Physica A 507 (2018) 524–533

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

The changing economic regimes and expected time to recover of the peripheral countries under the euro: A nonparametric approach

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HIGHLIGHTS

- A nonparametric method for estimating the expected time to recover from a negative or positive shock or change is proposed.
- The proposed method relies on the basis of two assumptions: a Markovian property and stationarity.
- The method is applied to appreciate the impact of the monetary regime change on the dynamics of the peripheral countries in Europe.
- We show that the Euro generated a regime change in the macrodynamics of the economic space we consider.

ARTICLE INFO

Article history:
Received 2 November 2017
Received in revised form 1 March 2018
Available online 17 May 2018

Keywords:
Economic regime change
Economic divergence
Markov chain
Expected hitting times

ABSTRACT

A nonparametric method is presented in order to estimate the expected time to cross a threshold on the basis of two assumptions, a Markovian property and stationarity. An empirical application is provided, using this method to investigate the dynamics of the GDP of 16 countries of the European Union for a long period, 1962–2016, and to detect the patterns of growth rates and expected mean reversion time after a negative, i.e a recession, or a positive deviation from the trend. The conclusion supports the hypothesis of an economic regime change in the eurozone, affecting in particular the peripheral countries of southern Europe, ignited by the creation of the common currency.

1. Introduction

The expected time to cross a given threshold is an important concept in stochastic analysis, although not commonly used in economic investigations. In the case of this paper, we develop a new method [1] to compute the expected time to recover or to adapt from a negative or positive shock or change. Independently of considerations on the endogenous or exogenous nature of perturbations in the dynamics of the aggregate measure of economic activity, the GDP, and accepting for the purpose of the computation the approximation provided by the required two assumptions (Markovian property and transformation for stationarization of data), we apply this method to appreciate the impact of the monetary regime change occurring from 1999 on the dynamics of the economies of the peripheral countries in Europe. Section 2 summarizes the methodology and Section 3 the empirical results, whereas Section 4 presents a conclusion.

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https://doi.org/10.1016/j.physa.2018.05.089
0378-4371/

2. Methodology: a nonparametric method to estimate the expected time

The expected time for the economy to recover after a slump is an important indicator on how robust the economy is to shocks and how effective the policies and institutions are to regain the path of *normal growth*.

The econometric literature offers few alternative approaches to analyze this issue. A possible measure, commonly related to the level of persistence of a time series, is the half-life which is usually defined as the number of periods required for the impulse response to a unit shock of a time series to dissipate by half. However, empirical studies of half-lives have documented some issues related to the precision and unbiasedness of the estimates [2]. Most of the problems are related to incorrect model specification (apart from other sources such as temporal aggregation, structural breaks, etc.). Furthermore, half-life implies that a positive and negative shock of equal magnitude has the same impact on the impulse response function; however, the reversion to a fixed point (e.g. stationary mean) may display different behavior depending on whether the process is below or above that point.

Another way to discuss the time to recover can be based on the concept of expected time (ET) to cross some thresholds. For example, suppose that the GDP growth rate crosses some negative value say x_0, indicating that the economy is in recession; then define a higher level or threshold that the process eventually reaches in the future, say x_1. The expected time for the process to go from x_0 to x_1 is an indication of how resilient and robust the economy is to recover from recession. The ET concept has received little attention in economics. One of the reasons is probably the difficulty in obtaining a simple procedure to calculate, for example, the expected time (ET) to reach a threshold. In fact, analytical results on first hitting time problems (from which expected time may be calculated) are mostly based on stochastic processes of diffusion type or Markov chains where explicit analytical expressions are usually available. First hitting times are often used in mathematical finance, biology and other life sciences, where Markov chains and stochastic differential equations are more commonly used, for example, to study time to extinction or default (in finance). Nonetheless, ET may also be a very useful tool in economics to discuss topics such as the speed of mean-reversion, the time to equilibrium, and especially in the current case the time to recovery.

In this paper, we use a new estimator by Nicolau [1] to estimate the expected time to cross some thresholds. This estimator is formulated in a completely nonparametric framework and uses only two assumptions: Markovian property and stationarity. Standard errors can also be computed. We sketched the main ideas of the method here.

Let y be the GDP growth process with state space $\mathbb{R}$. We assume that: (A1) y is a Markov process of order r $(1 \le r < \infty)$ and (A2) y is a strictly stationary process. Under assumption A2, it can be proved that starting the process from a level a not belonging to the generic set A, the process y visits A an infinite number of times as $t \to \infty$, almost surely, see [3, chap. 9]. This property is of course crucial for (pointwise) identification.

We consider the hitting time $T := T_{x_1} = \min\{t > 0 : y_t \ge x_1\}$ and suppose that the process starts at value $x_0 < x_1$. The case $x_0 > x_1$ with $T_{x_1} = \min\{t > 0 : y_t \le x_1\}$ is almost analogous. A brief remark on this case will be made later on. The distribution of T is usually difficult to deduce for general non-linear processes. However, there is a simple nonparametric method to estimate these quantities. Set $S_0 = 1$ if $y_0 = x_0$ (note that the process starts at $y_0 = x_0$). Now define the following transformation for $k \ge 0$

$$S_t = \begin{cases} 1 & \text{if } y_t < x_1, y_{t-1} < x_1, \ldots, y_{t-k+1} < x_1, y_{t-k} \le x_0 \\ 2 & \text{if } x_0 < y_t \le x_1, x_0 < y_{t-1} \le x_1, \ldots, x_0 < y_{t-k+1} \le x_1, y_{t-k} \ge x_1 \\ 3 & \text{otherwise.} \end{cases} \tag{2.1}$$

Fig. 1 illustrates the map (2.1) for a hypothetical trajectory of y.

The probabilities of T, which can be difficult or impossible to obtain from y, may be easily calculated from process S_t. It can be proved that

$$P(T = t) = (1 - p_t) \prod_{i=1}^{t-1} p_i = (1 - p_t)\, p_{t-1} p_{t-2} \ldots . p_1$$

where $p_t = P(S_t = 1 | S_{t-1} = 1, S_{t-2} = 1, \ldots, S_0 = 1)$. Our strategy is to treat S_t as a Markov chain with state space $\{1, 2, 3\}$ from which we then estimate the relevant parameters. The following result supports our approach.

Proposition 2.1. *Suppose that y is a rth order Markov process. Then S is a rth order Markov chain.*

From the A1 assumption and previous proposition, one has $p_t = P(S_t = 1 | S_{t-1} = 1, S_{t-2} = 1, \ldots, S_{t-r} = 1)$. The probabilities p_t can be estimated from standard Markov chain inference theory.

We first analyze the case $r = 1$. To emphasize the dependence of S_t on the thresholds x_0, x_1, we write the transition probability matrix as $\mathbf{P}(x_0, x_1) = \left[P_{ij}(x_0, x_1)\right]_{3\times 3}$ where $P_{ij} = P_{ij}(x_0, x_1) := P(S_t = j | S_{t-1} = i)$. The only parameter of interest is P_{11}. If S is a first order Markov chain, i.e. $r = 1$, then $p_t = P(S_t = 1 | S_{t-1} = 1) = P_{11}$ and

$$\mathbf{E}[T] = \sum_{t=1}^{\infty} t p_t = (1 - P_{11}) \sum_{t=1}^{\infty} t P_{11}^{t-1} = \frac{1}{1 - P_{11}}. \tag{2.2}$$

This quantity can be easily estimated from the maximum likelihood estimate $\hat{P}_{11} = n_{11}/n_1$ where n_{11} is the number of transitions of type $S_{t-1} = 1$, $S_t = 1$ and n_1 counts the number of ones (i.e. $S_t = 1$) in the sample.