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## Robust estimation and inference for threshold models with integrated regressors

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# Robust Estimation and Inference for Threshold Models with Integrated Regressors

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# Robust Estimation and Inference for Threshold Models with Integrated Regressors

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## Abstract

This paper studies the robust estimation and inference of threshold models with integrated regressors. We derive the asymptotic distribution of the profiled least squares (LS) estimator under the diminishing threshold effect assumption that the size of the threshold effect converges to zero. Depending on how rapidly this sequence converges, the model may be identified or only weakly identified and asymptotic theorems are developed for both cases. As the convergence rate is unknown in practice, a model-selection procedure is applied to determine the model identification strength and to construct robust confidence intervals, which have the correct asymptotic size irrespective of the magnitude of the threshold effect. The model is then generalized to incorporate endogeneity and serial correlation in error terms, under which, we design a Cochrane-Orcutt feasible generalized least squares (FGLS) estimator which enjoys efficiency gains and robustness against different error specifications, including both  $I(0)$  and  $I(1)$  errors. Based on this FGLS estimator, we further develop a sup-Wald statistic to test for the existence of the threshold effect. Monte Carlo simulations show that our estimators and test statistics perform well.

JEL Classification: C12, C22, C52

Keywords: Threshold effects; Integrated processes; Nonlinear cointegration; Weak identification.

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# 1 Introduction

Threshold models, in which the model parameters switch when the value of a certain variable crosses a threshold, have received much attention over the past two decades. Given their ability to capture a very rich set of stylized facts of modern economics, such as multiple states, asymmetries and cyclical effects, the use of threshold models has been advocated in many empirical applications. Examples include the analysis of asymmetries in persistence in US output growth (Potter, 1995), nonlinearities in unemployment rates (Hansen, 1997), and multiple states in cross-country growth regressions (Durlauf and Johnson, 1995, Hansen, 2000), among numerous others. The estimation and asymptotics for variants of threshold models have been well established by Chan (1993), Hansen (1996, 2000), Tsay (1998), Gonzalo and Pitarakis (2002), and Seo and Linton (2007) etc.. More recently, Yu (2012) studies likelihood-based estimation and inference for a parametric discontinuous threshold regression model while Li and Ling (2012) study the least squares (LS) estimator of the multiple-regime threshold autoregressive (TAR) model.

However, most of the aforementioned studies maintain a restrictive assumption that the data should be either i.i.d. or stationary processes. Two exceptions are Caner and Hansen (2001) who study a threshold autoregressive model with a unit root and Gonzalo and Pitarakis (2006) who design a Wald statistic to test the threshold effect in a cointegrating regression. To the best of our knowledge, the asymptotic properties of threshold estimators, when all or some of the regressors are integrated processes, have not been established. In this paper, we investigate the robust estimation of threshold models with integrated regressors and establish its asymptotic properties allowing for different model identification strengths, endogenous regressors and serially correlated error terms, including both  $I(0)$  and  $I(1)$  errors.

Specifically, we consider a threshold model of the following form:

$$y_t = \begin{cases} \alpha'_1 x_t + u_t, & \text{if } q_t \leq \gamma_0 \\ \alpha'_2 x_t + u_t, & \text{if } q_t > \gamma_0 \end{cases}, \quad (1)$$

where  $x_t$  is a  $d_1$ -dimensional vector of integrated process of order 1 ( $I(1)$ ) and  $y_t$  is the dependent variable.<sup>1</sup> The error term, which will be specified more precisely later, is denoted by  $u_t$ , and  $q_t$  is the threshold variable. The threshold value  $\gamma_0 \in [\underline{\gamma}, \bar{\gamma}]$  is an unknown parameter pending estimation. If  $u_t$  is a stationary process, Equation (1) can be regarded as a special case of nonlinear cointegration models,<sup>2</sup> see Karlsen et al. (2007), Wang and Phillips (2009), Gao et al. (2009a, 2009b), Bierens and Martins (2010) and Choi and Saikkonen (2010).

Equation (1) can be rewritten as

$$y_t = \alpha' x_t + \delta' x_t I(q_t \leq \gamma_0) + u_t, \quad (2)$$

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<sup>1</sup>The model could be extended to include an intercept term and stationary regressors.

<sup>2</sup>Loosely speaking, if the response variable  $y_t$  is generated by a nonlinear transformation of integrated regressors  $x_t$  plus a stationary error term, then there exists a nonlinear cointegrating relationship between  $y_t$  and  $x_t$ .

where  $\alpha = \alpha_2$  and  $\delta = \alpha_1 - \alpha_2$ . Here  $I(q_t \leq \gamma_0)$  is an indicator function taking the value one if  $q_t \leq \gamma_0$  and zero otherwise. The vector  $(1, -\alpha)$  can be regarded as a benchmark long-run relationship between  $y_t$  and  $x_t$  and the term  $\delta x_t I(q_t \leq \gamma_0)$  captures the deviation from the linear equilibrium. In the literature,  $\delta$  is often assumed to be a deterministic sequence converging to zero at some rate as the sample size  $n$  increases. This assumption is not only convenient for deriving the asymptotic distribution of threshold estimators as in Hansen (2000), but is also relevant in many empirical applications. For example, an important issue in the empirical finance literature is to investigate whether fundamental variables, such as the dividend-price ratio and the earning-price ratio, can predict asset returns. Linear prediction models have been extensively studied, but have failed to generate any unanimous conclusion (for more detail, refer to Campbell and Yogo, 2006).<sup>3</sup> Recently, Gonzalo and Pitarakis (2012) document a regime-specific predictability of S&P 500 index returns from the dividend ratio based on a threshold model. However, as is well known, stock returns commonly behave as martingale differences, while fundamental variables are highly persistent (integrated or nearly integrated processes). This imbalance on the order of integration implies that such predictive relationship should be very weak, which happens if and only if  $\alpha = 0$  and  $\delta$  is around zero in Equation (2).

In this paper, we follow the literature by assuming the size of threshold effect converges to zero. Depending on how rapidly this sequence converges, the threshold value  $\gamma_0$  may be identified or only weakly identified and we develop asymptotic theorems for both cases.<sup>4</sup> In the first case, we show that the profiled LS estimator is consistent and that its confidence intervals (CIs) can be constructed through inversion of certain standard test statistics; whereas in the second case, the profiled LS estimator is inconsistent and its limiting distribution depends on some inestimable nuisance parameters. The standard method to construct CIs does not control the coverage probability. We take the supremum of quantiles for all possible values of nuisance parameters and then construct the least favorable CIs. These CIs have the correct asymptotic size under the weak identification case, but can be unnecessarily long when the model is identified. Motivated by Cheng (2008) and Shi and Phillips (2012), we then propose a model-selection procedure to choose the CIs. It can be shown that the CIs chosen by this method have approximately correct coverage probability irrespective of the magnitude of the threshold effect.

Furthermore, in a generalized model, we consider endogeneity and serial correlation, which are common in empirical studies with integrated regressors. Following Saikkonen (1991), we assume the error term to be an autoregressive (*AR*) process, and use leads and lags of innovations as extra regressors to deal with endogeneity. We then design a Cochrane-Orcutt feasible generalized least squares (FGLS) estimator to estimate the model. It is well known that, in linear cointegration models, the FGLS estimator cannot improve the estimation efficiency, as Phillips and Park (1988) demonstrate by establishing their asymptotic equivalence. However, this equivalence does not hold when there exists

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<sup>3</sup>Marmer (2008) shows that linear regression techniques actually may lead to spurious forecasts if there exist small departures from the linear structure, but improvements of the forecast accuracy are possible if the nonlinear components are properly considered.

<sup>4</sup>See Elliott and Müller (2007) and Caner (2007) for weak identification in break-point models; Cheng (2008) and Shi and Phillips (2012) for weak identification in general nonlinear models.

a threshold effect and we analytically and numerically show that the FGLS estimation achieves more efficiency compared to the profiled LS estimation. The method to construct the robust CIs of the LS estimator can also be generalized for the FGLS estimator.

Another attraction of the FGLS estimator is its robustness with respect to different error specifications, including both  $I(0)$  and  $I(1)$  errors. This robustness allows us to design a sup-Wald statistic to test for the existence of threshold effects without any requirement on the stationarity of the regression error term and thus avoid the so-called joint hypothesis test problem in such models (see Balke and Fomby, 1997). The idea is similar to Perron and Yabu (2009), who consider testing for structural changes in the trend function of a time series using a quasi-FGLS procedure, without any requirement on whether the noise component is stationary or integrated. In our case, we use the sup-Wald test statistic based on the FGLS estimator to test for the existence of a threshold effect and the critical values are generated from a bootstrap method. Monte Carlo simulations show that the FGLS estimator and the test statistic perform very well, even the error is an  $I(1)$  process.

The remainder of the paper is organized as follows. Section 2 presents the basic model. Section 3 considers the estimator and its asymptotics for the basic model. Section 4 generalizes the basic model to allow for serially correlated errors and model endogeneity. Monte Carlo simulations are discussed in Section 5. Section 6 concludes the paper. All proofs are in the appendices.

Throughout the paper,  $[ns]$  denotes the integer part of  $ns$ . The symbol ' $\xrightarrow{p}$ ' represents convergence in probability, ' $\Rightarrow$ ' represents weak convergence, and ' $\xrightarrow{a.s.}$ ' represents almost sure convergence. All limits are defined as the sample size  $n \rightarrow \infty$  unless otherwise stated. For a vector  $x$ ,  $\|\cdot\|$  signifies the Euclidean norm, i.e.,  $\|x\| = \sum x_i^2$ . For a matrix  $A$ ,  $|A| = (tr(A'A))^{1/2}$  denotes the Euclidean norm and  $A'$  denotes its transpose.  $\int$  denotes integration from 0 to 1.

## 2 The Basic Model

The basic model we consider in the paper is given by

$$y_t = \begin{cases} \alpha'_1 x_t + u_t, & \text{if } q_t \leq \gamma_0 \\ \alpha'_2 x_t + u_t, & \text{if } q_t > \gamma_0 \end{cases},$$

where  $x_t$  is a  $d_1$ -dimensional vector of unit root processes whose generating mechanism is given by

$$x_t = x_{t-1} + v_t, \quad t = 1, 2, \dots, n$$

and we set  $x_0 = 0$  for convenience, although  $x_0 = o_{a.s.}(\sqrt{n})$  is sufficient for the asymptotic results.

For the component time series  $u_t$  and  $v_t$ , we define the following partial sums as

$$U_n(s) \equiv \frac{1}{\sqrt{n}} \sum_{t=1}^{[ns]} u_t, \quad \text{and} \quad V_n(s) \equiv \frac{1}{\sqrt{n}} \sum_{t=1}^{[ns]} v_t. \quad (3)$$

Before going further, we make the following assumptions.

(A1)  $\sup_{s \in [0,1]} \|(U_n(s), V_n(s)) - (B_u(s), \mathbf{B}_v(s))\| \xrightarrow{a.s.} 0$  as  $n \rightarrow \infty$ , where  $(B_u(s), \mathbf{B}_v(s))$  is a vector of Brownian motions with a positive definite long-run covariance matrix.

(A2) The error term  $u_t$  satisfies: i)  $E(u_t) = 0$ ,  $E|u_t|^4 < \infty$ ; ii) For each  $n$ , there exists a filtration  $F_{n,t}$ ,  $t = 1, \dots, n$ , such that  $\{(u_t, F_{n,t}) : t \geq 1\}$  is a stationary and ergodic martingale difference sequence with  $E(u_t^2 | F_{n,t-1}) = \sigma_u^2 < \infty$  almost surely for all  $t = 1, \dots, n$ ; iii) The term  $(q_t, x_t)$  is adapted to the filtration  $F_{n,t-1}$ ,  $t = 1, \dots, n$ .

(A3) i) The threshold parameter  $\gamma_0 \in [\underline{\gamma}, \bar{\gamma}]$ ; ii) The threshold variable  $q_t$  is strictly stationary, ergodic and  $\alpha$ -mixing with mixing coefficients  $\alpha_m$  satisfying  $\sum_{m=1}^{\infty} \alpha_m^{\frac{1}{2} - \frac{1}{r}} < \infty$  for  $r > 2$ ; iii)  $q_t$  has a continuous distribution  $F(\cdot)$  and  $f(\cdot)$  is the corresponding density function satisfying  $0 < f(\gamma) \leq \bar{f} < \infty$  for all  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ .

(A4) The  $d_1$  dimensional  $I(1)$  vector  $x_t$  is not cointegrated.

Assumption (A1) considers a strong approximation for  $(U_n(s), V_n(s))$ , which is needed to derive the convergence rate of the threshold estimator. This assumption is stronger than the weak convergence result established by the multivariate invariance principle, but it is quite common in the literature, see Park and Phillips (2001), Kasparis (2008), Wang and Phillips (2009a, 2009b) and Shi and Phillips (2012), among others. Sufficient conditions to derive the strong approximation are also well developed in the literature. For example, Park and Hahn (1999) establish conditions of strong approximations for general linear processes. Shao and Lu (1987) and Cai et al. (2009) provide conditions of strong approximations for an  $\alpha$ -mixing process.

Assumption (A2) supposes  $\{(u_t, F_{n,t}) : t \geq 1\}$  to be a martingale difference sequence and  $(q_t, x_t)$  is adapted to the filtration  $F_{n,t-1}$ ,  $t = 1, \dots, n$ . Under this assumption,  $q_t$  and  $x_t$  become predetermined given the filtration  $F_{n,t-1}$ . One natural example of  $F_t$  is the  $\sigma$ -field generated by the information set  $\{(u_i, q_{i+1}, x_{i+1}) : 1 \leq i \leq t\}$ . This assumption might be restrictive in linear cointegration models, but it is common in fully specified cointegrating regression models. It allows for arguments based on the martingale central limit theory to establish a weak convergence result for the empirical process  $\sum_{t=1}^{[ns]} I_t(q_t \leq \gamma) u_t$  as in Caner and Hansen (2001).<sup>5</sup> Assumption (A2) does not allow for serially correlated errors and model endogeneity. However, in Section 4, we relax this assumption by adopting the so-called “leads and lags” approach or dynamic OLS estimator proposed by Saikkonen (1991).

(A3) is very conventional in the literature of threshold models. The threshold variable  $q_t$  is assumed to be strictly stationary and strong mixing for asymptotic purposes. The assumption excludes the case where  $q_t$  is a unit root process, under which one may need to use another technique such as the triangular array asymptotics proposed by Andrews and McDermott (1995). Assumption (A4) is standard in the literature of regressions with integrated processes.

Following Caner and Hansen (2001), we define  $W(s, \mu)$  as a two-parameter Brownian motion on

<sup>5</sup>The assumption (A2) can be relaxed under certain circumstances. For instance,  $u_t$  could be generalized to follow a linear moving average process of finite order  $l$ . However, fully generalizing the model to allow for serially correlated errors would involve substantial added complexity (see Gonzalo and Pitarakis, 2006).

$(s, \mu) \in [0, 1]^2$ , which is a zero-mean Gaussian process with covariance given by

$$E(W(s_1, \mu_1)W(s_2, \mu_2)) = (s_1 \wedge s_2)(\mu_1 \wedge \mu_2).$$

The two-parameter Brownian motion is a special tool to derive the limiting distribution in threshold models with integrated processes. Note that when  $\mu = 1$ , we have  $W(s, 1) \equiv W(s)$ , which is a Brownian motion on  $s \in [0, 1]$ .

Moreover, we can define the following stochastic integration with respect to  $W(s, \mu)$  on the first argument ( $s$ ) while holding the second argument ( $\mu$ ) constant as

$$\mathbf{J}_1(\mu) = \int \mathbf{B}_v(s) dW(s, \mu) = \lim_{n \rightarrow \infty} \sum_{t=1}^n (\mathbf{B}_v(\frac{t-1}{n}) \left( W(\frac{t}{n}, \mu) - W(\frac{t-1}{n}, \mu) \right)), \quad (4)$$

where  $\mathbf{J}_1(\mu)$  is a Gaussian process with an almost surely continuous sample path and the covariance kernel

$$E(\mathbf{J}_1(\mu_1)\mathbf{J}_1(\mu_2)) = (\mu_1 \wedge \mu_2) \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds.$$

### 3 Main Results

#### 3.1 Profiled LS Estimation and Asymptotics

For ease of manipulation, we rewrite Equation (2) in a more compacted form:

$$y_t = \theta' A_t(\gamma_0) + u_t, \quad (5)$$

where  $A_t(\gamma_0) = (x_t', x_t'(\gamma_0))'$ ,  $x_t(\gamma_0) = x_t I(q_t \leq \gamma_0)$ , and  $\theta = (\alpha', \delta')'$ .

For any fixed  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , the following model is estimated:

$$y_t = \hat{\theta}(\gamma)' A_t(\gamma) + \hat{u}_t(\gamma),$$

where  $\hat{\theta}(\gamma)$  is given by

$$\hat{\theta}(\gamma) = \left[ \sum_{t=1}^n A_t(\gamma) A_t(\gamma)' \right]^{-1} \left[ \sum_{t=1}^n A_t(\gamma) y_t \right].$$

The sum of squared residuals is defined as

$$SSR_n(\gamma) = \sum_{t=1}^n \hat{u}_t(\gamma)^2 = \sum_{t=1}^n \left( y_t - \hat{\theta}(\gamma)' A_t(\gamma) \right)^2, \quad (6)$$

and we define the profiled LS estimator of  $\gamma_0$  as the value that minimizes  $SSR_n(\gamma)$ , i.e.,

$$\hat{\gamma}_n = \arg \min_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} SSR_n(\gamma).$$



The term  $SSR_n(\gamma)$  is not differentiable due to the presence of the indicator functions; thus, we can not write  $\hat{\gamma}_n$  in closed form from first-order conditions. Following Hansen (2000), we adopt a grid-searching method. Specifically, we divide  $[\gamma, \bar{\gamma}]$  into  $N$  quantiles and let  $\Gamma_N = \{q_1, q_2, \dots, q_N\}$ . The estimator  $\hat{\gamma}_N = \arg \min_{\gamma \in \Gamma_N} SSR_n(\gamma)$  is a good approximation to  $\hat{\gamma}_n$  when  $N$  is large enough. The other parameters are then estimated by using the point estimate  $\hat{\gamma}_n$  via  $\hat{\theta} = \hat{\theta}(\hat{\gamma}_n)$  and  $\hat{\sigma}_u^2 = \frac{1}{n} \sum_{t=1}^n \hat{u}_t(\hat{\gamma}_n)^2$ .

In what follows, we set  $\delta = \delta_n = n^{-1/2-\tau} \delta_0$ , where  $-1/2 < \tau \leq 1/2$  and  $\delta_0 \in R$  is a fixed parameter. Under this assumption, the size of the threshold effect converges to zero with the rate  $n^{-1/2-\tau}$ , where the value of  $\tau$  determines the identification strength of the threshold value  $\gamma_0$ . We exclude the case with  $\tau > 1/2$  since the nonlinear term is negligible asymptotically. In addition, when  $\tau < -1/2$ , the nonlinear term is explosive and is also excluded. We also exclude the case of  $\tau = -1/2$  to focus on the limiting behavior of  $\hat{\gamma}_n$  when  $\delta_n \rightarrow 0$ .

The following theorem states the limiting results for  $\hat{\gamma}_n$  according to the value of  $\tau$ .

**THEOREM 3.1** *Under Assumptions (A1)–(A4) and  $\delta_n = n^{-1/2-\tau} \delta_0$ , the following limiting results hold:*

*Case 1: if  $-1/2 < \tau < 1/2$ , then*

$$n^{1-2\tau} |\hat{\gamma}_n - \gamma_0| = O_p(1).$$

*Furthermore,*

$$n^{1-2\tau} \lambda(\hat{\gamma} - \gamma_0) = r^* \Rightarrow \arg \max_{r \in (-\infty, \infty)} (\Lambda(r) - \frac{1}{2}|r|),$$

*where*

$$\lambda = \frac{\delta'_0 \left( \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \right) \delta_0 f_0}{\sigma_u^2},$$

*with  $f_0 = f(\gamma_0)$  and  $\Lambda(r)$  is a two-sided Brownian motion on the real line defined as:*

$$\Lambda(r) = \begin{cases} \Lambda_1(r) & \text{if } r > 0 \\ 0 & \text{if } r = 0 \\ \Lambda_2(-r) & \text{if } r < 0 \end{cases} \quad (7)$$

*The processes  $\Lambda_1(r)$  and  $\Lambda_2(r)$  are two independent standard Brownian motions on  $[0, \infty)$ .*

*Case 2: if  $\tau = 1/2$ , then  $\hat{\gamma}_n \Rightarrow \gamma(\gamma_0, \delta_0)$  and  $\gamma(\gamma_0, \delta_0)$  is a random variable that maximizes  $Q(\gamma, \gamma_0, \delta_0)$ , where*

$$Q(\gamma, \gamma_0, \delta_0) = \frac{1}{F(\gamma)(1 - F(\gamma))} \Gamma'_1(\gamma) \left( \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \right)^{-1} \Gamma_1(\gamma), \quad (8)$$

*with*

$$\Gamma_1(\gamma) = \Gamma(\gamma) + [F(\gamma \wedge \gamma_0) - F(\gamma)F(\gamma_0)] \left( \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \right) \delta_0, \quad (9)$$

and

$$\Gamma(\gamma) = \sigma_u \int \mathbf{B}_v(s) d[W(s, F(\gamma)) - F(\gamma)W(s)]. \quad (10)$$

Theorem 3.1 shows that the convergence results for  $\hat{\gamma}_n$  depend critically on the value of  $\tau$ , which characterizes the convergence speed of  $\delta_n$ .<sup>6</sup>

If  $-1/2 < \tau < 1/2$ , the threshold effect is identifiable and  $\hat{\gamma}_n$  is a consistent estimator. The rate of convergence is  $n^{1-2\tau}$ , which is decreasing in  $\tau$ . The limiting distribution of  $\hat{\gamma}_n$  has the same form as that found for the stationary threshold model in Hansen (2000), but the scale factor  $\lambda$  is different. Note that  $f_0$  is the density of  $q_t$  at  $\gamma_0$ . Intuitively, a larger  $f_0$  implies more data points around  $\gamma_0$ , making  $\hat{\gamma}$  more accurate.

To generate the confidence interval of  $\gamma$ , we invert the following likelihood ratio statistic for the null hypothesis  $\gamma = \gamma_0$ , given by

$$LR_n(\gamma_0) = n \frac{SSR_n(\gamma_0) - SSR_n(\hat{\gamma}_n)}{SSR_n(\hat{\gamma}_n)}, \quad (11)$$

where  $\hat{\gamma}_n$  is the profiled LS estimator. Following Hansen (2000), it can be shown that  $LR_n(\gamma_0) \Rightarrow \sup_{r \in (-\infty, \infty)} (2\Lambda(r) - |r|)$ . Denote  $q_{\gamma, 1-a}^I$  as the  $1-a$  quantile of the random variable  $\sup_{r \in (-\infty, \infty)} (2\Lambda(r) - |r|)$  and  $q_{\gamma, 1-a}^I$  can be calculated by the formula  $q_{\gamma, 1-a}^I = -2 \ln(1 - \sqrt{1-a})$ . Thus, the  $a$ -level confidence interval of  $\gamma$  in the case of identification can be expressed as

$$CI_{\gamma, n}^I(\alpha) = \{\gamma : LR_n(\gamma) \leq q_{\gamma, 1-a}^I\}. \quad (12)$$

If  $\tau = 1/2$ , the threshold effect is only weakly identified. The profiled LS estimator  $\hat{\gamma}_n$  converges to a random variable  $\gamma(\gamma_0, \delta_0)$ , reflecting the lack of information. Since  $\gamma_0$  and  $\delta_0$  are not estimable, any statistical inference based on them is impossible. Following Cheng (2008) and Shi and Phillips (2012), we define the least favorable CI which is large enough for all possible  $\gamma_0$  and  $\delta_0$ . Denote  $q_{\gamma, 1-a}^W(\gamma_0, \delta_0)$  as the  $1-a$  quantile of  $|\gamma(\gamma_0, \delta_0) - \gamma_0|$  for each  $\gamma_0 \in [\underline{\gamma}, \bar{\gamma}]$  and  $\delta_0 \in R$ . The  $a$ -level CI, given  $\gamma_0$  and  $\delta_0$ , is then defined as

$$CI_{\gamma, n}^W(1-a, \gamma_0, \delta_0) = \{\gamma : |\hat{\gamma}_n - \gamma| \leq q_{\gamma, 1-a}^W(\gamma_0, \delta_0)\}. \quad (13)$$

Since  $\gamma_0$  and  $\delta_0$  are two unknown variables, we define a robust quantile by taking the supremum of all possible  $\gamma_0$  and  $\delta_0$ . Let

$$q_{\gamma, 1-a}^W = \sup_{\gamma_0 \in [\underline{\gamma}, \bar{\gamma}]} \sup_{\delta_0 \in R} q_{\gamma, 1-a}^W(\gamma_0, \delta_0). \quad (14)$$

The  $a$ -level least favorable CI in the case of weak identification is then defined as

$$CI_{\gamma, n}^W(a) = \{\gamma : |\hat{\gamma}_n - \gamma| \leq q_{\gamma, 1-a}^W\}. \quad (15)$$

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<sup>6</sup>In an early version of this paper, we have also established the limiting distribution of the coefficient estimators  $\hat{\theta}(\hat{\gamma}_n)$ . We show that, if  $-1/2 < \tau < 1/2$ , the limiting distribution of the coefficients estimators is mixed normal, which makes conventional *t*-test and *chi-square* tests applicable, whereas if  $\tau = 1/2$ , the limiting result contains a bias term  $\Pi(\hat{\gamma}_n, \gamma_0, \delta_0)$  due to the inconsistency of  $\hat{\gamma}_n$ .

### 3.2 Robust Confidence Interval

In empirical studies,  $\tau$  is unknown, raising the question of which CI should be used. In this subsection, based on a model selection procedure, we construct a robust CI which has approximately correct coverage probability irrespective of the value of  $\tau$ .

For a fixed  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , let  $X(\gamma) = (x_1(\gamma), x_2(\gamma), \dots, x_n(\gamma))'$  and  $X = (x_1, x_2, \dots, x_n)'$ . The Wald test statistic for testing  $H_0 : \delta_n = 0$  can be defined as

$$T_n(\gamma) = \hat{\delta}_n(\gamma)'(X(\gamma)(I - P_n)X(\gamma))\hat{\delta}_n(\gamma)/\hat{\sigma}_u^2, \quad (16)$$

where  $P_n$  is the projection matrix of  $X$ , given by  $P_n = X(X'X)^{-1}X'$ . Following Hansen (1996), we define the sup-Wald test statistic as

$$T_n = \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} T_n(\gamma).$$

The following theorem explores the limiting behaviors of the sup-Wald statistic under different model identification strengths.

**THEOREM 3.2** *Under Assumptions (A1) – (A4) and  $\delta_n = n^{-1/2-\tau}\delta_0$ , where  $\delta_0$  is a nonzero constant, the following limiting results hold:*

- i) if  $-1/2 < \tau < 1/2$ , then  $T_n \xrightarrow{p} \infty$ .
- ii) if  $\tau = 1/2$ , then

$$T_n \Rightarrow T_1 = \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} T_1(\gamma) = \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} \frac{1}{\sigma_u^2(F(\gamma)(1 - F(\gamma)))} \Gamma_1(\gamma)' \left( \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \right)^{-1} \Gamma_1(\gamma), \quad (17)$$

where  $\Gamma_1(\gamma)$  is defined by Equation (9).

Theorem 3.2 shows that  $T_n \xrightarrow{p} \infty$  if  $-1/2 < \tau < 1/2$  and  $T_n < \infty$  if  $\tau = 1/2$ . This result enables us to develop the following model selection procedure. We define  $\{\kappa_n : n \geq 1\}$  as a sequence of constants that diverge to infinity as  $n \rightarrow \infty$ . The parameter  $\kappa_n$  is referred to as a tuning parameter and we require the sequence  $\kappa_n$  to diverge to infinity at a rate slower than  $n^\nu$  for any  $\nu > 0$ , i.e.,

$$n^{-\nu} \kappa_n^{1/2} \rightarrow 0. \quad (18)$$

Suitable choices of  $\kappa_n$  include  $d(\ln(n))^2$  where  $d$  is a positive constant, in accordance with *BIC*. The model selection procedure is designed to choose the model with the identified threshold effect if  $T_n > \kappa_n$  and to choose the model with the weakly identified threshold effect otherwise. We use the CI chosen through this procedure as the final CI.

Specifically, for each confidence level  $a$ , define

$$CI_{\gamma,n}(a) = \begin{cases} CI_{\gamma,n}^I(a), & \text{if } T_n > \kappa_n \\ CI_{\gamma,n}^W(a), & \text{if } T_n \leq \kappa_n \end{cases}.$$

We focus on the smallest finite sample coverage probability of  $CI_{\gamma,n}(a)$  over the whole parameter space, which can be approximated by the following asymptotic size

$$AsySZ_{\gamma}(a) = \lim_{n \rightarrow \infty} \inf_{\delta_0 \in R} \inf_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} \Pr(\gamma \in CI_{\gamma,n}(a)). \quad (19)$$

The following theorem shows that the robust CI has the correct asymptotic size.

**THEOREM 3.3** *Under Assumptions (A1) – (A4), for any  $a \in (0, 1)$ , we have  $AsySZ_{\gamma}(a) = a$ .*

## 4 The Generalized Model

In many economic applications of cointegration, error terms are serially correlated and correlated with regressors. Under these conditions, it is well known that the ordinary least squares (OLS) estimator contains a second-order bias in linear cointegration models. Several efficient estimators have been proposed, such as the fully modified (FM) OLS estimator of Phillips and Hansen (1990), the canonical cointegrating regressions (CCR) estimator of Park (1992) and the dynamic ordinary least squares (DOLS) estimator proposed by Saikkonen (1991) and Stock and Watson (1993). In the following, we generalize the basic model in Section 2 to allow for serial correlation and model endogeneity.

More formally, we introduce Assumptions (A1') and (A2') to replace Assumptions (A1) and (A2). Assumptions (A3) and (A4) are applicable to the generalized model.

(A1') In Equation (1),  $u_t$  can be decomposed as

$$\begin{aligned} u_t &= \sum_{i=1}^{d_1} \sum_{j=-K}^K \beta_{ij} v_{i,t-j} + \eta_t = \beta' z_t + \eta_t, \\ \eta_t &= \rho \eta_{t-1} + \varepsilon_t, \text{ with } \rho \in (-1, 1], \end{aligned} \quad (20)$$

where  $z_t = (v_{1,t-K}, \dots, v_{d_1,t+K})$  and  $\beta = (\beta_{1,-K}, \dots, \beta_{d_1,K})$ . The error term  $\varepsilon_t$  satisfies i)  $E(\varepsilon_t) = 0$ ,  $E|\varepsilon_t|^4 < \infty$ ; ii) For each  $n$ , there exists a filtration  $F_{n,t}$ ,  $t = 1, \dots, n$ , such that  $\{(\varepsilon_t, F_{n,t}) : t \geq 1\}$  is a stationary and ergodic martingale difference sequence with  $E(\varepsilon_t^2 | F_{n,t-1}) = \sigma^2 < \infty$  almost surely for all  $t = 1, \dots, n$ ; iii) The term  $(q_t, x_t)$  is adapted to the filtration  $F_{n,t-1}$ ,  $t = 1, \dots, n$ .

(A2') Let  $\xi_n(s) \equiv \frac{1}{\sqrt{n}} \sum_{t=1}^{[ns]} \varepsilon_t$  and  $\sup_{s \in [0,1]} \|(\xi_n(s), V_n(s)) - (B_{\varepsilon}(s), \mathbf{B}_v(s))\| \xrightarrow{a.s.} 0$  as  $n \rightarrow \infty$ , where  $(B_{\varepsilon}(s), \mathbf{B}_v(s))$  is a vector of Brownian motions with a positive definite long-run covariance matrix.

Under Assumption (A1'), the model endogeneity can be fully captured by  $\beta' z_t$ , where  $z_t$  is a vector of leads and lags of  $\Delta x_t$ . The parameter  $K$  can diverge to infinity as the sample size increases. The idea of using leads and lags to deal with endogeneity in cointegration models was proposed by Saikkonen (1991). We assume  $\beta$  remains constant to focus on the threshold effect occurring in the cointegrating relationship. The extension allowing  $\beta$  to be regime-sensitive would be interesting and is left to future study. The term  $\eta_t$  is assumed to be  $AR(1)$  and  $\rho$  controls the stationarity of  $\eta_t$ . If  $\rho = 1$ ,  $\eta_t$  is a

unit root process and the model describes a structural spurious relationship,<sup>7</sup> while if  $\rho < 1$ ,  $\eta_t$  is a stationary process and the model is a cointegrating relationship.

To estimate a regression with serial correlation, the Cochrane-Orcutt FGLS procedure is usually adopted. In linear cointegration models, as shown in Phillips and Park (1988), the FGLS estimator and the OLS estimator are equivalent in asymptotics. The Cochrane-Orcutt FGLS estimator also works for spurious regressions, as Phillips and Hodgson (1994) demonstrate by proving the asymptotic equivalence of the FGLS estimator to the OLS estimator when the error is an I(1) process. However, in the presence of threshold effects, there is no asymptotic equivalence between FGLS and OLS estimators. The following simple sketch may help to illustrate this difference.

For a linear cointegrating regression after transformation,

$$y_t - \rho y_{t-1} = \alpha'(x_t - \rho x_{t-1}) + (\eta_t - \rho \eta_{t-1}),$$

and it follows that

$$\begin{aligned} n(\hat{\alpha}_{FGLS} - \alpha) &= \left( \sum_{t=1}^n (x_t - \rho x_{t-1})(x_t - \rho x_{t-1})' \right)^{-1} \left( \sum_{t=1}^n (x_t - \rho x_{t-1})(\eta_t - \rho \eta_{t-1}) \right) \\ &\Rightarrow \left( (1 - \rho)^2 \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \right)^{-1} (1 - \rho)^2 \int \mathbf{B}_v(s) dB_\eta(s) \\ &= \left( \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \right)^{-1} \int \mathbf{B}_v(s) dB_\eta(s), \end{aligned}$$

which is the same as the limiting result of the OLS estimator.

However, for a cointegrating regression with a threshold effect after transformation,

$$\begin{aligned} y_t - \rho y_{t-1} &= \alpha'(x_t - \rho x_{t-1}) + \delta_n'(x_t(\gamma) - \rho x_{t-1}(\gamma)) + (\eta_t - \rho \eta_{t-1}) \\ &= \alpha' \tilde{x}_t + \delta_n' \tilde{x}_t(\gamma) + (\eta_t - \rho \eta_{t-1}), \end{aligned}$$

where  $\rho$  can not be canceled in the limiting result because

$$\sum_{t=1}^n \tilde{x}_t(\gamma) \tilde{x}_t(\gamma)' \Rightarrow ((1 + \rho^2)F(\gamma) - 2\rho F_1(\gamma, \gamma)) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds,$$

which depends on  $\rho$ , the marginal distribution function  $F(\gamma) \equiv \Pr(q_t \leq \gamma)$  and the joint distribution  $F_1(\gamma, \gamma) \equiv \Pr(q_t \leq \gamma, q_{t-1} \leq \gamma)$ , whereas

$$\sum_{t=1}^n \tilde{x}_t(\gamma)(\eta_t - \rho \eta_{t-1}) \Rightarrow (1 - \rho^2) \int \mathbf{B}_v(s) dB_\eta(s).$$

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<sup>7</sup>Structural spurious regressions can be due to integrated measurement errors and missing integrated regressors. See Choi et al. (2008).

## 4.1 FGLS Estimator

To obtain a feasible GLS estimator, we first estimate the threshold value  $\gamma_0$  through the profiled LS estimator without considering serial correlation and endogeneity. Then we estimate  $\hat{\rho}$  from the estimated error terms. Finally, we construct the Cochrane-Orcutt FGLS estimator based on  $\hat{\rho}$ .

Specifically, we estimate  $\gamma_0$  using

$$\hat{\gamma}_n = \arg \min_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} SSR_n(\gamma),$$

where  $SSR_n(\gamma)$  is the sum of squared residuals for the regression

$$y_t = \hat{\alpha}' x_t + \hat{\delta}'_n x_t I(q_t \leq \gamma) + \hat{\beta}' z_t + \hat{\eta}_t.$$

By estimating the *AR* model

$$\hat{\eta}_t(\hat{\gamma}_n) = \hat{\rho} \hat{\eta}_{t-1}(\hat{\gamma}_n) + \hat{\varepsilon}_t,$$

the OLS estimator  $\hat{\rho}$  is estimated, where  $\hat{\eta}_t(\hat{\gamma}_n) = y_t - \hat{\alpha}'(\hat{\gamma}_n)x_t - \hat{\delta}'_n(\hat{\gamma}_n)x_t I(q_t \leq \hat{\gamma}_n) - \hat{\beta}'(\hat{\gamma}_n)z_t$ .

The following theorem establishes the consistency and the convergence rate of  $\hat{\rho}$ .

**THEOREM 4.1** *Under Assumptions (A1'), (A2'), (A3) and (A4),  $\hat{\rho} \rightarrow \rho$  as  $n \rightarrow \infty$ . Furthermore,  $|\hat{\rho} - \rho| = O_p(n^{-1/2})$  if  $\rho < 1$ , and  $|\hat{\rho} - 1| = O_p(n^{-1})$  if  $\rho = 1$ .*

Theorem 4.1 shows that  $\hat{\rho}$  is consistent even when  $\rho = 1$ , i.e., the regression is a spurious relationship. The convergence rates are different due to the different convergence speeds of integrated and stationary processes. Moreover, we find that the limiting behavior of  $\hat{\rho}$  is not affected by the identification strength of the threshold effect. The intuition is as follows. If  $\tau < 1/2$ ,  $\gamma_0$  can be consistently estimated by  $\hat{\gamma}_n$ . In each regime, if  $\rho < 1$ , the coefficients can be consistently estimated as well and thus it is obvious that  $\hat{\rho} \xrightarrow{P} \rho$ . If  $\rho = 1$ , the coefficient estimators are not consistent; however, this inconsistency implies that the residual term  $\hat{\eta}_t(\hat{\gamma}_n)$  is a unit root and that  $\hat{\rho} \xrightarrow{P} \rho = 1$ . If  $\tau = 1/2$ ,  $\hat{\gamma}_n$  is not consistent as shown in Theorem 3.1; however, the nonlinear term  $\hat{\delta}'_n x_t I(q_t \leq \gamma)$  decays to zero so fast that it has no impact on the estimation of  $\rho$  asymptotically. Following Choi et al. (2008), the consistency of  $\hat{\rho}$  can also be obtained.

Based on the consistent estimator  $\hat{\rho}$ , we construct the following Cochrane-Orcutt FGLS estimators. We first define  $\tilde{y}_t = y_t - \hat{\rho} y_{t-1}$ , and  $\tilde{z}_t, \tilde{x}_t, \tilde{\eta}_t$  in the same way. For each  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , define

$$\tilde{x}_t(\gamma) = x_t I(q_t \leq \gamma) - \hat{\rho} x_{t-1} I(q_{t-1} \leq \gamma).$$

Let  $\tilde{A}_{1t}(\gamma) = (\tilde{x}'_t, \tilde{x}'_t(\gamma), \tilde{z}'_t)'$  and stack  $\tilde{x}_t, \tilde{y}_t, \tilde{z}_t, \tilde{x}_t(\gamma)$  and  $\tilde{A}_{1t}(\gamma)$  to get the matrices:  $\tilde{X}, \tilde{Y}, \tilde{Z}, \tilde{X}(\gamma)$  and  $\tilde{A}_1(\gamma)$ .

After the transformation,

$$\tilde{y}_t = \alpha' \tilde{x}_t + \delta'_n \tilde{x}_t(\gamma) + \beta' \tilde{z}_t + \tilde{\eta}_t = \tilde{\theta}' \tilde{A}_{1t}(\gamma) + \tilde{\eta}_t, \quad (21)$$

where  $\tilde{\theta} = (\alpha', \delta'_n, \beta')'$ .

Using Equation (21), for each  $\gamma$ , we can define

$$\hat{\tilde{\theta}}(\gamma) = \left[ \sum_{t=2}^n \tilde{A}_{1t}(\gamma) \tilde{A}_{1t}(\gamma)' \right]^{-1} \left[ \sum_{t=2}^n \tilde{A}_{1t}(\gamma) \tilde{y}_t \right], \quad (22)$$

and the FGLS threshold estimator can be defined as

$$\tilde{\gamma}_n = \arg \min_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} (\widetilde{SSR}_n(\gamma)),$$

where  $\widetilde{SSR}_n(\gamma)$  is the sum of squared residuals given by

$$\widetilde{SSR}_n(\gamma) = \sum_{t=2}^n \left( \tilde{y}_t(\gamma) - \hat{\tilde{\theta}}(\gamma)' \tilde{A}_{1t}(\gamma) \right)^2. \quad (23)$$

The following theorem establishes the limiting results of the FGLS estimator.

**THEOREM 4.2** *Under Assumptions (A1'), (A2'), (A3) and (A4), the following results hold:*

*Case 1: if  $-1/2 < \tau < 1/2$ , then  $n^{1-2\tau} |\tilde{\gamma}_n - \gamma_0| = O_p(1)$ . Furthermore,*

$$n^{1-2\tau} \tilde{\lambda}(\tilde{\gamma}_n - \gamma_0) = r^* \Rightarrow \arg \max_{r \in (-\infty, \infty)} (\Lambda(r) - \frac{1}{2}|r|),$$

where

$$\tilde{\lambda} = \frac{(1 + \rho^2) (\delta'_0 \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \delta_0) f_0}{\sigma^2}, \quad (24)$$

and  $\Lambda(r)$  is defined by Equation (7).

*Case 2: if  $\tau = 1/2$ , then  $\tilde{\gamma}_n \Rightarrow \tilde{\gamma}(\gamma_0, \delta_0)$  and  $\tilde{\gamma}(\gamma_0, \delta_0)$  is a random variable that maximizes  $\tilde{Q}(\gamma, \gamma_0, \delta_0)$  where*

$$\tilde{Q}(\gamma, \gamma_0, \delta_0) = \tilde{\Gamma}'_1(\gamma) \left( \tilde{G}_{22}(\gamma) - \begin{pmatrix} \tilde{G}_{21}(\gamma) \\ \tilde{G}_{23}(\gamma) \end{pmatrix}' \begin{pmatrix} \tilde{G}_{11}, \tilde{G}_{13} \\ \tilde{G}_{31}, \tilde{G}_{33} \end{pmatrix}^{-1} \begin{pmatrix} \tilde{G}_{12}(\gamma) \\ \tilde{G}_{32}(\gamma) \end{pmatrix} \right)^{-1} \tilde{\Gamma}_1(\gamma),$$

with

$$\tilde{\Gamma}_1(\gamma) = \tilde{\Gamma}(\gamma) + \left( \tilde{G}_{22}(\gamma) - \begin{pmatrix} \tilde{G}_{21}(\gamma) \\ \tilde{G}_{23}(\gamma) \end{pmatrix}' \begin{pmatrix} \tilde{G}_{11}, \tilde{G}_{13} \\ \tilde{G}_{31}, \tilde{G}_{33} \end{pmatrix}^{-1} \begin{pmatrix} \tilde{G}_{12}(\gamma) \\ \tilde{G}_{32}(\gamma) \end{pmatrix} \right) \delta_0,$$

and

$$\tilde{\Gamma}(\gamma) = \tilde{\phi}_2(\gamma) - \begin{pmatrix} \tilde{G}_{21}(\gamma) \\ \tilde{G}_{23}(\gamma) \end{pmatrix}' \begin{pmatrix} \tilde{G}_{11}, \tilde{G}_{13} \\ \tilde{G}_{31}, \tilde{G}_{33} \end{pmatrix}^{-1} \begin{pmatrix} \tilde{\phi}_1(\gamma) \\ \tilde{\phi}_3(\gamma) \end{pmatrix}, \quad (25)$$

where the random matrix  $\tilde{G}(\gamma) = \begin{pmatrix} \tilde{G}_{11}(\gamma), \tilde{G}_{12}(\gamma), \tilde{G}_{13}(\gamma) \\ \tilde{G}_{21}(\gamma), \tilde{G}_{22}(\gamma), \tilde{G}_{23}(\gamma) \\ \tilde{G}_{31}(\gamma), \tilde{G}_{32}(\gamma), \tilde{G}_{33}(\gamma) \end{pmatrix}$  and the random vector  $\tilde{\phi}(\gamma) = \begin{pmatrix} \tilde{\phi}_1(\gamma) \\ \tilde{\phi}_2(\gamma) \\ \tilde{\phi}_3(\gamma) \end{pmatrix}$  are specified in Lemma B.4 of the appendix.

Theorem 4.2 establishes the convergence results for the FGLS estimator  $\tilde{\gamma}_n$ . If  $-1/2 < \tau < 1/2$ , the threshold value can be consistently estimated and its limiting distribution depends on the persistence parameter  $\rho$ . Note that  $\tilde{\lambda} = (1 + \rho^2) \lambda$ , implying that the FGLS estimator is more efficient than the profiled LS estimator when  $\rho \neq 0$ . The simulations in Section 5 demonstrate this result.

## 4.2 Generalized Sup-Wald Statistics

Testing for the existence of the threshold effect in a cointegration regression is challenging since it is a joint hypothesis problem (see Balke and Fomby, 1997). For example, when testing for the existence of threshold effects, the statistics based on error correction models (ECM) need to assume the model is a cointegrating regression. Therefore, the rejection of the null hypothesis does not necessarily indicate that there is a threshold effect. It may mean that the regression is a spurious relationship. Thanks to the robustness of the FGLS estimator, we can design a generalized sup-Wald test statistic based on this estimator to test for the existence of threshold effects, without any requirement on the stationarity of the error term.

The null hypothesis is

$$H_0 : \delta_n = 0,$$

and the alternative is

$$H_1 : \delta_n \neq 0.$$

Under the null, after transformation, the model is

$$\tilde{y}_t = \alpha' \tilde{x}_t + \beta' \tilde{z}_t + \tilde{\eta}_t, \quad (26)$$

while under the alternative, the transformed model is

$$\begin{aligned} \tilde{y}_t &= \alpha' \tilde{x}_t + \delta'_n \tilde{x}_t(\gamma_0) + \beta' \tilde{z}_t + \tilde{\eta}_t \\ &= \tilde{\theta}' \tilde{A}_{1t}(\gamma_0) + \tilde{\eta}_t. \end{aligned} \quad (27)$$

Let  $\tilde{V}_1 = (\tilde{X}, \tilde{Z})$ , then a generalized Wald statistic can be defined as

$$\tilde{T}_n(\gamma) = \tilde{\delta}_n(\gamma)' (\tilde{X}(\gamma)(I - \tilde{P}(\gamma))\tilde{X}(\gamma)) \tilde{\delta}_n(\gamma) / \tilde{\sigma}^2,$$

where  $\tilde{P}(\gamma)$  is the projection matrix for  $\tilde{V}_1$  and  $\tilde{\sigma}^2 = \widetilde{SSR}_n(\gamma)/n$ .



The generalized sup-Wald statistic is defined as

$$\tilde{T}_n = \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} \tilde{T}_n(\gamma).$$

**THEOREM 4.3** *Under Assumptions (A1'), (A2'), (A3), (A4) and  $H_0 : \delta_n = 0$ , the following limiting result holds:*

$$\begin{aligned} \tilde{T}_n &\Rightarrow \tilde{T} = \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} \tilde{T}(\gamma) \\ &= \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} \frac{1}{\sigma^2} \tilde{\Gamma}'(\gamma) \left( \tilde{G}_{22}(\gamma) - \begin{pmatrix} \tilde{G}_{21}(\gamma) \\ \tilde{G}_{23}(\gamma) \end{pmatrix}' \begin{pmatrix} \tilde{G}_{11}, \tilde{G}_{13} \\ \tilde{G}_{31}, \tilde{G}_{33} \end{pmatrix}^{-1} \begin{pmatrix} \tilde{G}_{12}(\gamma) \\ \tilde{G}_{32}(\gamma) \end{pmatrix} \right)^{-1} \tilde{\Gamma}(\gamma), \end{aligned}$$

where  $\tilde{\Gamma}(\gamma)$  is defined by Equation (25).

Theorem 4.3 establishes the limiting distribution of the generalized sup-Wald test statistic, which is nonstandard and we generate the critical values using a parametric bootstrap method. We first estimate  $\hat{\theta}_R$  using Equation (26) under the null. Then, we obtain the residual terms  $\{\hat{\eta}_t(\tilde{\gamma}_n)\}_{t=2}^n$  using Equation (27) under the alternative. We draw a random variable  $\tilde{\eta}_t^b$  from the sample  $\{\hat{\eta}_t(\tilde{\gamma}_n)\}_{t=2}^n$  for all  $t = 2, \dots, n$ , and generate a new sequence  $\{\tilde{y}_t^b\}_{t=1}^n$  by  $\tilde{y}_t^b = \hat{\alpha}'_R \tilde{x}_t + \hat{\beta}'_R \tilde{z}_t + \tilde{\eta}_t^b$ . Define  $y_1^b = y_1$  and  $y_t^b = \tilde{y}_t^b + \hat{\rho} y_{t-1}^b$  for all  $t = 2, \dots, n$ . Let  $\tilde{T}_n^b$  be the sup-Wald test calculated from the new data set  $\{y_t^b, x_t, z_t, q_t\}_{t=2}^n$ . Under the null, the distribution of  $\tilde{T}_n^b$  approximates the distribution of  $\tilde{T}_n$ . The bootstrap  $p$ -value is obtained by calculating the frequency of simulated  $\tilde{T}_n^b$  that exceeds  $\tilde{T}_n$  when the number of simulations is sufficiently large. Following Hansen (1996), one can show that the generated  $p$ -value converges to the true size.

One can use the generalized sup-Wald statistic  $\tilde{T}_n$  to construct robust CIs for the threshold model following the procedures described in Section 3.2.

## 5 Simulations

This section demonstrates the finite sample performance of the estimators and test statistics through two simulation experiments.

**Simulation 1:** We examine the consistency of the profiled LS estimator and the FGLS estimator under different model settings. We make comparisons between these two estimators to demonstrate the advantage of the FGLS estimator when serial correlation and model endogeneity exist.

We consider the simple regression model

$$y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t,$$

where  $x_t = x_{t-1} + v_t$  and  $u_t = \rho u_{t-1} + \varepsilon_t$ . The threshold variable  $q_t$  is generated by an  $AR(1)$  process:

$q_t = 0.5q_{t-1} + e_t$ . The innovation processes  $v_t$ ,  $\varepsilon_t$  and  $e_t$  follow i.i.d.  $N(0, 1)$  and are independent of each other. The true threshold value is set as  $\gamma_0 = 0$  and the coefficient  $\alpha$  is set as 1. The parameter  $\beta$  is set as 0 or 0.5, which controls the correlation between  $x_t$  and  $u_t$ . To check the impact of the serial correlation of  $u_t$  on the estimation, we set  $\rho$  as either 0, 1, 0.95 or  $-0.95$ . Moreover, we set the size of the threshold effect as  $\delta_n = 2n^{-1/2-\tau}$  with  $\tau$  chosen as either 0 or 0.5, corresponding to the case with identification or the case with weak identification. The number of replications is  $N = 1000$ . The sample size  $n$  is set as 100, 200 or 400. We let the number of lags  $K = 5$  in the FGLS estimator.<sup>8</sup>

Tables 1a and 1b report the mean square errors (MSE) of the profiled LS and the FGLS estimators for the threshold value and regression coefficients, respectively.

**Here insert Tables 1a and 1b**

Specifically, Table 1a compares the performance of the profiled LS and the FGLS estimators of the threshold value under different model settings. Panel A displays the results when  $\tau = 0$  (the case with identification). The profiled LS estimator  $\hat{\gamma}$  is consistent when  $\rho < 1$  (the error term  $u_t$  is stationary) no matter whether there exists regressor endogeneity or not, but it is inconsistent when  $\rho = 1$  (the error term  $u_t$  is a unit root process). On the other hand, the FGLS estimator  $\tilde{\gamma}$  is always consistent. Of particular interest is that the FGLS estimator performs better than the profiled LS estimator when serial correlation and regressor endogeneity exist, which is consistent with the theoretical result. Panel B reports the results when  $\tau = 0.5$  (the case with weak identification). Both profiled LS and FGLS estimators are inconsistent since their MSE do not converge to zero as the sample size increases to infinity. However, the FGLS estimators still have smaller MSE than the profiled LS estimators in most cases. Similar conclusions can be drawn from Table 1b, which reports the MSE of the regression coefficient estimators.

**Simulation 2:** In this experiment, we examine the performance of the sup-Wald test statistics and the model selection procedure. The data generating process is the same as in Simulation 1, but we consider an additional case with  $\delta_n = 0$  to evaluate the size performance of the test statistics.

Table 2a reports the size performance of the sup-Wald statistic  $T_n$  and the generalized sup-Wald statistic  $\tilde{T}_n$ , which are based on the profiled LS estimator and the FGLS estimator, respectively. Comparing Panel A with Panel B, one can see that  $\tilde{T}_n$  has better size performance than  $T_n$  when serial correlation or regressor endogeneity exists. In an unreported result with the sample size  $n = 1000$ , the rejection rate of  $\tilde{T}_n$  is close to the size, but not for  $T_n$ . Thus, we suggest that the generalized sup-Wald statistic  $\tilde{T}_n$  should be used in practice.

**Here insert Table 2a**

Tables 2b through 2d report the power performance for  $T_n$  and  $\tilde{T}_n$  with different sample sizes. In all three tables, Panel A shows the results for the case with identification and Panel B shows the case with weak identification.

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<sup>8</sup>Other values for  $K$ , such as 10 and 15, are also applied with little change in the results.

**Here insert Tables 2b, 2c and 2d**

When the threshold effect is identified, both  $T_n$  and  $\tilde{T}_n$  seem to be consistent since their power converges to one as the sample size increases. In particular,  $\tilde{T}_n$  performs better than  $T_n$  when there exists serial correlation, model endogeneity or both; the advantage of the generalized sup-Wald statistic is confirmed.

However, when the threshold effect is only weakly identified, both statistics seem to have low power even when the sample size is 400, which is consistent with the theoretical results. In practice, one may use the model selection procedure described in Section 3.2 to detect the case with weak identification. We choose  $(\ln(n))^2$  as the tuning parameter  $\kappa_n$  and judge that the model is weakly identified if  $T_n$  or  $\tilde{T}_n$  is smaller than  $\kappa_n$ . From the columns corresponding to  $(\ln(n))^2$  in Tables 2b-2d, one can find that the model selection procedure based on  $\tilde{T}_n$  works very well in all cases.

## 6 Conclusion

In the literature, statistical theory for threshold models with stationary explanatory variables has been well developed by Hansen (1996, 2000). However, in empirical macroeconomics and finance, many explanatory variables are nonstationary. This paper establishes statistical theory for threshold models with nonstationary regressors under the diminishing threshold effect assumption. Our work can also be related to the literature of nonlinear cointegration. The proposed approach offers some flexibility of the cointegrating structure such that it can capture threshold effects in the long-run relationship. The merits of the method have been successfully demonstrated through Monte Carlo simulations.

There are several directions open for further work. First, it may be interesting to develop a more general model with multiple threshold effects, each with a different identification strength. A sequential procedure can be applied to determine the number of regimes and their identification strengths. Second, the model can be extended to allow for stationary regressors. Moreover, there are many interesting applications. For example, one can use the model to study the regime-sensitive Taylor rule (Taylor, 1993), where the dependent variable  $y_t$  could be the short-term interest rate, the explanatory variables  $x_t$  could be macroeconomic variables such as the inflation rate and the unemployment rate, and the threshold variable  $q_t$  could be the GDP growth rate. Another application is to model the regime-dependent predictability of the fundamental ratios, such as the dividend-price ratio and the earning-price ratio, to equity returns. The threshold variable could be a variable indicating the status of the economy. All these are left for future studies.

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# Appendix

In this appendix, Part A provides the proofs related to the basic model while Part B is for the generalized model. To save space, we skip the details for some intermediary results and a more detailed presentation can be found in Chen (2013).

## Part A

**Lemma A.1:** Under Assumptions (A1)–(A3), for any  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , we have  $\frac{1}{\sqrt{n}} \sum_{t=1}^{\lfloor ns \rfloor} I_t(q_t \leq \gamma) u_t \Rightarrow \sigma_u W(s, F(\gamma))$ .

**Lemma A.2:** Under Assumptions (A1)–(A4), for any  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , we have

$$\frac{1}{n} \sum_{t=1}^n x_t I_t(\gamma) u_t \Rightarrow \sigma_u \int \mathbf{B}_v(s) dW(s, F(\gamma)).$$

**Lemma A.3:** Under Assumptions (A1)–(A4), for any  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , as  $n \rightarrow \infty$ , we have

$$a) \ n^{-2} \sum_{t=1}^n A_t(\gamma) A'_t(\gamma) = M(\gamma) + o_{a.s.}(1),$$

$$b) \ n^{-1} \sum_{t=1}^n A_t(\gamma) u_t \Rightarrow \sigma_u \begin{pmatrix} \int \mathbf{B}_v(s) dW(s) \\ \int \mathbf{B}_v(s) dW(s, F(\gamma)) \end{pmatrix},$$

$$\text{where } A_t(\gamma) \text{ is defined in Equation (5) and } M(\gamma) = \begin{pmatrix} \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds & F(\gamma) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \\ F(\gamma) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds & F(\gamma) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \end{pmatrix}.$$

**Lemma A.4:** Under Assumptions (A1)–(A4), we have

$$n(\hat{\theta}(\gamma_0) - \theta) \Rightarrow \sigma_u M(\gamma_0)^{-1} \begin{pmatrix} \int \mathbf{B}_v(s) dW(s) \\ \int \mathbf{B}_v(s) dW(s, F(\gamma_0)) \end{pmatrix}.$$

For any  $\gamma \neq \gamma_0$ , if  $-1/2 < \tau < 1/2$ , we have

$$n^{\tau+1/2}(\hat{\theta}(\gamma) - \theta) \Rightarrow M(\gamma)^{-1} \Pi(\gamma, \gamma_0, \delta_0);$$

if  $\tau = 1/2$ ,

$$n(\hat{\theta}(\gamma) - \theta) \Rightarrow \sigma_u M(\gamma)^{-1} \begin{pmatrix} \int \mathbf{B}_v(s) dW(s) \\ \int \mathbf{B}_v(s) dW(s, F(\gamma)) \end{pmatrix} + M(\gamma)^{-1} \Pi(\gamma, \gamma_0, \delta_0),$$

where

$$\Pi(\gamma, \gamma_0, \delta_0) = - \begin{pmatrix} (F(\gamma) - F(\gamma_0)) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \\ (F(\gamma) - F(\gamma_0 \wedge \gamma)) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \end{pmatrix} \delta_0.$$

**Proof of Lemma A.1–A.4:** The proofs are standard and are skipped here.

**Lemma A.5:** If  $-1/2 < \tau < 1/2$ , we have  $\hat{\gamma}_n \xrightarrow{P} \gamma_0$ .

**Proof:** To establish the consistency of  $\hat{\gamma}_n$ , we need to prove  $\Pr(|\hat{\gamma}_n - \gamma_0| > \varepsilon) \rightarrow 0$  for any  $\varepsilon > 0$ . Denote  $B(\varepsilon) = \{\gamma : |\gamma - \gamma_0| > \varepsilon\}$  and  $\bar{B}(\varepsilon) = [\underline{\gamma}, \bar{\gamma}] \setminus B(\varepsilon)$ . By the definition of  $\hat{\gamma}_n$ , we have

$$\begin{aligned} \Pr(|\hat{\gamma}_n - \gamma_0| > \varepsilon) &= \Pr \left( \inf_{\gamma \in B(\varepsilon)} SSR_n(\gamma) < \inf_{\gamma \in \bar{B}(\varepsilon)} SSR_n(\gamma) \right) \leq \Pr \left( \inf_{\gamma \in B(\varepsilon)} SSR_n(\gamma) < SSR_n(\gamma_0) \right) \\ &= \Pr \left( \inf_{\gamma \in B(\varepsilon)} n^{2\tau-1} (SSR_n(\gamma) - SSR_n(\gamma_0)) < 0 \right). \end{aligned}$$

Thus, to prove  $\Pr(|\hat{\gamma}_n - \gamma_0| > \varepsilon) \rightarrow 0$ , it suffices to show that  $\inf_{\gamma \in B(\varepsilon)} n^{2\tau-1} (SSR_n(\gamma) - SSR_n(\gamma_0)) > 0$  with probability 1.

Rewrite Equation (2) as a matrix compacted form:  $Y = X'\alpha + X(\gamma_0)'\delta_n + u$ , where  $Y, X, X(\gamma_0)$  and  $u$  stack  $y_t, x_t, x_t(q_t \leq \gamma_0)$  and  $u_t$ , respectively. Denote  $X^*(\gamma) = (X(\gamma), X - X(\gamma))$  and define its projection matrix  $P_\gamma^* = X^*(\gamma)(X^*(\gamma)'X^*(\gamma))^{-1}X^*(\gamma)'$ . By some simple algebra, we have

$$SSR_n(\gamma) = Y'(I - P_\gamma^*)Y = \delta_n'X(\gamma_0)'(I - P_\gamma^*)X(\gamma_0)\delta_n + 2\delta_n'X(\gamma_0)'(I - P_\gamma^*)u + u'(I - P_\gamma^*)u,$$

where the second equation uses the fact that  $X'(I - P_\gamma^*) = 0$ , since  $X$  is a linear combination of  $(X(\gamma), X - X(\gamma))$ .

When  $\gamma = \gamma_0$ , we have  $SSR_n(\gamma_0) = u'(I - P_{\gamma_0}^*)u$ , and it follows that

$$\begin{aligned} n^{2\tau-1}(SSR_n(\gamma) - SSR_n(\gamma_0)) &= n^{-1+2\tau}\delta_n'X(\gamma_0)'(I - P_\gamma^*)X(\gamma_0)\delta_n + n^{-1+2\tau}2\delta_n'X(\gamma_0)'(I - P_\gamma^*)u \\ &\quad + n^{-1+2\tau}(u'(I - P_\gamma^*)u - u'(I - P_{\gamma_0}^*)u) \equiv S_1 + S_2 + S_3, \text{ say.} \end{aligned} \quad (\text{A.1})$$

Next, we will show that  $S_1 + S_2 + S_3$  uniformly converges to a function  $b(\gamma)$  which is positive for any  $\gamma \in B(\epsilon)$ . Given  $-1/2 < \tau < 1/2$ , by Lemma A.3, it can be shown that

$$S_2 = n^{-1/2+\tau}2\left(n^{1/2+\tau}\delta_n\right)'\frac{1}{n}X(\gamma_0)'(I - P_\gamma^*)u = n^{-1/2+\tau}2\delta_0'\frac{1}{n}X(\gamma_0)'(I - P_\gamma^*)u = O_p(n^{-1/2+\tau}) \xrightarrow{p} 0,$$

$$S_3 = n^{-1+2\tau}(u'(I - P_\gamma^*)u - u'(I - P_{\gamma_0}^*)u) = n^{-1+2\tau}(u'P_{\gamma_0}^*u - u'P_\gamma^*u) = O_p(n^{-1+2\tau}) \xrightarrow{p} 0.$$

Using a similar argument of Lemma A.5 in Hansen(2000), we can show, for any  $\gamma \geq \gamma_0$ ,

$$S_1 = n^{-1+2\tau}\delta_n'X'(\gamma_0)(I - P_\gamma^*)X(\gamma_0)\delta_n \xrightarrow{p} (F(\gamma_0) - F(\gamma_0)F(\gamma)^{-1}F(\gamma_0))\delta_0' \left( \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds \right) \delta_0 \equiv b_1(\gamma)$$

uniformly. Since  $(F(\gamma_0) - F(\gamma_0)F(\gamma)^{-1}F(\gamma_0)) \geq 0$  and  $\int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds$  is positive definite random matrix,  $b_1(\gamma) \geq 0$  and the equality holds if and only if  $\gamma = \gamma_0$ .

For  $\gamma \leq \gamma_0$ , we can show

$$S_1 \xrightarrow{p} (F(\gamma_0) - F(\gamma))\delta_0' \left( \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds \right) \delta_0 \equiv b_2(\gamma)$$

uniformly, where  $b_2(\gamma) \geq 0$  and the equality holds if and only if  $\gamma = \gamma_0$ . Define  $b(\gamma) = b_1(\gamma)I(\gamma \geq \gamma_0) + b_2(\gamma)I(\gamma \leq \gamma_0)$ , and we have shown that

$$n^{-1+2\tau}(SSR_n(\gamma) - SSR_n(\gamma_0)) \xrightarrow{p} b(\gamma)$$

uniformly for any  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$  and  $b(\gamma)$  is strictly positive when  $\gamma \in B(\epsilon)$ . Thus,  $\Pr(\inf_{\gamma \in B(\epsilon)} n^{2\tau-1}(SSR_n(\gamma) - SSR_n(\gamma_0)) > 0) \rightarrow 1$ .

**Proof of Theorem 3.1:** We first prove the limiting results for the case with  $-1/2 < \tau < 1/2$ . Let  $a_n = n^{1-2\tau}$ . To prove  $\hat{\gamma}_n$  converge to  $\gamma_0$  with rate  $a_n$ , we need to prove that  $a_n|\hat{\gamma}_n - \gamma_0| = O_p(1)$ , or there exists a constant  $\bar{v} > 0$ ,  $\lim_{n \rightarrow \infty} \Pr(|\hat{\gamma}_n - \gamma_0| \leq \bar{v}/a_n) = 1$ . For any  $B > 0$ , define  $V_B = \{\gamma : |\gamma - \gamma_0| < B\}$ . When  $n$  is large enough, we have  $\bar{v}/a_n < B$ . Since  $\hat{\gamma}_n \xrightarrow{p} \gamma_0$  according to Lemma A.5,  $\Pr(\{\hat{\gamma}_n \in V_B\}) \xrightarrow{p} 1$ . Therefore, we only need to examine the limiting behavior of  $\gamma$  in  $V_B$ .

Define a subset  $V_B(\bar{v}) = \{\gamma : \bar{v}/a_n < |\gamma - \gamma_0| < B\}$ . Thus,  $V_B(\bar{v}) \subset V_B$ . To prove  $\Pr(|\hat{\gamma}_n - \gamma_0| \leq \bar{v}/a_n) = 1$ , we just need to prove  $\Pr(\hat{\gamma}_n \in V_B(\bar{v})) = 0$ . Let  $\hat{\theta}$  and  $\hat{\delta}$  be the estimation of  $\hat{\theta}(\hat{\gamma}_n)$  and  $\hat{\delta}(\hat{\gamma}_n)$ . Also, we denote  $SSR_n^*(\gamma) = \sum_{t=1}^n (y_t - \hat{\theta}' A_t(\gamma))^2$  and  $SSR_n^*(\gamma_0) = \sum_{t=1}^n (y_t - \hat{\theta}' A_t(\gamma_0))^2$ . By the definition of  $\hat{\gamma}_n$ , we have  $SSR_n^*(\hat{\gamma}_n) \leq SSR_n^*(\gamma_0)$ . Hence, it suffices to prove that for any  $\gamma \in V_B(\bar{v})$ ,  $SSR_n^*(\gamma) > SSR_n^*(\gamma_0)$  with probability 1.



We consider the case of  $\gamma > \gamma^0$  first. Using an argument of symmetry, we can, without loss of generality, prove the result for the case of  $\gamma < \gamma_0$ . Note that

$$\begin{aligned}
SSR_n^*(\gamma) - SSR_n^*(\gamma_0) &= \sum_{t=1}^n (y_t - \hat{\theta}' A_t(\gamma))^2 - \sum_{t=1}^n (y_t - \hat{\theta}' A_t(\gamma_0))^2 \\
&= \sum_{t=1}^n \delta_n' (x_t(\gamma) - x_t(\gamma_0)) (x_t(\gamma) - x_t(\gamma_0))' \delta_n - 2\delta_n' \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) u + 2\hat{\delta}' \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) (x_t(\gamma) - x_t(\gamma_0))' (\hat{\theta} - \theta) \\
&\quad + 2 \sum_{t=1}^n (\hat{\delta} + \delta_n)' (x_t(\gamma) - x_t(\gamma_0)) (x_t(\gamma) - x_t(\gamma_0))' (\hat{\delta} - \delta_n) + 2(\delta_n' - \hat{\delta}') \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) u \\
&\equiv R_1 - R_2 + R_3 + R_4 + R_5, \text{ say.}
\end{aligned} \tag{A.2}$$

Next, we show that  $\frac{R_1 + R_2 + R_3 + R_4 + R_5}{a_n(\gamma - \gamma_0)}$  converges to a positive random variable almost surely by studying the limiting behavior for each term specifically. First, note that

$$\begin{aligned}
\frac{R_1}{a_n} &= \frac{1}{a_n} \sum_{t=1}^n \delta_n' (x_t(\gamma) - x_t(\gamma_0)) (x_t(\gamma) - x_t(\gamma_0))' \delta_n = (F(\gamma) - F(\gamma_0)) \delta_0' \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \delta_0 + o_p(1) \\
&= f(\gamma_0)(\gamma - \gamma_0) \delta_0' \left( \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \right) \delta_0 + o_p(1).
\end{aligned}$$

The last equation uses the first-order Taylor approximation of  $F(\gamma)$  around  $\gamma_0$ .

Noting that  $\bar{v}/a_n < |\gamma - \gamma_0| < B$  and  $a_n = n^{1-2\tau}$  with  $\tau < 1/2$ , We have  $\sqrt{\bar{v}} < \sqrt{a_n} \sqrt{(|\gamma - \gamma_0|)}$ . Thus, there exists  $k > 0$ , such that

$$\frac{R_2}{a_n(\gamma - \gamma_0)} = \frac{2\delta_0' \frac{1}{n} \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) u}{\sqrt{a_n}(\gamma - \gamma_0)} = O_p\left(\frac{1}{\sqrt{a_n} \sqrt{(|\gamma - \gamma_0|)}}\right) \leq k/\sqrt{\bar{v}}.$$

For any  $B \rightarrow 0_+$ , there exists  $\bar{v} > 0$  and  $N$ , such that  $k/\sqrt{\bar{v}} < f(\gamma_0) \delta_0' \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \delta_0$  with probability 1 and  $\bar{v}/a_n < B$  when  $n > N$ . Therefore, for any  $\gamma \in V_B(\bar{v})$ , we have

$$\frac{R_1}{a_n(\gamma - \gamma_0)} - \frac{R_2}{a_n(\gamma - \gamma_0)} > 0, \tag{A.3}$$

Furthermore, from Lemma A.4, we have  $n^{\tau+1/2}((\hat{\theta} - \theta) = O_p(\hat{\gamma}_n - \gamma_0)$  and  $n^{\tau+1/2}(\hat{\delta}_n - \delta_n) = O_p(\hat{\gamma}_n - \gamma_0)$ , thus

$$\frac{R_3}{a_n(\gamma - \gamma_0)} = \frac{2n^{\tau+1/2} \hat{\delta}_n' n^{-2} \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) (x_t(\gamma) - x_t(\gamma_0))' n^{\tau+1/2} (\hat{\theta} - \theta)}{(\gamma - \gamma_0)} = O_p(\hat{\gamma}_n - \gamma_0) = o_p(1), \tag{A.4}$$

$$\begin{aligned}
\frac{R_4}{a_n(\gamma - \gamma_0)} &= \frac{2n^{\tau+1/2} (\hat{\delta} + \delta_n)' n^{-2} \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) (x_t(\gamma) - x_t(\gamma_0))' n^{\tau+1/2} (\hat{\delta} - \delta_n)}{(\gamma - \gamma_0)} \\
&= O_p(n^{\tau+1/2} (\hat{\delta} - \delta_n)) = O_p(\hat{\gamma}_n - \gamma_0) = o_p(1),
\end{aligned} \tag{A.5}$$

$$\frac{R_5}{a_n(\gamma - \gamma_0)} = \frac{2n^{2\tau} (\delta_n' - \hat{\delta}') n^{-1} \sum_{t=1}^n (x_t(\gamma) - x_t(\gamma_0)) u}{(\gamma - \gamma_0)} = O_p(n^{\tau+1/2} (\hat{\delta} - \delta_n) n^{\tau-1/2}) = o_p(1). \tag{A.6}$$

Combining the results of Equations (A.3) through (A.6), we have  $\frac{SSR_n^*(\gamma) - SSR_n^*(\gamma_0)}{a_n(\gamma - \gamma_0)} > 0$  with probability 1 for any  $\gamma \in V_B(\bar{v})$  and  $\gamma > \gamma^0$ . Similarly, we can prove  $SSR_n^*(\gamma) > SSR_n^*(\gamma^0)$  when  $\gamma < \gamma^0$  and  $\gamma \in V_B(\bar{v})$  with probability 1.

Next, we study the limiting distribution for the estimator  $\hat{\gamma}$ . Given  $-1/2 < \tau < 1/2$ ,  $\hat{\gamma}$  is a consistent estimator with convergence rate  $a_n$ , thus, we could focus on its asymptotic behavior in the neighborhood of the true thresholds. Let  $\gamma = \gamma_0 + \frac{\omega}{a_n}$ . By the definition of  $\hat{\gamma}_n$ , we have

$$a_n(\hat{\gamma}_n - \gamma_0) = \omega^* = \arg \min_{\omega \in (-\infty, \infty)} \left( SSR_n^*(\gamma_0 + \frac{\omega}{a_n}) - SSR_n^*(\gamma_0) \right).$$

By Equation (A.2), we know  $SSR_n^*(\gamma_0 + \frac{\omega}{a_n}) - SSR_n^*(\gamma_0) = R_1 - R_2 + R_3 + R_4 + R_5$ , with  $\gamma$  replaced by  $\gamma_0 + \frac{\omega}{a_n}$ . Next, we turn to study the limiting behavior for each term. We only provide the proof for the case where  $\omega > 0$ , as the proof for the case with  $\omega \leq 0$  is analogous. Given  $\omega > 0$ , we have

$$\begin{aligned} R_1 &= \delta'_n \sum_{t=1}^n \left( x_t(\gamma_0 + \frac{\omega}{a_n}) - x_t(\gamma_0) \right) \left( x_t(\gamma_0 + \frac{\omega}{a_n}) - x_t(\gamma_0) \right)' \delta_n \\ &= n^{1-2\tau} \delta'_0 n^{-2} \sum_{t=1}^n \left( x_t(\gamma_0 + \frac{\omega}{a_n}) - x_t(\gamma_0) \right) \left( x_t(\gamma_0 + \frac{\omega}{a_n}) - x_t(\gamma_0) \right)' \delta_0 \\ &= n^{1-2\tau} \delta'_0 (F(\gamma_0 + \frac{\omega}{a_n}) - F(\gamma_0)) \left( \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \right) \delta_0 + o_p(1) \\ &\xrightarrow{p} f(\gamma_0) \omega \delta'_0 \left( \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \right) \delta_0. \end{aligned} \tag{A.7}$$

Note that the last equation uses the first-order Taylor expansion of  $F(\gamma_0 + \frac{\omega}{a_n})$  around  $\gamma_0$ . For  $R_2$ , we have

$$\begin{aligned} R_2 &= -2 \sum_{t=1}^n \delta'_n \left( x_t(\gamma_0 + \frac{\omega}{a_n}) - x_t(\gamma_0) \right) u_t = -2n^{1/2-\tau} \delta'_0 \frac{1}{n} \sum_{t=1}^n \left( x_t(\gamma_0 + \frac{\omega}{a_n}) - x_t(\gamma_0) \right) u_t \\ &\Rightarrow -2\sqrt{a_n} \delta'_0 \sigma_u \int \mathbf{B}_v(s) d \left( W(s, F(\gamma_0 + \frac{\omega}{a_n})) - W(s, F(\gamma_0)) \right) \\ &= -2\sqrt{a_n} \delta'_0 \sigma_u \left( \mathbf{J}_1(F(\gamma_0 + \frac{\omega}{a_n})) - \mathbf{J}_1(F(\gamma_0)) \right). \end{aligned} \tag{A.8}$$

Note that  $\mathbf{J}_1(\mu) = \int \mathbf{B}_v(s) dW(s, \mu)$  is a mean-zero Gaussian process with an almost surely continuous sample path and with the covariance kernel

$$E(\mathbf{J}_1(\mu_1) \mathbf{J}_1(\mu_2)) = (\mu_1 \wedge \mu_2) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds.$$

Thus,  $D(\omega) = \sqrt{a_n} \delta'_0 \sigma_u \left( \mathbf{J}_1(F(\gamma_0 + \frac{\omega}{a_n})) - \mathbf{J}_1(F(\gamma_0)) \right)$  is also a Brownian motion with

$$\begin{aligned} Var(D(\omega)) &= \sigma_u^2 a_n (F(\gamma_0 + \frac{\omega}{a_n}) - F(\gamma_0)) \delta'_0 \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \delta_0 \\ &= \sigma_u^2 f_0 \omega \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds + o_p(1). \end{aligned}$$

By Equations (A.4) to (A.6), we have  $R_3 + R_4 + R_5 = \omega o_p(1) = o_p(1)$ . Combining the convergence results of

Equations (A.7) and (A.8), we have

$$\begin{aligned} SSR_n^*(\gamma) - SSR_n^*(\gamma_0) &\Rightarrow f_0\omega\delta'_0 \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds\delta_0 - 2D(\omega) \\ &= f_0\omega\delta'_0 \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds\delta_0 - 2\sigma_u \sqrt{f_0\omega\delta'_0 \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds\delta_0} \Lambda_1(\omega), \end{aligned}$$

where  $\Lambda_1(\omega)$  is a standard Brownian motion on  $[0, \infty)$ . Making the change of variables as follows

$$\omega = \frac{\sigma_u^2}{\delta'_0 \left( \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds \right) \delta_0 f_0} r,$$

we have

$$SSR_n^*(\gamma) - SSR_n^*(\gamma_0) \Rightarrow 2\sigma_u^2 \left( \frac{r}{2} - \Lambda_1(r) \right). \quad (\text{A.9})$$

Using continuous mapping theorem, the asymptotic distribution of  $\hat{\gamma}$  can be expressed as

$$n^{1-2\tau} \lambda(\hat{\gamma} - \gamma_0) = r^* \Rightarrow \arg \max_{r \in (0, \infty)} (\Lambda_1(r) - \frac{1}{2}|r|).$$

Lastly, we establish the limiting results for  $\hat{\gamma}_n$  when  $\tau = 1/2$ , i.e., the threshold is only weakly identified. By the definition of  $\hat{\gamma}_n$ , we have  $\hat{\gamma}_n = \arg \min_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} SSR_n(\gamma) = \arg \max_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} (SSR_n - SSR_n(\gamma))$ , where  $SSR_n$  is defined as the sum of squared residuals by regressing  $y_t$  to  $x_t$ . By some standard algebra, we have

$$SSR_n - SSR_n(\gamma) = Y'(I - P_n)X(\gamma)(X'(\gamma)(I - P_n)X(\gamma))^{-1}X'(\gamma)(I - P_n)Y,$$

where  $X(\gamma) = (x_1(\gamma), x_2(\gamma), \dots, x_n(\gamma))'$  and  $X = (x_1, x_2, \dots, x_n)'$ .  $P_n = X(X'X)^{-1}X'$  is the projection matrix of  $X$ . Define  $\Gamma_n(\gamma) = n^{-1}X'(\gamma)(I - P_n)Y$ . By substituting the true model  $Y = X\alpha + X(\gamma_0)\delta_n + u$ , it can be shown that

$$\Gamma_n(\gamma) = n^{-1}X'(\gamma)X(\gamma_0)\delta_n - n^{-1}X'(\gamma)X(X'X)^{-1}X'X(\gamma_0)\delta_n + n^{-1}X'(\gamma)(I - P_n)u.$$

Given  $\tau = 1/2$ , we have  $n\delta_n = \delta_0$ . By Lemma A.3, it can be shown that

$$\Gamma_n(\gamma) \Rightarrow \sigma_u \int \mathbf{B}_v(s)d(W(s, F(\gamma)) - F(\gamma)W(s)) + (F(\gamma \wedge \gamma_0) - F(\gamma)F(\gamma_0)) \left( \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds \right) \delta_0 \equiv \Gamma_1(\gamma).$$

Since

$$n^{-2}X'(\gamma)(I - P_n)X(\gamma) = n^{-2}X'(\gamma)X(\gamma) - n^{-2}X'(\gamma)X(X'X)^{-1}X'X(\gamma) \Rightarrow F(\gamma)(1 - F(\gamma)) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds,$$

by continuous mapping theorem, we can show that

$$\begin{aligned} (SSR_n - SSR_n(\gamma)) &= \Gamma'_n(\gamma)(X'(\gamma)(I - P_n)X(\gamma)/n^2)^{-1}\Gamma_n(\gamma) \\ &\Rightarrow \frac{1}{F(\gamma)(1 - F(\gamma))} \Gamma'_1(\gamma) \left( \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds \right)^{-1} \Gamma_1(\gamma) = Q(\gamma, \gamma_0, \delta_0). \end{aligned}$$

**Proof of Theorem 3.2:** Note that

$$\begin{aligned}
T_n(\gamma) &= \widehat{\delta}_n(\gamma)'(X(\gamma)(I - P(\gamma))X(\gamma))\widehat{\delta}_n(\gamma)/\widehat{\sigma}_u^2 \\
&= (I - P_n)Y'X(\gamma)(X'(\gamma)(I - P_n)X(\gamma))^{-1}X'(\gamma)(I - P_n)Y/\widehat{\sigma}_u^2 \\
&= \Gamma_n(\gamma)'(n^{-2}X(\gamma)'X(\gamma) - n^{-2}X(\gamma)'X(X'X)^{-1}XX(\gamma))^{-1}\Gamma_n(\gamma)/\widehat{\sigma}_u^2.
\end{aligned} \tag{A.10}$$

By Lemma A.3, we have

$$n^{-2}X(\gamma)'X(\gamma) - n^{-2}X(\gamma)'X(X'X)^{-1}XX(\gamma) \xrightarrow{a.s.} (F(\gamma) - F(\gamma)^2) \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds.$$

Next, we consider the limiting result for  $\Gamma_n(\gamma)$  for different  $\tau$ . When  $-1/2 < \tau < 1/2$ , we have

$$\begin{aligned}
\Gamma_n(\gamma) &= \frac{1}{n}X'(\gamma)(I - P_n)Y = \frac{1}{n}X'(\gamma)u - \frac{1}{n}X'(\gamma)X(X'X)^{-1}X'u + \frac{1}{n}X'(\gamma)X(\gamma_0)\delta_n - \frac{1}{n}X'(\gamma)X(X'X)^{-1}X'X(\gamma_0)\delta_n \\
&\Rightarrow \sigma_u \int_0^1 \mathbf{B}_v(s)d(W(s, F(\gamma)) - F(\gamma)W(s)) + n^{1/2-\tau}(F(\gamma \wedge \gamma_0) - F(\gamma)F(\gamma_0)) \left( \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds \right) \delta_0 \\
&= O_p(n^{1/2-\tau}) \xrightarrow{p} \infty.
\end{aligned}$$

It follows that  $T_n(\gamma) = O_p(n^{1-2\tau}) \xrightarrow{p} \infty$ . When  $\tau = 1/2$ , we have

$$\begin{aligned}
\Gamma_n(\gamma) &= \frac{1}{n}X'(\gamma)u - \frac{1}{n}X'(\gamma)X(X'X)^{-1}X'u + \frac{1}{n}X'(\gamma)X(\gamma_0)\delta_n - \frac{1}{n}X'(\gamma)X(X'X)^{-1}X'X(\gamma_0)\delta_n \\
&\Rightarrow \Gamma(\gamma) + (F(\gamma \wedge \gamma_0) - F(\gamma)F(\gamma_0)) \left( \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds \right) \delta_0 = \Gamma_1(\gamma).
\end{aligned}$$

It follows that

$$T_n(\gamma) \Rightarrow \frac{1}{\sigma_u^2 F(\gamma)(1 - F(\gamma))} \Gamma_1'(\gamma) \left( \int \mathbf{B}_v(s)\mathbf{B}_v'(s)ds \right)^{-1} \Gamma_1(\gamma).$$

**Proof of Theorem 3.3:** We prove the equality by showing the following two inequalities:  $AsySZ_\gamma(a) \geq 1 - a$  and  $AsySZ_\gamma(a) \leq 1 - a$  hold simultaneously. We first consider the proof of  $AsySZ_\gamma(a) \geq 1 - a$ .

By the definition of  $AsySZ_\gamma(a)$  as Equation (20), we can find a parameter sequence  $(\delta_n, \gamma_n)$  such that  $AsySZ_\gamma(a) = \liminf_{n \rightarrow \infty} \Pr_{(\delta_n, \gamma_n)}(\gamma_n \in CI_{\gamma, n}(a))$ . Let  $\{b_n\}$  be a subsequence of  $\{n\}$  such that  $AsySZ_\gamma(a) = \lim_{n \rightarrow \infty} \Pr_{(\delta_{b_n}, \gamma_{b_n})}(\gamma_{b_n} \in CI_{\gamma, b_n}(a))$ . Denote  $\delta_0^* = n\delta_n$  where  $\delta_0^* \in R \cup \{-\infty, \infty\}$ . Because the Euclidean space is complete, we can always find a subsequence  $\{c_n\}$  of  $\{b_n\}$  such that  $(c_n\delta_{c_n}, \gamma_{c_n}) \rightarrow (\delta_0^*, \gamma_0)$ .

If  $\tau = 1/2$ , we have  $\delta_0^* = nn^{-1/2-\tau}\delta_0 = \delta_0 \in R$ . By Theorem 3.2, we have  $T_n = O_p(n^{1-2\tau}) = O_p(1) < \kappa_n$  with probability one. Thus,  $CI_{\gamma, n}(a) = CI_{\gamma, n}^W(a)$ , and

$$\begin{aligned}
AsySZ_\gamma(a) &= \lim_{n \rightarrow \infty} \Pr_{(\delta_{c_n}, \gamma_{c_n})}(\gamma_{c_n} \in CI_{\gamma, c_n}(a)) = \lim_{n \rightarrow \infty} \Pr_{(\delta_{c_n}, \gamma_{c_n})}(|\widehat{\gamma}_{c_n} - \gamma_{c_n}| \leq \widehat{q}_{\gamma, 1-a}^W) \\
&\geq \lim_{n \rightarrow \infty} \Pr_{(\delta_{c_n}, \gamma_{c_n})}(|\widehat{\gamma}_{c_n} - \gamma_{c_n}| \leq \widehat{q}_{\gamma, 1-a}^W(\gamma_0, \delta_0)) = 1 - a.
\end{aligned}$$

The inequality uses the fact that  $\widehat{q}_{\gamma, 1-a}^W = \sup_{\gamma \in [\underline{\gamma}, \bar{\gamma}]} \sup_{\delta \in R} q_{\gamma, 1-a}^W(\gamma, \delta)$ . The last equation uses the fact that  $|\widehat{\gamma}_{c_n} - \gamma_{c_n}|$  converges to  $|\widehat{\gamma}(\gamma_0, \delta_0) - \gamma_0|$  and  $\widehat{q}_{\gamma, 1-a}^W(\gamma_0, \delta_0)$  is defined as the  $(1 - a)$  quantile of the limiting distribution of  $|\widehat{\gamma}(\gamma_0, \delta_0) - \gamma_0|$ .

If  $-1/2 < \tau < 1/2$ ,  $\delta_0^* = nn^{-1/2-\tau}\delta_0 = n^{1/2-\tau}\delta_0 = \pm\infty$ . Note that  $n^{-\nu}\kappa_n^{1/2} \rightarrow 0$  for any  $\nu > 0$ , we have

$T_n = O_p(n^{1-2\tau}) > \kappa_n$  with probability approaching one. Thus,  $CI_{\gamma, c_n}(a) = CI_{\gamma, c_n}^I(a)$  and

$$AsySZ_\gamma(a) = \lim_{n \rightarrow \infty} \Pr_{(\delta_{c_n}, \gamma_{c_n})}(\gamma_{c_n} \in CI_{\gamma, c_n}(a)) = \lim_{n \rightarrow \infty} \Pr(\gamma_{c_n} \in CI_{\gamma, c_n}^I(a)) = \lim_{n \rightarrow \infty} \Pr(LR(\gamma_{c_n}) \leq q_{1-\alpha}^I).$$

As  $LR_n(\gamma_n) \Rightarrow \sup_{r \in (-\infty, \infty)}(2\Lambda(r) - |r|)$ ,  $LR_{c_n}(\gamma_{c_n})$  converges to  $\sup_{r \in (-\infty, \infty)}(2\Lambda(r) - |r|)$  and  $q_{1-\alpha}^I$  is the  $1-a$  quantile of  $\sup_{r \in (-\infty, \infty)}(2\Lambda(r) - |r|)$ . Thus,

$$AsySZ_\gamma(a) = \lim_{n \rightarrow \infty} \Pr(LR(\gamma_{c_n}) \leq q_{1-\alpha}^I) \geq 1-a.$$

Next, we consider the other side  $AsySZ_\gamma(a) \leq 1-a$ . Let  $\delta_n = n^{-1/2}\delta_0$  and  $\gamma_n = \gamma_0$  with  $\delta_0 \in R/\{0\}$ . By definition, we have

$$AsySZ_\gamma(a) \leq \liminf_{n \rightarrow \infty} \Pr_{(\delta_0, \gamma_0)}(\gamma_0 \in CI_{\gamma, n}(a)).$$

When  $\delta_n = n^{-1/2}\delta_0$ , we have  $T_n = O_p(n^{1-2\tau}) = O_p(n) > \kappa_n$  with probability approaching one. Thus,  $CI_{\gamma, n}(a) = CI_{\gamma, n}^I(a)$ , and

$$\liminf_{n \rightarrow \infty} \Pr_{(\delta_n, \gamma_0)}(\gamma_0 \in CI_{\gamma, n}(a)) = \liminf_{n \rightarrow \infty} \Pr(\gamma_0 \in CI_{\gamma, n}^I(a)) = \liminf_{n \rightarrow \infty} \Pr(LR_n(\gamma_0) \leq q_{1-\alpha}^I) = 1-a.$$

where the last equality holds because  $LR_n(\gamma_0) \Rightarrow \sup_{r \in (-\infty, \infty)}(2\Lambda(r) - |r|)$ .

## Part B

Define the moment functionals for the stationary regressors  $z_t$

$$\begin{aligned} h(\gamma) &= E(z_t I(q_t \leq \gamma)), \quad h_1(\gamma) = E(z_t I(q_{t-1} \leq \gamma)), \quad h_2(\gamma) = E(z_{t-1} I(q_t \leq \gamma)), \\ H &= E(z_t z_t'), \quad H_1 = E(z_t z_{t-1}'). \end{aligned}$$

**Lemma B.1:** Under Assumptions A1', A2', A3 and A4, for any  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ , as  $n \rightarrow \infty$ ,

- a)  $n^{-3/2} \sum_{t=1}^n z_t x_t'(\gamma) = h(\gamma) \int \mathbf{B}_v'(s) ds + o_p(1)$ ,
- b)  $n^{-3/2} \sum_{t=1}^n z_t x_{t-1}'(\gamma) = h_1(\gamma) \int \mathbf{B}_v'(s) ds + o_p(1)$ ,
- c)  $n^{-3/2} \sum_{t=1}^n z_{t-1} x_t'(\gamma) = h_2(\gamma) \int \mathbf{B}_v'(s) ds + o_p(1)$ ,
- d)  $n^{-1} \sum_{t=1}^n z_t z_t' = H + o_p(1)$ ,
- e)  $n^{-1} \sum_{t=1}^n z_t z_{t-1}' = H_1 + o_p(1)$ .

**Lemma B.2:** Under Assumptions A1', A2', A3 and A4, for any  $\gamma \in [\underline{\gamma}, \bar{\gamma}]$  and  $\mu = F(\gamma)$  as  $n \rightarrow \infty$ ,

- a)  $: n^{-1/2} \sum_{t=1}^n I(q_t \leq \gamma) \varepsilon_t \Rightarrow \sigma W(s, \mu)$ ,
- b)  $: n^{-1/2} \sum_{t=1}^n I(q_{t-1} \leq \gamma) \varepsilon_t \Rightarrow \sigma W_1(s, \mu)$ ,
- c)  $: n^{-1} \sum_{t=1}^n x_t(\gamma)' \varepsilon_t \Rightarrow \sigma \int \mathbf{B}_v'(s) dW(s, \mu)$ ,
- d)  $: n^{-1} \sum_{t=1}^n x_{t-1}(\gamma)' \varepsilon_t \Rightarrow \sigma \int \mathbf{B}_v'(s) dW_1(s, \mu)$ ,
- e)  $: n^{-1/2} \sum_{t=1}^n z_t \varepsilon_t \Rightarrow \sigma J_2$ ,
- f)  $: n^{-1/2} \sum_{t=1}^n z_{t-1} \varepsilon_t \Rightarrow \sigma J_3$ ,

where  $J_2$  and  $J_3$  are Gaussian random variable with mean zero and variance  $H$ .  $W(s, \mu)$  and  $W_1(s, \mu)$  are two two-parameter Brownian motions.

**Proof of Lemma B.1-B.2:** The proofs are standard and are skipped for space considerations.

**Lemma B.3:** If  $-1/2 < \tau < 1/2$ , under Assumptions A1', A2', A3 and A4, we have  $\hat{\gamma}_n \xrightarrow{p} \gamma_0$  for any  $\rho \in (-1, 1]$ .

**Proof:** We conduct the proof by considering two cases according to the value of  $\rho$ . When  $\rho < 1$ ,  $u_t = \beta' z_t + \eta_t$  is stationary process. The proof is similar to Lemma A.5 and is skipped for brevity. When  $\rho = 1$ ,  $u_t = \beta' z_t + \eta_t$  is nonstationary since  $\eta_t$  is a unit root process. Using a similar argument of Lemma A.5, we only need to show that  $n^{-1+2\tau}(SSR_n(\gamma) - SSR_n(\gamma_0))$  uniformly converges to a function  $b(\gamma)$  which is positive when  $\gamma \in B(\epsilon)$ , where  $B(\epsilon) = \{\gamma : |\gamma - \gamma_0| > \epsilon\}$  for any  $\epsilon > 0$ . Note that Equation (A.1) still holds, i.e.,  $n^{-1+2\tau}(SSR_n(\gamma) - SSR_n(\gamma_0)) = S_1 + S_2 + S_3$ . Next, we will show that both  $S_2$  and  $S_3$  converge to zero but  $S_1$  uniformly converges a function  $b(\gamma)$  which is positive when  $\gamma \in B(\epsilon)$ .

First, note that the stationary component  $\beta' z_t$  of  $u_t$  is asymptotically negligible, implying that

$$S_3 = n^{-1+2\tau}(u'(I - P_\gamma^*)u - u'(I - P_{\gamma_0}^*)u) = n^{-1+2\tau}(\eta' P_\gamma^* \eta - \eta' P_{\gamma_0}^* \eta) + o_p(1).$$

Denote  $B_\eta(s)$  as a Brownian motion such that  $\frac{1}{\sqrt{n}}\eta_{[ns]} \Rightarrow B_\eta(s)$ . By Lemma B.1, we have

$$\begin{aligned} & n^{-2}\eta' X^*(\gamma)(X^*(\gamma)' X^*(\gamma))^{-1} X^*(\gamma)' \eta = n^{-2}\eta' X^*(\gamma)(n^{-2} X^*(\gamma)' X^*(\gamma))^{-1} n^{-2} X_1^*(\gamma)' \eta \\ &= \begin{pmatrix} F(\gamma) \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \\ (1 - F(\gamma)) \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \end{pmatrix}' \begin{pmatrix} F(\gamma) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds, 0 \\ 0, (1 - F(\gamma)) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \end{pmatrix}^{-1} \begin{pmatrix} F(\gamma) \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \\ (1 - F(\gamma)) \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \end{pmatrix} + o_p(1) \\ &= \begin{pmatrix} F(\gamma) \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \\ (1 - F(\gamma)) \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \end{pmatrix}' \begin{pmatrix} (\int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds)^{-1} \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \\ (\int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds)^{-1} \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \end{pmatrix} + o_p(1) \\ &= \left( \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \right)' \left( \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \right)^{-1} \left( \int_0^1 \mathbf{B}_v(s) B_\eta(s) ds \right) + o_p(1), \end{aligned}$$

which is unrelated to  $\gamma$ . Thus,  $\eta' P_\gamma^* \eta - \eta' P_{\gamma_0}^* \eta = o_p(1)$  and it follows that  $S_3 = n^{-1+2\tau}(\eta' P_\gamma^* \eta - \eta' P_{\gamma_0}^* \eta) + o_p(1) = o_p(1)$ .

To prove  $S_2$  converge to zero almost surely, we first consider the case where  $\gamma > \gamma_0$ . For the case where  $\gamma \leq \gamma_0$ , the proof is similar and not repeated here. Given  $\gamma > \gamma_0$ , We have

$$n^{-2} X'(\gamma) X(\gamma_0) = n^{-2} X'(\gamma_0) X(\gamma_0) = F(\gamma_0) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds + o_p(1),$$

$$n^{-2} X(\gamma_0)' (X - X(\gamma)) = 0,$$

$$n^{-2} (X - X(\gamma_0))' X(\gamma) = (F(\gamma) - F(\gamma_0)) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds + o_p(1).$$

It follows that

$$n^{-2} X^*(\gamma_0)' X^*(\gamma) = \begin{pmatrix} F(\gamma_0) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds, 0 \\ (F(\gamma) - F(\gamma_0)) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds, (1 - F(\gamma)) \int \mathbf{B}_v(s) \mathbf{B}_v'(s) ds \end{pmatrix} + o_p(1).$$

Furthermore, it can be shown that

$$n^{-1+2\tau} 2\delta_n' X(\gamma_0)' \eta = 2n^{1/2+\tau} \delta_0' n^{-2} \sum_{t=1}^n x_t(\gamma_0) \eta = 2n^{1/2+\tau} \delta_0' \begin{pmatrix} F(\gamma_0) \int \mathbf{B}_v(s) B_\eta(s) ds \\ (1 - F(\gamma_0)) \int \mathbf{B}_v(s) B_\eta(s) ds \end{pmatrix} + o_p(1),$$

and

$$\begin{aligned}
2n^{-1+2\tau}\delta'_n X(\gamma_0)' P_\gamma^* \eta &= 2n^{1/2+\tau} \delta' \begin{pmatrix} F(\gamma_0) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds, 0 \\ (F(\gamma) - F(\gamma_0)) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds, (1 - F(\gamma)) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \end{pmatrix} \\
&\quad \begin{pmatrix} F(\gamma) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds, 0 \\ 0, (1 - F(\gamma)) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \end{pmatrix}^{-1} \begin{pmatrix} F(\gamma) \int \mathbf{B}_v(s) B_\eta(s) ds \\ (1 - F(\gamma)) \int \mathbf{B}_v(s) B_\eta(s) ds \end{pmatrix} \\
&= 2n^{1/2+\tau} \delta'_0 \begin{pmatrix} F(\gamma_0) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \\ (1 - F(\gamma_0)) \int \mathbf{B}_v(s) \mathbf{B}'_v(s) ds \end{pmatrix} + o_p(1).
\end{aligned}$$

Thus,

$$S_2 = n^{-1+2\tau} 2\delta'_n X(\gamma_0)' (I - P_\gamma^*) \xi = n^{-1+2\tau} 2\delta'_n X(\gamma_0)' \eta - 2n^{-1+2\tau} \delta'_n X(\gamma_0)' P_\gamma^* \eta + o_p(1) = o_p(1).$$

Using a similar argument in Lemma A.5, we can show  $S_1 \xrightarrow{p} b(\gamma)$  uniformly and  $b(\gamma)$  is strictly positive when  $\gamma \in B(\epsilon)$ . Combining the convergence results for  $S_1$ ,  $S_2$  and  $S_3$ , we complete the proof.

**Proof of Theorem 4.1:** Under Assumption A1', the model can be rewritten as

$$y_t = \alpha' x_t + \delta'_n x_t(\gamma_0) + u_t = \theta'_1 x_t^*(\hat{\gamma}) + \eta_t^*,$$

where  $x_t^*(\hat{\gamma}) = (x_t(\hat{\gamma})', x_t' - x_t'(\hat{\gamma}), z_t')'$ ,  $\theta_1 = (\alpha' + \delta'_n, \alpha', \beta')'$  and  $\eta_t^* = \eta_t + \theta_1'(x_t^*(\gamma_0) - x_t^*(\hat{\gamma}))$ .

Since  $\theta_1'(x_t^*(\gamma_0) - x_t^*(\hat{\gamma})) = \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma}))$ , we have  $\eta_t^* = \eta_t + \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma}))$ . The LS residual  $\eta_t(\hat{\gamma})$  can be expressed as

$$\hat{\eta}_t(\hat{\gamma}) = y_t - \hat{\theta}_1(\hat{\gamma})' x_t^*(\hat{\gamma}) = \eta_t + \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) + (\hat{\theta}_1(\hat{\gamma}) - \theta_1)' x_t^*(\hat{\gamma}).$$

Next, we conduct the proof by considering two cases according to the value of  $\tau$ .

Case 1:  $-1/2 < \tau < 1/2$ , by Lemma B.3, we have  $\hat{\gamma} \xrightarrow{p} \gamma_0$  and  $\delta'_n = O_p(n^{-1/2-\tau}) = o_p(1)$ . Thus  $\delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) = o_p(1)$ .

If  $\rho = 1$ ,  $\eta_t$  is a unit root; thus,  $\hat{\eta}_t(\hat{\gamma}) = \eta_t + \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) + (\hat{\theta}_1(\hat{\gamma}) - \theta_1)' x_t^*(\hat{\gamma})$  is also a unit root process and it can be shown that  $\hat{\rho} = 1 + O_p(\frac{1}{n})$ .

If  $\rho < 1$ ,  $\eta_t$  is stationary. Since  $\hat{\gamma} \xrightarrow{p} \gamma_0$ , it can be shown that  $D_n(\hat{\theta}_1(\hat{\gamma}) - \theta_1) = O_p(n^{-1/2})$ , where  $D_n = \text{diag}\{n^{1/2}I_{d_1}, n^{1/2}I_{d_1}, I_{d_2}\}$  is a weighting matrix.

It follows that  $\hat{\eta}_t(\hat{\gamma}) = \eta_t + \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) + (\hat{\theta}_1(\hat{\gamma}) - \theta_1)' x_t^*(\hat{\gamma}) = \eta_t + o_p(1) + (\hat{\theta}_1(\hat{\gamma}) - \theta_1)' D_n D_n^{-1} x_t^*(\hat{\gamma})' \xrightarrow{p} \eta_t$ .

As  $\eta_t$  is assumed to be  $\eta_t = \rho\eta_{t-1} + \varepsilon_t$ , it can be shown that  $\hat{\rho} = \rho + O_p(\frac{1}{\sqrt{n}})$ .

Case 2:  $\tau = 1/2$ ,  $\hat{\gamma}$  is inconsistent. Noting that  $n\delta_n = \delta_0$ , we have  $\delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) = O_p(\frac{1}{\sqrt{n}}) = o_p(1)$ . If  $\rho = 1$ , the term  $\hat{\eta}_t(\hat{\gamma}) = \eta_t + \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) + (\hat{\theta}_1(\hat{\gamma}) - \theta_1)' x_t^*(\hat{\gamma})$  is an I(1) process and it can be shown that  $\hat{\rho}(\hat{\gamma}) = 1 + O_p(\frac{1}{n})$ .

If  $\rho < 1$ , using a similar argument of Lemma A.2, we can show that  $D_n(\hat{\theta}_1(\hat{\gamma}) - \theta_1) = O_p(n^{-1/2})$ . Thus, the following convergence still holds:  $\hat{\eta}_t(\hat{\gamma}) = \eta_t + \delta'_n(x_t(\gamma_0) - x_t(\hat{\gamma})) + (\hat{\theta}_1(\hat{\gamma}) - \theta_1)' x_t^*(\hat{\gamma}) \xrightarrow{p} \eta_t$ , implying that  $\hat{\rho} = \rho + O_p(\frac{1}{\sqrt{n}})$ .

**Lemma B.4:** For any  $\rho \in (-1, 1]$ , there exists a nonrandom weighting matrix  $\tilde{D}_n$  such that

$$a) : n^{-1} \tilde{D}_n^{-1} \tilde{A}_1(\gamma)' \tilde{A}_1(\gamma) \tilde{D}_n^{-1} = \tilde{G}(\gamma) + o_p(1),$$

$$b) : n^{-1/2} \tilde{D}_n^{-1} \tilde{A}_1(\gamma)' \tilde{\eta} \Rightarrow \tilde{\phi}(\gamma).$$

where  $\tilde{G}(\gamma)$  and  $\tilde{\phi}(\gamma)$  are defined below.

**Proof:** When  $\rho < 1$ , define the weighting matrix  $\tilde{D}_n = \text{diag}\{n^{1/2}I_{d_1}, n^{1/2}I_{d_2}\}$ ,

$$G(\gamma) = \begin{pmatrix} \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & F(\gamma) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & 0 \\ F(\gamma) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & F(\gamma) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & (\int \mathbf{B}_v(s)ds) h(\gamma)' \\ 0 & h(\gamma) (\int \mathbf{B}'_v(s)ds) & H \end{pmatrix},$$

$$G_1(\gamma) = \begin{pmatrix} \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & F(\gamma) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & 0 \\ F(\gamma) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & F_1(\gamma) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & (\int \mathbf{B}_v(s)ds) h'_2(\gamma) \\ 0 & h_1(\gamma) (\int \mathbf{B}'_v(s)ds) & H_1 \end{pmatrix},$$

$$\tilde{G}(\gamma) = G(\gamma) + \rho^2 G(\gamma) - \rho (G_1(\gamma) + G'_1(\gamma)),$$

and

$$\tilde{\phi}(\gamma) = \begin{pmatrix} \sigma \int \mathbf{B}_v(s) d\tilde{W}(s) \\ \sigma \int \mathbf{B}_v(s) d\tilde{W}(s, F(\gamma)) \\ \sigma \tilde{J} \end{pmatrix},$$

where  $\tilde{W}(s) = (1 - \rho)W(s)$ ,  $\tilde{W}(s, \gamma) = W(s, F(\gamma)) - \rho W_1(s, F(\gamma))$  and  $\tilde{J} = J_2 - \rho J_3$ .

By Lemmas B.1, B.2 and Theorem 4.1, it can be shown that

$$\begin{aligned} n^{-1} \sum_{t=1}^n \tilde{D}_n^{-1} \tilde{A}_{1t}(\gamma) \tilde{A}_{1t}(\gamma)' \tilde{D}_n^{-1} &= n^{-1} \sum_{t=1}^n \tilde{D}_n^{-1} A_{1t}(\gamma) A_{1t}(\gamma)' \tilde{D}_n^{-1} + n^{-1} \hat{\rho}^2 \sum_{t=1}^n \tilde{D}_n^{-1} A_{1t-1}(\gamma) A_{1t-1}(\gamma)' \tilde{D}_n^{-1} \\ &\quad - \hat{\rho} \sum_{t=1}^n \tilde{D}_n^{-1} A_{1t}(\gamma) A_{1t-1}(\gamma)' \tilde{D}_n^{-1} - \hat{\rho} \sum_{t=1}^n \tilde{D}_n^{-1} A_{1t-1}(\gamma) A_{1t}(\gamma)' \tilde{D}_n^{-1} \\ &\xrightarrow{p} G(\gamma) + \rho^2 G(\gamma) - \rho (G_1(\gamma) + G'_1(\gamma)). \end{aligned}$$

By Lemmas B.1, B.2 and Theorem 4.1, we can also show that

$$n^{-1/2} \sum_{t=1}^n \tilde{D}_n^{-1} \tilde{A}_{1t}(\gamma) \tilde{\eta}_t = \begin{pmatrix} n^{-1} \sum_{t=1}^n \tilde{x}_t \tilde{\eta}_t \\ n^{-1} \sum_{t=1}^n \tilde{D}_n^{-1} \tilde{x}_t(\gamma) \tilde{\eta}_t \\ n^{-1/2} \sum_{t=1}^n \tilde{z}_t \tilde{\eta}_t \end{pmatrix} \Rightarrow \tilde{\phi}(\gamma).$$

When  $\rho = 1$ , define the weighting matrix  $\tilde{D}_n = \{I_{d_1}, n^{1/2}I_{d_2}\}$ ,

$$\tilde{G}(\gamma) = \begin{pmatrix} H & (h(\gamma) - h_1(\gamma)) \int \mathbf{B}'_v(s)ds & H - H_1 \\ (\int \mathbf{B}_v(s)ds) (h(\gamma) - h_1(\gamma))' & 2(F(\gamma) - F_1(\gamma)) \int \mathbf{B}_v(s)\mathbf{B}'_v(s)ds & \int_0^1 \mathbf{B}_v(s)ds (2h(\gamma) - h_1(\gamma) - h_2(\gamma))' \\ H' - H'_1 & (2h(\gamma) - h_1(\gamma) - h_2(\gamma)) \int_0^1 \mathbf{B}'_v(s)ds & 2H - H_1 - H'_1 \end{pmatrix},$$

and

$$\tilde{\phi}(\gamma) = \begin{pmatrix} \sigma J_2 \\ \sigma \int_0^1 \mathbf{B}_v(s) d\tilde{W}(s, \gamma) \\ \sigma \tilde{J} \end{pmatrix}.$$

Using a similar argument for the case of  $\rho < 1$ , we can establish the convergence results a) and b).

**Proof of Theorem 4.2:** The proof is similar to that of Theorem 3.1 and is skipped for brevity.

**Proof of Theorem 4.3:** The proof is similar to that of Theorem 3.2 and is skipped for brevity.



**Table 1a: The Mean Squared Errors (MSE) of Threshold Estimators**

		$n = 100$		$n = 200$		$n = 400$	
Panel A: $\tau = 0$							
$\rho$	$\beta$	MSE( $\hat{\gamma}$ )	MSE( $\tilde{\gamma}$ )	MSE( $\hat{\gamma}$ )	MSE( $\tilde{\gamma}$ )	MSE( $\hat{\gamma}$ )	MSE( $\tilde{\gamma}$ )
0	0	.012	.019	.004	.0040	.0021	.0022
0	.5	.013	.009	.004	.0020	.0008	.0003
1	0	.191	.002	.221	.0056	.2030	.0002
1	.5	.314	.005	.197	.0019	.2340	.0002
.95	0	.129	.019	.097	.0010	.0320	.0001
.95	.5	.125	.002	.129	.0031	.0310	.0004
-.95	0	.093	.004	.043	.0002	.0270	.0002
-.95	.5	.171	.020	.095	.0031	.0230	.0003
Panel B: $\tau = 0.5$							
0	0	.365	.379	.485	.4720	.4540	.4550
0	.5	.519	.509	.518	.4880	.5100	.4540
1	0	1.17	.592	.654	.5270	.7170	.4080
1	.5	.435	.302	.460	.3890	.5440	.4290
.95	0	.586	.410	.572	.3800	.5220	.4040
.95	.5	.375	.359	.557	.4400	.4940	.3670
-.95	0	.800	.608	.422	.3640	.6060	.4120
-.95	.5	.742	.530	.532	.4200	.6220	.3560

Note: The model is  $y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t$  with  $x_t = x_{t-1} + v_t$ ,  $u_t = \rho u_{t-1} + \varepsilon_t$  and  $q_t = 0.5q_{t-1} + e_t$ , where  $v_t$ ,  $\varepsilon_t$  and  $e_t$  are i.i.d.  $N(0, 1)$ . The true threshold value is set as  $\gamma_0 = 0$  and  $\alpha$  is set as 1. Parameter  $\rho$  is set as either 0, 1, 0.95 or -0.95. Parameter  $\beta$  is set as 0 or 0.5. The size of the threshold effect  $\delta_n$  is set as  $\delta_n = 2n^{-1/2-\tau}$ , where  $\tau$  is 0 or 0.5. MSE( $\hat{\gamma}$ ) is the MSE calculated for the profiled LS estimator of  $\gamma_0$  and MSE( $\tilde{\gamma}$ ) is for the FGLS estimator. The sample size  $n$  takes either 100, 200 or 400. The replication number is 1000.

**Table 1b: The Mean Squared Errors of Coefficients Estimators**

		$n = 100$		$n = 200$		$n = 400$	
Panel A: $\tau = 0$							
$\rho$	$\beta$	$\text{MSE}(\widehat{\theta})$	$\text{MSE}(\widetilde{\theta})$	$\text{MSE}(\widehat{\theta})$	$\text{MSE}(\widetilde{\theta})$	$\text{MSE}(\widehat{\theta})$	$\text{MSE}(\widetilde{\theta})$
0	0	$3.70e^{-3}$	$4.50e^{-3}$	$8.40e^{-4}$	$9.3e^{-4}$	$2.13e^{-4}$	$2.10e^{-4}$
0	.5	$5.90e^{-3}$	$5.50e^{-3}$	$1.14e^{-3}$	$8.40e^{-4}$	$2.60e^{-4}$	$2.13e^{-4}$
1	0	1.34	$2.60e^{-1}$	1.25	$1.40e^{-1}$	1.27	$6.80e^{-2}$
1	.5	1.39	$2.10e^{-1}$	$9.80e^{-1}$	$1.30e^{-1}$	$9.97e^{-1}$	$9.10e^{-2}$
.95	0	$1.66e^{-1}$	$4.68e^{-2}$	$3.80e^{-2}$	$1.70e^{-2}$	$1.70e^{-2}$	$5.70e^{-3}$
.95	.5	$1.81e^{-1}$	$4.57e^{-2}$	$4.10e^{-2}$	$1.60e^{-2}$	$1.50e^{-2}$	$5.90e^{-3}$
−.95	0	$3.50e^{-2}$	$1.34e^{-3}$	$2.43e^{-3}$	$3.50e^{-4}$	$1.29e^{-3}$	$9.80e^{-5}$
−.95	.5	$4.20e^{-2}$	$1.70e^{-3}$	$1.93e^{-3}$	$4.98e^{-4}$	$1.89e^{-3}$	$1.08e^{-4}$
Panel B: $\tau = 0.5$							
0	0	$1.36e^{-2}$	$1.44e^{-2}$	$3.19e^{-3}$	$3.49e^{-3}$	$6.89e^{-4}$	$1.00e^{-3}$
0	.5	$1.60e^{-2}$	$1.44e^{-2}$	$4.20e^{-3}$	$3.70e^{-3}$	$1.13e^{-3}$	$9.50e^{-4}$
1	0	1.88	$2.01e^{-1}$	1.09	$1.05e^{-1}$	$9.62e^{-1}$	$6.15e^{-2}$
1	.5	1.66	$2.10e^{-1}$	1.50	$1.41e^{-1}$	$9.80e^{-1}$	$6.56e^{-2}$
.95	0	$1.81e^{-1}$	$4.89e^{-2}$	$7.50e^{-2}$	$2.14e^{-2}$	$2.11e^{-2}$	$6.30e^{-3}$
.95	.5	$2.40e^{-1}$	$5.29e^{-2}$	$9.50e^{-2}$	$1.81e^{-2}$	$2.48e^{-2}$	$5.93e^{-3}$
−.95	0	$1.40e^{-1}$	$5.70e^{-3}$	$3.22e^{-2}$	$1.59e^{-3}$	$5.90e^{-3}$	$2.66e^{-4}$
−.95	.5	$1.06e^{-1}$	$5.20e^{-3}$	$2.25e^{-2}$	$1.43e^{-3}$	$7.40e^{-3}$	$1.16e^{-4}$

Note: The model is  $y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t$  with  $x_t = x_{t-1} + v_t$ ,  $u_t = \rho u_{t-1} + \varepsilon_t$  and  $q_t = 0.5q_{t-1} + e_t$ , where  $v_t$ ,  $\varepsilon_t$  and  $e_t$  are i.i.d.  $N(0, 1)$ . The true threshold value is set as  $\gamma_0 = 0$  and  $\alpha$  is set as 1. Parameter  $\rho$  is set as either 0, 1, 0.95 or -0.95. Parameter  $\beta$  is set as 0 or 0.5. The size of the threshold effect  $\delta_n$  is set as  $\delta_n = 2n^{-1/2-\tau}$ , where  $\tau$  is 0 or 0.5.  $\text{MSE}(\hat{\theta})$  is defined as the sum of  $\text{MSE}(\hat{\alpha})$  and  $\text{MSE}(\hat{\delta}_n)$ , where  $\text{MSE}(\hat{\alpha})$  is the MSE calculated for the profiled LS estimator of  $\alpha$  and  $\text{MSE}(\hat{\delta}_n)$  is MSE calculated for the profiled LS estimator of  $\delta$ .  $\text{MSE}(\tilde{\theta})$  is defined as the sum of  $\text{MSE}(\tilde{\alpha})$  and  $\text{MSE}(\tilde{\delta}_n)$ , where  $\text{MSE}(\tilde{\alpha})$  is the MSE for the FGLS estimator of  $\alpha$  and  $\text{MSE}(\tilde{\delta}_n)$  is for the FGLS estimator of  $\delta_n$ . The sample size  $n$  takes either 100, 200 or 400. The replication number is 1000.

**Table 2a: Size Performance**

			$n = 100$			$n = 200$			$n = 400$		
$\rho$	$\delta_n$	$\beta$	10%	5%	1%	10%	5%	1%	10%	5%	1%
Panel A: $\mathbf{T}_n$											
0	0	0	.078	.028	.005	.114	.056	.018	.098	.046	.008
0	0	.5	.120	.092	.034	.084	.050	.008	.076	.052	.010
1	0	0	.132	.082	.030	.064	.034	.014	.068	.044	.013
1	0	.5	.086	.052	.022	.134	.074	.022	.112	.076	.018
.95	0	0	.128	.073	.042	.178	.072	.030	.104	.046	.008
.95	0	.5	.134	.075	.020	.146	.064	.004	.132	.061	.016
−.95	0	0	.120	.072	.010	.106	.060	.018	.093	.042	.015
−.95	0	.5	.070	.034	.008	.118	.064	.006	.092	.039	.006
Panel B: $\tilde{\mathbf{T}}_n$											
0	0	0	.110	.072	.030	.102	.062	.022	.098	.047	.010
0	0	.5	.144	.084	.028	.076	.044	.014	.088	.046	.008
1	0	0	.084	.058	.020	.112	.038	.018	.104	.054	.014
1	0	.5	.130	.062	.014	.082	.042	.014	.116	.055	.012
.95	0	0	.114	.062	.002	.072	.060	.008	.082	.042	.008
.95	0	.5	.128	.064	.032	.132	.076	.020	.094	.037	.008
−.95	0	0	.086	.036	.016	.142	.078	.024	.090	.044	.010
−.95	0	.5	.116	.066	.022	.089	.046	.016	.091	.058	.015

Note: The model is  $y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t$  with  $x_t = x_{t-1} + v_t$ ,  $u_t = \rho u_{t-1} + \varepsilon_t$  and  $q_t = 0.5q_{t-1} + e_t$ , where  $v_t$ ,  $\varepsilon_t$  and  $e_t$  are i.i.d.  $N(0, 1)$ . The true threshold value is set as  $\gamma_0 = 0$  and  $\alpha$  is set as 1. Parameter  $\rho$  is set as either 0, 1, 0.95 or −0.95. Parameter  $\beta$  is set as 0 or 0.5. The size of the threshold effect  $\delta_n$  is set as 0 to check the size performance.  $n$  is the sample size. The replication number is 1000.

**Table 2b: Power Performance**

$n = 100$		$\mathbf{T}_n$				$\tilde{\mathbf{T}}_n$			
Panel A: $\tau = 0$									
$\rho$	$\beta$	10%	5%	1%	$> (\ln(n))^2$	10%	5%	1%	$> (\ln(n))^2$
0	0	1.00	.994	.984	.956	1.00	.998	.988	.970
0	.5	.992	.980	.968	.904	.998	.994	.984	.952
1	0	.478	.436	.360	.462	.998	.996	.982	.958
1	.5	.506	.460	.312	.486	1.00	.998	.992	.970
.95	0	.796	.720	.564	.610	.986	.986	.968	.968
.95	.5	.830	.772	.654	.636	.996	.996	.994	.978
−.95	0	.956	.922	.884	.464	1.00	.998	.994	.994
−.95	.5	.856	.802	.708	.444	1.00	1.00	.998	.996
Panel B: $\tau = 0.5$									
0	0	.322	.224	.074	.024	.324	.206	.110	.034
0	.5	.258	.150	.030	.020	.206	.090	.030	.032
1	0	.164	.098	.050	.100	.278	.190	.078	.044
1	.5	.090	.043	.010	.030	.298	.240	.100	.048
.95	0	.070	.034	.010	.018	.296	.206	.118	.068
.95	.5	.322	.234	.072	.024	.268	.196	.084	.072
−.95	0	.296	.236	.146	.002	.550	.434	.182	.110
−.95	.5	.308	.198	.050	.004	.500	.392	.266	.088

Note: The model is  $y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t$  with  $x_t = x_{t-1} + v_t$ ,  $u_t = \rho u_{t-1} + \varepsilon_t$  and  $q_t = 0.5q_{t-1} + e_t$ , where  $v_t$ ,  $\varepsilon_t$  and  $e_t$  are i.i.d.  $N(0, 1)$ . The true threshold value is set as  $\gamma_0 = 0$  and  $\alpha$  is set as 1. Parameter  $\rho$  is set as either 0, 1, 0.95 or -0.95. Parameter  $\beta$  is set as 0 or 0.5. The size of the threshold effect  $\delta_n$  is set as  $\delta_n = 2n^{-1/2-\tau}$ , where  $\tau$  is 0 or 0.5.  $n$  is the sample size. The replication number is 1000.

**Table 2c: Power Performance**

$n = 200$		$\mathbf{T}_n$				$\widetilde{\mathbf{T}}_n$			
Panel A: $\tau = 0$									
$\rho$	$\beta$	10%	5%	1%	$> (\ln(n))^2$	10%	5%	1%	$> (\ln(n))^2$
0	0	1.00	1.00	.998	.982	1.00	1.00	.998	.984
0	.5	1.00	1.00	.996	.974	1.00	1.00	1.00	.990
1	0	.854	.836	.816	.328	1.00	1.00	1.00	.992
1	.5	.668	.614	.540	.346	1.00	1.00	1.00	.988
.95	0	.856	.820	.732	.624	1.00	1.00	1.00	.986
.95	.5	.790	.750	.708	.584	1.00	1.00	1.00	.992
−.95	0	.962	.950	.912	.506	1.00	1.00	1.00	1.00
−.95	.5	.964	.956	.906	.502	1.00	1.00	1.00	1.00
Panel B: $\tau = 0.5$									
0	0	.284	.222	.098	.004	.256	.198	.108	.004
0	.5	.254	.144	.078	.002	.250	.170	.066	.008
1	0	.098	.050	.016	.000	.280	.212	.126	.080
1	.5	.116	.050	.010	.030	.292	.174	.072	.014
.95	0	.082	.034	.016	.000	.428	.336	.194	.020
.95	.5	.078	.044	.002	.034	.308	.228	.068	.016
−.95	0	.318	.220	.124	.000	.442	.352	.268	.034
−.95	.5	.110	.050	.016	.000	.402	.292	.160	.030

Note: The model is  $y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t$  with  $x_t = x_{t-1} + v_t$ ,  $u_t = \rho u_{t-1} + \varepsilon_t$  and  $q_t = 0.5q_{t-1} + e_t$ , where  $v_t$ ,  $\varepsilon_t$  and  $e_t$  are i.i.d.  $N(0, 1)$ . The true threshold value is set as  $\gamma_0 = 0$  and  $\alpha$  is set as 1. Parameter  $\rho$  is set as either 0, 1, 0.95 or -0.95. Parameter  $\beta$  is set as 0 or 0.5. The size of the threshold effect  $\delta_n$  is set as  $\delta_n = 2n^{-1/2-\tau}$ , where  $\tau$  is 0 or 0.5.  $n$  is the sample size. The replication number is 1000.

**Table 2d: Power Performance**

$n = 400$		$\mathbf{T}_n$				$\widetilde{\mathbf{T}}_n$			
Panel A: $\tau = 0$									
$\rho$	$\beta$	10%	5%	1%	$> (\ln(n))^2$	10%	5%	1%	$> (\ln(n))^2$
0	0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0	.5	1.00	1.00	1.00	.994	1.00	1.00	1.00	.998
1	0	.742	.692	.586	.234	1.00	1.00	1.00	1.00
1	.5	.546	.488	.410	.266	1.00	1.00	1.00	.998
.95	0	.910	.884	.820	.722	1.00	1.00	1.00	1.00
.95	.5	.942	.916	.868	.668	1.00	1.00	1.00	.998
−.95	0	.994	.986	.958	.596	1.00	1.00	1.00	1.00
−.95	.5	.996	.984	.958	.648	1.00	1.00	1.00	1.00
Panel B: $\tau = 0.5$									
0	0	.294	.196	.042	.002	.264	.166	.052	.000
0	.5	.166	.124	.054	.000	.272	.192	.108	.002
1	0	.386	.312	.160	.000	.248	.162	.052	.000
1	.5	.020	.012	.002	.012	.228	.146	.050	.002
.95	0	.074	.026	.004	.002	.264	.186	.068	.002
.95	.5	.094	.052	.010	.000	.292	.210	.082	.000
−.95	0	.092	.042	.020	.000	.546	.448	.302	.010
−.95	.5	.134	.064	.018	.000	.320	.204	.134	.010

Note: The model is  $y_t = \alpha x_t + \delta_n x_t (q_t \leq \gamma_0) + \beta v_t + u_t$  with  $x_t = x_{t-1} + v_t$ ,  $u_t = \rho u_{t-1} + \varepsilon_t$  and  $q_t = 0.5q_{t-1} + e_t$ , where  $v_t$ ,  $\varepsilon_t$  and  $e_t$  are i.i.d.  $N(0, 1)$ . The true threshold value is set as  $\gamma_0 = 0$  and  $\alpha$  is set as 1. Parameter  $\rho$  is set as either 0, 1, 0.95 or -0.95. Parameter  $\beta$  is set as 0 or 0.5. The size of the threshold effect  $\delta_n$  is set as  $\delta_n = 2n^{-1/2-\tau}$ , where  $\tau$  is 0 or 0.5.  $n$  is the sample size. The replication number is 1000.

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