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Is the South African economy likely to fall back into recession in 2018-2019?

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Is the South African economy likely to fall back into recession in 2018-2019?

Abstract

This paper has two main objectives: on the one hand, to establish the occurrence of a recession of the South African economy during the years 2015-2016; on the other hand, to build a predictive model to determine whether South Africa is likely to fall back into contraction in the years 2018-2019.

Consequently, we first propose a turning point chronology for the business cycle based on a classical conception of economic cycles and a non-parametric algorithm – called BBQ for Bry-Boschan Quarterly – applied to the real GDP series for the period 1970-2017. Its implementation allows us to detect one recession in the economic activity which lasted four quarters in 2015 and 2016. Special attention is given to the macroeconomic context of the analysis.

Secondly, a dynamic probit model is built, which includes only one predictor, namely the total credit supply. In-sample results show that this dynamic specification performs very well. A real-time forecast leads to the result that the probability that the South African economy will fall back into recession during the 2018Q1-2019Q1 period, is extremely small.

Keywords

Business cycles, forecasting, dynamic probit model, recessions, turning points

JEL classification

C41, C53, E32

1. Introduction

This article has a twofold purpose: first, to show that the South African economy recorded a new recession in 2015-2016; second, to make a real-time forecast for the near future, especially the year 2018 and the first quarter of 2019. In this way, it will be possible to answer the question of whether a new recession is likely or not during this period.

However, the implement of this work program immediately raises a new question: what is the business cycle? From this viewpoint, Mitchell (1913, p. 20) had already specified that "to observe, analyze, and systematize the phenomena of prosperity, crisis, and depression is the chief task". Later, Burns and Mitchell (1946, p.5) defined the cycle as a succession of phases of expansion and contraction or recession in economic activity. In this perspective, a recession is nothing more than a "marked decline" in this activity. The American NBER gives an identical definition when it points out that "a recession is a significant decline in activity spread across the economy."[1]

Moreover, for Burns and Mitchell (1946, p. 72), "aggregate activity can be given a definite meaning and made conceptually measurable by identifying it with gross national product at current prices". However the two authors specified immediately – in 1946! – that this series frequency was neither monthly nor quarterly; consequently they suggested using a set of replacement series which could be used to determine the aggregate reference cycle, essentially through graphic methods, i.e. by observing clusters of turning points.

In modern terms, by using GDP, economic activity can be then represented by a binary variable, which takes the value one during recessions and the value zero during expansions. The major problem is then to determine the cyclical turning points, i.e. the peaks and the troughs of the indicator chosen for representing economic trajectory.

The article will be organized as follows. Section 2 presents a brief literature review on the measurement of business cycles and on the forecasting of the turning points in economic activity. Section 3 develops some methodological issues related to the measurement of cycles and to the probit model as a forecasting tool. Section 4 presents an overview of the different chronologies of the business cycle, then uses the BBQ algorithm to precisely date the 2016-2016 recession.

[1] Consultable at www.nber.org/cycles.

The following section is devoted to the building of a dynamic probit model. The search for a good specification of the predictive model receives a particular care. The model is then used to answer, in real time, the question asked: Is the South African economy likely to fall back into recession in 2018-2019? Special attention is also paid to the 2007-2017 macroeconomic context. Finally, section 6 contains concluding remarks and proposes some future research perspectives.

2. A brief literature review

We begin with a picture of the literature available to date the recessions before to present that devoted to the forecasting of turning points.

2.1 The measurement of business cycles

The relevant literature is divided into four main categories: univariate methods to isolate the turning points, either automated or based on a parametric model; multivariate procedures, either automated or model-based.

In the first class, the pioneering work is that of Bry-Boschan (BB). A description of their method and its programming in Fortran is given in Bry-Boschan (1971, pp. 19-29). Harding and Pagan (2002) developed an algorithm which is a quarterly version of the BB-algorithm and is independent of any model. Engel and Ouliaris gave instructions to implement BBQ computer programs in Matlab, GAUSS and Excel.[2] Du Plessis (2006b) and Bismans and Majetti (2012) have applied this methodology to South African economy.

At the opposite, Hamilton (1989) argues that the movement of the economy is governed by a univariate Markov regime-switching model. The simplest form for the model is the following:

$$y_t = \lambda(s_t) + \phi y_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0,\sigma^2), \quad t = 1,\cdots,T. \tag{1}$$

where y_t denotes the logarithmic real quarterly GDP, and s_t is a regime or state variable, latent and stochastic, which takes the value one in recessions and the value zero in expansions. It follows a finite Markov chain with two states. The model was refined for example by Filardo (1994), Boldin (1996), and Clements and Krolzig (1998). The relevant papers applying the Markovian approach to South Africa are those of Moolman (2004), Altug and Bildirici (2010), Bosch and Ruch (2013), and Bismans and Le Roux (2013).

[2] see http://www.ncer.edu.au/resources/data-and-code.php

What is the optimal method to get the turning points? The question is strongly debated among economists – see particularly the discussion between Hamilton (2003) and Harding and Pagan (2003a, 2003b). The first author especially puts forward a strong argument: the probabilistic nature of the approach based on models, which allows intensive use of inferential techniques. The latter emphasizes the great facilities for reproducing the results from a non-parametric viewpoint. This last argument seems particularly valid.

To present the multivariate dating approach, consider a vector $\mathbf{y}_t$, which is compound of n time series, meant to represent economic activity. To automatize the selection of the turning points common to these n series, Harding and Pagan (2006) have developed a non-parametric computational algorithm of extraction from the common cycle. Of course, many authors use alternatively a model to determine the common cycle. Stock and Watson (1991) is a good example. The Generalized Dynamic Factor Model (GDFM) of Forni et al. (2000) is another example. To the best of our knowledge, the only paper which applies multivariate methods to the determination of South African business cycles is that of Bosch and Ruch (2013).

It is now necessary to say a few words about the approach of the American NBER, which does not fall into any of the preceding categories. Indeed, the methodology implemented by the NBER is not automated nor model-based. It relies on a subjective, qualitative analysis of eight coincident economic series – see NBER (2010). However, it is valuable to note, following Romer (1994, p. 574), that the used methods evolved over time, especially because the cyclical profile of the economy before 1927 was based on detrended data, which is no longer the case later.

The South African Reserve Bank applies a similar methodology, except that it tries to measure the growth cycle. Van der Walt (1989, 1995), Smit and Vanderwalt (1982), Venter and Pretorius (2001), and Venter (2009, 2011, 2016) present the procedure used to locate the turning points of the cycle. Venter (2005) gives a good summary of the SARB's methodology. This approach, also referred to as the "deviation" cycle, goes back to the pioneering works of Friedman and Schwartz (1963) and Mintz (1969, 1972). As emphasized by Canova (1998, 1999) or by Zarnowitz and Ozyldirim (2006), the major problem intrinsic to the growth cycle relies on the extraction of its trend component, insofar as various methods exist and each of them may lead to very different turning point chronologies.

2.2 Forecasting turning points

It is convenient to distinguish three great approaches to find turning points in the economic activity. (From now on, we will use real GDP as an indicator of the global movement of the economy.)

Firstly, it is possible to get peaks and troughs in the GDP series as a by-product of forecasting models. In other terms, if you predict future diminutions in the level of real domestic product, you also forecast a recession. Of course, these models may be very different in nature: large-scale macroeconomic models; univariate or multivariate time series models; microfounded structural models like real business cycle (RBC) or dynamic stochastic general equilibrium (DSGE) models, naïve prediction, and so one. For a nice survey of macroeconomic forecasting and its main historical trends, see Diebold (1998).

The second approach is based on using composite leading indicators (CLI). These indicators have a long history, well tracking by Moore (1983, chapter 24) for their early steps. Indeed, the first indicators were built by Burns and Mitchell in 1938. Since, the technique has known many developments. Important from this viewpoint are the contributions by Zellner et al. (1991), and Zellner and Min (1999). Today, fundamentally, two ways are available for the construction of composite leading indexes: non model and model. The one faced to the question of the choice of a weighting scheme for the components of index; the other is based on Vector Autoregressions (VAR), factors or Markov-switching models. (See for a synthetic, but deep treatment, Marcellino, 2006.) Several criticisms can be made about CLIs methodology. Particularly, we agree with the conclusion of Clements and Hendry (1998, p.226) that "CLIs seem at best an adjunct to, and not a substitute for, econometric modelling".

The third approach consists of using a discrete choice model which directly predicts the recessions in economic activity. In fact, such an approach is based on a qualitative, non-linear, static probit or logit model. The static probit model was introduced in business cycle analysis by Estrella and Hardouvelis (1991) and largely used e.g. by Estrella and Mishkin (1997, 1998) and Chin et al. (2000). Also noteworthy for South Africa is the work of, and Moolman (2003) Aye et al. (2016). Del Negro (2001) has shown that this model strongly outperforms rival structures such as econometric or leading indicators models.

A supplementary step forward with the use of a true dynamic probit. Such a model is a simplified form of the Binary Autoregressive model, BARX(*p*), suggested by Zeger and Qaqish (1988). If we are not mistaken, the first economic paper to use a dynamic probit is that of

Eichengreen et al. (1985). Thereafter, Dueker (1997), Chauvet and Potter (2005), Kauppi and Saikkonen (2008), Startz (2008), Bismans and Majetti (2013), and Vermeulen et al. (2017), have forcefully used the same model. (For a quick survey of the economic and econometric literature on the subject, see de Jong and Woutersen, 2011.)

3. Methodological issues

In this section, we will focus on the dual problem of cycle's measurement and turning points forecasting.

3.1 The measurement of business cycles

Consider again the series of the logarithmic real quarterly GDP $y_t = \ln Y_t$ and define a recession or contraction as the temporal interval between a peak and a trough in this GDP. The task is then to select the turning points, which will be realized by using the automated algorithm, called BBQ (Bry- Boschan Quarterly). As a contraction must last at least two quarters, which will eliminate some of too many turning points, the algorithm the algorithm goes through the following steps:

1. Taking account of two quarters rule, the algorithm will detect all the peaks (troughs), i.e. the points such as a peak (a trough) at t is equivalent to the condition $y_t > y_{t\pm k},\ k = 1,2$ ($y_t < y_{t\pm k},\ k = 1,2$).

2. The algorithm also implements a censoring rule so far as a complete cycle (say from a peak to a peak or from a trough to a trough) must overlap a minimum of five quarters in time.

3. Once these turning points are so selected, it is easy to determine the expansion and contraction phases for the studied economy.

Finally, by using the output of BBQ algorithm, an indicator of recessions R_t is built, where R_t is a binary variable, taking the value one during contractions and the value zero during expansions.

3.2 Forecasting turning points with a dynamic probit model

The dynamic probit model will be fully written:

$$P_t = \Phi(z_t), \tag{2}$$

where P_t is a probability determined by the normal cumulative distribution function (CDF) $\Phi(\cdot)$ and

$$z_t = \sum_{j=1}^{p} \gamma_j R_{t-j} + \mathbf{x}'_{t-1}\boldsymbol{\beta}. \tag{3}$$

Therefore, the CDF depends on a set of predictors and own past values of R_t. Of course, the row vector $\mathbf{x}'_{t-1}$ may – in reality, it must necessarily – include lagged values of predictors. That's the reason why the subscript $t-1$ is associated to it.

Applying the criterion of minimizing the mean-square error of *h* periods ahead forecasting to the probit model defined by (2)-(3) and using the law of iterated conditional expectations yields the formula

$$E\left(P_{t+h}(R_{t+h}=1) \mid I_t\right) = P_{t+h|t}(R_{t+h}=1) = E\left(\Phi(z_{t+h}) \mid I_t\right). \tag{4}$$

The RHS of (4) furnishes the *h*-period forecasted probability conditional on the information set in the period *t*, i.e. the recession indicator *R* and the predictor *x*, both appropriately lagged. This predicted probability is statistically optimal, a well-known result in mathematical statistics.

Furthermore, the predicting process can be conducted of two manners: direct versus iterated forecasting – for a good discussion of the problem, see Chevillon and Hendry (2005). Indeed, the choice is between a multi-period model associated to the forecast horizon, and a one-period model iterated for a number of periods equal to this horizon.

Which procedure – direct or iterative – must be selected? From a theoretical viewpoint, researchers usually conclude to the superiority of the direct method with respect to iterated forecasting when using a dynamic model – see again Chevillon and Hendry (2005). Empirically, the opinions are much divided. Marcellino et al. (2006) analysing a sample of 170 US macroeconomic time series variables lead to mixed results, but rather pro-iterated procedure. In the specific context of dynamic probit models, Kauppi and Saikkonen (2008) and Bismans and Majetti (2013) conclude without hesitation to the greatest efficiency of iterated forecasting approach.

4. The cyclical profile of South Africa

We begin with a comparative chronology of SA business cycle on the period from 1970 to 2010.

4.1 A comparative table of available chronologies

Remember that for South Africa, we have three different ways to date the cycle: BBQ algorithm; univariate or multivariate Markov-switching models and also the qualitative methodology of SARB. However, in this last case[3], it is not the classical business cycle which is measured, but the growth cycle, i.e. as Venter (2005, pp. 5-6) has indicated, the deviations of a composite index based on five series from its long-term trend.

Here is a table comparing the chronologies found in Bismans and Majetti (2012), Bismans and Le Roux (2013), SARB (various dates), and Bosch and Ruch (2013)[4]. They are respectively denoted by BM, B-LR, SARB and BR. Note that the original datation of SARB and BR was provided monthly, which necessitated to transform the dates in quarterly results.

Table 1. Turning points: A comparison (1980-2009)

Peaks				Troughs			
BM	**B-LR**	**SARB**	**BR**	**BM**	**B-LR**	**SARB**	**BR**
1981 Q3	1981 Q4	1981 Q3	1982 Q1	1983 Q1	1983 Q2	1983 Q1	1983 Q4
1984 Q2	1984 Q2	1984 Q2	1984 Q4	1986 Q1	1986 Q1	1986 Q1	1987 Q1
1989 Q3	1990 Q1	1989 Q2	1989 Q3	1992 Q4	1992 Q4	1993 Q2	1993 Q3
-	-	1996 Q4	1997 Q3	-	-	1999 Q3	1999 Q2
2008 Q3	2008 Q3	2007 Q4	2008 Q4	2009 Q2	2009 Q3	2009 Q3	-

Sources: Bismans and Majetti (2012), Bismans and Le Roux (2013), SARB (various dates), and Bosch and Ruch (2013)

The differences between BM and B-LR datations are extremely weak. The only noteworthy gap is towards the end of the sample. On the other hand, the deviations between the first two methods and the two seconds are important. Firstly, there is one supplementary cycle when measuring the growth cycle and not the classical business cycle (CBC). Secondly, the date for the beginning of the great recession differs significantly: 2007 Q4 for SARB chronology, 2008 Q4 for BM.

In general, the use of the growth cycle to determine turning points leads to isolate more cycles than the CBC-based procedure, which had already been observed by Berge and Jordà (2011) in the case of the United States.

[3] The paper by Bosch and Ruch (2013) follows also the growth rate approach.

[4] Laubscher (2014) is a refinement of the SARB dating procedure. Therefore his periodization of the SA business cycle will not be repeated here.

4.2 The 2015-2016 recession

As noted by Laubscher (2014, p.21), "the official SARB determination (…) lags actual turning points by 18 to 24 months (and longer)". In contrast, the BBQ algorithm can immediately isolate the recession phases in view of the evolution of real GDP level. Since then, the alternative is to use the BBQ algorithm.

But from the beginning of 2015, the South African economy entered an area of turbulence, as evidenced by the evolution of real GDP[5].

Table 2. The recent motion in the South African economy

	2015				2016				2017		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
GDP	3071,2	3056,9	3060,2	3064,1	3052,7	3076,5	3079,9	3077,5	3073,0	3094,5	3109,7
REC	0	1	1	1	1	0	0	0	0	0	0

Notes. 1. GDP is measured in billions of rands and at constant 2010 prices; seasonally adjusted; 2. REC is the recession indicator obtained by applying BBQ algorithm.
Source: SARB; own computations.

Our algorithm detects a peak in the first quarter of 2015. So the recession begins in the second quarter of that year. Hereafter, a low point of the cycle is reached in the beginning of 2016. Consequently, the economy enters a new expansion phase one quarter later. In total, the recession will have lasted a whole year.

The dynamics of the real GDP is much more shocked. Admittedly, the same peak is visible in the first quarter of 2015, but GDP then increases slightly during the third and fourth quarters before falling in the first quarter of the following year. In addition, GDP falls again in the last quarter of 2016 and in the first quarter of the following year.

These apparent contradictions are the direct product of the implementation of the algorithm. Remember indeed that the minimum duration of a recession is two quarters and that of a complete cycle of five quarters.

[5] Of course, it is important to remember that the first estimates of quarterly GDP are published 50 to 60 days after the end of the quarter in question and are therefore subject to subsequent revisions. These revisions are not insignificant, especially for the South African economy. The problem has been studied with the desired depth by Fotoyi (2016).

5. Predicting in real time

Using mainly Venter (2016) and OECD (2017), we will first look at the macroeconomic context in the years after the Great Recession of 2008-2009.

5.1 After the Great Recession

As we saw before, South Africa has emerged from the recession in the third quarter of 2009. The contraction itself is largely the product of the world financial crisis of 2008. Indeed, Laubscher (2004) has shown[6] that the South African business cycle was strongly impacted by the economic situation abroad. The recovery also was initially influenced by a strong increase in export demand from China in particular, accompanied by an increase in the price of international goods. Demand for consumption and also for investment then took over. Only public expenditure was rising sharply, which in 2012/2013 should lead to a public deficit of around 5 per cent of GDP.

However, from the fourth quarter of 2011 onwards, the price of the goods turned around. At the same time, the recovery was very weak in the euro area and even turned into a recession in 2012-2013 following the sovereign debt crisis. These factors negatively affected South African growth, which weakened further as a result of several internal supply factors:

- the increasing cost and declining reliability of electricity supply, which penalized the big energy consuming sectors;
- the increasing number of strike movements in the manufacturing sector;
- the weakness of private investment.

Furthermore, consumer price index jumped from 3 percent in 2010 to more than six percent three years later, while the current account of the balance of payments registered an equal deficit of 5 percent of GDP in 2014.

By the end of 2013 growth is stalling. The SARB – see Venter (2016, p.112) – signals that a peak in the growth cycle was reached in November 2013. From 2014, all components of aggregate demand are trending downward and as has been shown, a true recession occurs between the second quarter of 2015 and the first quarter of the following year.

[6] Laubscher (2004, p.26) speaks of "an extraordinary correlation" between the G7 industrial production and the SA cyclical movement.

During the year 2016, the government tried to revive the economic machine by increasing its expenditure (+ 2% in volume, 2010 prices). However, the decrease of the gross fixed capital formation was very marked (-3.9%), so that the increase in final domestic demand was only 0.1%.

Table 3 shows how real GDP has changed over the course of 2017.

Table 3. Real gross domestic product
(Quarter-to-quarter change at seasonally adjusted annualized rates)

Sector	Q1	Q2	Q3	Q4
Primary	15.5	13.9	13.7	4.9
Secondary	-3.7	2.8	1.5	3.1
Tertiary	-1.7	1.2	1.1	2.7
TOTAL	-0.5	2.9	2.3	3.1

Source: Stats New

Looking at this table, we can conclude that despite the mixed results of the first quarter of 2017, growth seems to be strengthening at the end of the year. Note also the great volatility of the growth in the primary sector.

5.2 Building a dynamic probit model

Selection of predictors and lags is made following the general to specific (GETS) methodology associated to the researches of Hendry and his collaborators – see, for example, Hendry and Doornik (2014). However, this procedure is not directly relevant for our research, essentially because the probit to use is a purely predictive model, not an explanatory or policy analysis model. Thus we are constrained to innovate and to define a particular algorithm to specify the dynamic probit model.

In synthetizing, the manual procedure to select relevant predictors and their corresponding lags goes through three steps:

(i) in a first step, we select the optimal number of lags for a set of predictors: the difference of logs of monetary stocks M1, M2, M2-M1; the index of shares prices from Johannesburg Stock Exchange; the interest rate on the South African Treasury Bills with a maturity of three months; the interest rate on 10-year South African Government Bonds; the yield spread defined as the difference between the two previous rates; the spread between US and South African 3-month treasury bills; the gap between South

African exports and imports; global credit supply, and also a Composite Leading Indicator established by the South African Reserve Bank. We eliminate irrelevant predictors for a static probit model by using three statistical indicators: 1. significance of estimates; 2. adjusted R-squares; 3. information criteria.

(ii) the second step consists to estimate a first dynamic probit model including the predictors selected at the previous step;

(iii) the last step will lead to the final model via a set of reduction operations, also based on the three indicators used in the first stage.

Enforcing significant coefficients, information criteria and pseudo-R^2 yields five predictors of recessions: D_L_CREDIT (-5), D_L_M2-M1 (-5), Spread (-2), GB_10 (-2), and TB3M (-2)[7]. Appendix 1 details the procedure for one of the selecting predictors: the credit variable. At this point, note that the presence of the spread in this equation should not be surprising as it is a variable that has long been used as a predictor of recessions. (See, for example, Estrella and Hardouvelis (1991), Estrella and Mishkin (1997, 1998), Dueker (1997), Chauvet and Potter (2005), Bismans and Majetti (2013), and for South Africa, Botha and Keeton (2014).)

The second step leads to the following model:

Table 4. The general unrestricted forecasting model (1980-2017)

Variables	Coefficient	*t*-statistic	Marginal effect
Constant	-2.79	-2.77	-
$\mathbf{Rec}_{t-1}$	2.56	6.22	0.71
$\mathbf{Spread}_{t-2}$	-0.16	-1.88	-0.02
$\mathbf{GB\_10}_{t-2}$	0.03	0.5	0.004
$\mathbf{DLCREDIT}_{t-5}$	15.96	1.26	2.55
$\mathbf{DLM2M1}_{t-5}$	6.78	1.47	1.09

Note: TB3M (-2) is omitted due to exact collinearity.

In the last step, we apply sequential reduction operations to the previous model using the three statistical indicators detailed above. The details of this process are fully given in the appendix 2.

[7] D denotes first difference, L logarithm. GB_10 denotes government bonds with a maturity of ten years and TB3M is the rate on the treasury bonds with a maturity of three months.

Finally, there then remains only two predictors: the credit lagged of five quarters and the binary variable Rec with one quarter lag. (This last practice is well established among the users of probit models – see, for example, Kauppi and Saikkonen (2008) or Bismans and Majetti (2013). It is economically justified by the fact that a recession lasts at least two quarters.)

The final dynamic reduced model is reproduced in table 6, which especially gives the coefficients of the two predictive variables, standard error, *t*-statistics and also the so-called "marginal effects"[8].

Table 6. The predictive model

Variables	Coefficient	Standard error	*t*-statistic	Marginal effect
Constant	-2.87	0.63	-4.52	-
Rec $_{t-1}$	2.81	0.39	7.22	0.78
DL_CREDIT$_{t-5}$	21.81	12.01	1.82	3.66
Adjusted pseudo- R^2 =0.563		LR test = 92.15 (0.000)		BJ = 1.57 (0.456)

5.3 Interpreting the final model

Several statistical remarks can be made based on the results of estimation synthetized in table 6:

1. The pseudo-R^2 computed according to Mc Fadden or Estrella (1998) is near of 0.6, which represents a good fitting for a probit model. Moreover, the p-value of the likelihood ratio test leads to rejection of the null hypothesis that the coefficients associated to the predictors are all equal to zero. For its part, the Bera-Jarque (BJ) test suggests that the residues of the model are normally distributed.

2. All the coefficients of the final model are highly significant, without exception. The decayed binary variable *Rec* affects positively the recession probabilities, while a positive variation (in percent) of the credit supply entails increasing recession probabilities.

[8] The presence of marginal effects in a qualitative model is due to the deep non-linearity of the probit functional form.

3. Particularly interesting is the review of the marginal effects associated with the different predictors. In this perspective, the principal determinant of recession probabilities is the lagged credit supply: when this latter grows by one percent, then the probability of being in recession in the next period increases of 4.43 percent. On the other hand, the effect of the recession indicator Rec on these probabilities is lower.

It now remains to justify economically the positive relationship between credit and probability of contraction. It should be noted, however, that it is the increase in the rate of credit growth - a first difference in logarithms! - that increases the likelihood of a recession in the economy.

That the effects of credit growth are macroeconomically destabilizing is not a new thinking in economics. Just remember the names of Schumpeter, von Mises[9], Minsky or Kindleberger. Such a view, which is otherwise rather minor, can be summarized by the formula: “Credit booms gone bust.” More important to us is the analysis of Nobel Prize winner Maurice Allais (1984), which is summarized as follows.

Modern bank creates money *ex nihilo* through the fractional deposit coverage system. Indeed, only a fraction of deposits is covered by central bank money; the rest is lent and therefore constitutes credit money, loans making deposits.

Moreover, the creation of money by the credit mechanism is a profitable system for the banks, which lends as much as they can. In total, the growth of money supply and of its banking component is uncontrollable. To this extent, as Allais (1984, p. 498) writes, “The system is fundamentally instable”. Allais (1984, p. 513 sq.) also shows the existence of a strong correlation between short term variations in the money supply, global expenditure and the level of employment.

On a purely empirical level, the economic historians Schularick and Taylor (2012) built an impressive data base incorporating many economic variables relating to money, credit and to a set of macroeconomic indicators, and covering 14 developed countries (The United States, Germany, France, Great Britain, etc.) over the years 1870-2008. The two authors showed that “in the aftermath of postwar financial crises, output dropped a cumulative 7.9 percent relative to trend, and real investment by more than 25 percent.” By using a predictive logit model,

[99] Von Mises: “The expansion of credit (…) inevitably leads into the slump”.

Schularick and Taylor (2012, p.1045) also obtained an interesting result – we quote: "a credit boom over the previous five years is indicative of a heightened risk of a financial crisis."

These analyzes and results support the existence of a positive relationship between the acceleration of credit growth – acceleration, not simply, the growth of the credit –, and the likelihood of recessions.

5.5 A set of forecasts in real time

Our task is now to answer to the question: Is a new recession likely to occur in 2018-2019? To do this, we will use the dynamic probit model as estimated in subsection 5.2. More precisely, we predict the recession probabilities in real time for the period 2018Q1-2019Q1. The prediction horizon is thus $h = 5$, that is the lag of the CREDIT variable.

In accordance with the iterated approach of forecasting, we generate the recession probability in $t+1$ by using the value for Rec in period *t*. Of course, we will adopt in this regard a precise rule to determine the state – expansion or contraction – of the economy: if the recession probability is equal or higher than 50%, it follows that the economy is in a contraction phase and then Rec = 1; this is the opposite if this probability is below the threshold of 0.5. In this last case, Rec takes the value 0.

Here are the results for this predictive attempt.

Table 7. Real time forecasts (2018Q1-2019Q1)

	2018Q1	**2018Q2**	**2018Q3**	**2018Q4**	**2019Q1**
Prob (Rec)	0.0151	0.0184	0.0094	0.0113	0.0197

Throughout 2018, the probabilities of recession are less than 2 percent. For the 3rd quarter of that year, the probability is even lower than the percent. For the first quarter of the following year, this probability is almost 2 per cent.

It can therefore be concluded that the risk to the South African economy of falling back into recession is extremely low over the period of the model's forecast horizon. Obviously, these are only probabilities, not certainties.

Of course, only the future will be able to indicate if this prediction is correct or not. This is a risk that no one can escape once a real-time forecast is realized!

6. Concluding remarks

The implementation of the BBQ algorithm to the real GDP data has allowed to identify a new recession during the period 2015Q2-2016Q1, which succeeded the one that occurred in 2008-2009. In this way, the South African economy has experienced a long phase of growth during twenty-four successive quarters. (This periodization differs from that established by the SARB, which isolates a peak in November 2013. Such a difference is due to the fact that the Bank is interested in measuring the growth cycle and not the classical business cycle, as we are.)

The constructed dynamic probit model is very parsimonious. Indeed, it includes only one predictor, namely the first difference of the logarithm of credit supply. Moreover this predictor is lagged by five quarters, so that the forecast horizon is equal to the year 2018 and the first quarter of 2019. It delivers one interesting result: A real-time forecast leads to the result that the probability that the South African economy will fall back into recession during the 2018Q1-2019Q1 period is extremely small – consistently less than 2 percent.

A natural outlet for this work would be to refine the base model so as to publish quarterly a forecast of the probabilities of recession for the next 5 successive quarters. Such real-time forecasts would be added to those provided by traditional forecasting models, which, in general, are not very reliable – see Juhn and Loungani (2002) or Harding and Pagan (2010), and for South Africa, van Walbeek (2013).

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Appendix 1. The selection of predictors

We are taking the example of the variable Credit. The procedure is similar for the four other predictors selected. We will use the following indicators to conduct the choice of the lags: *t*-statistic for the estimated coefficient; adjusted pseudo-R^2; information criteria: Akaike information criterion (AIC), Bayesian Information criterion (BIC), and Hannan-Quinn criterion (HQC).

Lags	*t*-statistic	pseudo-R^2	AIC	BIC	HQC
k = 3	1.95	- 0.006	154.97	160.95	157.40
k = 4	3.2	0.03	149.00	154.97	151.42
k = 5	4.10	0.077	141.29	147.25	143.71

Note: We have suppressed the data for one or two lags in Credit variable, which are not interesting.

As seen in this table, all the indicators yield the same conclusion: we must select five lags for credit, because the *t*-statistic betters and the pseudo-R^2 is also improving. As for the information criteria, they are minimal for $k = 5$.

Appendix 2. The sequential reduction process

We are beginning with the initial general unrestricted model in the table 4. Subsequently, we sequentially eliminate the redundant variables using the following indicators: *F*-tests on the omitted variables and their associated p-values; pseudo-R^2; the three information criteria (AIC, BIC, and HQC). Recall that in step 0, there are five predictors in the corresponding equation: Rec, Spread, GB_10, d_l_M2M1 and CREDIT.

Step	Omitted variables	p-value	pseudo-R^2	AIC	BIC	HQC
0			0.56	67.12	84.98	74.38
1	Spread (-2), GB_10 (-2)	0.15	0.56	66.85	78.76	71.69
2	d_l_M2M1(-5)	0.1	0.56	66.9	75.84	70.53

Note: The p-value is that corresponding to a *F*-test on omitted predictor(s) as we said previously.

At the first stage, all the information criteria are minimal and the p-value for the null – Spread and Government Bonds equal to zero – is higher than the size of 5 percent. Therefore, we accept the null hypothesis. Similarly, in the second step, we also accept the null and conclude that the variable M2-M1 can be omitted from the model. In addition, two of the information criteria are improved in this configuration, which reinforces the previous conclusion.

At the end of the reduction process, we obtain the final model able to realize the optimal forecasts – a parsimonious model, well-defined.