longer lead, from six months to two years (long lead models). The best six leading variables of recessions in capital goods were selected. Among these variables, there are some which have a good forecasting power both with short and long leads. Table 2 presents the best leading series, taking into account all the methods mentioned above.

The set of Figures 3 shows the dynamics of those variables selected for the short-term model, where the influence occurs one to two quarters ahead, and for long-term models, with a forecasting horizon of one to two years. The shaded areas indicate the recession dates found in the previous section for capital goods production.

The first issue to consider is the economic relevance of these series. Two of them are typically related to the raw material sectors, such as coal extraction and manufacturing of organic chemical products. Two of them show an interme-

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[12]Albeit useful, this method has some practical shortcomings such as the fact that it measures only the linear relationship between the variables and that extreme values can influence the estimated cross correlation. In any case, it does signal a leading behavior.

[13]This method decomposes the time series into a frequency series that represents fixed length cycles. The comparison of these frequencies between the reference and the candidate leading series allows identifying whether there is a common cyclical behavior. The larger the proportion of variance explained, the higher the coherence between the two series.

Figure 3
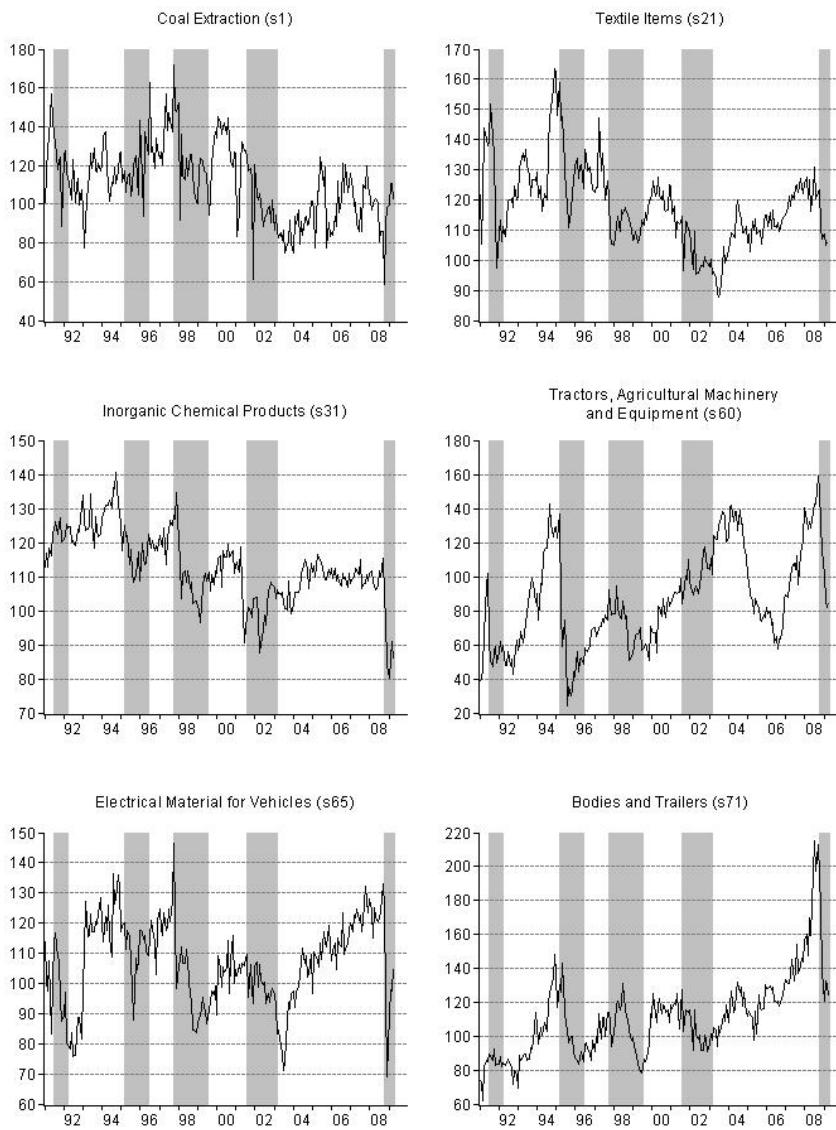Leading Variables and Business Cycle Dating of Capital Goods Production

Table 2
Selected leading variables

Code	Production series
S1	Coal extraction
S21	Textile items
S31	Inorganic chemical products
S60	Tractors, agricultural machinery and equipment, including parts and accessories
S65	Electrical material for vehicles
S71	Bodies and trailers

Source of the raw data: IBGE.

diate relation with the final goods industry, such as manufacturing of electrical material for vehicles, bodies and trailers. Finally, the manufacturing of tractors and agricultural machinery is taken into account in the composition of the capital goods production index. However, as it is well-known, this index includes other activities. In any case, the cyclical movements of manufacturing of tractors and agricultural machinery were the most significant in the prediction of the aggregate capital goods industry.

6. Results

In addition to the probit model, the turning points of each series were compared with the dating of capital goods business cycle using the B-B method. Next, the Quadratic Probability Score (QPS) was used to evaluate the forecasting performance with respect to turning points, as well as an analysis of lead-lag relationship comparing the cycle of leading series with the reference cycle of the capital goods sector.

6.1 Best models

Once the leading variables and their associated leads that best predict the business cycle phases are selected, the next step is to evaluate the forecasting power of the combination of these variables in probit models.

At first, hundreds of models were estimated. These models contained different combinations of leading variables classified according to the specification tests described in the previous section. As a result of this analysis, six models were selected: the best specifications for the simple probit model, for the proposed dynamic probit model, and for the probit model of Chauvet and Potter (2005), all with short and long leads. The dynamic probit model with recurrent breaks yielded parameter estimates that are not statistically different across the capital goods production cycles. This result is in contrast with that obtained by Chauvet

and Morais (2008) for aggregate Brazilian industrial production, whose parameters are significantly different across cycles. The result for the capital goods sector is confirmed by the structural break test of Andrews and Ploberger (1994), which indicates that it is not possible to reject the null hypothesis of no structural break in the capital goods industrial production series.

The specification tests indicate that the best short-term model combines all the series described in Table 3, except for coal extraction.[14] For longer leads, the best combination includes coal extraction, manufacturing of tractors, agricultural machinery and equipment, and manufacturing of electrical material for vehicles. These models are used to forecast capital goods production in the past decades as well as to obtain out-of-sample recession probabilities for the 2008-2009 period. The recession probabilities of the generalized dynamic probit model are compared with the probabilities obtained from the simple probit model and from the probit model of Chauvet and Potter (C-P 2005). Therefore, the following specifications are estimated:

Model 1-sl: simple probit model with short lead;

Model 2-sl: probit model with latent and autoregressive binary process with short lead;

Model C-P-sl: probit model of Chauvet and Potter (2005) with short lead;

Model 1-ll: simple probit model with long lead;

Model 2-ll: probit model with latent and autoregressive binary process with long lead;

Model C-P-ll: probit model of Chauvet and Potter (2005) with long lead.

6.2 Forecasting recessions in the capital goods industry – In-sample analysis

The data for the leading series and for the business cycle chronology go from 1991:01 to 2009:04. The forecasting horizon K is the same as the minimum forecasting horizon in the models. A total of 100,000 iterations were used to estimate the probit models through the Gibbs sampling. The sampler is initiated from the maximum likelihood estimate for the full sample of the simple probit model, but the posterior properties are calculated only after 10,000 draws (a total of 90,000 draws).

In the within-sample analysis, the models were estimated from 1991:01 to 2006:12 and the remainder of the sample, from 2007:01 to 2009:04, was used in the subsequent section for the out-of-sample analysis.

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[14]The results for the dynamic probit model with recurrent breaks are not shown due to space consideration, but are available from the authors upon request.

Tables 3 and 4 show the posterior means of the parameters for the alternative specifications for short and long leads, respectively. The values of the autoregressive coefficients in the dynamic probit model are positive and relatively high, indicating that there is considerable persistence in the latent variable and in the binary indicator, representing recession periods. In fact, as discussed in the previous section, recessions in the capital goods production sector are often long and last longer than those of the Brazilian aggregate economy.

There is strong evidence in favor of the autoregressive process for the latent variable and for the binary indicator. The natural logarithm of the Bayes' factor, which compares the dynamic probit model and the simple probit model, is $-242, 2$ between model 2_sl and model 1_sl, and $-215, 1$ between model 2_ll and model 1_ll. According to Jeffrey's criterion (1961), this evidence is decisive against the null hypothesis (simple probit model).[15] This result is also confirmed by McFadden's R^2. The simple probit model with short lead (model 1_sl) has an R^2 of only 17% whereas this rate is 84% for the proposed dynamic probit model (model 2_sl). For long lead models, the inclusion of the autoregressive process also leads to a remarkable increase in McFadden's R^2 for model 2_ll (91%) compared with model 1_ll (57%). Note that both models use exactly the same series with the same lags. Therefore, the increase in likelihood, as measured by McFadden's pseudo R^2, is due to the inclusion of autoregressive dynamics of the latent variable and of the binary indicator.

The Bayes' factor test also indicates evidence in favor of the autoregressive model for the latent variable and the binary indicator (the model proposed in this paper) compared to the probit model with autoregressive process only for the latent variable (the model proposed in Chauvet and Potter, 2005). The natural logarithm of Bayes' factor comparing these two versions is -16.8 for the short lead and -42.5 for the long lead.

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[15] Jeffrey's rule concerning the evidence against the null hypothesis is as follows: $\ln BF > 0$ indicates evidence in favor of the null hypothesis; $-1.15 < \ln BF < 0$ indicates very weak evidence against the null; $-2.3 < \ln BF < -1.15$ indicates weak evidence against the null; $-4.6 < \ln BF < -2.3$ indicates strong to very strong evidence against the null hypothesis and, finally, $\ln BF < -4.6$ indicates compelling evidence against the null hypothesis.

Table 3
Posterior mean of the parameters – Short-run models

Parameters	Short lead		
	Simple probit 1-sl model	Autoregressive probit 2-sl model	Chauvet and Potter's (2005) model
β_0^c	-0.202	-2.601	-3.542
$\beta_{1,t-2}^c$	-0.033	-0.032	-0.041
$\beta_{2,t-1}^c$	-0.041	-0.006	-0.009
$\beta_{2,t-2}^c$	-0.059	-0.032	-0.041
$\beta_{2,t-3}^c$	-0.059	0.026	0.029
$\beta_{2,t-4}^c$	-0.031	0.018	0.020
$\beta_{3,t-3}^c$	-0.024	-0.021	-0.036
$\beta_{3,t-5}^c$	-0.022	-0.049	-0.053
$\beta_{4,t-1}^c$	-0.007	0.015	0.017
$\beta_{5,t-2}^c$	-0.002	0.011	0.013
θ^{sr}	-	0.572	0.822
ϕ^{sr}	-	0.417	-
McFadden R^2	0.171	0.841	0.785

The series for the short-run models are: s21, s31, s60, s65, and s71, respectively.

Table 4
Posterior mean of the parameters – Long-run models

Parameters	Long lead (1)		
	Simple probit 1-ll model	Autoregressive probit 2-ll model	Chauvet and Potter's (2005) model
β_0^L	-21.289	-10.562	-12.423
$\beta_{1,t-19}^L$	0.028	0.003	0.004
$\beta_{1,t-20}^L$	0.008	-0.001	-0.001
$\beta_{1,t-21}^L$	0.023	0.028	0.037
$\beta_{1,t-22}^L$	0.016	-0.013	-0.016
$\beta_{2,t-18}^L$	0.035	0.0421	0.051
$\beta_{2,t-19}^L$	0.011	-0.004	-0.005
$\beta_{2,t-20}^L$	0.032	0.007	0.008
$\beta_{3,t-14}^c$	0.041	0.016	0.020
θ^{lr}	$-$	0.464	0.738
ϕ^{lr}	$-$	0.356	$-$
McFadden R^2	0.572	0.913	0.824

The series for the long-run models are: s1, s60, and s65, respectively.

Recession Probabilities

The estimated recession probabilities confirm the importance of considering an autoregressive process for the latent variable and for the binary indicator, with quite different signal-to-noise ratios from the recession forecasts. The posterior mean of the recession probabilities from the probit models is given by the normal cumulative distribution function $\Phi(.)$, shown in Figure 4 and 5 for the short- and long-run models, respectively.

For the short-run models (Figure 4), recession probabilities increase before each of the five recessions observed in the sample, as dated in Section 4. However, there is a large difference between the signal-to-noise ratios obtained from the simple probit model and from the dynamic probit model, yielding very different recession forecasts. The probabilities obtained from model 1_sl (simple probit model) are noisy during expansionary periods and indicate recessions with relatively low probability values. On the other hand, the performance of dynamic models is a lot better than the simpler version. The recession probabilities from the proposed model, which includes an autoregressive process for the latent variable and for the binary indicator show a clear difference between recessions and expansions and, therefore, less uncertainty about their interpretation. The probit model of Chauvet and Potter (C-P 2005) also has a quite better performance from the simple probit model. However, compared with the recession probabilities of the probit model proposed in this paper, the probabilities of the C-P_sl model are noisier during expansions and oscillate more during recessions, resulting in larger uncertainty about the state of the economy.

If we assume that the capital goods sector enters into recession when its recession probabilities exceed 50%, the simple probit model yields several false recession signals.[16] Some of them are spikes in single months, but in 2005 this model falsely indicates that the capital goods sector had a recession in the first six months of that year. These false peaks during expansions are particularly problematic as they cause great uncertainty about the end of expansions, in addition to affecting the cumulative recession probabilities. Another drawback of model 1_sl is that recession probabilities oscillate around 50% several times during recessionary periods, hindering the interpretation of the recession signal and of its end. The simple probit model, thus, shows a very weak performance in terms of sensitivity (percentage of correctly predicted recessions) and specificity (percentage of correctly predicted expansions).

On the other hand, an autoregressive process substantially increases the sensitivity and specificity of the model (Figure 4, second panel). The recession probabilities of the autoregressive probit model are smoother and their values are closer to 0 or 1, showing a clear distinction between recessionary and expansionary peri-

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[16]The false signals are observed in 1992:11, 1992:12, 1993:02, 1996:12, 1999:08, 2004:12, 2005:01, 2005:02, 2005:03, 2005:04, 2005:06, 2006:08 and 2006:09.

Figure 4
Posterior Mean of Recession Probabilities: Simple Probit Model (Model 1 sl),
Autoregressive Probit Model (Model 2 sl) and Chauvet and Potter's Model (Model C-P
2005) with short lead. The shaded area corresponds to the capital goods production
business cycle dating
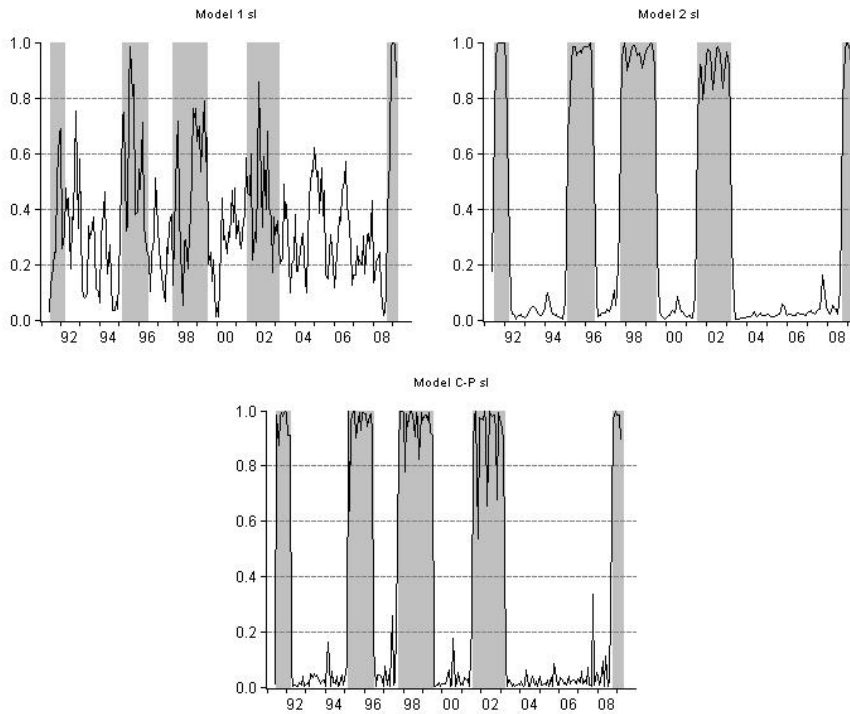
ods. Note that the probabilities consistently increase above 80% before and during each recession in the sample. The resolution and accuracy of the probabilities are considerably better than those of the simple probit model, both for forecasting recessions and expansions. The resolution and accuracy of this model are also better than those of Chauvet and Potter's (2005) probit model.

With regard to the long-run models, the probabilities display more similar general patterns (Figure 5). Both the simple probit and the dynamic probit models forecast recessions with a horizon of 6 to 14 months. Although the recession probabilities of the long-run simple probit model (model 1-ll) have better forecasting properties than the probabilities of this same model in the short run (model 1-sl), they still present some important drawbacks. The long-run probabilities of recessions consistently rise over 60% before recessions, but with a variable lead between 1 to 3 years. Moreover, the probabilities oscillate around 50% even after they have signaled a future recession, as occurred in 1996-1997 and in 2001-2002. Finally, the probabilities rise over 50% during the expansion of 2006, falsely signaling a recession. These characteristics of the probabilities hinder their interpretation as well as their use as a real-time forecasting tool.

On the other hand, the autoregressive probit model has a more homogeneous performance in the short and long run, despite the inclusion of different series on each horizon. The dynamic probit model 2_ll correctly signals all recessions with a stable forecasting lead. Furthermore, this model does not give any false alarm of recessions. Compared with Chauvet and Potter's (2005) model, the recession probabilities of the proposed dynamic model display fewer oscillations during recessions and, therefore, yields less uncertain signs of transitions between cycle phases.

6.3 Recession Forecast for 2008-2009

This section examines the differences among the several models discussed previously in a real-time recession forecasting exercise. In particular, the posterior mean of the hitting probabilities, probability intervals given by the posterior forecasting distribution, and the cumulative product of individual probabilities, in addition to traditional monthly recession probabilities of the probit model, are used to study the 2008-2009 recession.

The severe financial crisis that impacted the U.S. in mid-2008 was preceded by a recession that had begun in December 2007, according to the NBER. At first, this recession was relatively mild, with a moderate but positive growth in U.S. GDP (0.6%) in the second quarter of 2008. However, with the insolvency of large financial institutions and a sequence of negative shocks, the U.S. economic activity experienced high negative rates, mainly in the fourth quarter of 2008 and in the first quarter of 2009 (-6.8% and -4.9%, respectively). The U.S. financial crisis spread quickly around the world and turned into a recession in Brazil from the second half of 2008 onwards. The Brazilian GDP fell 3.5% in the fourth quarter

Figure 5
Posterior Mean Recession Probabilities: Simple Probit Model (Model 1 ll),
Autoregressive Probit Model (Model 2 ll) and Model of Chauvet and Potter (Model
C-P 2005) with Long Lead. The shaded area corresponds to capital goods production
business cycle dating
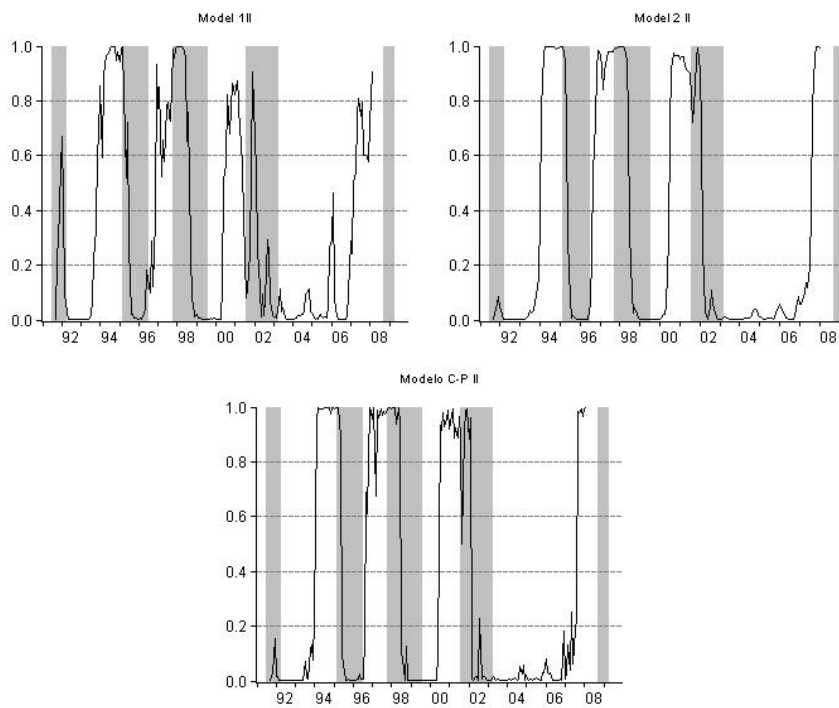
of 2008 and 1.5% in the first quarter of 2009. According to CODACE, the end of the expansion (peak) in the Brazilian aggregate economic activity occurred in the third quarter of 2008.

Based on the analysis carried out in Section 4, a corresponding recession in the capital goods industry began in October 2008. The last monthly observation for the series used available as of July 2009, month in which the first version of this paper was written, was April 2009.[17] Using the Bry-Boschan method based on this information, the capital goods sector still had not come out of recession. However, the probit models analyzed in this paper allow predicting the beginning and end of recessions in the capital goods industry from 1 to 14 months *before* their occurrence. Given the uncertainty about the beginning and end of recessions, the analysis in this section illustrates the importance of developing leading models that give effective signals of business cycle turning points in real time, before a dating identifying the beginning and end of a recession is available.

Two forecasting exercises are implemented in this section. First, the forecasting power of the models is tested with respect to their ability to identify the peak in October 2008. This is implemented by estimating the models up to December 2007, and leaving the months from January 2008 to April 2009 for the out-of-sample real-time forecast analysis. Second, the models are used to predict the end of this recession in real time. The real-time forecast is undertaken assuming that the capital goods sector was still in a recession up to December 2008. The subsequent months in 2009 are then used for the real-time forecast.

Month-to-Month Traditional Probabilities – Out-of-Sample Forecast

Figures 6 and 7 show the posterior mean of the recession probabilities obtained out of sample for individual months in 2008-2009 for all models considered.

The forecasting horizon used in the short-term model is $K = 1$ month. As can be observed in Figure 6, the simple probit model 1_sl indicates a recession in the capital goods industry only in November 2008. In other words, instead of forecasting a recession, the signal from this model is lagged, predicting the recession only one month after beginning. On the other hand, the recession probability from the autoregressive probit model 2_sl increases above 50% in August 2008, forecasting the beginning of recession two months ahead, whereas model C-P_sl forecasts the recession one month ahead. All models indicate decrease in the recession probability from February 2009 on, but the proposed model 2_sl displays a sharper decline.

Figure 7 shows the forecast results for the long-run probit models. Again, the recession probability of simple probit model 1-ll only increases above 50% in November 2008, although this model was built to forecast recessions with a long

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[17]The B-B method only identifies a turning point at least six months after its occurrence. Updating the analysis with more recent data (up to April 2011), we note that the end of the recession in the capital goods industry occurred in May 2009, as discussed in Section 4.

Figure 6
Real-Time Recession Probabilities: Simple Probit Model (Model 1 sl —),
Autoregressive Probit Model (Model 2 sl _) and Chauvet and Potter's Probit Model
(Model CP sl - - -) with Short Lead (The vertical line indicates the beginning of the
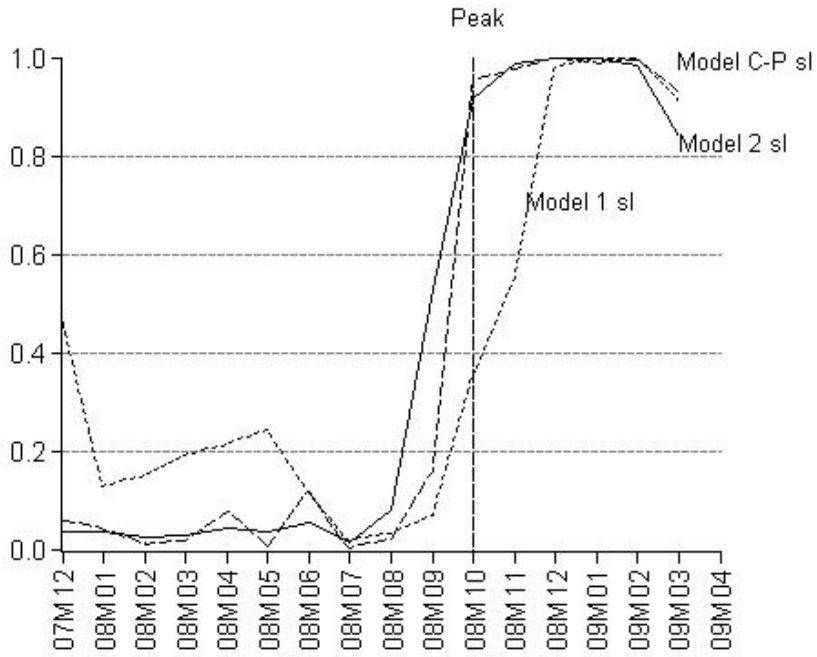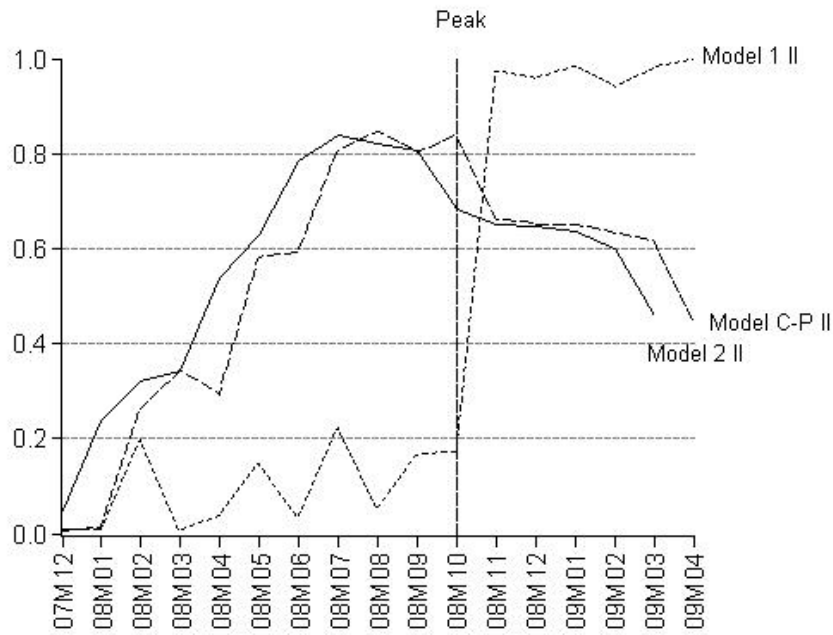recession in the capital goods sector)

Figure 7
Real-Time Recession Probabilities: Simple Probit Model (Model 1 ll —),
Autoregressive Probit Model (Model 2 ll _) and Chauvet and Potter's Probit Model
(Model CP ll - - -) with Long Lead (The vertical line indicates the beginning of the
recession in the capital goods sector)

lead. On the other hand, the recession probabilities of the proposed autoregressive probit model 2-ll increase above 50% from April 2008 on, forecasting this recession with a six-month lead, whereas the model C-P_ll forecasts the peak with a five-month lead. Note also that the probabilities of the proposed autoregressive probit model decrease from September 2008 on, correctly forecasting the end of the recession in the first quarter of 2009, as also determined by CODACE for the aggregate Brazilian economic activity.[18] The recession probabilities of the simple probit model, on the other hand, show an uptrend until the last observation, incorrectly indicating a continuation of the recession throughout 2009.

First-Time Hitting Probabilities – Real-Time Forecast

One of the major contributions of the method used is the possibility of forecasting recession through the analysis of the posterior mean of the first-time hitting probabilities, which yield more accurate forecasts. The method discussed in Section 3 is applied to the long lead models, which allow analysis of the future performance of the economy on a horizon greater than six months. This is implemented by building real-time probabilities that the capital goods industry was still in recession in July 2009. Table 5 summarizes these results.

Table 5
Real-time probabilities

	Model 1 ll	Model 2 ll	Model CP ll
Probability of Expansion in 2009:07	12.4%	58.1%	52.3%
Above — 97.5 percentile	86.8%	81.9%	85.4%
Below — 2.5 percentile	25.3%	52.7%	47.6%

The first-time hitting probability of expansion in July 2009 is only 12% for the simple probit model. However, the uncertainty about this probability of expansion is large, with an interval between 25% and 87%. Thus, this confidence interval includes both the possibility that the economy was in expansion in that month (probability of expansion greater than 50%) or that it remained in recession (probability of expansion less than 50%). On the other hand, the first-time hitting probability of expansion in June 2009 was 58% for the proposed autoregressive probit model and 52% for the C-P model. In the case of the proposed model, the uncertainty over this value is substantially lower than that of the simple probit model, with values between 53% and 82%. Therefore, this model shows clear signs that the capital goods industry was in an expansion in July 2009. Note that this information is based only on data up to December 2008.[19] The C-P model also

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[18]CODACE announced in May 2009 that the recession in Brazil had ended in the first quarter of 2009.

[19]In addition, when the first version of this paper was written, in July 2009, there was large

indicates signs of expansion in the sector in July 2009. However, note that the probability confidence interval is between 48% and 85%. The uncertainty around the probability from this model is larger than that of the proposed autoregressive model, and the interval includes the possibility that the economy was still in recession (the probability of expansion is below 50% for the 2.5% percentile).

In summary, the out-of-sample signals from the long-run simple and dynamic probit models with respect to the 2008-2009 recession are quite different. The recession probabilities from the simple probit model show large uncertainty over their values, hindering a more conclusive interpretation of the end of the 2008-2009 recession. On the other hand, the recession probabilities from the autoregressive probit model decrease considerably in the first half of 2009. The probability that a recession in the capital goods industry had already ended in June 2009 is high, and this forecast is less uncertain than that of the simple probit model. The proposed autoregressive model also displays less uncertainty about this forecast, compared with Chauvet and Potter's (2005) probit model.

7. Conclusion

The main goal of this paper is the construction of leading indicators of the capital goods industrial production, as well as the determination of their recession and expansion periods, using the proposed autoregressive probit model. Simple and dynamic probit models are used to forecast recessions in this industry within- and out-of-sample. From 1991 to 2009, this sector was characterized by five recessionary periods, with a mean recession duration of 15 months and of 36 months for expansionary periods. The phases of the business cycle in this industry are, thus, longer-lasting and more intense than in the aggregate economy.

In order to identify turning points in real time in the capital goods production sector, one needs information on economic series several months after the turning point takes place. Thus, if a turning point occurs at the end of the available sample, its identification is hindered in real time. However, the beginning and end of recessions can be forecast with a long lead through the use of leading indicators as constructed in this paper, even when turning points occur at the end of the sample. Starting from around 200 variables, we select six best series, which are economically and statistically important in predicting the business cycle of the capital goods production in the short and long run. The probit models are used to form real-time forecasts. The models in this paper allow forecasting the beginning and end of recessions in the capital goods industry between 1 and 14 months *before* their occurrence. Given the uncertainty over the end of the last recession in the capital goods industry at the time this paper was written,

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uncertainty over the end of recession, since the latest available data were for April 2009. CODACE announced in May 2009 that the recession in Brazil ended in the first quarter of 2009. As explained in Section 4, the application of the B-B method for more recent data, up to April 2011, indicates that the trough in the capital goods production sector occurred in May 2009.

the analysis illustrates the importance of developing leading models that provide effective signals of business cycle turning points.

The models imply different signals concerning the probability of future recessions. The recession probabilities of the simple probit model display a large uncertainty interval, hindering assessment regarding the end of the 2008-2009 recession. On the other hand, the real-time recession probabilities of the dynamic probit model proposed in this paper indicate that the recession probabilities were sharply decreasing in the first half of 2009. The probability that the recession had already ended in July 2009 is high, and this forecast is less uncertain than the one from the simple probit model.

References

Andrews, D. W. K. & Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica*, 62:1383–414.

Araújo, E., Carpena, I., & Cunha, A. (2008). Brazilian business cycles and growth from 1850 to 2000. *Estudos Econômicos*, 38:557–581.

Bajari, P., Chu, C. S., & Park, M. (2008). An empirical model of subprime mortgage default from 2000 to 2007. Working Paper 14625, NBER.

Barros, A. R. (1993). A periodization of the business cycles in the Brazilian economy, 1856-1985. *Revista Brasileira de Economia*, 47:53–82.

Bry, G. & Boschan, C. (1971). Cyclical analysis of time series: Selected procedures and computer programs. Technical Paper 20, NBER.

Burns, A. & Mitchell, W. (1946). *Measuring Business Cycles*. National Bureau of Economic Research, New York.

Campelo Júnior, A. (2008). Indicadores antecedentes de atividade industrial no Brasil. Master's thesis, EPGE/FGV.

Chauvet, M. (1998). An econometric characterization of business cycle dynamics with factor structure and regime switching. *International Economic Review*, 39:969–96.

Chauvet, M. (2001a). Leading indicators of the Brazilian inflation. *Pesquisa e Planejamento Economico*, 31:323–354.

Chauvet, M. (2001b). A monthly indicator of Brazilian of GDP. *Brazilian Review of Econometrics*, 21:1–15.

Chauvet, M. (2002). The Brazilian business and growth cycles. *Revista Brasileira de Economia*, 56:75–106.

Chauvet, M. (2012). Cronologia e previsões de ciclos econômicos de Minas Gerais. *Cadernos Econômicos de Minas Gerais*, dezembro:1–32.

Chauvet, M., Lima, E. C. R., Domingues, G., & Vasquez, B. (2006). Forecasting Brazilian output and its turning points in real time in the presence of breaks: A comparison of linear and nonlinear models. *Estudos Econômicos*, 36:5–46.

Chauvet, M. & Morais, I. A. C. (2008). Predicting recessions in Brazil. In *LAMES/LACEA Meeting*, Rio de Janeiro, Brazil.

Chauvet, M. & Potter, S. (2001). Recent changes in the U.S. business cycle. *The Manchester School*, 69:481–508.

Chauvet, M. & Potter, S. (2005). Forecasting recessions using the yield curve. *Journal of Forecasting*, 24:77–103.

Chauvet, M. & Potter, S. (2010). Business cycle monitoring with structural changes. *International Journal of Forecasting*, 6:777–793.

Chauvet, M. & Silva, J. A. B. (2004). Leading indicators of recession for the Brazilian economy. In *Anais do XXVI Encontro da Sociedade Brasileira de Econometria*, João Pessoa, Brazil.

Contador, R. C. & Ferraz, C. (2001). *Previsão com Indicadores Antecedentes*. Silcon, Rio de Janeiro.

Dickey, D. A. & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Society*, 74:427–31.

Duarte, A. J. M., Issler, J. V., & Spacov, A. (2004). Indicadores coincidentes de atividade econômica e uma cronologia de recessões para o Brasil. *Pesquisa e Planejamento Econômico*, 34:1–37.

Dueker, M. (1997). Strengthening the case for the yield curve as a predictor of U.S. recessions. *Federal Reserve Bank of St. Louis Economic Review*, 79:41–51.

Ellery Jr, R., Gomes, V., & Sachsida, A. (2002). Business cycle fluctuations in Brazil. *Revista Brasileira de Economia*, 56:269–308.

Engle, R. F. & Issler, J. V. (1993). Common trends and common cycles in Latin America. *Revista Brasileira de Economia*, 47:149–76.

Ferreira, R., Bieren, H., & Castelar, I. (2005). Forecasting quarterly Brazilian GDP rate with linear and nonlinear diffusion index models. *Revista Economia*, 6:205–229.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57:357–384.

Hamilton, J. D. (1990). Analysis of time series subject to changes in regime. *Journal of Econometrics*, 45:39–70.

Harding, D. & Pagan, A. (2003). A comparison of two business cycle dating methods. *Journal of Economic Dynamics and Control*, 27:1681–1690.

Haywood, E. (1973). The deviation cycle: A new index of the Australian business cycle, 1950-1973. *Australian Economic Review*, 4:31–39.

Hollauer, G. E., Issler, J. V., & Notini, H. H. (2009). Novo indicador coincidente para a atividade industrial brasileira. *Revista de Economia Aplicada*, 13:5–28.

IMF (2008). Financial stress, downturns, and recoveries. World Economic Outlook (WEO).

Jeffrey, H. (1961). *Theory of Probability*. Clarendon Press, Oxford, 3rd. edition.

Kose, M. A., Otrok, C., & Prasad, E. S. (2008). Global business cycles: Convergence or decoupling? Working Paper 14292, NBER.

Lima, I. C., Moro, S., & Jayme Jr, F. G. (2006). Ciclos e previsão cíclica: Um modelo de indicadores antecedentes para a economia brasileira. In *Anais do XXXIV Encontro Brasileiro de Economia*. ANPEC.

Milas, C., Rothman, P., & Dijik, D. V. (2006). *Nonlinear times series analysis of business cycles*. Elsevier.

Moore, G. H. (1983). *Business Cycles, Inflation, and Forecasting*. NBER Book Series Studies in Business Cycles.

Morais, I. A. C. & Frainer, V. (2005). Uma investigação sobre o ciclo dos negócios na indústria da Bahia. *Revista Econômica do Nordeste*, 36:378–410.

Morais, I. A. C. & Portugal, M. S. (2007). Um novo Índice coincidente para a atividade industrial do Estado do Rio Grande do Sul. *Estudos Econômicos*, 37:35–70.

Morais, I. A. C. & Portugal, M. S. (2008). Business cycle in the industrial production of Brazilian states. *Análise Econômica*, 50:1–20. (UFRGS).

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica*, 57:1361–1401.

Phillips, P. C. B. & Perron, P. (1998). Testing for a unit root in time series regression. *Biometrika*, 75:335–46.

Picchetti, P. & Toledo, C. (2002). Estimating and interpreting a common stochastic component for the Brazilian industrial production index. *Revista Brasileira de Economia*, 56:107–120.

Stock, J. H. & Watson, M. W. (1989). New indexes of leading and coincident economic indicators. In *NBER Macroeconomic Annual*, pages 351–95. NBER.

Stock, J. H. & Watson, M. W. (1991). A probability model of the coincident economic indicators. In Lahiri, K. & Moore, G., editors, *Leading Economic Indicators: New Approaches and Forecasting Records*. Cambridge University Press, New York.

Stock, J. H. & Watson, M. W. (1993). A procedure for predicting recessions with leading economic indicators: Econometric issues and recent experience. In Stock, J. H. & Watson, M. W., editors, *New research on Business Cycles, Indicators and Forecasting*, pages 255–284. University of Chicago Press, for NBER, Chicago.

Zarnowitz, V. (1992). *Business Cycles: Theory, History, Indicators, and Forecasting*. The University of Chicago Press.