Debt ceiling and fiscal sustainability in Brazil: A quantile autoregression approach

Luiz Renato Lima,⁎, Wagner Piazza Gaglianone, Raquel M.B. Sampaio

Graduate School of Economics, Getulio Vargas Foundation, Praia de Botafogo 190, s. 1104, Rio de Janeiro, RJ22253-900, Brazil
Central Bank of Brazil, Brazil and Graduate School of Economics, Getulio Vargas Foundation, Brazil
Midi-Pyrénées Sciences Economiques, Université de Toulouse I — Sciences Sociales, Manufacture des Tabacs, 31042 Toulouse Cedex, France

Received 28 October 2005; received in revised form 3 November 2007; accepted 5 November 2007

Abstract

In this paper we investigate fiscal sustainability by using a quantile autoregression (QAR) model. We propose a novel methodology to separate periods of nonstationarity from stationary ones, allowing us to identify various trajectories of public debt that are compatible with fiscal sustainability. We use such trajectories to construct a debt ceiling, that is, the largest value of public debt that does not jeopardize long-run fiscal sustainability. We make an out-of-sample forecast of such a ceiling and show how it could be used by policy makers interested in keeping the public debt on a sustainable path. We illustrate the applicability of our results using Brazilian data.

© 2007 Elsevier B.V. All rights reserved.

JEL classification: C22; E60; H60
Keywords: Fiscal policy; Debt ceiling; Quantile autoregression

1. Introduction

For decades, a lot of effort has been devoted to investigating whether long-lasting budget deficits represent a threat to public-debt sustainability. Hamilton and Flavin (1986) was one of the first studies to address this question testing for the nonexistence of a Ponzi scheme in public debt. They conducted a battery of tests using data from the period 1962–84 with the assumption of a fixed interest rate. Their results indicate that the government’s intertemporal budget constraint holds. In a later work, Wilcox (1989) extends Hamilton and Flavin’s work by allowing for stochastic variation in the real interest rate. His focus was on testing for the validity of the present-value borrowing constraint, which means that public debt will be sustainable in a dynamically efficient economy if the discounted public debt is stationary with an unconditional mean equal to zero.

An important and common feature in the aforementioned studies is the underlying assumption that economic...
time series possess symmetric dynamics. In recent years, considerable research effort has been devoted to studying the effect of different fiscal regimes on long-run sustainability of the public debt. When the public debt possesses a nonlinear dynamic, it may be sustainable in the long-run but can present episodes of unsustainability in the short-run. Indeed, some studies have reported the existence of short-run fiscal imbalances. For instance, Sarno (2001) uses a smooth transition autoregressive (STAR) model to investigate the U.S. debt–GDP ratio and states that the difficulty encountered in the literature in detecting mean reversion of the debt process may be due to the linear hypothesis commonly adopted in the testing procedures. According to the author, the U.S. debt–GDP ratio is well characterized by a nonlinearly mean reverting process, and governments respond more to primary deficits (surpluses) when public debt is particularly high (low).

More recently, Davig (2005) uses a Markov-switching time series model to analyze the behavior of the discounted U.S. federal debt. The author uses an extended version of Hamilton and Flavin (1986) and Wilcox (1989) data and identifies two fiscal regimes: in the first one, the discounted federal debt is expanding, whereas, it is collapsing in the second one. He concludes that although the expanding regime is not sustainable, it does not pose a threat to the long-run sustainability of the discounted U.S. federal debt. Arestis et al. (2004) consider a threshold autoregressive model and, by using quarterly deficit data from the period 1947:2 to 2002:1, they find evidence that the U.S. budget deficit is sustainable in the long-run, but that fiscal authorities only intervene to reduce budget deficits when they reach a certain threshold, deemed to be unsustainable.

A common finding in the studies of Sarno (2001), Arestis et al. (2004), and Davig (2005) is that the presence of a nonlinear dynamic in public debt permits the existence of short episodes in which public debt exhibits a nonsustainable behavior. Such short-run behavior, however, does not pose a threat to long-run sustainability. Therefore, there could be three possible paths for public debt: (i) long-run sustainable paths with episodes of fiscal imbalances; (ii) long-run sustainable paths without episodes of fiscal imbalances and; (iii) long-run unsustainable paths. How can we identify and separate each of the aforementioned paths? This paper addresses this question by proposing a novel measurement of debt ceiling that can be used to guide fiscal-policy managers in their task of keeping public debt sustainable in the long run.

The methodology developed in this paper is based on the so-called quantile autoregressive (QAR) model, introduced by Koenker and Xiao (2002, 2004a,b). The QAR approach provides a way to directly examine how past information affects the conditional distribution of a time series. This feature of the QAR model is fundamental to the methodology proposed in this paper since our measurement of debt ceiling ($\tilde{D}_t$) will be nothing more than the upper conditional quantile of the public debt that satisfies the transversality condition of a no-Ponzi game. Compared to the QAR approach, other nonlinear methods such as smooth transition autoregressive (STAR), threshold autoregressive (TAR) or Markov switching are not able to estimate conditional quantiles since they were originally proposed to estimate nonlinear models for conditional means (or variance).

The proposed measurement of debt ceiling has the following main feature: if public debt $y_t$ has nonstationary behavior at time $t=t_A$, then $y_t > \tilde{D}_t$ at $t=t_A$, otherwise $y_t \leq \tilde{D}_t$. We also estimate $H = \frac{1}{T} \sum_{t=A}^{T} I (y_t > \tilde{D}_t)$, where $I(\cdot)$ is an indicator function and $T$ is the sample size, representing the percentage of periods in which public debt had an (local) unsustainable behavior. There are, therefore, two important issues we want to address in this paper. Firstly, how to identify $\tilde{D}_t$ and, consequently, $H$? With this information in hand, the policy maker can evaluate whether a given fiscal policy is at risk, that is, if $y_t$ is above $\tilde{D}_t$, or whether it is sustainable but too austere, in the sense that $y_t$ is too far below $\tilde{D}_t$. Secondly, how to make multi-step-ahead forecasts of the debt ceiling? A decision maker (fiscal authority) can use such a forecast to decide whether or not to take some action against long-run unsustainable paths of public debt.

The methodology developed in this paper complements the study by Garcia and Rigobon (2004), which proposed a very attractive technique to study debt sustainability from a risk management perspective by using a Value at Risk (VaR) approach based on Monte Carlo simulations. However, in their article, the choice of the quantile needed to compute the “risky” threshold of sustainability for public debt was somewhat arbitrary. The methodology proposed in this paper goes beyond their approach by computing the exact quantile, the so-called critical quantile, that is used to separate sustainable fiscal policies from unsustainable ones. Therefore, our measurement of debt ceiling can be viewed as a more elaborated concept of VaR in the sense that it appropriately uses economic theory to identify the quantile needed to compute the “risky” threshold, rather than choosing it arbitrarily.

We illustrate the applicability of our debt-ceiling measurement by using data from the Brazilian public debt. Fiscal stabilization in Latin American countries, and especially in Brazil, has received a lot of attention.
over the last decade. In effect, Issler and Lima (2000) showed that public-debt sustainability in Brazil from 1947 to 1992 was achieved mostly through the usage of revenue from seigniorage. However, after the Brazilian stabilization plan in 1994, this source of revenue disappeared, leading fiscal authorities to propose tax increases in order to run high primary surpluses needed to guarantee fiscal sustainability. The need for obtaining high primary surpluses possibly implied a shift to fiscal austerity and probably a cost in terms of foregone output and higher unemployment. Has the fiscal policy in Brazil been too austere or has it been just restrictive and higher unemployment. Has the fiscal policy in

2. Methodology

2.1. Theoretical model

There is extensive literature on the government’s intertemporal budget constraint. The general conclusion is that fiscal policy is sustainable if the government budget constraint holds in present-value terms. In other words, the current debt should be offset by the sum of expected future discounted primary budget surpluses. The approaches used to analyze sustainability of fiscal policy consist in testing if the public debt and/or budget deficit is a stationary process.

The theoretical framework used here to investigate the sustainability of the Brazilian federal debt follows Uctum and Wickens (2000), which extends the results of Wilcox (1989) to a stochastic and time-varying discount rate, considering a discounted primary deficit that can be either strongly or weakly exogenous. According to the authors, a necessary and sufficient condition for sustainability is that the discounted debt–GDP ratio should be a stationary zero-mean process. As a starting point of the analysis, Uctum and Wickens (2000) investigate the one-period government intertemporal budget constraint, which can be written in nominal terms as

\[ G_t - T_t + i_tB_{t-1} = \Delta B_t + \Delta M_t = -S_t, \quad (1) \]

where \( G = \) government expenditure, \( T = \) tax revenue, \( B = \) government debt at the end of period \( t, M = \) monetary base, \( S = \) total budget surplus, \( i = \) interest rate on government debt. Dividing each term of Eq. (1) by nominal GDP, one could obtain the budget constraint in terms of proportion of GDP

\[ g_t - \tau_t + (\pi_t - \eta_t)b_{t-1} = \Delta b_t + \Delta \eta_t + (\pi_t + \eta_t)m_{t-1} = -s_t. \quad (2) \]

The variables \( g, \tau, b, m, \) and \( s \) denote the ratio of the respective variables to nominal GDP, \( \pi_t = (P_t - P_{t-1})/P_{t-1} \) and \( \eta_t = (Y_t - Y_{t-1})/Y_{t-1}, \) with \( P \) and \( Y \) standing for the price level and real GDP. This way, Eq. (2) can be rewritten as

\[ d_t + \rho b_{t-1} = \Delta b_t, \quad (3) \]

where \( d_t = g_t - \tau_t - \Delta \eta_t - (\pi_t + \eta_t)m_{t-1} \) is the primary government deficit expressed as a ratio to nominal GDP, and \( \rho_t = \delta_t - \gamma_t \) is the real ex-post interest rate adjusted for real output growth. According to the authors, if \( \rho_t < 0 \) for all \( t \) then Eq. (3) is a stable difference equation, which can therefore be solved backwards, implying that the debt–GDP ratio \( b_t \) will remain finite for any sequence of finite primary deficits \( d_t. \) It should be noted that for the constants \( \rho \) and \( d, \) the steady-state value of \( b \) is given by \( -d/\rho. \)

On the other hand, if \( \rho_t > 0 \) for all \( t, \) then the debt–GDP ratio will eventually explode for \( d_t > 0. \) Thus, primary surpluses are required to avoid this case (i.e. \( d_t < 0), \) and Eq. (3) must be solved forwards, in order to determine whether the sum of expected future discounted surpluses is sufficient to meet the current level of debt–GDP ratio. In addition, the authors rewrite (in ex-ante terms) the budget constraint for period \( t + 1 \) as

\[ b_t = E_t\left[ (1 + \rho_{t+1})^{-1}(b_{t+1} - d_{t+1}) \right], \quad (4) \]

where \( b_t \) is known in period \( t, \) and expectations are taken based on information at time \( t. \) Eq. (4) is solved forwards, resulting in the \( n \)-period intertemporal budget constraint

\[ b_t = E_t\delta_{t,n}b_{t+n} - E_t\sum_{i=1}^{n} \delta_{t,i}d_{t+i}, \quad (5) \]

where \( \delta_{t,n} = \Pi_{i=1}^{n}(1 + \rho_{i+1})^{-1} \) is the time-varying real discount factor \( n \) periods ahead, adjusted for real GDP growth rate. The discount factor \( \delta_{t,i} \) can also be written as \( \delta_{t,n} = a_t + a/n, \) where \( a_t = \Pi_{i=1}^{n}(1 + \rho_i)^{-1}. \)

The authors normalize \( a_0 = 1 \) and define \( X_t = a_t b_t \) and \( Z_t = a_t d_t \) as the discounted debt–GDP and primary
deficit–GDP ratios respectively. This way, Eq. (5), representing the present-value borrowing constraint (PVBC), can be rewritten as

\[ a_t b_t = E_t a_{t+n} b_{t+n} - E_t \sum_{i=1}^{n} a_{t+i} d_{t+i}, \]  

or as

\[ X_t = E_t X_{t+n} - E_t \sum_{i=1}^{n} Z_{t+i}. \]  

The one-period budget constraint given by expression (3) can also be written in discounted terms, in the following way

\[ b_{t-1} = (1 + \rho_t)^{-1} (b_t - d_t) = (a_t / a_{t-1}) (b_t - d_t), \]  

\[ X_{t-1} = a_t b_{t-1} = a_t b_t - a_t d_t = X_t - Z_t. \]  

Hence, Eq. (4) can be expressed by

\[ X_t = E_t (X_{t+1} - Z_{t+1}). \]  

2.2. Sustainability for infinite horizon

According to Uctum and Wickens (2000), a necessary and sufficient condition for sustainability is that as \( n \) goes toward infinity, the expected value of the discounted debt–GDP ratio converges to zero. This condition is usually known in the literature as the transversality condition (or no-Ponzi-scheme condition), and can be summarized by

\[ \lim_{n \to \infty} E_t X_{t+n} = 0. \]

This way, the current debt–GDP ratio is counter-balanced by the sum of current and expected future discounted surpluses, also expressed as a proportion of GDP, implying that the government’s budget constraint is given (in present-value terms) by

\[ b_t = - \lim_{n \to \infty} E_t \sum_{i=1}^{n} \delta_t d_{t+i}, \]  

or

\[ X_t = - \lim_{n \to \infty} E_t \sum_{i=1}^{n} Z_{t+i}. \]

Uctum and Wickens (2000) show that the necessary and sufficient condition for the intertemporal budget constraint (13) to hold is that the discounted debt–GDP ratio \((X_t)\) be a stationary zero-mean process. This way, if fiscal policy is currently (locally) unsustainable, then it will need to change in the future to guarantee (global) sustainability. In addition, the transversality condition requires the discounted debt–GDP ratio to converge to zero.

A starting point for investigating this condition arises from a graphical analysis of the discounted debt time series, which should be declining over the sample period. In this paper, we perform a formal test of the sustainability of the Brazilian federal debt, investigating the validity of the (necessary and sufficient) condition of stationarity with zero mean for the discounted debt–GDP ratio process. We will do so by using the quantile autoregression model which is briefly described in the next section.

3. The quantile autoregression model

In a sequence of recent papers Koenker and Xiao (2002, 2004a, b) introduced the so-called quantile autoregression (QAR) model. In this paper, we will show how one can separate nonstationary observations from stationary ones by using the QAR model. This result will have important implications on the literature of public-debt sustainability as shown in the next sections. For now, consider the following assumptions:

**Assumption 1.** Let \( \{U_t\} \) be a sequence of iid standard uniform random variables;

**Assumption 2.** Let \( \alpha_i(U_t), i=0,\ldots, p \) be comonotonic random variables.\(^2\)

We define the \( p \)th order autoregressive process as follows,

\[ y_t = \alpha_0(U_t) + \alpha_1(U_t) y_{t-1} + \ldots + \alpha_p(U_t) y_{t-p}, \]

where \( \alpha_j \)'s are unknown functions \([0, 1] \to \mathbb{R}\) that we will want to estimate. We will refer to this model as the QAR(\(p\)) model. Given Assumptions 1 and 2, the conditional quantile of \( y_t \) is given by

\[ Q_{\tau}(y_t|F_{t-1}) = \alpha_0(\tau) + \alpha_1(\tau) y_{t-1} + \ldots + \alpha_p(\tau) y_{t-p}, \]

\(^2\) According to Koenker (2005, p. 60), two random variables \(X, Y: \Omega \to \mathbb{R}\) are said to be comonotonic if there exists a third random variable \( Z: \Omega \to \mathbb{R} \) and increasing functions \( f \) and \( g \) such that \( X=f(Z) \) and \( Y=g(Z) \). In our paper, \( \beta_{ij}=\alpha_i(U_t), i=0,1,\ldots,p \) are comonotonic and \( \alpha_i(\cdot) \) are, by definition, increasing functions. See our proofs in the Appendix to understand the crucial usefulness of this assumption.
where \( F_{t-1} = (y_{t-1}, ..., y_{t-p}) \) and \( \tau \) is the quantile of \( U_t \). In order to develop intuitive understanding of the QAR model, let us consider the following simple example

\[
y_t = \alpha_0(U_t) + \alpha_1(U_t)y_{t-1},
\]

which is simply a QAR(1) model. It should be noted that the QAR model can play a useful role in expanding the territory between classical stationary linear time series and their unit-root alternatives. To see this, suppose in our QAR(1) example that \( \alpha_1(U_t) = U_t + 0.5 \). In this case, if \( 0.5 \leq U_t < 1 \) then the model generates \( y_t \) according to the nonstationary model, but for smaller realizations of \( U_t \), we have mean reversion tendency. Thus, the model exhibits a form of asymmetric persistence in the sense that sequences of strongly positive innovations of the iid standard uniform random variable \( U_t \) tend to reinforce its nonstationary like behavior, while occasional smaller realizations induce mean reversion and thus undermine the persistency of the process. Therefore, it is possible to have locally nonstationary time series being globally stationary.

### 3.1. Identifying nonstationary observations

We continue our reasoning by considering again the QAR(1) model (15) with the same autoregressive coefficient \( \alpha_1(U_t) = U_t + 0.5 \). If at a given period \( t = t_A \), \( U_{tA} = 0.2 \), then \( \alpha_1(U_{tA}) = 0.7 \) and the model will present a mean reversion tendency at \( t = t_A \). However, if at \( t = t_B \), \( U_{tB} = 0.5 \), then \( \alpha_1(U_{tB}) = 1 \), and \( y_t \) will have a local unit-root behavior. Suppose, for illustrative purposes, that this model can be represented by the stochastic process depicted in Fig. 1, in which \( y_t \) has a mean reversion tendency around the period \( t_A \). Now assume that for periods \( t > t_A \), there is a sequence of strong realizations of \( U_t \) inducing the model to nonstationary behavior at period \( t_B \).

A natural question that arises in this context is how to separate periods of stationary from periods where \( y_t \) exhibits nonstationary behavior? In other words, is it possible to construct a function \( Q_{yt} (\cdot) \) such that if \( y_t \) has a mean reversion tendency at time \( t = t_A \) then \( Q_{yt}(\cdot) \geq y_{t_A} \), but if \( y_t \) presents nonstationary behavior at time \( t = t_B \) then \( Q_{yt}(\cdot) < y_{t_A} \) (Fig. 2)?

This is a theoretical question that we aim to answer in this paper by using the QAR approach. In order to separate observations of \( y_t \) that exhibit a unit-root behavior from other observations with stationary behavior, we will need the following definitions:

**Definition 1.** Critical Quantile (\( \tau_{\text{crit}} \)) is the largest quantile \( \tau \in \Omega = (0, 1) \) such that \( \alpha_1(\tau) = \sum_{i=1}^{p} \gamma_i(\tau) < 1 \), where \( \tau \) is the quantile of \( U_t \).

**Definition 2.** Critical Conditional Quantile of \( y_t: Q_{yt}(\tau_{\text{crit}} | F_{t-1}) = \alpha_0(\tau_{\text{crit}}) + \alpha_1(\tau_{\text{crit}})y_{t-1} + \ldots + \alpha_p(\tau_{\text{crit}})y_{t-p} \) where \( F_{t-1} = (y_{t-1}, ..., y_{t-p}) \).

The critical quantile \( \tau_{\text{crit}} \) can easily be identified by using the Koenker and Xiao (2004b) test for \( H_0: \alpha_1(\tau) = 1 \) for selected quantiles \( \tau \in \Omega = (0, 1) \), presented in the Appendix. The critical conditional quantile \( Q_{yt}(\tau_{\text{crit}} | F_{t-1}) \), is merely the \( r \)th conditional quantile function of \( y_t \) evaluated at \( \tau = \tau_{\text{crit}} \). Consider the additional assumption.

**Assumption 3.** Let \( \Omega = (t_1, t_2, ..., t_T) \) be the set of all observations. Assume that for the subset of time periods \( T \subset \Omega \), the time series \( y_t \) exhibits nonstationary behavior, i.e., unit-root model. Now we can state proposition 1.5

---

3 See the Appendix for further details regarding the QAR model, including alternative representations, stationarity conditions, central limit theorem, estimation, autoregressive order choice, global stationarity, unconditional mean tests, and local analysis through the Koenker and Xiao (2004b) test.

4 The DGP used to construct this example is represented by the QAR(1) model \( y_t = \alpha_1(U_t)y_{t-1} \) where \{\( U_t \)\} is a sequence of iid standard uniform random variables, and the coefficients \( \alpha_1 \) is a function on \([0, 1]\), given by \( \alpha_1(U_t) = \min\{1; \gamma_1 \cdot U_t\} \), where \( F: \mathbb{R} \rightarrow [0, 1] \) is the standard normal cumulative distribution function. We set the parameter \( \gamma_1 = 0.8 \) for \( t = (1, ..., 65) \); 10 for \( t = (66, ..., 90) \); 5 for \( t = (91, ..., 152) \) and 0.8 for \( t = (153, ..., 200) \).

5 A Monte Carlo experiment is presented in the Appendix to verify the result of Proposition 1 in finite samples. The simulation reveals that the critical conditional quantile indeed exhibits good behavior in finite samples, by correctly separating nonstationary periods from stationary ones.
Proposition 1. Consider the QAR(p) model (14) and Assumptions 1, 2 and 3. The critical conditional quantile of $y_t$ will always be lower than $y_t$ for all periods in which $y_t$ exhibits a unit-root behavior, that is, $Q_{yt}(\tau_{crit.}|F_{t-1}) < y_t$; $\forall t \in T$.

Proof. See Appendix.

In order to clarify this result, suppose that all observations of $y_t$, $t=1,...,T$, exhibit unit-root (stationary) behavior. In this case, the path of $y_t$ would always be above the path generated by $Q_y(\tau_{crit.}|F_{t-1})$ only at the periods where $y_t$ has a unit root.

In addition, by just comparing both time series $y_t$ and $Q_y(\tau_{crit.}|F_{t-1})$, one can compute the statistic $H$, which represents the percentage of periods in which $y_t$ exhibits (local) nonstationary behavior.

Definition 3. Let $H$ be the relative frequency of nonstationary periods, that is, $H = \frac{1}{T} \sum_{t=1}^{T} I_t \{ y_t > Q_y(\tau_{crit.}|F_{t-1}) \}$, where $T$ is the sample size and $I_t$ is an indicator function such that $I_t = \begin{cases} 1 & \text{if } y_t > Q_y(\tau_{crit.}|F_{t-1}) \\ 0 & \text{otherwise} \end{cases}$.

In order to link the statistic $H$ with the critical quantile, we can also state Proposition 2:

Proposition 2. If Assumptions 1 and 2 hold, then $H = (1 - \tau_{crit.})$.

Proof. See Appendix.

These two propositions enable us to identify periods in which the time series $y_t$ exhibits nonstationary (stationary) behavior. This methodology will be crucial to our analysis of fiscal sustainability as further described in Section 4.

3.2. Out-of-sample forecast

In the previous sections, we showed how to identify the critical conditional quantile. Now, we show how to make multi-step-ahead forecasts for the critical conditional quantile. In order to do so, we first forecast $y_t$ based on the simple idea of recursive generation of its conditional density, which is a quite novel approach introduced by Koenker and Xiao in 2006.

Recall that $T$ is the sample size and let $s$ be the forecast horizon. Given an estimated QAR model $\hat{Q}_y(\tau|F_{t-1}) = \hat{x}^T \hat{\alpha}(\tau)$ based on data $t=1,...,T$ we can forecast

$$\hat{y}_{T+s} = \hat{x}^T \hat{\alpha}(U_{T+s}) \quad \text{for } s = 1,...,s_{max} \quad (16)$$

where $U_{T+s} \sim$ iid Uniform (0, 1); $\hat{x}_{T+s} = [1, \hat{y}_{T+s-1},...,\hat{y}_{T+s-p}]$ and $\hat{\alpha} = \{ \hat{\alpha}_1, \text{if } t \leq T \}$.

Conditional density forecasts can be made based on an "ensemble" of such forecast paths, i.e., a great number ($k$) of future trajectories of $y_t$ enables us to construct the conditional density of $y_t$ at each future period $T+s$.

To better understand this idea, notice that $U_{T+s} \sim$ iid Uniform (0, 1). Hence, it is always possible to establish a 1:1 relationship between $\tau$ and a realization, $u_{T+s}$, of this iid standard uniform random variable $U_{T+s}$. Thus, for each realization of $U_{T+s}$, there is a 1:1 corresponding quantile $\tau = u_{T+s}$. Moreover, in estimating the conditional quantile function of $y_t$, $Q_y(\tau|F_{t-1})$, one can find the estimated coefficients $\hat{\alpha}(\tau)$ for each $\tau$ and, therefore, we can find $\hat{\alpha}(U_{T+s})$ for any realization of $U_{T+s}$. We proceed by generating a sequence of realizations of $U_{T+s}$ of size $s_{max}$, that is, $\{ u_{T+s} \}$, $s=1,2,...,s_{max}$. This way, we can make an out-of-sample trajectory of $y_t$ through Eq. (16). If we repeat the above steps $k$ times, then we will end up with an ensemble of forecast paths. We can now forecast the critical conditional quantile based on this ensemble of forecasts. In order words, for a given period $T+s$, $Q_y^*(\tau_{crit.}|F_{t})=\hat{\gamma}_{T+s}$ so that $Pr(\hat{\gamma}_{T+s} \leq y_{T+s} | F_T) = \tau_{crit.}$ This way, we are able to generate the sequence $\{ \hat{Q}_y(\tau_{crit.}|F_T) \}$ for $s=1,...,s_{max}$, which is nothing more than the forecast path of the critical conditional quantile. This methodology allows us to

---

Koenker and Xiao presented this forecasting approach at the Econometrics in Rio conference, which took place at the economic department of the Getulio Vargas Foundation, Rio de Janeiro, Brazil.
classify the future observations of the time series \( y_t \) into stationary and nonstationary ones.\(^7\)

In order to clarify the idea of a multi-step-ahead forecast, consider again the QAR(1) model discussed in Section 3.1. Thus, based on the estimated coefficients \( \hat{\alpha}_i(\tau) \) and the generation of \( k \) sequences of \( U_{T+s} \sim \text{iid Uniform} \) of size \( s_{\text{max}} \), we can compute (see Fig. 3) the conditional densities of \( y_{T+s} \) for the forecast horizons \( s=1, \ldots, s_{\text{max}} \). In our example, we considered \( k=1000 \) trajectories and \( s_{\text{max}}=200 \) periods.

Fig. 3 summarizes the above discussion. The red line represents the forecast of the critical conditional quantile. We can see that the out-of-sample forecast of the critical conditional quantile splits the ensemble of forecasts into two regions, A and B. All the paths in region A are nonstationary whereas they are stationary in region B. As we will show in our empirical exercise in Section 5, this separation has strong economic implications. Furthermore, the out-of-sample forecast of the critical conditional quantile apparently tends toward zero as long as the forecast horizon increases. In fact, as we will formally show in Proposition 3, if the time series process \( y_t \) is a zero-mean stationary process, then its critical conditional quantile will converge to zero at an infinite horizon.

4. Debt ceiling and fiscal sustainability

Hereafter let \( y_t \) be the discounted debt–GDP ratio process \( (X_t) \) presented in Section 2. Before introducing a "sustainability" concept, let’s consider the following (testable) additional assumptions:

**Assumption 4.** The time series \( y_t \) is covariance stationary.

**Assumption 5.** The unconditional mean of \( y_t \) is zero, i.e., \( \mu_y = 0 \).

Notice that Assumption 5 holds if we set \( \alpha_0(U_t)=0 \) in Eq. (14). In this case, the out-of-sample forecast \( \tilde{y}_{T+s} = \tilde{x}_{T+s}' \hat{\alpha}(U_{T+s}) \) would be computed from a vector without intercept \( \tilde{x}_{T+s} = [\tilde{y}_{T+s-1}, \ldots, \tilde{y}_{T+s-p}] \).

Hence, based on the study by Uctum and Wickens (2000), we adopt the following concept of public-debt sustainability:

**Definition 4.** A fiscal policy is “globally sustainable” if and only if the discounted debt–GDP ratio \( y_t \) is a stationary zero-mean process, that is, it satisfies Assumptions 4 and 5.

---

\(^7\) See Appendix for further details regarding the numerical procedure.
The previous assumptions denote that \( y_t \) is a stationary zero-mean process, which is a necessary and sufficient condition for global sustainability. If a fiscal policy is sustainable in the long run, there can still be local episodes of fiscal imbalances. How can we identify such local episodes and separate sustainable fiscal policies from unsustainable ones? In order to answer these questions, we define the concept of debt ceiling.

**Definition 5.** Debt ceiling \((\widehat{D}_t)\) is equal to the critical conditional quantile when Assumptions 1–5 hold.

The above definition establishes that the debt ceiling is nothing other than the critical conditional quantile of the discounted debt–GDP ratio, \( \widehat{D}_t = Q_{\gamma_t} (\tau_{\text{crit}}, |F_{t-1}|) \). In order to clarify the concept of debt ceiling, suppose that all the observations of \( y_t \), \( t = 1, \ldots, T \), exhibit sustainable behavior. In this case, they would always be below or on the path generated by \( \widehat{D}_t \). There may exist an intermediate case in which the public debt is still globally sustainable despite some episodes of local unsustainability. In this case, the path of \( y_t \) would be above the path generated by \( \widehat{D}_t \) only at the periods where \( y_t \) takes on unsustainable behavior. The proposed debt ceiling is a simple way to separate paths of public debt (fiscal policies) that are not sustainable from ones that satisfy the long-run transversality condition. This discussion is summarized in the following corollary.

**Corollary 1.** Consider the QAR(p) model (14), where \( y_t \) now represents the discounted debt–GDP ratio process. If Assumptions 1–5 hold, then the respective Debt Ceiling \((\widehat{D}_t)\) will always be lower than \( y_t \) in all periods where \( y_t \) is nonsustainable, that is, \( \widehat{D}_t < y_t \), \( \forall t \in T \).

**Proof.** See Appendix.

Corollary 1 is an immediate consequence of Proposition 1 when the Definitions 4 and 5 and the Assumptions 4 and 5 are also considered. Based on Corollary 1, we have the nice result that \( y_t > \widehat{D}_t \) for all periods in which the public debt takes on an unsustainable dynamic. Moreover, given that \( y_t \) is, by (testable) assumptions, a stationary zero-mean process, by just comparing \( y_t \) and \( \widehat{D}_t \) one can also compute what we call “debt tolerance”, that is, the percentage of episodes of local unsustainability that does not jeopardize long-run sustainability, that is:

\[
H = \frac{1}{T} \sum_{t=1}^{T} I_{\{y_t > \widehat{D}_t\}},
\]

where \( I(\cdot) \) is an indicator function and \( T \) is the sample size. Therefore, given a globally sustainable fiscal policy, \( H \) represents the percentage of violations of the transversality condition still compatible with long-run fiscal sustainability.\(^8\)

Regarding the out-of-sample forecast, the following proposition guarantees that the forecast path of debt ceiling will go to zero as the forecast horizon goes to infinity. This is an expected result from the literature on public-debt sustainability, since the transversality condition (or no-Ponzi-game condition) states that the forecast value of a sustainable (discounted) debt–GDP ratio must converge to zero.

**Proposition 3.** If Assumptions 1 to 5 hold, then the forecast path of the Debt Ceiling \((\widehat{D}_{T+s})\) will go to zero as the forecast horizon \( s \) goes to infinity, i.e.,

\[
\lim_{s \to \infty} \widehat{D}_{T+s} = 0.
\]

**Proof.** See Appendix.

In the next section, we show that the debt-ceiling concept can also be seen as a more elaborate concept of Value at Risk.

### 4.1. Debt ceiling and Value at Risk

In the financial literature, Value at Risk (VaR) is a measurement representing the worst expected loss of an asset or portfolio over a specific time interval, at a given confidence level. It is typically used by security houses or investment banks to measure the market risk of their asset portfolios.\(^9\) The VaR, can be defined as

\[
\Pr (r_t \leq \text{VaR}_t | F_{t-1}) = \tau,
\]

where \( r_t \) is the return on some financial asset, \( F_{t-1} \) is the information set available at time \( t-1 \), and \( \tau \in (0, 1) \) is the confidence level. From this definition, it is clear that finding a VaR is basically the same as finding a conditional quantile.

Following Hafner and Linton (2006), it is straightforward to show that the estimation of a VaR, is a natural application of the QAR model, that is

\[
\Pr (y_t \leq \text{VaR}_t | F_{t-1}) = \tau_{\text{crit}},
\]

\(^8\) Reinhart et al. (2003) developed the concept of “debt intolerance” based on a historical analysis of external debt. They divided the countries into debtors’ clubs and vulnerability regions, depending principally on a country’s own history of default and high inflation.\(^9\) For instance, if a given portfolio has a 1day VaR of $5 million (at a 95% confidence level), this implies, with a probability of 95%, that the value of its portfolio is expected to decrease by 5 million or less during 1day.
In our application of the QAR model, we estimate the exact conditional quantile that represents the limit of stationarity (our critical conditional quantile), which is used to define the debt ceiling, in accordance with the government’s intertemporal budget constraint. Thus, our proposed debt ceiling is nothing more than a “qualified” Value at Risk, that is

$$\bar{D}_t = Q_{\tau_{\text{crit}}}(F_{t-1}) = \text{VaR}_t.$$  

It is important to note, however, that the proposed “qualified” VaR concept goes far beyond the financial applications, in which an “ad-hoc” value for $\tau_{\text{crit}}$ is adopted (usually 1% or 5%). In our approach, we identify the exact critical quantile that represents a threshold, $\tau_{\text{crit}}$, according to a given theoretical economic model. This is a novel approach in the literature of public-debt sustainability, but it may have other applications in finance and macroeconomics. Garcia and Rigobon (2004) studied debt sustainability from a risk management perspective by using a Value at Risk (VaR) approach. The authors proposed a very attractive technique, based on Monte Carlo simulations, to compute “risk probabilities”, i.e., probabilities that the simulated debt–GDP ratio exceeds a given threshold deemed “risky”. However, their choice of the quantile needed to compute the “risky” threshold of sustainability was somehow arbitrary (see Fig. 4 of Garcia and Rigobon, 2004). The methodology proposed in this paper complements their approach by computing the exact “risky” quantile, the so-called $\tau_{\text{crit}}$, which enables us to properly separate nonsustainable paths of public debt from sustainable ones, instead of choosing an “ad-hoc” threshold of sustainability.\(^{11}\)

5. Empirical results

5.1. The database

The methodology presented in this paper is applied to the analysis of the discounted Brazilian federal debt. All data are quarterly and are obtained from the Central Bank of Brazil (BCB), the Institute of Applied Economic Research (IPEA), and the Brazilian Institute of Geography and Statistics (IBGE). Our sample covers the period from 1976.I to 2005.I (117 observations). The undiscounted debt represents the series “Dívida Mobiliária Interna Federal fora do Banco Central”, or federal domestic debt held by the public, in percentage of GDP.\(^{12}\) The discounted debt is given by the undiscounted debt series multiplied by the stochastic discount factor. Bohn (2004) mentions that the debt–GDP ratio suggests a “more benign view” of fiscal policy than the nominal and real series. The stochastic discount factor ($a_t$), as previously mentioned in the theoretical model, is generated from $\rho_t$ (the real ex-post interest rate adjusted for real output growth), which depends on the inflation and nominal interest rates, and real output growth. The inflation rate ($\pi_t$) is measured in a standard approach by a general price index (IGP-DI), and the nominal interest rate ($i_t$) is measured by the over/selic interest rate (equivalent to the U.S. Fed funds rate). Regarding real output growth ($\eta_t$), we generate a quarterly series based on the quarterly GDP, which is released by IBGE, with seasonal adjustments made by the MA(12)\(^{13}\) and X-11 methods.\(^{14}\)

$$a_t = \frac{1}{\prod_{i=0}^{t-1}(1 + \rho_i)} ; \quad a_0 = 1$$

$$1 + \rho_t = \frac{(1 + i_t)}{(1 + \pi_t)(1 + \eta_t)} .$$

\(^{11}\) Moreover, this paper presents a distribution-free approach to make out-of-sample forecasts of the debt ceiling. The same does not happen in Garcia and Rigobon (2004) since their simulations are based on the assumption of normal distribution innovations.

\(^{12}\) Following Rocha (1997), we focused the analysis on the domestic debt, since the sustainability of external debt is guaranteed by current account surpluses, and not by fiscal surpluses or seigniorage. Despite the fact that the debt–GDP ratio is not high in comparison to other nations, its sharp increase in the last decade is very concerning.

\(^{13}\) Following Garcia and Rigobon (2004).

\(^{14}\) Since the results based on these two techniques are very similar, we only report the MA (12) results.
According to Uctum and Wickens (2000), there are two major issues that must be addressed when using government debt data: whether to measure debt at market value or at face value (at par), and how to measure the discount rate. The authors state that the correct implementation of the government’s intertemporal budget constraint requires the use of the discounted net market value of debt. However, the market value of debt is usually not available, and the debt is generally expressed at par. An estimate of the market value of debt is obtained by multiplying the face value by the implied market price $1/(1+p_t)$, where $p_t$ is the yield on government debt. Some studies on the sustainability of the Brazilian public debt, such as Pastore (1995), Rocha (1997) and Giambiagi and Ronci (2004), used debt value at par, whereas Luporini (2000) uses market value. In our case, the analysis will only be conducted for the discounted debt at face value, since these two series, in our sample period, are very similar.

Fig. 4 presents the undiscounted and discounted Brazilian federal debt–GDP ratio. A simply visual inspection of Fig. 4 suggests that the discounted debt seems to be stationary, despite the sharply increasing path of the undiscounted series in the 1990s. The formal evidence on sustainability of the Brazilian public debt is investigated in the following sections.

5.2. Autoregressive order choice

We first determine the autoregressive order of the QAR(p) model (14) using the Kolmogorov–Smirnov test based on LR statistics, following Koenker and Machado (1999). We start estimating the quantile regression below with $p=p_{max}=3$, that is:

$$Q_{y_t}(\tau|y_{t-1}, \ldots, y_{t-p}) = \alpha_0(\tau) + \alpha_1(\tau)y_{t-1} + \alpha_2(\tau)y_{t-2} + \alpha_3(\tau)y_{t-3}.$$  

The index set used for quantiles is $\tau \in \Gamma=[0.1, 0.9]$ with steps of 0.005. Next, we test if the third order covariate is relevant in our model, i.e., we considered the null hypothesis:

$$H_0 : \alpha_3(\tau) = 0, \quad \text{for all } \tau \in \Gamma.$$  

The results are reported in Table 1. Using critical values obtained in Andrews (1993), we can infer that the autoregressive variable $y_{t-3}$ can be excluded from our econometric model.

<table>
<thead>
<tr>
<th>Excluded variable</th>
<th>$sup_{\tau \in \Gamma} L_\alpha(\tau)$</th>
<th>5% critical value</th>
<th>10% critical value</th>
<th>$H_0$</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_{t-3}$</td>
<td>3.989</td>
<td>9.31</td>
<td>7.36</td>
<td>$\alpha_3(\tau) = 0$</td>
<td>Do not reject</td>
</tr>
<tr>
<td>$y_{t-2}$</td>
<td>23.79831</td>
<td>9.31</td>
<td>7.36</td>
<td>$\alpha_2(\tau) = 0$</td>
<td>Reject</td>
</tr>
</tbody>
</table>

Since the third order is not relevant, we proceed by analyzing if the second order covariate is relevant.

Thus, we considered the null hypothesis:

$$H_0 : \alpha_2(\tau) = 0, \quad \text{for all } \tau \in \Gamma,$$

whose results are also presented in Table 1. Indeed, we verify that the second autoregressive variable cannot be excluded. Thus, the optimal choice of lag length in our model is $p=2$ and this order will be used in the subsequent estimation and hypothesis tests presented in this paper. In summary, our econometric model will be:

$$y_t = \alpha_0(U_t) + \alpha_1(U_t)y_{t-1} + \alpha_2(U_t)y_{t-2},$$  

and the associated ADF formulation is:

$$y_t = \mu_0 + \alpha_{1,t}y_{t-1} + \alpha_{2,t}y_{t-2} + \mu_t,$$

where

$$\alpha_{1,t} = \sum_{i=1}^{2} \alpha_i(U_i)$$
$$\alpha_{2,t} = -\alpha_2(U_t),$$
$$\mu_t = \alpha_0(U_t - \mu_0).$$

5.3. Global sustainability

The concept of global sustainability used in this paper states that local episodes of fiscal imbalances must be offset by periods of fiscal responsibility, so that the PVBC condition holds in the long-run. Recall from Section 2 that the necessary and sufficient condition for the intertemporal budget constraint (13) to hold is that the discounted debt–GDP ratio, represented by $y_t$,

---

According to Giambiagi and Ronci (2004), one should ideally use net-of-taxes real rate of interest. However, net-of-tax yield is a difficult task since tax rates vary according to security holder, and there is limited information on its identity.

---

16 As usual, we performed the test for exclusion of $y_{t-2}$ with same sample size used to test the exclusion of $y_{t-3}$.

17 For the sake of completion, we carried out the same tests in the ADF form. As expected, the Kolmogorov–Smirnov based on LR statistics estimates were exactly the same as the estimates reported in Table 2.
must be a stationary zero-mean process. If this happens, then the Brazilian federal debt will be globally sustainable.

In order to test for global stationarity, we need to test the null hypothesis \( H_0: \alpha_{1,t}=1 \) in Eq. (23). If such a null hypothesis is rejected against the alternative \( H_1: \alpha_{1,t}<1 \), then we say that the Brazilian federal debt is globally stationary. We test \( H_0: \alpha_{1,t}=1 \) by using the so-called Quantile Komogorov–Smirnoff (QKS) test proposed by Konker and Xiao (2004a,b). The computational details on the QKS test statistic are described in the Appendix. The critical values used in the QKS test are computed by the residual-based block (RBB) bootstrap recently proposed by Paparoditis and Politis (2003). Therefore, the critical values will ultimately depend on the block length arbitrarily chosen by the user. Table 2 reports the statistics and critical values for eight different block lengths, \( b \), arbitrarily chosen. We considered 10,000 bootstrap replications.

There is evidence that the discounted debt is not a unit-root process, with a significance level of 10% for almost all values of \( b \) (except for \( b=24 \) and 26, where we reject the unit-root null at a significance level of 5%). Overall, the results in Table 2 suggest that, at worst, the discounted Brazilian debt is globally stationary at 10% of significance.

We now test the null hypothesis that \( y_t \) has zero unconditional mean, i.e., \( H_0: \mu_y=0 \). We conduct a \( t \)-test for the unconditional mean and use the NBB resampling method with 10,000 replications to compute 5% critical values. Table 3 reports the \( t \)-statistic for the discounted public-debt series. The reported results suggest that the unconditional mean of the autoregressive process is not statistically different from zero. The result of the test depends on the block length used to compute the bootstrap sample. The results in Table 3 proved to be robust to various values of the block length (\( b \)).

Putting it all together, the discounted Brazilian federal debt is indeed globally sustainable. This result is in accordance with many previous studies, such as in Pastore (1995), Rocha (1997), and Issler and Lima (2000), suggesting the sustainability of the Brazilian public debt.

### 5.4. Local sustainability test

Given that the Brazilian public debt is a stationary zero-mean process, we can now proceed to the “local” analysis by using the Koenker and Xiao (2004b) test. In order to identify the debt ceiling of the Brazilian public debt, we need to test the null hypothesis \( H_0: \alpha_{t} (\tau)=1 \) at various quantiles by using the \( t \)-ratio test \( t_\alpha(\tau) \) proposed by Koenker and Xiao (2004b), with the zero-mean restriction imposed in the ADF representation of Eq. (22). Table 4 reports the results. The second column displays the estimate of the autoregressive term at each decile. Note that, in accordance with our theoretical

---

**Table 2**

Results for the global stationarity test

<table>
<thead>
<tr>
<th>Block length ( b )</th>
<th>QKS critical value</th>
<th>5% critical value</th>
<th>10% critical value</th>
<th>( H_0: \alpha_{1,t}=1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>13.2753601</td>
<td>14.0261732</td>
<td>11.9415994</td>
<td>Reject at 10%</td>
</tr>
<tr>
<td>14</td>
<td>13.2753601</td>
<td>14.971102</td>
<td>12.18249493</td>
<td>Reject at 10%</td>
</tr>
<tr>
<td>16</td>
<td>13.2753601</td>
<td>14.2410137</td>
<td>12.0697801</td>
<td>Reject at 10%</td>
</tr>
<tr>
<td>18</td>
<td>13.2753601</td>
<td>15.4325526</td>
<td>12.76201548</td>
<td>Reject at 10%</td>
</tr>
<tr>
<td>20</td>
<td>13.2753601</td>
<td>14.270703</td>
<td>11.12157297</td>
<td>Reject at 5%</td>
</tr>
<tr>
<td>22</td>
<td>13.2753601</td>
<td>12.3618035</td>
<td>10.87127688</td>
<td>Reject at 5%</td>
</tr>
</tbody>
</table>

---

**Table 3**

Results for the unconditional mean test

<table>
<thead>
<tr>
<th>Block length ( b )</th>
<th>Intercept critical value</th>
<th>2.5% critical value</th>
<th>97.5% critical value</th>
<th>( H_0: \text{intercept}=0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>28.9146968</td>
<td>17.8434187</td>
<td>32.8290331</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>14</td>
<td>28.9146968</td>
<td>19.5784337</td>
<td>34.5324403</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>16</td>
<td>28.9146968</td>
<td>21.241210</td>
<td>35.579257</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>18</td>
<td>28.9146968</td>
<td>22.7204141</td>
<td>36.7304168</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>20</td>
<td>28.9146968</td>
<td>24.1544067</td>
<td>38.4237097</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>22</td>
<td>28.9146968</td>
<td>25.4286859</td>
<td>39.7284730</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>24</td>
<td>28.9146968</td>
<td>26.7328681</td>
<td>40.4919047</td>
<td>Do not reject at 5%</td>
</tr>
<tr>
<td>26</td>
<td>28.9146968</td>
<td>28.0966684</td>
<td>41.7003689</td>
<td>Do not reject at 5%</td>
</tr>
</tbody>
</table>

---

**Table 4**

Koenker–Xiao test

<table>
<thead>
<tr>
<th>( \tau )</th>
<th>( \hat{\alpha}_1 (\tau) )</th>
<th>( \hat{\alpha}_0 (\tau) )</th>
<th>( \delta^2 )</th>
<th>( H_0: \alpha_{1,t}=1 )</th>
<th>Sustainability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>0.8955590</td>
<td>5.89314</td>
<td>0.1233821</td>
<td>Reject</td>
<td>OK</td>
</tr>
<tr>
<td>0.20</td>
<td>0.9547887</td>
<td>3.58005</td>
<td>0.0924561</td>
<td>Reject</td>
<td>OK</td>
</tr>
<tr>
<td>0.30</td>
<td>0.9671567</td>
<td>4.85814</td>
<td>0.2803427</td>
<td>Reject</td>
<td>OK</td>
</tr>
<tr>
<td>0.40</td>
<td>0.9810935</td>
<td>3.53123</td>
<td>0.1628078</td>
<td>Reject</td>
<td>OK</td>
</tr>
<tr>
<td>0.50</td>
<td>0.9963589</td>
<td>0.49040</td>
<td>0.1326469</td>
<td>Do not reject</td>
<td>–</td>
</tr>
<tr>
<td>0.60</td>
<td>1.0093934</td>
<td>1.05544</td>
<td>0.1993731</td>
<td>Do not reject</td>
<td>–</td>
</tr>
<tr>
<td>0.70</td>
<td>1.0339169</td>
<td>2.81045</td>
<td>0.1869188</td>
<td>Do not reject</td>
<td>–</td>
</tr>
<tr>
<td>0.80</td>
<td>1.0694750</td>
<td>5.68227</td>
<td>0.0400721</td>
<td>Do not reject</td>
<td>–</td>
</tr>
<tr>
<td>0.90</td>
<td>1.0948026</td>
<td>6.29170</td>
<td>0.0227941</td>
<td>Do not reject</td>
<td>–</td>
</tr>
</tbody>
</table>

---

18 The fundamental issue of the RBB bootstrap is its ability to simulate the weak dependence appearing in the original data series by separating the residuals in blocks. For more details, see Lima and Sampaio (2005).
model, \( \hat{\alpha}_1(\tau) \) is monotonic increasing in \( \tau \), and it is close to unity when we move towards upper quantiles. Table 4 shows that the null hypothesis \( H_0: \alpha_1(\tau) = 1 \) is rejected against the alternative hypothesis \( H_1: \alpha_1(\tau) < 1 \) for \( \tau \in [0.1; 0.4] \). The critical values were obtained by interpolation of the critical values extracted from Hansen (1995, page 1155). The last column summarizes the local sustainability analysis.

Table 4 shows that the critical quantile found using Brazilian public-debt data is equal to 0.40 (\( \tau_{crit.} = 0.40 \)). Consequently, the debt ceiling of the Brazilian debt–GDP ratio corresponds to the path generated by the fourth conditional decile, that is, \( \tilde{D}_t = \hat{Q}_{yt}(0.40|y_{t-1}, ..., y_{t-p}) \). Hence, according to Corollary 1 in this paper, if a given fiscal policy yielding a path of the (discounted) debt–GDP ratio above \( \hat{Q}_{yt}(0.40|y_{t-1}, ..., y_{t-p}) \) were to persist forever, then such a fiscal policy would not be sustainable in the long run. Fig. 5 displays the in-sample path of the debt-ceiling which is nothing more than the in-sample forecast of the 0.4th conditional decile function.

The gray bar in Fig. 5 indicates episodes in which the public debt presented unsustainable behavior. Recall that Tables 2 and 3 show that the discounted debt–GDP ratio in Brazil is globally sustainable. It means that despite the many episodes of fiscal imbalances exhibited in Fig. 5 by the gray bars, there were other episodes of fiscal adjustments (white bars) that were enough to guarantee global sustainability of the Brazilian debt. These episodes of fiscal imbalances were triggered by external shocks, such as oil price shocks in the 70s, and the sequence of financial crises in the 80s and 90s. In the domestic scenario, some recent macroeconomic shocks, such as the exchange rate fluctuation in 1999, and the political uncertainty related to the presidential elections of 2002, are also related to periods of local unsustainability of Brazilian debt.

In sum, the results displayed by Fig. 5 suggest that the Brazilian authorities are able to intervene through deficit cuts when debt has reached high levels. However, as suggested in Issler and Lima (2000), their mechanism of intervention is never based on spending cuts: it is either based on increases in the tax burden or on the usage of seigniorage revenue.

Table 5 gives us a historical perspective of the Brazilian public-debt solvency. The overall result of Table 5 reveals that the debt tolerance \( \hat{H} = 0.60 \), i.e., the percentage of episodes in our sample period in which the discounted debt–GDP ratio was above its debt ceiling \( (y_t > \tilde{D}_t) \) was 60%, which is perfectly compatible
with Proposition 2, since we have found \( \tau_{\text{crit}} = 0.40 \).\(^{19}\)

Furthermore, due to the nonlinear dynamics of \( y_t \), it is possible to identify different fiscal regimes by estimating, for each historical period, the respective statistic \( H \). Indeed, our estimates for the fiscal policy by the end of the military regime suggest that for 59% of this period the public debt was above the debt ceiling, which is an amount slightly below the theoretical value for the debt tolerance \( H \). As for the beginning of the new republic, in the Sarney administration (1985.II–1990.I), the fiscal policy implemented during the period was not sustainable 55% of the time, which is lower than the debt tolerance of 60%. However, we should point out that seigniorage revenue played a crucial role in balancing the public budget in that period.

Regarding the Collor and Franco administration (1990.II–1994.IV), it is important to notice that the fiscal stabilization plan launched in the middle of March 1990 was responsible for the sharp decrease observed in public-debt stock, since around 80% of the money stock was “frozen” (M4=M1 + all other financial assets).\(^{20}\) As a result, the percentage of periods in which the public debt moved above its debt ceiling was only 53%.

Notice, however, that such a number should be analyzed with some caution since the Brazilian Supreme Court decided that the majority part of this “unpaid” debt had to be repaid in the Cardoso government under the denomination of hidden liabilities (skeletons). Indeed, regarding Cardoso’s first term (1995.I–1998.IV), the episodes of fiscal unsustainability were equal to 75%, well above the 60% debt tolerance. The elevation of the debt–GDP ratio was mainly due to the recognition of skeletons of around 10% of GDP. However, despite the sharp increase in the debt, the recognition of skeletons improved the fiscal statistics, providing greater transparency and accuracy in Brazil’s fiscal position.

Table 5 shows an improvement of the Brazilian fiscal position in the second term of President Cardoso. This improvement occurred despite the significant real exchange rate depreciation starting in 1999.I,\(^{21}\) which provoked a considerable increase in debt because most Brazilian bonds at that time were indexed to hard currencies. Since government spending did not stop rising in Cardoso’s second term, most of the fiscal effort was based on the fact that tax revenue increased much faster than government spending.

More recently, regarding President Lula’s administration, it should be noticed that despite the fiscal effort to keep discounted debt on a sustainable path, the majority of the observations are beyond the debt ceiling. Therefore, we find that the fiscal policy in effect since the beginning of 2003 has not been austere enough to guarantee long-run sustainability.

Next, we present the out-of-sample forecasts of the Brazilian public debt, based on the methodology of recursive generation of conditional densities of \( y_t \), previously described in Section 3.2. The out-of-sample forecasts were constructed with a maximum forecast horizon \( s_{\text{max}}=80 \) periods (or 20years), with 1000 trajectories for the \( y_t \) process (Fig. 6):

The red line represents the forecast debt ceiling, which is the upper trajectory that satisfies the transversality condition of no-Ponzi scheme. Notice that it is indeed decreasing, in accordance with Proposition 3, which states that it must converge to zero in the long run. A decision maker will use the debt-ceiling forecast to decide whether or not to take some action. For example, if the future values of public debt are above its predicted ceiling, then the fiscal authorities may decide to cut expenditure or increase tax revenue to bring public debt back to its sustainable path. Based on the information available up to time \( T \), one can consider the following additional statistic:

**Definition 6.** Future percentage of violations \( H^* = \frac{\sum_{t=1}^{T+s_{\text{max}}} I_t^*}{s_{\text{max}}} \), where \( I_t^* \) is an indicator function, for \( t = T + s \) and \( s = 1, \ldots, s_{\text{max}} \), such that:

\[
I_t^* = \begin{cases} 
1 & \text{if } y_t > y_t^* \\
0 & \text{otherwise}
\end{cases}
\]

Based on the above definition, we could classify the future paths of the public debt into three different categories:

(i) Globally sustainable fiscal policies: those trajectories always below the “red line”, i.e., \( H^* = 0 \);

(ii) Unsustainable fiscal policies: those paths always above the red line, or with a percentage of violations above 60%; i.e., \( H^* > 0.6 \);

(iii) Globally sustainable fiscal policies but with some local unsustainable episodes: those trajectories with percentage of violations below 60%, i.e., \( H^* \leq 0.6 \);

Therefore, a decision maker (fiscal authority) may decide to intervene in the path of public debt (by increasing budget surplus) if the percentage of violations (\( H^* \)) during, say, the next four quarters is larger.

---

\(^{19}\) The Brazilian debt is globally sustainable despite the fact that 60% of its observations exhibit (local) unsustainable behavior. This finding results from the combination of the global stationarity and unconditional mean tests with local investigation in a selected range of quantiles, based on the Koenker and Xiao (2004b) test.

\(^{20}\) See Rocha (1997).

\(^{21}\) Real exchange rate adjustment has occurred under the new floating exchange regime.
Fig. 6. Out-of-sample forecast of Brazilian debt.

Notes: (a) The pictures respectively show the out-of-sample forecasts for 100 and 1,000 trajectories.
(b) The right picture exhibits (with the red line) the in-sample and out-of-sample forecast of the critical conditional quantile.
than 60%. Since our sample ends in 2005.I, and (by now) new observations have become available, we can compare them to the forecast debt ceiling. Notice that the actual undiscounted debt–GDP ratio for the periods 2005.II, 2005.III, 2005.IV, and 2006.I was respectively 47.21%, 48.95%, 49.53% and 50.76%. However, the predicted debt ceiling for the same period was 42.83%, 42.78%, 42.75%, and 42.51%, respectively. Hence, for the 4 quarters considered, the number of violations was 100%, that is, $H^* = 1$. Therefore, the out-of-sample forecast based analysis reveals that the more recent dynamic of the Brazilian public debt is not sustainable and additional fiscal efforts are needed to bring the debt–GDP ratio back to values below the debt ceiling.

It is important to mention that other decision-making parameters might also be considered by the fiscal authority. For example, the government might have to decide today (at the time that the forecast is made) how many expenditure cuts or tax revenue increases should occur in the next four quarters in order to guarantee that the public debt would be lower than its forecast ceiling. Another interesting application is to define the public debt would be lower than its forecast ceiling. If public expenditures keep rising faster than tax revenue, we might expect that the fiscal position in Brazil will worsen in the near future. Notice, however, that a new presidential term will start in January, 2007. Based on the fact that popularity concerns\textsuperscript{22} (political constraints) are partially eliminated at the beginning of a new term, we could expect that a fiscal policy based on expenditure cuts through the reduction of interest rate payments is perfectly viable in Brazil as long as the market believes that the new government is able to implement a reform agenda that would increase the productivity of the Brazilian economy in the long run. Such an agenda should include changes in job-market legislation, the social security system, the educational system, and simplification of the bureaucracy, among other changes needed to increase the productivity of the Brazilian economy.\textsuperscript{23} Without such reforms, it will be hard for the Brazilian fiscal authorities to convince the market that they will be able to bring the debt–GDP ratio back to its sustainable path, unless, of course, they decide to resort to seigniorage revenue (Table 6).

6. Conclusions

After the fiscal stabilization plan of 1994, the Brazilian government was no longer able to use seigniorage as a (major) source of revenue. In order to avoid an

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Periods & Debt ceiling (discounted debt) & Debt ceiling (undiscounted debt) & Observed debt \\
\hline
2005.II & 15.71 & 42.83 & 47.21 \\
2005.III & 15.69 & 42.78 & 48.95 \\
2005.IV & 15.68 & 42.75 & 49.53 \\
2006.I & 15.59 & 42.51 & 50.76 \\
2006.II & 15.54 & 42.37 & – \\
2006.III & 15.43 & 42.06 & – \\
\hline
\end{tabular}
\caption{Out-of-sample forecast of Brazilian debt (% GDP)}
\end{table}

\textsuperscript{22} The existence of delayed stabilization in Brazil was recently reported by Lima and Simonassi (2005) who investigated whether the Brazilian public debt is sustainable in the long run by considering threshold effects on the Brazilian budget deficit. They show that popularity concerns (political constraints) taking place in the end of the presidential term are the main reason for the existence of delays in the fiscal stabilization in Brazil.

\textsuperscript{23} It is important to notice that government intervention through deficit cuts might not necessarily be incompatible with the minimization of output and employment loss. Indeed, Giavazzi and Pagano (1990) found empirical evidence, for some European Countries, in favour of an “expansionary expectational effect” of a fiscal consolidation.
excessive build up of debt and consequent pressure on monetary policy, fiscal authorities had to adopt re-
strictive fiscal policies. The fiscal austerity led to very low rates of growth for the Brazilian economy, with negative impact on employment. Some politicians have constantly argued that Brazil’s primary budget surplus in Brazil is too large and, therefore, should be reduced to allow for an increase in public spending on infrastructure, education and health services. They claim that fiscal policy would still be sustainable (without the necessity to use seigniorage) with lower budget surpluses.

Running lower budget surpluses without resorting to seigniorage revenue would ultimately lead to an increase in public debt. In this paper, we attempted to answer the following question: how austere should fiscal policy be to guarantee long-run sustainability? By using a fresh econometric model, we showed that: (i) contrary to the opinions of many politicians, Brazilian public debt is not currently low enough to guarantee long-run sustainability and, therefore, the budget surplus should rise rather than be decreased. In other words, we found that the debt–GDP ratio has moved beyond its ceiling during the majority of quarters in the last two years; (ii) in the absence of shocks, the Brazilian government would have to reduce the debt–GDP ratio during the next quarters to guarantee long-run fiscal sustainability and; (iii) despite occasional periods in which the Brazilian public debt moved beyond its sustainability ceiling, our historical analysis reveals that public debt in Brazil has been globally sustainable, suggesting that Brazilian government authorities have reacted to high levels of public debt, mainly through increases in the tax burden or seigniorage revenue.

Issler and Lima (2000) concluded their article with a brief reflection on the solvency of the Brazilian public debt. They suggested that, for exogenous expenditures, as they verified in the sample from 1947–1992, there would be just two polar forms for restoring long-run sustainability in Brazil: tax increases or increases of seigniorage revenue. Since the overall tax burden has risen almost twofold and already reached 38% of GDP,24 it seems that Brazilian fiscal authorities did opt to balance the budget via tax increases. With such a tax burden, Brazilians are now the most heavily taxed citizens in Latin America and, therefore, may start penalizing politicians who propose additional tax increases. Hence, the aforementioned fiscal goal of raising the primary surplus will probably have to be achieved through expenditure cuts or increases in seigniorage revenue. In the second case, inflation will increase again, a price Brazilians may be willing to pay for tax relief. As in Issler and Lima (2000), we all hope that expenditures will cease to be “exogenous” in Brazil.

Despite the process of institutional transformations and the recent austere fiscal policy adopted in Brazil with the implementation of a target for the budget surplus, Brazil has an unfortunate history of serious difficulties in balancing its public budget. Therefore, it appears that the construction of indebtedness targets for Brazil is necessary, to provide a benchmark to guide fiscal authorities in their task of keeping the public debt on a sustainable path. The measure of debt ceiling introduced in this paper aims to contribute in this direction, developing a “debt-warning system” that helps the macroeconomist to identify “dangerous” debt paths, deemed to be unsustainable.

Acknowledgements

We would like to thank Zhijie Xiao and Roger Koenker for their insightful advice, and the participants of Econometrics in Rio (July, 2006) where this paper was presented. We are also grateful to Co-Editor Lant Pritchett and two anonymous referees, for their helpful comments and suggestions, and seminar participants at EPGE-FGV (August, 2006), specially Antônio Galvão, Caio Ibsen, Carlos E. da Costa, Fernando de Holanda Barbosa, Luis H. B. Braid, Maria Cristina Terra and Renato Fragelli Cardoso. Luiz Renato Lima thanks CNPq for financial support. The opinions in this paper are those of the authors and do not necessarily reflect the point of view of the Central Bank of Brazil. Any remaining errors are ours.

Appendix A. Inference methods of the QAR model

A.1. Other representations and regularity conditions of the QAR(p) model

We define the pth order autoregressive process as follows,

\[ y_t = \alpha_0(U_t) + \alpha_1(U_t)y_{t-1} + \ldots + \alpha_p(U_t)y_{t-p}, \]

where \( \alpha_j \)'s are unknown functions \([0, 1] \rightarrow \mathbb{R} \) that we will want to estimate. We will refer to this model as the QAR(p) model.25

24 In the first semester of 2006.

25 More on regularity condition underlying model (14) are found in Koenker and Xiao (2004) as well as in the Appendix of this paper.
In order to investigate stationarity of the $y_t$ process, we initially rewrite the QAR(p) model in a vector QAR(1) representation, as follows

$$Y_t = \mu + A_t Y_{t-1} + V_t,$$

where

$$Y_t = \left[ y_{1t}, \ldots, y_{p-t+1} \right]; \quad \mu = \left[ \mu_0 \right]_{0 \times 1};$$

$$A_t = \left[ \alpha_1(U_t), \ldots, \alpha_p(U_t) \right]; \quad V_t = \left[ u_t \right]_{0 \times 1};$$

$$a_t = \left[ \alpha_1(U_t), \ldots, \alpha_{p-1}(U_t) \right]$$

and

$$u_t = z_0(U_t) - \mu_0.$$ 

Then, let's assume the following conditions:

C.1 $\{u_t\}$ is iid with mean 0 and variance $\sigma^2 < \infty$. The CDF of $u_t$, $F$, has a continuous density $f$ with $f(\cdot) > 0$ on $U = \{u: 0 < F(u) < 1\}$.

C.2 Eigenvalues of $\Omega = E(A_t \otimes A_t)$ have moduli less than unity.

Koenker and Xiao (2004b) state that under conditions C.1 and C.2, the QAR(p) process $y_t$ is covariance stationary and satisfies a central limit theorem

$$\frac{1}{\sqrt{n}} \sum_{t=1}^{n} (y_t - \mu_y) \Rightarrow N \left( 0, \omega_y \right) \tag{24}$$

with

$$\mu_y = \frac{\mu_0}{1 - \sum_{j=1}^{p} \beta_j};$$

$$\beta_j = E(\alpha_j(U_t)), \quad j = 1, \ldots, p;$$

$$\omega_y^2 = \lim_{n \to \infty} \frac{1}{n} E \left[ \sum_{t=1}^{n} (y_t - \mu_y)^2 \right]. \tag{25}$$

The QAR(p) model (14) can be reformulated in a more conventional random coefficient notation as

$$y_t = \mu_0 + \beta_{1,t} y_{t-1} + \ldots + \beta_{p,t} y_{t-p} + u_t, \tag{26}$$

where

$$\mu_0 = E z_0(U_t);$$

$$u_t = z_0(U_t) - \mu_0;$$

$$\beta_{j,t} = z_j(U_t), \quad j = 1, \ldots, p.$$ 

Thus, $\{u_t\}$ is an iid sequence of random variables with distribution $F(\cdot) = z_0^{-1}(\cdot + \mu_0)$, and the $\beta_{j,t}$ coefficients are functions of this $u_t$ innovation random variable.

An alternative form of model (26) widely used in economic applications is the ADF (augmented Dickey–Fuller) representation (27). According to Koenker and Xiao (2004b), in the ADF formulation the first order autoregressive coefficient plays an important role in measuring persistence in economic and financial time series, which in our case will be crucial to determining the sustainability of public debt:

$$y_t = \mu_0 + \alpha_{1,t} y_{t-1} + \sum_{j=1}^{p-1} \alpha_{j+1,t} A y_{t-j} + u_t, \tag{27}$$

where, corresponding to Eq. (14),

$$\alpha_{1,t} = \sum_{i=1}^{p} \alpha_i(U_t);$$

$$\alpha_{j+1,t} = -\sum_{i=j}^{p} \alpha_i(U_t), \quad j = 1, \ldots, p.$$ 

Under regularity conditions, if $\alpha_{1,t} = 1$, $y_t$ contains a unit root and is persistent; and if $|\alpha_{1,t}| < 1$, $y_t$ is stationary. Notice that Eqs. (14), (26) and (27) are equivalent representations of our econometric model. Each representation is convenient for inference analysis.

**Appendix B. Proofs of propositions**

**Proof of Proposition 1.** Consider the ADF representation of the QAR(p) model (27). The existence and uniqueness of the critical conditional quantile is proven by the following simple argument:

For $\forall \tau \in \mathcal{T}$, let $u_t$ be a realization of the iid uniform random variable $U_t$, such that $\alpha_{1,t} = \sum_{i=1}^{p-1} \alpha_i(u_t) = 1$, and $\alpha_{j+1,t} = -\sum_{i=j+1}^{p} \alpha_i(u_t)$, $j = 1, \ldots, p$. By Assumptions 1 and 2, $\alpha_i(u_t)$ are increasing functions in $u_t$. Since the sum of monotone increasing functions is itself a monotone increasing function, it follows that $\alpha_{1,t}(u_t)$ and $\alpha_{j+1,t}(u_t)$ are monotone increasing. Assumptions 1 and 2 guarantee that $Q_{\alpha_{1,t}(u_t)} = Q_{\alpha_{j+1,t}(u_t)}$, which is an increasing function in $\tau$. Moreover, monotonicity guarantees that $Q_{\sum_{i=1}^{p} \alpha_i(U_t)} = \sum_{i=1}^{p} Q_{\alpha_i(U_t)} = \sum_{i=1}^{p} \alpha_i(Q_{\alpha_i(U_t)}) = \sum_{i=1}^{p} \alpha_i(U_t) = \sum_{i=1}^{p} \alpha_i(U_t)$, which implies that $\alpha_{1,t}(\tau)$ and $\alpha_{j+1,t}(\tau)$ are monotone increasing in $\tau$. Thus, Assumptions 1 and 2 guarantee that the conditional quantile function of $y_t$ is monotone increasing in $\tau$.

Given Assumption 1, we know that $u_t \in (0, 1)$. Based on the above argument, it is always possible to find a unique quantile $\tau^*$ such that $2\tau^* = \sum_{i=1}^{p} \alpha_i(U_t)$.
and \( x_{j+1,a}^{\ast} (\tau^\ast) = -\sum_{j'} p^-_{j'+1} x_{j'a}(\tau^\ast) = x_{j+1} \). This suggests the nice result that

\[
Q_{y_t} (\tau^\ast | F_{t-1}) = y_t, \; \forall t \in \mathcal{T}
\]

that is, the trajectory of the conditional quantile function \( Q_{y_t} (\tau^\ast | F_{t-1}) \) will hit the points in which the time series process \( y_t \) has a unit-root behavior.

Now recall that the critical quantile \( \tau_{\text{crit}} \) is the largest quantile \( \tau \) such that \( x_{1,a} (\tau) < 1 \). Define \( \tilde{\tau} \) as the subset of quantiles so that \( x_{1,a} (\tau) < 1 \). Hence, based on the fact that \( x_{1,a} (\tau) \) is monotone increasing in \( \tau \), it follows that the critical quantile is

\[
\tau_{\text{crit}} = \sup \tilde{\tau}.
\]

Thus, \( \tau_{\text{crit}} < \tau^\ast \) by definition and, since \( Q_{y_t} (\tau | F_{t-1}) \) is monotone increasing in \( \tau \), we must have that \( Q_{y_t} (\tau_{\text{crit}} | F_{t-1}) \) must lie below \( y_t \) in all periods where \( y_t \) is nonstationary, that is, \( Q_{y_t} (\tau_{\text{crit}} | F_{t-1}) < y_t = Q_{y_t} (\tau^\ast | F_{t-1}) \), \( \forall t \in \mathcal{T} \). □

**Proof of Corollary 1.** Based Assumptions 4 and 5, we have that the public debt process \( y_t \) for \( \forall t \in \mathcal{T} \) is now represented by

\[
y_t = y_{t-1} + \sum_{j=1}^{p-1} x_{j+1,a} y_{t-j}; \quad i = 1, \ldots, N
\]

which is the same \( y_t \) process discussed in Proposition 1, but without intercept. In the same manner, the conditional quantile function can be written, by using the ADF formulation, as

\[
Q_{y_t} (\tau | F_{t-1}) = x_{1,a} (\tau) y_{t-1} + \sum_{j=1}^{p-1} x_{j+1,a} (\tau) y_{t-j}.
\]

This way, the proof of Corollary 1 is achieved in a straightforward manner, by just following the proof of Proposition 1 considering no intercept in the stochastic process \( y_t \), given that the local analysis of public debt depends on the zero-mean process assumption (or global sustainability for public debt). □

**Proof of Proposition 2.** By definition, we have that \( H = \frac{1}{t} \sum_{\tau \in \mathcal{T}} \mathbf{I}_{\left\{ y_t > Q_{y_t} (\tau_{\text{crit}} | F_{t-1}) \right\}} \), where \( \mathbf{I} (\cdot) \) an indicator function and \( T \) is the sample size. By Assumption 3, we can rewrite this expression as \( H = \frac{1}{t} \left( \sum_{\tau \in \mathcal{T}} \mathbf{I}_{\left\{ y_t > Q_{y_t} (\tau_{\text{crit}} | F_{t-1}) \right\}} + \sum_{\tau \in \mathcal{T}} \mathbf{I}_{\left\{ y_t > Q_{y_t} (\tau_{\text{crit}} | F_{t-1}) \right\}} \right) = (N+0) \), based on the Proposition 1. On the other hand, we can state the critical quantile as \( \tau_{\text{crit}} = \text{Pr} (y_t > Q_{y_t} (\tau_{\text{crit}} | F_{t-1}) \) = \text{Pr} (t \in [\Omega / T] | F_{t-1}) = \text{Pr} (t \in \Omega | F_{t-1}) - \text{Pr} (t \in \mathcal{T} | F_{t-1}) = 1 - \frac{N}{T} = 1 - H \). □

**Proof of Proposition 3.** Notice that for each realization of \( U_{T+s} \), there is a 1:1 corresponding quantile \( \tau = u_{T+s} \). Hence, let \( u_{\text{crit}} \) be the largest realization of \( U_{T+s} \) so that \( x_{1,a} \sum_{j=1}^{p-1} x_{j,a} (U_{T+s}) < 1 \), which guarantees stationarity whenever the realization \( u_{\text{crit}} \) takes place. By Proposition 1, there exist a critical quantile \( u_{\text{crit}} = u_{\text{crit}} \), and its corresponding conditional critical quantile \( D_{T+s} = \hat{Q}_{y_{T+s}} (\tau_{\text{crit}} | F_T) \), so that \( \hat{y}_{T+s} = D_{T+s} \) whenever the realization \( u_{\text{crit}} \) takes place. Given that the process \( y_t \) has zero mean (no intercept) and \( \hat{y}_{T+s} \) is a forecasted path of \( y_t \), it follows that \( \lim_{s \to \infty} D_{T+s} = 0 \). □

**Appendix C. Estimation and hypothesis testing**

Provided that the right hand side of Eq. (14) is monotone increasing in \( U_t \), it follows that the \( r \)th conditional quantile function of \( y_t \) can be written as

\[
Q_{y_t} (\tau | y_{t-1}, \ldots, y_{t-p}) = x_{0} (\tau) + x_1 (\tau) y_{t-1} + \ldots + x_p (\tau) y_{t-p},
\]

or somewhat more compactly as

\[
Q_{y_t} (\tau | y_{t-1}, \ldots, y_{t-p}) = x_{0} (\tau),
\]

where \( x_{0} = (1, y_{t-1}, \ldots, y_{t-p})' \). The transition from Eqs. (14)–(28) is an immediate consequence of the fact that for any monotone increasing function \( g \) and a standard uniform random variable, \( U_t \), we have:

\[
Q_{g}(U) (\tau) = g (Q_U (\tau)) = g (\tau),
\]

where \( Q_U (\tau) = r \) is the quantile function of \( U_t \). Analogous to quantile estimation, quantile autoregression estimation involves the solution to the problem

\[
\min_{\{x \in \mathbb{R}^{p+1} \}} \sum_{t=1}^{n} \rho_\tau (y_t - x' z),
\]

where \( \rho_\tau \) is defined as in Koenker and Bassett (1978):

\[
\rho_\tau (u) = \begin{cases} \tau u, & u \geq 0 \\ (\tau - 1)u, & u < 0 \end{cases}.
\]

The quantile regression method is robust in distributional assumptions, a property that is inherited from the robustness of the ordinary sample quantiles. Moreover, in quantile regression, it is not the magnitude of the dependent variable that matters but its position relative to the estimated hyperplane. As a result, the estimated coefficients are less sensitive to outlier observations than, for example, the OLS estimator. This superiority over OLS estimator is common to any \( M \)-estimator.\(^{26}\)

\(^{26}\) The quantile estimator is (in fact) an \( M \)-estimator.
C.1. Autoregressive order choice

Eq. (14) gives our $p$th order quantile autoregression model. We now discuss how to choose the optimal lag length $p$. We follow Koenker and Machado (1999) in testing for the null hypothesis of exclusion for the $p$th control variable $\tau$

$$H_0 : \alpha_p(\tau) = 0, \quad \text{for all } \tau \in \Gamma,$$

and some index set $\Gamma \subset (0, 1)$. Let $\hat{\alpha}(\tau)$ denote the minimizer of

$$\hat{V}(\tau) = \min_{\{x \in \mathbb{R}^{p+1}\}} \sum \rho_t(y_t - x'_t z),$$

where $x'_t = (1, y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$ and $\hat{\alpha}(\tau)$ denotes the minimizer for the corresponding constrained problem without the $p$th autoregressive variable, with

$$\tilde{V}(\tau) = \min_{\{x \in \mathbb{R}^{p}\}} \sum \rho_t(y_t - x'_t z),$$

where $x'_t = (1, y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$. Thus, $\hat{\alpha}(\tau)$ and $\tilde{\alpha}(\tau)$ denote that unrestricted and restricted quantile regression estimates. Koenker and Machado (1999) state that we can test the null hypothesis (30) using a related version of the likelihood process for a quantile regression with respect to several quantiles. Suppose that the $\{u_t\}$ are iid but drawn from some distribution, say, $F$, and satisfying some regularity conditions. The LR statistics at a fixed quantile is derived as follows:

$$L_n(\tau) = \frac{2(\hat{V}(\tau) - \tilde{V}(\tau))}{\tau(1-\tau)s(\tau)} ,$$

where $s(\tau)$ is the sparsity function

$$s(\tau) = \frac{1}{f(F^{-1}(\tau))} .$$

The sparsity function, also termed the quantile–density function, plays the role of a nuisance parameter. We want to carry out a joint test about the significance of the $p$th autoregressive coefficient with respect to a set of quantiles $\Gamma$ (not only at fixed quantile). Koenker and Machado (1999) suggest using the Kolmogorov–Smirnov (KS) type test based on the regression quantile process for the null hypothesis (30) using a related version of the Likelihood process for a quantile regression based statistics for testing the null hypothesis of a unit root:

$$Q_{KS} = \sup_{\tau \in \Gamma} |U_n(\tau)| ,$$

where $U_n(\tau)$ is the coefficient based statistics given by:

$$U_n(\tau) = n(\tilde{z}_1(\tau) - 1).$$

Koenker and Xiao (2004b) suggest the approximation of the limiting distribution of Eq. (32) under the null hypothesis by using the autoregressive bootstrap (ARB). In this paper, we approximate the distribution under the null using the residual-based block bootstrap procedure (RBB). The advantages of the RBB over ARB are documented in Lima and Sampaio (2005).

C.2. Global stationarity

Given the choice of the optimal lag length $p$, one must check for global stationarity of the $y_t$ process, in order to verify whether conditions C.1 and C.2 described in Section 3 indeed hold, and $y_t$ is covariance stationary in the sense of Koenker and Xiao (2004b). An approach for testing the unit-root property is to examine it over a range of quantiles $\tau \in \Gamma$, instead of focusing only on a selected quantile. We may, then, construct a Kolmogorov–Smirnov (KS) type test based on the regression quantile process for $\tau \in \Gamma$. We considered $\tau \in \Gamma = [0.1, 0.9]$ with steps of 0.005. Koenker and Xiao (2004b) proposed the following quantile regression based statistics for testing the null hypothesis of a unit root:

$$Q_\tau = \sup_{\tau \in \Gamma} |U_n(\tau)| ,$$

and it does not allow us to identify the intercept coefficient $\mu_0$, since $Q_\tau(\tau) = \alpha_0(\tau) - \mu_0$, where $\tau = Q_\tau(\tau)$ is the quantile function of $U$. Thus, the next natural attempt would be to ignore the existence of an asymmetric

C.3. Unconditional mean test

In order to test whether or not the unconditional mean of the process is zero, we recall that the following null hypotheses are equivalent:

$$H_0 : \mu_y = 0 \quad H'_0 : \mu_0 = 0 .$$

Consider the $p$th order quantile autoregressive process given by

$$y_t = \alpha_0(U_t) + \alpha_1(U_t)y_{t-1} + \ldots + \alpha_p(U_t)y_{t-p} + u_t,$$

where $u_t = \alpha_0(U_t) - \mu_0$. Now note that the $\tau$th conditional quantile function of $y_t$ is given by

$$Q_{\tau}(\tau|y_{t-1}, \ldots, y_{t-p}) = \alpha_0(\tau) + \alpha_1(\tau)y_{t-1} + \ldots + \alpha_p(\tau)y_{t-p} ,$$

and it does not allow us to identify the intercept coefficient $\mu_0$, since $Q_\tau(\tau) = \alpha_0(\tau) - \mu_0$, where $\tau = Q_\tau(\tau)$ is the quantile function of $U$. Thus, the next natural attempt would be to ignore the existence of an asymmetric.
dynamic and estimate a symmetric regression (constant coefficient model)
\[ y_t = \mu_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \nu_t. \]  
(33)

The null hypothesis \( H_0' \) could be tested using conventional \( t \)-statistics
\[ t = \frac{\hat{\mu}_0}{SE(\mu_0)}. \]

However, in omitting asymmetries, the new error term \( v_t \) is no longer an iid sequence, i.e.,
\[ v_t = (\beta_1 - \beta_1) y_{t-1} + \ldots + (\beta_p - \beta_p) y_{t-p} + u_t, \]
which invalidates the conventional \( t \)-statistics type test. Putting that aside, we decided to directly test the null hypothesis \( H_0' : \mu_0 = 0 \) using a resampling method for dependent data according to Carlstein (1986), named Nonoverlapping Block Bootstrap (NBB). The key feature of this bootstrap method is that its blocking rule is based on nonoverlapped segments of the data, making it able to simulate the weak dependence in the original series, \( y_t \). Further details regarding NBB bootstrap are available in Lahiri (2003).

C.4. The Koenker–Xiao Test

In this section, we introduce the Koenker–Xiao test, which is used to test the null hypothesis \( H_0' : \alpha_1(\tau) = 1 \), for a given \( \tau \in (0, 1) \). We express the null hypothesis in the ADF representation (16) as:
\[ H_0 : \alpha_1(\tau) = 1, \quad \text{for selected quantiles } \tau \in (0, 1). \]

In order to test such a hypothesis, Koenker and Xiao (2004b) proposed a statistic similar to the conventional augmented Dick–Fuller (ADF) \( t \)-ratio statistic. The \( t \) statistic is the quantile autoregression counterpart of the ADF \( t \)-ratio test for a unit root and is given by:
\[ t_\alpha(\tau) = \frac{f\left( F^{-1}(\tau) \right)}{\sqrt{\tau(1 - \tau)}} \left( Y^T P_X Y \right)^{-1/2} \tilde{z}_1(\tau) - 1, \]
where, \( f\left( F^{-1}(\tau) \right) \) is a consistent estimator of \( f(F^{-1}(\tau)) \), \( Y \) is a vector of lagged dependent variables \( (y_{t-1}) \) and \( P_X \) is the projection matrix onto the space orthogonal to \( X = (1, \Delta y_{t-1}, \ldots, \Delta y_{t-\rho+1}) \). Koenker and Xiao (2004b) show that the limiting distribution of \( t_\alpha(\tau) \) can be written as:
\[ t_\alpha(\tau) \Rightarrow \delta \left( \int_0^1 W^2_1 \right)^{-1/2} \int_0^1 W_1 dW_1 + \sqrt{1 - \delta^2} N(0, 1), \]
where \( W_1(r) = W_1(r) - \int_0^1 W_1(s) ds \) and \( W_1(r) \) is a standard Brownian Motion. Thus, the limiting distribution of \( t_\alpha(\tau) \) is nonstandard and depends on parameter \( \delta \) given by:
\[ \delta = \delta(\tau) = \frac{\sigma_{o\psi}(\tau)}{\sigma_{o\psi}}, \]
and can be consistently estimated (see Koenker and Xiao, 2004b, for more details). Critical values for the statistic \( t_\alpha(\tau) \) are provided by Hansen (1995, page 1155) for values of \( \delta^2 \) in steps of 0.1. For intermediate values of \( \delta^2 \), Hansen suggests obtaining critical values by interpolation.

Appendix D. Monte Carlo simulation

A Monte Carlo simulation is designed to investigate the finite sample performance of the result shown in Proposition 1, that is, if the critical conditional quantile is able to separate nonstationary points from stationary ones. One of the critical issues regarding this experiment is the Data-Generating Process (DGP), which will be represented by the following QAR(1) model
\[ y_t = \alpha_0(U_t) + \alpha_1(U_t) y_{t-1}, \]  
(34)
where \( \{U_t\} \) is a sequence of iid standard uniform random variables, and the coefficients \( \alpha_0 \) and \( \alpha_1 \) are functions on \( [0, 1] \), given by \( \alpha_0(U_t) = F^{-1}(U_t) \), where \( F : \mathbb{R} \to [0, 1] \) is the standard normal cumulative distribution function, and \( \alpha_1(U_t) = \min \{1; \gamma_0 + \gamma_1 U_t \} \) with \( \gamma_0 \in (0, 1) \) and \( \gamma_1 > 0 \).

In our case, we initially assume \( \gamma_0 = 0.7 \) and \( \gamma_1 = 0.4 \) in order to limit the variance of \( \alpha_1 \). If \( U_t \geq \frac{1-0.7}{0.4} \), then the model generates \( y_t \) according to the unit-root model, but for smaller realizations of \( U_t \) we have a mean reversion tendency. In other words, we expect that 25% of the \( U_t \) realizations will induce a unit-root behavior. We also consider the case \( \gamma_0 = 0.8 \), which leads to 50% of the realizations of \( U_t \) generating a unit-root model.

In our experiment, we construct 10,000 replications of \( \{y_t\} \) with 100 or 300 observations. We adopt a hybrid solution for this experiment using R and Ox environments, since the proposed simulation is extremely computationally intensive. Ox is much faster than R in large computations. On the other hand, R language is more interactive and user-friendly than Ox, and the QAR model must be estimated in R, since its package for quantile regressions (quantreg) is more complete and updated than the Ox package. The main steps of the
algorithm used in the Monte Carlo simulation are as follows:27

a) Initialization of the R code (setting parameters $\gamma_0, \gamma_1$)
b) Generation of one DGP
   b.1) R code calls Ox code informing the input parameters
   b.2) Ox code generates one DGP $y_t$
b.3) R code imports the data generated by Ox code
c) Calculation of the optimal lag length (p) for the QAR (p) model
d) Estimation of the coefficients for the QAR (p) model
e) Testing for local unit root in all quantiles
f) Search for the critical quantile
g) Generation of the conditional quantiles
h) Computation of the Debt Ceiling
i) Save of the results for this DGP
j) Repeat steps (b) to (i) for 10,000 replications

Therefore, we proceed as follows: Ox code initially generates the time series $y_t$ and then returns these data to R, which estimates the QAR(p) model, computes the descriptive statistics and saves the results in a text file. Once the Ox code generates the $\{y_t\}$ process, the optimal lag length of the QAR(p) model is chosen based on the Koenker and Machado (1999) procedure. This way, the coefficients are estimated for all quantiles and a local unit-root test is conducted in order to find the critical quantile $\tau_{crit}$, i.e., the last quantile associated with an autoregressive coefficient, which still represents a mean reversion tendency (or in other words, where the null $H_0$: $\alpha_1(\tau)=1$ is still rejected, according to the Koenker–Xiao test for unit root). Furthermore, the R code generates the conditional quantiles, including the critical quantile, according to the following ADF formulation

$$\hat{Q}_{y_t}(\tau_{crit} | F_{t-1}) = \tilde{x}_0(\tau_{crit}) + \tilde{x}_1(\tau_{crit}) y_{t-1} + \sum_{j=1}^{p-1} \tilde{x}_{j+1}(\tau_{crit}) A y_{t-j}. \quad (35)$$

Based on the critical conditional quantile, one can verify if the adopted QAR(p) model for a finite sample is able to correctly identify the stationarity limit, by comparing the $\{y_t\}$ process with $\hat{Q}_{y_t}(\tau_{crit} | F_{t-1})$ for observations where the DGP imposes a unit-root model. To investigate this issue carefully, let’s initially define (for a given replication $i$) the following dummy variables $W_i^t$ and $Z_i^t$:

$$W_i^t = \left\{ \begin{array}{ll} 1 & ; \text{if } \alpha_1(U_t) = 1 \\ 0 & ; \text{otherwise} \end{array} \right\}, \quad (36)$$

$$Z_i^t = \left\{ \begin{array}{ll} 1 & ; \text{if } y_t > \hat{Q}_{y_t}(\tau_{crit} | F_{t-1}) \text{ and } \alpha_1(U_t) = 1 \\ 0 & ; \text{otherwise} \end{array} \right\}. \quad (37)$$

Thus, the $W_i^t$ variable indicates observations with an autoregressive coefficient equal to unity, according to the DGP, and $Z_i^t$ reveals observations associated with a unit-root behavior and, at the same time, where the generated $y_t$ time series is above the critical conditional quantile. Note that $\frac{1}{T} \sum_{t=1}^{T} Z_i^t = H^i$, which is exactly the $H$ statistic, presented in Definition 3, computed for replication $i$. Therefore, one can compute the ratio $R_i$ as follows

$$R_i = \frac{\frac{1}{T} \sum_{t=1}^{T} Z_i^t}{\frac{1}{T} \sum_{t=1}^{T} W_i^t}. \quad (38)$$

One should expect the ratio $R_i$ to be as close to unity as possible, since in the QAR(p) model all observations of the $y_t$ process associated with a unit-root model must be above the critical quantile, according to Proposition 1.

Our simulation computes the $R_i$ statistic for each replication $i$ and summarizes the results in the following histograms, where the frequency of $R_i$ is plotted for the set of 10,000 replications.28 It is worth mentioning that only the replications in which the null hypothesis of a local unit root for the $y_t$ process cannot be rejected are displayed in the following histograms. In other words, we select among the 10,000 replications only those representing a stochastic process $y_t$ containing at least one quantile with a local unit root, i.e., the null $H_0$: $\alpha_1(\tau)=1$ is not rejected for (at least) one quantile $\tau' \in (0, 1)$ Fig. 7.

Since $U_t$ follows a standard uniform distribution and $\alpha_1(U_t)=\min \{1; \gamma_0 + \gamma_1 U_t\}$ it is possible that for a given replication $j$ the stochastic process $\{y_t^j\}$ has no local unit root, i.e., $\alpha_1(\tau)<1; \forall \tau \in (0, 1)$. In fact, these cases occur for lower values of $\gamma_0$ and $\gamma_1$, but since they are not the object of our investigation we decided to not consider them in our analysis.

According to the Monte Carlo experiment, we found that the result of Proposition 1 indeed exhibits a good performance in the finite sample investigation. As long as the number of observations $T$ increases (for a given parameter $\gamma_0$), the empirical distribution of $R_i$ approaches the unity value, with a respective decreasing standard deviation, as we already expected. In our

27 Both R and Ox codes are available from the authors upon request.

28 Each vertical bar graph represents the frequency distribution of $R_i$, in which the height of the bar is proportional to the frequency within each class interval.
simulations, the distribution of $R^*$ for $\gamma_0=0.7$ is more concentrated than the respective distribution for $\gamma_0=0.8$, since the DGP for $\gamma_0=0.8$ induces a larger expected number $T^*$ of realizations of $U_t$ generating a unit-root model. In this case, for $\gamma_0=0.7$ and $T=100$ observations, we found that (on the average) the QAR model imposes 93.5% of observations of the $y_t$ process associated with a unit-root model ($T^*$) correctly above the estimated critical quantile Table 7.

### Appendix E. Out-of-sample forecast: generation of a discrete uniform random variable

In practical terms, the numerical procedure described in the construction of the out-of-sample forecast of $y_t$ must be implemented by an algorithm considering a perfect match between the discrete set of quantiles $\tau \in \Lambda = [0.1, 0.9]$ and a discrete support of the $U_t$ random variable. Firstly, we must choose the number of elements $n$ for the grid $\Lambda$ of quantiles and, then, estimate the QAR model to generate the set of coefficients $\hat{\alpha}_i(\tau)$ for all $\tau \in \Lambda$. The discrete set of quantiles $\Lambda$, containing $n$ elements, is defined by

$$\tau \in \Lambda = [0.1, 0.1 + \tau_{\text{step}}, 0.1 + 2\tau_{\text{step}}, \ldots, 0.9 - \tau_{\text{step}}, 0.9],$$

where $\tau_{\text{step}} = (0.9 - 0.1)/(n-1)$. In addition, one must ensure that the dropping of the discrete version of the random variable $U_t$, defined as $\tilde{U}_t$, is made based on the same set $\Lambda$, in order to guarantee that, for every realization

<table>
<thead>
<tr>
<th>Parameter $\gamma_0$</th>
<th>$T$</th>
<th>$T^*$</th>
<th>Mean $(R_t)$</th>
<th>Median $(R_t)$</th>
<th>S.D. $(R_t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_0=0.7$</td>
<td>100</td>
<td>25</td>
<td>0.935</td>
<td>1.000</td>
<td>0.131</td>
</tr>
<tr>
<td></td>
<td>300</td>
<td>75</td>
<td>0.951</td>
<td>1.000</td>
<td>0.112</td>
</tr>
<tr>
<td>$\gamma_0=0.8$</td>
<td>100</td>
<td>50</td>
<td>0.866</td>
<td>0.982</td>
<td>0.213</td>
</tr>
<tr>
<td></td>
<td>300</td>
<td>150</td>
<td>0.909</td>
<td>1.000</td>
<td>0.182</td>
</tr>
</tbody>
</table>

Notes: (a) Total of $i=10,000$ replications for each simulation, excluding those with no local unit root; (b) $T$ is the total number of observations and $T^*$ is the expected number of observations, across the 10,000 replications, associated with a unit-root model.
of \( U_t \), the algorithm correctly calculates the respective \( \tilde{U}_t \), in order to find an associated quantile \( \tau \) and, therefore, an estimated coefficient \( \hat{\alpha}(\tau=\tilde{U}_t) \).

This way, a perfect 1:1 mapping between \( \tau \) and \( U_t \) depends on the random variable \( \tilde{U}_t \), which can be obtained from the realization of the continuous random variable \( U_n \) in the following way: Assume that \( U_t \) belongs to the continuous set \([0.1, 0.9]\). If we define \( \tilde{U}_t \) as follows, we can guarantee that indeed \( \tilde{U}_t \) belongs to the same discrete set \( \Lambda \) of quantiles:

\[
\tilde{U}_t = 0.1 + \tau_{\text{step}} \cdot \text{round}\left(\frac{(U_t - 0.1)}{\tau_{\text{step}}}\right),
\]

where the \text{round}(\cdot) function approximates its argument to the nearest integer value.\(^{29}\)

References


Hansen, B., 1995. Rethinking the univariate approach to unit root tests: how to use covariates to increase power. Econometric Theory 8, 1148–1171.


