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Further application of Narayan and Liu (2015) unit root model for trending time series☆

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ABSTRACT

In this paper, we further subject the new GARCH-based unit root test for trending time series proposed by Narayan and Liu (NL) (2015) to empirical scrutiny. We utilize daily, weekly, and monthly data of 10-year bond yield for seventeen countries across the regions of America, Asia, and Europe. We find that the unit root test for sovereign bond yield data is better modeled in the presence of structural breaks, conditional heteroscedasticity, and time trend. More importantly, it may be necessary to pre-test for the existence of these statistical features when modeling with the bond yield data.

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1. Introduction

A new dimension to unit root testing procedures is gradually emerging and this development appears to have enhanced the level of sophistication of pre-tests when modeling time series with high frequency data. This development was pioneered by Kim and Schmidt (1993) and further examined by Ling and Li (1998), Seo (1999), Ling et al. (2003), and Cook (2008). This class of unit root test is classified as GARCH-based unit root tests as the tests are analyzed in the presence of GARCH error rather than the white noise error assumed in the standard Augmented Dickey Fuller (ADF)-type unit root tests. One of the attractions of the GARCH-based unit root tests relates to its ability to deal with conditional heteroscedasticity and non-normality which are prominent features of most time series that are available at a high frequency. Following Kim and Schmidt (1993) and Haldrup (1994), it has been noted that when error in the ADF-type test regression is a GARCH process and is ignored, the test is subject to typically moderate size distortion (Cook 2008).

However, one of the limitations of the GARCH-based unit root test of Kim and Schmidt (1993) and others (as previously mentioned) is that it does not account for structural breaks and therefore, the statistical inference may yield invalid estimates if there is evidence of significant structural breaks. In the spirit of the latter, Narayan and Liu [NL thereafter] (2011) and Narayan, Liu, and Westerlund [NLW thereafter] (2015) extended the GARCH-based unit root test to include two structural breaks, and this test is found to have better size and power properties than those without structural breaks. The application of the GARCH-based unit root test with structural breaks is increasingly gaining prominence in the literature. Recent studies that have applied the NL (2011) and NLW (2015) tests include Salisu and Fasanya (2013); Salisu and Mobolaji (2013) and Mishra and Smyth (2014a, b).

Recently, NL (2015) proposed an extension of the NLW (2015) to include a time trend and consequently, the performance of their test was compared with tests without structural breaks and time trend [such as the ADF test and the Cook (2008) test] and with structural breaks but no time trend [i.e. the NL (2011) and NLW (2015) tests]. They find that their proposed trend-GARCH-based structural break test is shown to be correctly sized among the competing tests, enjoys more power and helps to search for structural break dates more accurately. They further demonstrate that regardless of whether the break dates are chosen exogenously or endogenously, the size properties are close to the nominal 5% level. In other words, as long as a time trend is included, the manner in which structural breaks is chosen does not make the test unstable; they remain correctly sized (NL, 2015). Although, the ADF-type unit root test proposed by Narayan and Popp [NP thereafter] (2010) also accounts for both structural breaks and time trend in the test regressions; however, the test does not allow for conditional heteroscedasticity.

Motivated by these attractions, we extend the application of the NL (2015) test to sovereign bond yield data covering both developed and emerging financial markets. The main attractions to the bond yield

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data are as follows. First, unlike the energy series used in NL (2015), the bond yield data are downward trending, and therefore, it would be an interesting exercise to see how these variables will perform when subjected to the proposed test. Secondly, the considered series have also witnessed structural shifts in response to global events such as the global financial turmoil. Thirdly, because they are readily available at a high frequency, they are more likely to exhibit conditional heteroscedasticity. All these attractions agree with the underlying statistical assumptions for the implementation of the NL (2015) trend-GARCH-based unit root test with structural breaks. In addition, testing the stationarity properties of sovereign bond yields will aid in drawing meaningful inference and possible policy implications. If sovereign bond yield is non-stationary, the unit root may be transmitted to other macroeconomic variables. Thus, if there is a shock to sovereign bond yield, it may spill over to other financial markets such as the stock market and foreign exchange market, given its connection with these markets. Furthermore, when sovereign bond yields exhibits stationarity, it is possible to forecast future values of the series based on its past behavior.

In implementing the NL (2015) test on the sovereign bond yields, we utilize three different data frequencies, namely, daily, weekly, and monthly data frequencies. The consideration of these data frequencies is motivated by the findings of NL (2015) which indicate that the rejection rate of the unit root null hypothesis declines with data frequency. On the basis of the latter, they conclude that data frequency does matter for unit root testing. For robustness checks, we allow for different lag combinations of the GARCH terms [i.e. GARCH (1,2), GARCH (2,1), and GARCH(2,2)] and the resulting outcomes are compared with the test GARCH process [GARCH (1,1)].

In addition, we also consider other versions of the GARCH-based unit root tests such as the Cook (2008) and the NLW (2015) in order to clearly tease out the inherent statistical behavior of sovereign bond yield and more importantly to verify whether accounting for time trend and structural breaks matters for the series. Similarly, we also subject the sovereign bond yield data to the NP (2010) test which accounts for both structural breaks and time trend but does not allow for conditional heteroscedasticity. All these considerations enable us to robustly ascertain the behavior of sovereign bond yield data and how such behavior should be modeled empirically.

We structure the rest of the paper as follows. The next section explains the framework for the test. Section 3 presents data issues and preliminary analyses. The results of the trend-GARCH structural break model including other related unit root tests are presented in Section 4. Concluding remarks are rendered in Section 5.

2. The Narayan–Liu trend-GARCH-based structural break unit root test

The test regression proposed by NL (2015) for the GARCH-based unit root test that includes two endogenous breaks and a time trend is given below (see NL, 2015, pg. 396):

$$y_t = \lambda_0 + \lambda_1 t + \rho y_{t-1} + \sum_{i=1}^{k} D_i B_{it} + \varepsilon_t; \qquad i = 1, \ldots, k \tag{1}$$

where y_t denotes the series under consideration; t is a time trend; $B_{it} = 1$ if $t \geq T_{B_i}$ and $B_{it} = 0$ otherwise. The parameter λ_0 represents the intercept, λ_1 is the time trend coefficient, ρ is the autocorrelation coefficient, and D_i is the break dummy coefficient. The underlying null hypothesis for the test is that there is unit root, that is, $H_0 : \rho = 1$. For convenience of application, an alternative specification as given below is used as the test regression:

$$\Delta y_t = \lambda_0 + \lambda_1 t + \delta y_{t-1} + \sum_{i=1}^{k} D_i B_{it} + \varepsilon_t; \qquad i = 1, \ldots, k \tag{2}$$

where $\delta = (\rho - 1)$ and Δ, as usual, is the first difference operator. Thus, instead of estimating (1), we estimate (2) and therefore, the equivalent symbolic representation for null hypothesis of unit root is $H_0 : \delta = 0$.

Also, the error term ε_t is assumed to follow a GARCH process. For computational simplicity, the ε_t follows the first-order generalized autoregressive conditional heteroscedasticity model, denoted as GARCH (1, 1) as shown below:

$$\varepsilon_t = \eta_t h_t^{1/2}; \tag{3a}$$

$$h_t = \phi + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3b}$$

where $\varepsilon_t \sim \text{NID}(0,1)$; $\phi > 0$;$\alpha \geq 0$; and $\beta \geq 0$. Since we are using endogenously determined structural breaks as the break dates are unknown, the T_{B_i} has to be estimated and the resulting estimates are used for the unit root testing. In this paper, we follow the Bai and Perron [BP] (2003) multiple structural break test to determine the break dates.[1] We favor the use of BP test in determining the breaks as it allows for a maximum of five structural breaks in time series (see also, NL, 2015). It also involves a sequential application of sup $F_T(\ell+1|\ell)$ test which is assumed to work best in selecting the number of breaks. BP (2003) provide the following procedure to estimate the number of breaks in a time series data.

i. Consider a model and estimate with a small number of breaks or without breaks.
ii. Then, perform parameter constancy tests for each of the sub-samples (those obtained by cutting off at the estimated breaks), adding a break to a sub-sample associated with a rejection with the test sup $F_T(\ell+1|\ell)$.
iii. Repeat this process and increase ℓ sequentially until the test sup $F_T(\ell+1|\ell)$ fails to reject the null hypothesis of no additional structural changes.

The estimated endogenous structural breaks obtained through the BP (2003) process are then incorporated in Eq. (1) to test for unit root in the presence of a trend term, structural breaks, and conditional heteroscedasticity.

3. Data and preliminary analyses

We utilize daily, weekly, and monthly data of 10-year bond yield from data collected from Bloomberg terminal for seventeen (17) countries cutting across the three regions of America (United States, Canada, Mexico, Colombia, Brazil), Europe (Sweden, France, Finland, Netherlands, Germany, United Kingdom, Switzerland), and Asia/Pacific (Japan, New Zealand, Australia, South Korea, Hong Kong). Table 1 presents the start and end dates for the sovereign yield data covering the selected countries over the three data frequencies.[2] This period envelopes numerous significant financial market occurrences, including the recent global financial crisis and other structural breaks.

Just like the paper of NL (2015), we also provide graphical analyses as well as descriptive statistics. In addition, we include sign and size bias tests of Engle and Ng (1993) to test for the presence of asymmetric effect in the bond yield. This is necessary since the underlying univariate GARCH model for the test is the symmetric GARCH version which does not account for leverage effect.

As expected, all the series under consideration are trending (see Figs. 1 to 3) regardless of the data frequency. Interestingly, unlike the energy series examined by NL (2015) as previously noted, all the bond yield series considered here are trending downward and

[1] In any case, as noted by NL (2015), the manner in which structural breaks is chosen does not make the test unstable as long as there is a time trend in the test regression.

[2] Note that countries are arranged in alphabetical order for convenience and easy reference.

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