Testing Structural Change in Conditional Distributions via Quantile Regressions

Liangjun Su, Zhijie Xiao

School of Economics, Singapore Management University, Singapore
Department of Economics, Boston College, Chestnut Hill, MA, USA

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Abstract

We propose tests for structural change in conditional distributions via quantile regressions. To avoid misspecification on the conditioning relationship, we construct the tests based on the residuals from local polynomial quantile regressions. In particular, the tests are based upon the cumulative sums of generalized residuals from quantile regressions and have power against local alternatives at rate $n^{-1/2}$. We derive the limiting distributions for our tests under the null hypothesis of no structural change and a sequence of local alternatives. The proposed tests apply to a wide range of dynamic models, including time series regressions with m.d.s. errors, as well as models with serially correlated errors. To deal with possible correlations in the error process, we also propose a simulation method to obtain the p-values for our tests. Finally, Monte Carlo simulations suggest that our tests behave well in finite samples.

JEL classifications: C12, C14, C22, C5

Key Words: Conditional distribution, Structural change, Local polynomial regression, Quantile regression, Block bootstrap

*Liangjun Su, School of Economics, Singapore Management University, 90 Stamford Road, Singapore 178903; Phone: +65 6828 0386; e-mail: ljsu@smu.edu.sg. Zhijie Xiao, Department of Economics, Boston College, Chestnut Hill, MA 02467, USA; phone: +1 617 5521709; e-mail: xiaoz@bc.edu. The first author gratefully acknowledges the financial support from a research grant (Grant number: 08-C244-SMU-015) from Singapore Management University.
1 Introduction

Structural instability is an empirically widespread phenomenon. The presence of structural instability may invalidate the conventional econometric inference that ignores it. For this reason, there has traditionally been a long-standing research effort in structural instability, among which much has been devoted to parametric models, especially linear models. In particular, there has been a large literature on testing parameter instability in linear regression models. See, inter alia, Page (1955), Brown, Durbin, and Evans (1975), Nyblom (1989), Ghysels and Hall (1990), Andrews (1993), Andrews and Ploberger (1994), Sowell (1996), Bai, Lumsdaine and Stock (1998), Hansen (2000), Elliott and Müller (2006), and Li (2008). See Csörgő and Horváth (1997) for an excellent review on this topic.

An important subfield that has attracted a lot of research attention is testing for structural change at the distributional level. Many economic and finance problems often confront structural instability in distribution. Demographic changes, capital accumulation, technological progress, and many other aspects in economic environment and policies, often change the distribution or conditional distribution of economic time series. Hansen (2000) noted that tests for structural changes in regression models are sensitive to a change in the marginal distribution of the regressors. Qu (2008) argued that structural change in conditional distributions may be of key importance under various circumstances. Take the income inequality study as an example. It is important to examine whether the distribution of wage differentials between different races or genders, controlled for relevant covariates, has changed over time or not. It can be the case where the conditional mean of the wage differentials remain unchanged but the conditional dispersion has changed. If so, traditional tests for structural changes that are based on the conditional mean regression models should be replaced by tests for conditional dispersion or distribution. In other scenarios, higher order conditional moments may have changed over time but both the conditional mean and dispersion remain unchanged. If this is the case, then the conditional mean and variance cease to be informative and tests in the conditional distributions should be employed. In light of this, it is important to test the distributional stability of a time series in regression models.

Several tests have been developed to test for distributional changes. Picard (1985) proposed tests for distributional change in time series by detecting changes in the spectrum in that time series. Bai (1994) considered tests for the distributional change in the i.i.d. error process of ARMA models based upon empirical distributions. Inoue (2001) proposed tests for distributional change based on a sequential empirical process for dependent data. Lee and Na (2004) proposed tests for distributional change based upon nonparametric kernel density estimation in the time series framework. All these tests are designed to test for structural changes in unconditional distributions.

In this paper, we study testing for structural change in the conditional distribution of a random variable $Y_t$ given relevant covariates $X_t$, where $X_t$ may include lagged variables of $Y_t$. We propose tests for distributional changes based on quantile regressions. Being the inverse of a conditional distribution function, the conditional quantile function is a natural object to examining conditional distributional changes. In the special case where the relationship between $Y_t$ and $X_t$ is characterized by a parametric model, testing for distributional change may be formulated as testing quantile regression coefficient instability. Su and Xiao (2008a) and Qu (2008) proposed tests for parameter
instability in linear quantile regression models. These tests can be applied to test for structural changes in conditional distribution if the specified linear relationship between $Y_t$ and $X_t$ is correct. In many applications, the functional form of the relationship between $Y_t$ and $X_t$ is unknown. Misspecification of econometric models can also manifest themselves in the form of structural changes. Misleading conclusions may be obtained if the linearity (or other parametric) assumption is violated.

To avoid spurious breaks from misspecification, we propose tests for distributional changes via nonparametric quantile regressions. Chaudhuri (1991) studied nonparametric quantile regression in the i.i.d. setting and derived its local Bahadur representation. Su and White (2009b) studied time series local polynomial quantile regression and established the uniform local Bahadur representation, where the uniformity holds in both quantiles and conditioning variables. Also see Yu and Jones (1998), Koenker, Ng, and Portnoy (1994) for other studies in nonparametric quantile regressions. In this paper, we use local polynomial quantile regressions to construct the proposed tests.

There are several important features associated with our tests. First, our tests are testing for structural changes at the distributional level without specifying any parametric form on any aspect of the conditional distribution, including conditional mean, conditional variance, or conditional quantile function. Second, comparing our tests with the existing literature, we consider tests for structural changes in the conditional distribution for time series data. This is important since economic and financial time series are not i.i.d. and conditional distributions may be affected by policy changes or critical social events. Third, our tests are flexible on the model dynamics and do not require the correct specification of the dynamics. Letting $\mathcal{F}_{t-1}$ be the information set at time $t$, we do not require that the distribution of $Y_t$ conditional on $\mathcal{F}_{t-1}$ be the same as that of $Y_t$ conditional on $X_t$. As a result, our tests cover a wide range of dynamic models and do not require that the error process in the quantile regression model be a martingale difference sequence (m.d.s. hereafter). As we will demonstrate, our tests are asymptotically pivotal if the m.d.s. condition is satisfied. For more general case, we propose a simulation method to facilitate statistical inference. Fourth, as in Su and White (2009a) we allow for small breaks in the covariate process $\{X_t\}$ under both the null and alternative hypotheses. Fifth, our tests allow us to focus on certain range of the conditional distributions. For example, one may focus on the median or (say) left-tail of the conditional distributions as in the value-at-risk (VaR) analysis. Finally, even though our tests are of nonparametric nature, they have non-trivial power against a sequence of Pitman local alternatives that converge to zero at the parametric $n^{-1/2}$-rate.

The rest of the paper is organized as follows. In Section 2 we introduce our hypotheses, local polynomial quantile regression estimates and test statistics. In Section 3 we study the asymptotic properties of our test statistics and propose a method to simulate the p-values. In Section 4 we provide a small set of Monte Carlo experiments to evaluate the finite sample performance of our tests. Section 5 contains concluding remarks. All proofs are relegated to the appendix.

A word on notation. Throughout the paper, we use $1(\cdot)$ to denote the indicator function and $\|\cdot\|$ to denote the Euclidean norm. Let $\pi_1 \wedge \pi_2 \equiv \min(\pi_1, \pi_2)$, where $x \equiv y$ indicates that $x$ is defined by $y$ or $y$ is defined by $x$, which is clear from the context. The operators $\Rightarrow$ and $\Rightarrow_D$ denote convergence in probability and distribution, respectively. We use $\Rightarrow$ to denote weak convergence and $\Rightarrow_S$ to denote weak convergence in probability as defined by Giné and Zinn (1990); see also Hansen (2000).
2 Hypotheses and Tests

2.1 Hypotheses

Let \( \{(Y_{nt}, X_{nt})\}_{t=1}^{n} \) be a sequence of time series random vectors, we are interested in testing the null hypothesis of no change in the conditional distribution of \( Y_{nt} \) given \( X_{nt} \in \mathbb{R}^d \). The triangular-array notation \( \{(Y_{nt}, X_{nt})\}_{t=1}^{n} \) facilitates the study of asymptotic local power properties of our test and allows for small deviations from stationarity. To avoid complicated notation we will mostly suppress reference to the \( n \) subscript in what follows, in particular, we write \( Y_t = Y_{nt}, X_t = X_{nt} \). If we denote the conditional distribution function of \( Y_t \) given \( X_t \) as \( F_t(\cdot|X_t) \), the null hypothesis can be written as

\[
H_0^* : F_t(\cdot|X_t) = F_0(\cdot|X_t) \quad \text{a.s. for some } F_0(\cdot) \text{ and all } t = 1, 2, \ldots
\]  

(2.1)

Alternatively, since the conditional quantile function is the inverse function of the conditional distribution function, we may also equivalently write the null hypothesis as

\[
H_0 : F_t^{-1}(\tau, X_t) = F_0^{-1}(\tau, X_t) \quad \text{a.s. for some } F_0^{-1}(\cdot, \cdot) \text{ and all } t = 1, 2, \ldots
\]  

(2.2)

where \( F_t^{-1}(\tau, x) \) is the \( \tau \)th conditional quantile function of \( Y_t \) given \( X_t = x \), that is,

\[
F_t^{-1}(\tau, x) \equiv \inf \{ y : F_t(y|x) \geq \tau \}.
\]

To test for structural changes in the conditional distribution of \( Y_t \), we may construct appropriate estimation for the conditional quantile function or the conditional distribution function and examine their stability over time. In this paper, we propose testing procedures for distributional changes via quantile regressions.

For notational convenience, we denote \( F_t^{-1}(\tau, X_t) = m_t(\tau, x) \), and \( F_0^{-1}(\tau, x) = m_0(\tau, x) \), so that the null hypothesis can be written as

\[
H_0 : m_t(\tau, X_t) = m_0(\tau, X_t) \quad \text{a.s. for some } m_0(\cdot, \cdot) \text{ and all } t = 1, 2, \ldots, n.
\]  

(2.3)

The alternative hypothesis is the negation of \( H_0^* \). In this paper, we study the asymptotic behavior of the proposed test under a sequence of Pitman local alternatives:

\[
H_{1n} : m_t(\tau, X_t) = m_0(\tau, X_t) + n^{-1/2}\delta(\tau, X_t, t/n),
\]  

(2.4)

where \( \delta(\cdot, \cdot, \cdot) \) is a non-constant measurable function. If \( \delta(\tau, x, t/n) = \delta_0(\tau, x) 1(t/n \geq \pi_0) \) in eq. (2.4), we have the special case of a one-time shift at time \( n\pi_0 \).

In practice, the functional form of the conditional distribution is usually unknown and misspecification of the conditional relationship manifests themselves in the form of structural changes. For this reason, we propose tests for distribution changes based on nonparametric quantile regressions.

2.2 Estimation

The approach proposed in this paper may be applied to different nonparametric estimators, including the simple kernel smoother and the local polynomial estimator. In this paper, we give asymptotic
analysis based on the local polynomial procedures. The basic idea of local polynomial fit is: if $m_0(\tau, x)$ is a smooth function of $x$, for any $x_i$ in a neighborhood of $x$, we have

$$m_0(\tau, x_i) \approx m_0(\tau, x) + \sum_{1 \leq |j| \leq p} \frac{1}{j!} D^{|j|}m_0(\tau, x)(x_i - x)^j + o(\|x_i - x\|^p)$$

$$\equiv \sum_{0 \leq |j| \leq p} \beta_j(\tau, x; h) ((x_i - x)/h)^j + o(\|x_i - x\|^p).$$

Here, we use the notation of Masry (1996): $j = (j_1, \ldots, j_d)$, $|j| = \sum_{l=1}^d j_l$, $x_j = \Pi_{1}^{d} x_{i}^{j_{l}}$, $\sum_{0 \leq |j| \leq p} = \sum_{k=0}^{p} \sum_{j_1=0}^{k} \cdots \sum_{j_d=0}^{k} D^{|j|}m_0(\tau, x) = \frac{\partial^{|j|}m(\tau, x)}{\partial x_{i_1} \cdots \partial x_{i_d}}$, $\beta_j(\tau, x; h) = \frac{h^{|j|}}{j!} D^{|j|}m_0(\tau, x)$, where $j! = \Pi_{1}^{d} j_{l}$!

and $h = h(n)$ is a bandwidth parameter that controls how “close” $x_i$ is from $x$. Thus, given observations $\{(Y_t, X_t)\}_{t=1}^{n}$, we may consider a local-polynomial quantile regression that minimizes the following objective function

$$Q_n(\tau, x; \beta) \equiv n^{-1} \sum_{t=1}^{n} \rho_{\tau} \left( Y_t - \sum_{0 \leq |j| \leq p} \beta_j((X_t - x)/h)^j \right) K((X_t - x)/h), \quad (2.5)$$

where $\rho_{\tau}(z)$ be the “check” function defined by $\rho_{\tau}(z) = z(\tau - 1(z \leq 0))$ with $1(\cdot)$ being the usual indicator function, $K$ is a nonnegative kernel function on $\mathbb{R}^d$, and $\beta$ is a stack of $\beta_j$ in the lexicographical order (with highest priority to last position so that $(0, 0, \ldots, l)$ is the first element in the sequence and $(l, 0, \ldots, 0)$ is the last element). Minimizing (2.5) with respect to $\beta_j$, $0 \leq |j| \leq p$, delivers an estimate $\hat{\beta}_j(\tau, x; h)$ of $\beta_j(\tau, x; h)$. The conditional quantile function $m_0(\tau, x)$ and its derivatives up to $p$-th order are then estimated respectively by

$$\hat{m}(\tau, x) = \hat{\beta}_0(\tau, x; h) \text{ and } \hat{D}^{|j|}m(\tau, x) = (j!/h^{|j|})\hat{\beta}_j(\tau, x; h) \text{ for } 1 \leq |j| \leq p.$$
and Truong (1994), Yu and Jones (1998), and Su and White (2009b) for studies on local-polynomial quantile regressions.

Let \( (X_t - x)/h \) be an \( N \times 1 \) vector that contains the regressors \( ((X_t - x)/h)^{j} \) in the local-polynomial quantile regression (2.5) in the lexicographical order. For example, if \( p = 1 \), then \( \mu ((X_t - x)/h) = (1, (X_t - x)^{j}/h)^{'} \). Define

\[
H_n (\tau, x) \equiv \frac{1}{n} \sum_{t=1}^{n} f_t (m_0 (\tau, x) \mid x) f_t (x) \mathbf{1}, \quad \text{and}
\]

\[
J_n (\tau, x) \equiv \frac{1}{\sqrt{nh^d}} \sum_{t=1}^{n} \psi_\tau (Y_t - m_0 (\tau, X_t)) \mu ((X_t - x)/h) K ((x - X_t)/h). 
\]

The following result is essentially Corollary 2.2 of Su and White (2009b).

**Proposition 2.1** Suppose that \( H_{1n} \) and Assumptions A1-A7 given below hold. Then uniformly in \((\tau, x) \in \mathcal{T} \times \mathcal{X}\),

\[
\sqrt{nh^d} (\hat{m} (\tau, x) - m_0 (\tau, x)) = e'_1 H_n (\tau, x)^{-1} J_n (\tau, x) [1 + \text{op} (1)] + \text{op} (h^{d/2}),
\]

where \( e'_1 = (1, 0, ..., 0)^{'} \) is an \( N \)-vector, \( \mathcal{T} = [\underline{\tau}, \overline{\tau}] \subset (0, 1) \) and \( \mathcal{X} \) is the support of the distribution of \( X_t \).

### 2.3 The proposed tests

Under the null hypothesis, \( F_t (m_0 (\tau, X_t) | X_t) = \tau \) a.s. for each \( t \), i.e., \( E [\mathbf{1} (Y_t \leq m_0 (\tau, X_t))] = \tau \). Let \( u_{\tau \tau} \equiv Y_t - m_0 (\tau, X_t) \), and \( \psi_\tau (u) \equiv \tau - \mathbf{1} (u \leq 0) \), then

\[
E [\psi_\tau (u_{\tau \tau})] = 0 \text{ under } H_0.
\]

This suggests, if \( u_{\tau \tau} \) were observable, one could test \( H_0 \) based on the following process

\[
S^{(1)}_n (\pi, \tau) = n^{-1/2} \sum_{t=1}^{[\pi \tau]} \psi_\tau (u_{\tau \tau}),
\]

where \([c]\) is the integer part of \( c \). Under the null hypothesis, \( \{S^{(1)}_n (\cdot, \cdot)\} \) converges to a zero-mean Gaussian process.

However, \( u_{\tau \tau} \) are not observed in practice. If we replace it by \( \hat{u}_{\tau \tau} \equiv Y_t - \hat{m} (\tau, X_t) \), we can consider the following residual-based CUSUM process

\[
S^{(2)}_n (\pi, \tau) = n^{-1/2} \sum_{t=1}^{[\pi \tau]} \{\tau - \mathbf{1} (\hat{u}_{\tau \tau} \leq 0)\}.
\]

Note that the indicator function is not everywhere differentiable on its support. Even if we can assume that the conditional quantile function \( m_0 (\tau, x) \) belongs to certain class of smooth functions (e.g., Van der Vaart and Wellner (1996, p.154)) so that \( S^{(1)}_n (\pi, \tau) \) obeys a version of Donsker theorem, it is hard to justify that the estimate \( \hat{m} (\tau, x) \) of \( m_0 (\tau, x) \) also belongs to the same class. For this
reason, we propose to approximate the indicator function by a smooth function \( G(\cdot) \) and consider the following two-parameter stochastic process:

\[
S_n(\pi, \tau) = n^{-1/2} \sum_{t=1}^{[n\pi]} \{ \tau - G_{\lambda_n}(\tilde{u}_{t\tau}) \},
\]

where \( G_{\lambda}(u) = G(-u/\lambda) \), and \( G(\cdot) \) behaves like a cumulative distribution function (c.d.f. hereafter) and \( \lambda_n \to 0 \) sufficiently fast as \( n \to \infty \). Since \( \psi_{t\tau}(u_{t\tau}) \) has conditional mean zero given \( X_t \) under the null, we can treat elements in the summation of \( S_n(\pi, \tau) \) as generalized quantile regression residuals.

The process \( \{S_n(\cdot, \cdot), n \geq 1\} \) will be the main ingredient of our test statistic. As we show in the next section, under some regularity conditions, it converges to a zero-mean Gaussian process under the null hypothesis and diverges for some value of \( (\pi, \tau) \) under the alternative. However, the estimation \( \hat{m}(\tau, x) \) of \( m_0(\tau, x) \) affects the limiting distribution of \( \{S_n(\cdot, \cdot), n \geq 1\} \), and thus brings additional difficulty to our inference problem. For this reason, we consider the following centered process

\[
S^c_n(\pi, \tau) = S_n(\pi, \tau) - \pi S_n(1, \tau).
\]

As we will demonstrate later in this paper, re-centering \( S_n(\pi, \tau) \) by the quantity \( \pi S_n(1, \tau) \) eliminates the preliminary estimation error under regularity conditions.

Inference procedures may be constructed based on different continuous functionals of \( S^c_n(\pi, \tau) \). We consider the leading cases of Kolmogorov-Smirnov and Cramér-von Mises testing statistics defined as follows

\[
KS_n \equiv \sup_{\tau \in [0, 1]} \sup_{\pi \in [0, 1]} |S^c_n(\pi, \tau)| = \max_{1 \leq j \leq n} \sup_{\tau \in [0, 1]} |S^c_n(j/n, \tau)|,
\]

\[
CM_n \equiv \int_T \int_0^1 S^c_n(\pi, \tau)^2 d\pi w (d\tau) = \int_T \frac{1}{n} \sum_{j=1}^n S^c_n(j/n, \tau)^2 w (d\tau),
\]

where \( T = [\underline{T}, \bar{T}] \) is a subset of \( (0, 1) \), and \( w(\tau) = 1/ (\tau - \underline{T}) \) if \( \tau \in T \) and 0 otherwise. Of course, other types of integrating functions for \( \tau \) are possible. We explore the asymptotic properties of the proposed tests in next section.

### 3 Asymptotic Theory

#### 3.1 Assumptions

For asymptotic analysis, we make the following assumptions.

**Assumption A1.** \( \{(Y_t, X_t) \equiv \{(Y_{nt}, X_{nt})\} \) is a strong mixing process with mixing coefficients \( \alpha(s) \) such that \( \sum_{s=0}^\infty s^5 \alpha(s)^{\eta/(6+\eta)} \leq C < \infty \) for some \( \eta > 0 \) with \( \eta/(6+\eta) \leq 1/2 \).

**Assumption A2.** (i) The probability density function (p.d.f.) \( f_t(\cdot) \equiv f_{nt}(\cdot) \) of \( X_t \) is bounded with compact support \( \mathcal{X} \) and has uniformly bounded first order partial derivatives for each \( t \). (ii) The conditional c.d.f. \( F_t(\cdot | X_t) \equiv F_{nt}(\cdot | X_t) \) of \( Y_t \) given \( X_t \) has Lebesgue density \( f_t(\cdot | X_t) \equiv f_{nt}(\cdot | X_t) \) such that \( \sup_{n \geq 1} \sup_{y} \int_T f_t(y|X_t) \leq C_1 \) a.s. for all \( t \), and \( |f_t(y_1|X_t) - f_t(y_2|X_t)| \leq C_2 \) \( |y_1 - y_2| \).
$y_2$ a.s. for all $t$, where $C_2 (\cdot)$ is a continuous function. \( \lim_{n \to \infty} n^{-1} \sum_{i=1}^{n} f_i (m_0 (\tau, x) x) f_i (x) > 0 \) uniformly in $\mathcal{T} \times \mathcal{X}$.

(iii) Let $F_{\tau-1} = \sigma(X_{\tau-i}, i \geq 0; Y_{\tau-j}, j \geq 1)$. The conditional c.d.f. $F_t (\cdot | \mathcal{F}_{\tau-1})$ of $Y_t$ given $\mathcal{F}_{\tau-1}$ and its Lebesgue density function $f_t (\cdot | \mathcal{F}_{\tau-1})$ have continuous derivatives up to $q$th order denoted, respectively, by $F_t^{(q)} (\cdot | \mathcal{F}_{\tau-1})$ and $f_t^{(q)} (\cdot | \mathcal{F}_{\tau-1}), s = 1, \cdots, q$. $F_t^{(q)} (\cdot | \mathcal{F}_{\tau-1})$ and $f_t^{(q)} (\cdot | \mathcal{F}_{\tau-1})$ are uniformly continuous a.s., $\sup_{y, F_t (y | \mathcal{F}_{\tau-1}) \in \mathcal{T}} | F_t^{(q)} (y | \mathcal{F}_{\tau-1}) | < \infty$ a.s., and $\sup_{y, F_t (y | \mathcal{F}_{\tau-1}) \in \mathcal{T}} | f_t^{(q)} (\cdot | \mathcal{F}_{\tau-1}) | < \infty$ a.s. (iv) Let $W_t \equiv (Y_t, X_t')$. The joint p.d.f. of $(W_{t_1}, W_{t_2}, \cdots, W_{t_{2n}})$ exists and is bounded.

**Assumption A3.** (i) $m_0 (\tau, x)$ is bounded uniformly in $(\tau, x) \in \mathcal{T} \times \mathcal{X}$. It is Lipschitz continuous in $(\tau, x)$ and has derivatives with respect to $x$ up to order $p + 1$. (ii) The $(p+1)$th order partial derivatives with respect to $x$, i.e., $D^k m_0 (\tau, x)$ with $|k| = p + 1$, are uniformly bounded in $(\tau, x) \in \mathcal{T} \times \mathcal{X}$, and are Hölder continuous in $(\tau, x)$ with exponent $\gamma_0 > 0$: $\|D^k m_0 (\tau, x) - D^k m_0 (\tau', x')\| \leq C_3 (|\tau - \tau'|^{\gamma_0} + |x - x'|^{\gamma_0})$ for some constant $C_3 < \infty$, and for all $\tau, \tau' \in \mathcal{T}$ and $x, x' \in \mathcal{X}$ and $|k| = p + 1$.

**Assumption A4.** The kernel function $K (\cdot)$ is a product kernel of $k (\cdot)$, which is a symmetric density function with compact support $A \equiv [-c_k, c_k]$. \( \sup_{a \in A} |k (a)| \leq \tau_1 < \infty \), and $|k (a) - k (a')| \leq \tau_2 |a - a'|$ for any $a, a' \in \mathbb{R}$ and some $\tau_2 < \infty$. The functions $H_j (x) = x^j K (x)$ for all $j$ with $0 \leq |j| \leq 2p + 1$ are Lipschitz continuous.

**Assumption A5.** (i) $G (\cdot)$ is monotone, $\lim_{u \to -\infty} G (u) = 0$, and $\lim_{u \to \infty} G (u) = 1$. (ii) $G (\cdot)$ is three times continuously differentiable with derivatives denoted by $G^{(i)} (\cdot)$ for $s = 1, 2, 3$. $G (\cdot)$ and its first derivative $G^{(1)} (\cdot)$ are uniformly bounded, and the integrals $\int_{-\infty}^{\infty} |G^{(s)} (u)| du$, $s = 1, 2, 3$, are finite. (iii) $g (\cdot) \equiv G^{(1)} (\cdot)$ is symmetric over its support. There exists an integer $q \geq 2$ such that $\int u^q g (u) du = 0$ for $s = 1, \cdots, q - 1$, and $\int |u^q g (u)| du$ is finite. (iv) For some $c_G < \infty$ and $A_G < \infty$, either $G^{(s)} (u) = 0$ for $|u| > A_G$ and for $u, u' \in \mathbb{R}$, $|G^{(s)} (u) - G^{(s)} (u')| \leq c_G |u - u'|$, or $G^{(s)} (u)$ is differentiable with $|G^{(s)} (u)| \leq c_G$ and for some $\omega > 1$, $|G^{(s)} (u)| \leq c_G |u|^{-\omega}$ for all $|u| > A_G$.

**Assumption A6.** As $n \to \infty$, $h \to 0$, $n h^d (\log n)^2 \to \infty$, $n h^{2(p+1)} \to 0$, $\lambda_n \to 0$, $n \lambda_n^{2q} \to 0$, $n^2 \lambda_n^{3} h^{d/2} / \log n \to \infty$, and $n^2 \lambda_n^{3} h^{d/2} / (\log n)^4 \to \infty$.

**Assumption A7.** (i) $\delta (\tau, x, s)$ is uniformly bounded in $(\tau, x, s) \in \mathcal{T} \times \mathcal{X} \times [0, 1]$. $\delta (\tau, x, s)$ is continuously differentiable in $\tau$ and uniformly bounded derivatives on $\mathcal{T} \times \mathcal{X} \times [0, 1]$.

(ii) Let $m_{at} \equiv m_0 (\tau, X_t)$, and $T_{\lfloor n \pi \rfloor} (x) \equiv n^{-1} \sum_{s=1}^{\lfloor n \pi \rfloor} f_s (x), n^{-1} \sum_{t=1}^{\lfloor n \pi \rfloor} f_t (m_{at} | X_t) \delta (\tau, X_t, t/n) - n \sum_{t=1}^{\lfloor n \pi \rfloor} \int_{\lfloor n t \pi \rfloor}^{\lfloor n \pi \rfloor} f_t (m_{at} | X_t) \delta (\tau, X_t, t/n) \to \Delta (s, \tau) + o (1)$ uniformly in $(\tau, \tau) \in [0, 1] \times \mathcal{T}$.

**Assumption A8.** (i) There exists a p.d.f. $f (\cdot)$ such that $|f_{at} (X_t) - f (X_t)| \to 0$ a.s. as $n \to \infty$.

(ii) Let $\varepsilon_{at} = Y_t - m_t (\tau, X_t)$ and $F_{n, at} (\tau, r') \equiv \mathbb{E} [1 (\varepsilon_{at} \leq 0) 1 (\varepsilon_{ar'} \leq 0)], \lim_{n \to \infty} F_{n, at} (\tau, r') = F_{t-a} (\tau, \tau')$ for all $t, s$.

Many parts of Assumptions A1 - A4 are similar to those of Masry (1996) and they are typical assumptions to ensure uniform results in nonparametric literature. Some of these assumptions can be relaxed with modifications on the proof. Assumption A1 restricts that the process $\{ (Y_t, X_t) \}$ to be strong mixing with mixing rates decaying sufficiently fast. Assumption A2 imposes smoothness conditions on the marginal and conditional density functions, where neither null nor local alternative
condition is imposed. The boundedness of the joint p.d.f. facilitates the determination of moments of certain U-statistics. Assumption A3 is required for the establishment of the uniform local Bahadur representation for our local polynomial estimates. Assumption A4 specifies typical conditions on the kernel used in local polynomial quantile regressions. Assumption A5(i) is required because we use \( G(\cdot) \) to approximate the indicator function. Assumptions A5(ii)-(iv) specify the smoothness conditions on the function \( G(\cdot) \). In particular, Assumption A5(iii) requires that \( g(\cdot) \) behaves like a \( q \)th order kernel and Assumption A5(iv) is used in studying the remainder term of a third order Taylor expansion. Assumption A6 imposes conditions on the bandwidth. In particular, the condition \( nh^{2(p+1)} \rightarrow 0 \) implies that undersmoothing is required for our tests. Note that the last requirement in A6 implies that \( n^{-1/2}h^{-d/2}\sqrt{\log n} = o(\lambda_n) \), i.e., \( n\lambda_n^2h^d/\log n \rightarrow \infty \). If we set \( h = n^{-1/7} \) and \( \lambda_n \propto n^{-1/2} \), then we need

\[
\max \left( \frac{6\gamma_1}{4\gamma_1 - 7d}, \frac{6\gamma_1}{3\gamma_1 - 4d} \right) < \gamma_2 < 2q.
\]

When the dimension \( d \) of the conditioning variable \( X_t \) is small, \( q = 2 \) will suffice. For example, if \( d = 1 \), \( p = 1 \), \( q = 2 \), \( h \propto n^{-1/3.5} \), then one can choose \( \gamma_2 \in (42/13,4) \); if \( d = 2 \), \( p = 3 \), \( q = 2 \), \( h \propto n^{-1/7} \), then one can choose \( \gamma_2 \in (42/13,4) \). Assumption A7 gives some properties of the local alternative; it is not minimal but simplifies our proofs. If the triangular array process \( \{(Y_t, X_t)\} \equiv \{(Y_{nt}, X_{nt})\} \) satisfies Assumption A8 and \( H_{1n} \), we say it is asymptotically stationary.

To proceed, it is worthwhile to specify the notation on the conditional c.d.f. and p.d.f. under the null hypothesis and local alternatives. First, given the triangular array nature of the process \( \{(Y_t, X_t)\} \equiv \{(Y_{nt}, X_{nt})\} \), the conditional p.d.f. \( f_t(\cdot|X_t) \) and c.d.f. \( F_t(\cdot|X_t) \) in Assumption A2 usually depend on both \( n \) and \( t \), that is, \( f_t(\cdot|X_t) = f_{nt}(\cdot|X_t) \) and \( F_t(\cdot|X_t) = F_{nt}(\cdot|X_t) \). An exception occurs when \( H_0 \) holds and \( f_t(\cdot|X_t) \) and \( F_t(\cdot|X_t) \) do not depend on \( t \). In this case, we will write \( f_t(\cdot|X_t) \) simply as \( f_0(\cdot|X_t) \), which is the conditional p.d.f. associated with the conditional c.d.f. \( F_0(\cdot|X_t) \) and the conditional quantile function \( m_0(\tau, X_t) \) under the null hypothesis. Second, letting \( m_{tr} \equiv m(\tau, X_t) \), it is easy to verify that under \( H_{1n} \) (see (2.4)) and Assumption A7 (i), we have

\[
f_t(m_{tr}|X_t) = f_0(m_{tr}|X_t) - n^{-1/2} f_0(m_{tr}|X_t)^2 \delta_t(\tau, x, t/n) + o_p \left( n^{-1/2} \right), \tag{3.1}
\]

where \( \delta_t(\tau, \cdot, \cdot) \equiv \partial \delta(\tau, \cdot, \cdot) / \partial \tau \). We will use this relationship in the subsequent asymptotic analysis.

### 3.2 Asymptotic distribution of \( S_n(\cdot, \cdot) \)

We first give a general asymptotic result of \( S_n(\cdot, \cdot) \) without Assumption A8. The general result helps us better understand the limiting behavior of the process. Let \( \varsigma_{nt}(\tau) = \mathcal{J}_{[nt]}(X_t) \mathcal{J}_n^{-1}(X_t) \), and
define

\[
\Gamma_{11}(\pi_1, \pi_2; \tau_1, \tau_2) = \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{[n\pi_1]} \sum_{j=1}^{[n\pi_2]} E\left[\psi_{\tau_1}(e_{i\tau_1}) \psi_{\tau_2}(e_{j\tau_2})\right],
\]

\[
\Gamma_{12}(\pi_1, \pi_2; \tau_1, \tau_2) = \lim_{n \to \infty} \frac{c_0}{n} \sum_{i=1}^{[n\pi_1]} \sum_{j=1}^{n} E[\psi_{\tau_1}(e_{i\tau_1}) \psi_{\tau_2}(e_{j\tau_2})],
\]

\[
\Gamma_{21}(\pi_1, \pi_2; \tau_1, \tau_2) = \lim_{n \to \infty} \frac{c_0}{n} \sum_{i=1}^{n} \sum_{j=1}^{[n\pi_2]} E[\psi_{\tau_1}(e_{i\tau_1}) \psi_{\tau_2}(e_{j\tau_2})],
\]

\[
\Gamma_{22}(\pi_1, \pi_2; \tau_1, \tau_2) = \lim_{n \to \infty} \frac{c_0}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} E[\psi_{\tau_1}(e_{i\tau_1}) \psi_{\tau_2}(e_{j\tau_2})].
\]

In the appendix, we demonstrate that the above limits are well defined by using the Davydov inequality (e.g., Hall and Heyde 1980, pp. 277-278). The following theorem establishes the limit distribution of \( S_n(\cdot, \cdot) \) under \( H_0 \) and \( H_{1n} \).

**Theorem 3.1** (i) Under \( H_0 \) and Assumptions A1-A6, \( S_n(\cdot, \cdot) \Rightarrow S_\infty(\cdot, \cdot) \) as \( n \to \infty \), where \( S_\infty(\cdot, \cdot) \) is a zero-mean Gaussian process with covariance kernel

\[
E[S_\infty(\pi_1, \tau_1) S_\infty(\pi_2, \tau_2)] = \sum_{i=1}^{2} \sum_{j=1}^{2} (-1)^{i+j} \Gamma_{ij}(\pi_1, \pi_2; \tau_1, \tau_2).
\]

(ii) Under \( H_{1n} \) and Assumptions A1-A7, \( S_n(\cdot, \cdot) \Rightarrow S_\infty(\cdot, \cdot) + \Delta(\cdot, \cdot) \) as \( n \to \infty \), where \( \Delta(\cdot, \cdot) \) is defined in Assumption A7.

The following remarks concern the interpretation and application of Theorem 3.1.

**Remark 1.** Theorem 3.1(i) indicates that the process \( \{S_n(\cdot, \cdot), n \geq 1\} \) converges to a zero-mean Gaussian process under the null hypothesis of no structural change in the conditional distribution. The covariance kernel of the limiting process \( \{S_\infty(\cdot, \cdot)\} \) depends on both the dependence structure in the data and the contribution of parameter estimation error as reflected by \( \Gamma_{12}, \Gamma_{21} \) and \( \Gamma_{22} \). Consequently \( S_\infty(\cdot, \cdot) \) is generally not a Kiefer process. Theorem 3.1(ii) implies that a test based on a continuous functional of the process \( \{S_n(\cdot, \cdot), n \geq 1\} \) potentially has non-trivial power in detecting \( n^{-1/2} \)-local alternatives provided \( \Delta(\pi, \tau) \neq 0 \) for \( (\pi, \tau) \) in a set of positive Lebesgue measure on \([0, 1] \times \mathcal{T}\).

**Remark 2.** In principle one can construct the KS and CM test statistics based upon the process \( \{S_n(\cdot, \cdot), n \geq 1\} \). The limiting distributions of these test statistics are not nuisance parameter free and so critical values cannot be tabulated. One may consider proposing a bootstrap procedure that takes into account the joint presence of data dependence structure and parameter estimation error, and imposes the null restriction at the same time. This turns out to be extremely difficult (if possible at all) in our framework. For example, if one follows Corradi and Swanson (2006) and proposes a block bootstrap procedure by resampling from the observed data \( \{(X_t, Y_t)\}_{t=1}^{n} \), the null restriction will not be imposed. A side problem with this type of resampling scheme is that it requires
re-estimating the conditional quantile function under the null restriction for each resample of the
data, and thus is computationally demanding. On the other hand, if one tries to apply the block
or stationary bootstrap procedure to resample \( \tilde{u}_{it}^* \) from the quantile residuals \( \{ \tilde{u}_{it} \} \), then there is
no simple way to construct the bootstrapped data for \( \{ Y_t \}_{t=1}^n \) because \( \tilde{m}(\tau, X_t) + \tilde{u}_{it}^* \) depends on \( \tau \)
and cannot be assigned to an object like \( Y_t^* \).

If the triangular array process \( \{(Y_t, X_t)\} \equiv \{(Y_{nt}, X_{nt})\} \) satisfies Assumption A8, the result in
Theorem 3.1 can be greatly simplified. We summarize the limiting behavior of the process in the
following corollary.

**Corollary 3.2** (i) Under \( H_0 \) and Assumptions A1-A6 and A8, \( S_n (\cdot, \cdot) \Rightarrow S_\infty (\cdot, \cdot) \) as \( n \to \infty \), where
\( S_\infty (\cdot, \cdot) \) is a zero-mean Gaussian process with covariance kernel
\[
E [ S_\infty (\pi_1, \tau_1) S_\infty (\pi_2, \tau_2) ] = \left[ (\pi_1 \wedge \pi_2) - 2c_0 \pi_1 \pi_2 + c_0^2 \pi_1 \pi_2 \right] \Gamma^0 (\tau_1, \tau_2),
\]
and \( \Gamma^0 (\tau_1, \tau_2) = \sum_{s=-\infty}^{\infty} [F_s (\tau_1, \tau_2) - \tau_1 \tau_2] \).

(ii) Under \( H_{1n} \) and Assumptions A1-A8, \( S_n (\cdot, \cdot) \Rightarrow S_\infty (\cdot, \cdot) + \Delta (\cdot, \cdot) \) as \( n \to \infty \), where \( \Delta (\pi, \tau) = \text{plim}_{n \to \infty} \left[ n^{-1} \sum_{i=1}^{[n \pi]} \delta nt(\tau) - n^{-1} \pi c_0 \sum_{i=1}^{n} \delta nt(\tau) \right] \), and \( \delta nt(\tau) = \int \left( m_{0\pi} | x \right) \delta(\tau, X_t, t/n) \).

**Remark 3.** Corollary 3.2(i) indicates that even under asymptotic stationarity, the null limit
distribution of the process \( \{ S_n (\cdot, \cdot), n \geq 1 \} \) is still not asymptotically pivotal: it depends on both
the dependence structure in the data and the contribution of parameter estimation error as reflected
by \( \Gamma^0 \) and \( c_0 \), respectively. In the proof of Corollary 3.2, we show that under \( H_0 \),
\[
S_n (\pi, \tau) = \frac{1}{n^{1/2}} \sum_{i=1}^{[n \pi]} \psi_{\pi} (\varepsilon_{i\tau}) - \frac{\pi c_0}{n^{1/2}} \sum_{i=1}^{n} \psi_{\pi} (\varepsilon_{i\tau}) + o_p (1),
\]
where \( o_p (1) \) holds uniformly in \( (\pi, \tau) \in [0, 1] \times T \). The second term on the right hand side of (3.2) is
of the same probability order as the first term and reflects the effect of parameter estimation error.
As typical block bootstrap requires resampling of blocks whose length \( l = l(n) \) is of order \( o(n) \), this
will cause the effect of parameter estimation error to vanish asymptotically in the bootstrap world.
As a consequence, this renders the limiting distribution of the bootstrap analog of \( S_n (\pi, \tau) \) unable to
approximate the null limit distribution of \( S_n (\pi, \tau) \) itself - see Theorem 3.5 and more discussions in
Section 3.3 for additional studies on this issue. For this reason, we consider the re-centered process
\( \{ S_n^c (\cdot, \cdot), n \geq 1 \} \).

The following theorem summarizes the limiting distributions of \( \{ S_n^c (\cdot, \cdot), n \geq 1 \} \) under both the
null and a sequence of local alternatives.

**Theorem 3.3** (i) Under \( H_0 \) and Assumptions A1-A6 and A8, \( S_n^c (\cdot, \cdot) \Rightarrow S_\infty^c (\cdot, \cdot) \) as \( n \to \infty \), where
\( S_\infty^c (\cdot, \cdot) \) is a zero-mean Gaussian process with covariance kernel
\[
E [ S_\infty^c (\pi_1, \tau_1) S_\infty^c (\pi_2, \tau_2) ] = (\pi_1 \wedge \pi_2 - \pi_1 \pi_2) \Gamma^0 (\tau_1, \tau_2),
\]
and \( \Gamma^0 (\tau_1, \tau_2) = \sum_{s=-\infty}^{\infty} [F_s (\tau_1, \tau_2) - \tau_1 \tau_2] \).

(ii) Under \( H_{1n} \) and Assumptions A1-A8, \( S_n^c (\cdot, \cdot) \Rightarrow S_\infty^c (\cdot, \cdot) + \Delta^c (\cdot, \cdot) \) as \( n \to \infty \), where
\( \Delta^c (\pi, \tau) = \Delta^0 (\pi, \tau) - \pi \Delta^0 (1, \tau) \) with \( \Delta^0 (\pi, \tau) = \int_0^\pi \int f_0 (m_{0\pi} \| x) f(x) \delta (\tau, x, s) duds. \)
Remark 4. Theorem 3.3(i) shows that under the null, the process \( \{S_n^q(\cdot, \cdot), n \geq 1\} \) converges to a two-parameter Kiefer process \( \{S^\infty_n(\cdot, \cdot)\} \) that is tied-down in the first argument (see Csörgő and Horváth, 1997, p. 320 or p. 384). By the continuous mapping theorem, Theorem 3.3 implies that

\[
KS_n \overset{D}{\to} \sup_{\pi \in [0,1]} \sup_{\tau \in T} |S^\infty_n(\pi, \tau)|, \quad CM_n \overset{D}{\to} \int_0^1 \int_0^1 S^\infty_n(\pi, \tau)^2 \, d\pi \, w(\tau) \text{ under } H_0, \quad \text{and}
\]

\[
KS_n \overset{D}{\to} \sup_{\pi \in [0,1]} \sup_{\tau \in T} |S^\infty_n(\pi, \tau) + \Delta^c(\pi, \tau)|, \quad CM_n \overset{D}{\to} \int_0^1 \int_0^1 [S^\infty_n(\pi, \tau) + \Delta^c(\pi, \tau)]^2 \, d\pi \, w(\tau) \text{ under } H_{1n}.
\]

Thus the tests \( KS_n \) and \( CM_n \) generally have non-trivial power in detecting Pitman local alternatives that decay to zero at the parametric \( n^{-1/2} \)-rate. If \( \delta(\tau, X_t, t/n) \) is orthogonal to the conditional p.d.f. \( f_0(m_0(\tau, X_t) | X_t) \) so that \( \lim_{n \to \infty} E[f_0(m_0(\tau, X_t) | X_t) \delta(\tau, X_t, t/n)] = 0 \) for essentially all \((t, \tau)\), then the tests have no power in detecting such deviations from the null. Similar phenomena occur in both parametric and nonparametric/semiparametric tests for structural changes in the conditional mean regression framework. In the parametric case, if the structural shifts in the finite dimensional parameters are orthogonal to the mean regressor then the residual-based CUSUM test is not consistent (e.g., Ploberger and Krämer, 1992, 1996). In the latter case, Su and Xiao (2008b) and Su and White (2009a) demonstrate their CUSUM-type tests for nonparametric and semiparametric structural changes also lose power in certain directions.

An important class of conditioning models is the case where \( X_t \) includes lagged dependent variables. In this case, a valid regression model usually requires that the residual process be an m.d.s. For such models, the asymptotic distributions of the tests \( KS_n \) and \( CM_n \) are free of nuisance parameters under the null hypothesis, as can be seen from the following corollary.

**Corollary 3.4** If \( \{\psi_\tau(e_{1\tau}, F_{1\tau})\} \) forms an m.d.s. for each \( \tau \), then the result of Theorem 3.3(i) holds with the simplified covariance kernel

\[
E[S^\infty_n(\pi_1, \tau_1) S^\infty_n(\pi_2, \tau_2)] = (\pi_1 \wedge \pi_2 - \pi_1 \pi_2)(\tau_1 \wedge \tau_2 - \tau_1 \tau_2).
\]

Thus null limit distributions of the tests \( KS_n \) and \( CM_n \) are free of nuisance parameter.

In the next subsection, we propose a simulation-based method that provides valid inference of our tests for general models with correlated errors. The simulation method is in the spirit of block bootstrap (e.g., Künsch (1989), Bühlmann (1994)), and can mimic the null limit distribution of our test statistics.

### 3.3 A simulation-based method

From the results of Theorem 3.3, we see that re-centering removes the effect of preliminary estimation, but not the effect of serial correlation. If the error process of the quantile regression model is not an m.d.s., the asymptotics of the tests \( KS_n \) and \( CM_n \) are generally not asymptotically pivotal. So the critical values for these tests cannot be tabulated. In this subsection, we propose a simulation method to obtain the simulated \( p \)-values for the case with correlated errors.
The proposed simulation method is similar to Inoue (2001) (also see Bühlmann 1994), and has some similarity in the spirit of block bootstrap but differs from the latter in several aspects. In short, we generate a weighted sum of blocks of the generalized residuals. Given a block length \( l \equiv l(n) \), we consider blocks with length \( l \) of the generalized residuals \( \{ \tau - G_{\lambda_n} (\bar{u}_{i\tau}) \} \). Let \( \{ z_j \}_{j=1}^{n-l+1} \) be a sequence of random weights whose properties are specified in Assumption A9 below, we define the following simulated process

\[
S_n^* (\pi, \tau) = n^{-1/2} \sum_{j=1}^{[n\pi]-l+1} z_j \sum_{i=j}^{j+l-1} \{ \tau - G_{\lambda_n} (\bar{u}_{i\tau}) \}.
\]

Let \( S_n^* (\pi, \tau) = S_n^* (\pi, \tau) - \pi S_n^* (1, \tau) \), we construct the bootstrap versions \( KS_n^* \) and \( CM_n^* \) of \( KS_n \) and \( CM_n \) based on \( S_n^* (\pi, \tau) \). Our purpose is to use the distribution of the bootstrapped process \( S_n^* (\pi, \tau) \) to approximate that of \( S_n^* (\pi, \tau) \). The requirements on \( l \) and \( z_j \)'s are stated in the next assumption.

**Assumption A9.** (i) \( \{ z_j \}_{j=1}^{n-l+1} \) are i.i.d. and independent of the process \( \{ (Y_t, X_t) \} \). (ii) \( E (z_j) = 0, \) \( E (z_j^2) = 1/l, \) and \( E (z_j^4) = O(1/l^2) \). (iii) As \( n \to \infty, \) \( l \to \infty, l/n^{1/2} \to 0, \) and \( nh^d/(l \log n) \to \infty. \)

The asymptotic property of the bootstrapped process is summarized in the following theorem.

**Theorem 3.5** Suppose Assumptions A1-A9 hold. Then under either \( H_0 \) or \( H_{1n}, \)

(i) \( S_n^* (\cdot, \cdot) \overset{D}{=} S_n^0 (\cdot, \cdot), \)

(ii) \( S_n^* (\cdot, \cdot) \overset{D}{=} S_n^\infty (\cdot, \cdot), \)

where \( S_n^0 (\cdot, \cdot) \) is a zero-mean Gaussian process with covariance kernel \( E [ S_n^0 (\pi_1, \tau_1) S_n^0 (\pi_2, \tau_2) ] = (\pi_1 \wedge \pi_2) \Gamma^0 (\tau_1, \tau_2), \) and \( \Gamma^0 (\cdot, \cdot) \) and \( S_n^\infty (\cdot, \cdot) \) are defined in Theorem 3.3.

**Remark 5.** Theorem 3.5 explains why we construct the testing statistic based on the re-centered process \( S_n^* (\cdot, \cdot) \) instead of \( S_n (\cdot, \cdot) \). Theorem 3.5(i) shows that the limit of the simulated process \( \{ S_n^* (\cdot, \cdot), n \geq 1 \} \) is different from that of the original process \( \{ S_n (\cdot, \cdot), n \geq 1 \} \) under \( H_0. \) Intuitively speaking, the \( n^{-1/2} \)-rate of local alternatives do not affect the limiting distribution of the simulated process, which causes the difference between the two limiting processes under \( H_0. \) This occurs because, due to the additional randomness of \( \{ z_j \} \) and the assumption \( l = o(n^{1/2}) \), the simulated process is less sensitive than the original process to the presence of parameter estimation error or any perturbation from the null restriction. The difference between \( S_n^\infty (\cdot, \cdot) \) and \( S_n^\infty (\cdot, \cdot) \) indicates that one cannot use \( \{ S_n^* (\cdot, \cdot), n \geq 1 \} \) to obtain the simulated \( p \)-values.

**Remark 6.** Theorem 3.5(ii) shows that each re-centered simulated process \( \{ S_n^* (\cdot, \cdot), n \geq 1 \} \) converges weakly to the same null limit process of \( \{ S_n (\cdot, \cdot), n \geq 1 \} \), thus providing a valid asymptotic basis for approximating the null limit distributions of test statistics based on \( \{ S_n (\cdot, \cdot) \} \). In practice, we repeat the bootstrap procedure \( B \) times to obtain the sequences \( \{ KS_{n,j}^* \}_{j=1}^{B} \) and \( \{ CM_{n,j}^* \}_{j=1}^{B} \).

We reject the null when, for example, \( p^* = B^{-1} \sum_{j=1}^{B} \mathbf{1} (KS_n \leq KS_{n,j}^*) \) is smaller than the desired significance level. Analogously, one can obtain the simulated \( p \)-values for the \( CM_n \) test.
4 Monte Carlo Simulations

In this section we present a small set of Monte Carlo experiments designed to evaluate the finite sample performance of our tests. We first focus on their finite sample performance under the null and then examine their power properties. Finally, we compare our nonparametric quantile regression-based tests with Qu’s (2008) parametric quantile regression-based tests.

4.1 Finite sample level

We consider three data generating processes (DGP) s for the level study:

DGP s1. \( Y_t = X_t - 0.5X_t^2 + \epsilon_t, \) where \( \epsilon_t = \sqrt{0.1 + 0.5X_t^2} \) \( \zeta_{1t}, \)

DGP s2. \( Y_t = X_t - 0.5X_t^2 + \epsilon_t, \) where \( \epsilon_t = \sqrt{0.1 + 0.5X_t^2} \) \( \zeta_{1t}, \) \( \vartheta_t = 0.05 + 0.95 \psi_{t-1} + 0.025\psi_{t-1}^2, \)

DGP s3. \( Y_t = X_t - 0.5X_t^2 + \epsilon_t, \) where \( \epsilon_t = \sqrt{0.1 + 0.5X_t^2} \) \( \zeta_{1t}, \) \( \vartheta_t = 0.05 + 0.95 \psi_{t-1} + 0.025\psi_{t-1}^2, \)

where \( X_t = 0.5 + 0.8X_{t-1} + \zeta_{2t} \) in DGP s1-s2, \( X_t = 0.5 + 0.4X_{t-1} + 0.4X_{t-1} \) \( 1 (t \geq [n/2]) + \zeta_{2t} \) in DGP s3, \( \zeta_{1t}, \zeta_{2t} \) are i.i.d. \( N(0,1), \zeta_{2t} \) are i.i.d. sum of 48 independent random variables each uniformly distributed on \([-0.25,0.25]\), and the two processes \( \{\zeta_{1t}\} \) and \( \{\zeta_{2t}\} \) are independent.

Clearly, DGP s1-s3 specify the same conditional mean model. But they are different in other aspects. First, DGP s1 specifies a traditional error process with conditional heteroskedasticity whereas DGP s2-s3 specifies a GARCH(1,1) error process. Secondly, the conditioning variable \( X_t \) exhibits a distributional change in DGP s3 but not in s1 and s2. To see the last difference, recall \( \mathcal{F}_{t-1} \equiv \sigma (X_{t-1}, i \geq 0, Y_{t-j}, j \geq 1), \) and \( \epsilon_{1t} \equiv Y_t - m_t (\tau, X_t). \) It is easy to verify that \( \{\psi_{\tau} (\epsilon_{1t}), \mathcal{F}_{t}\} \) forms an m.d.s. in DGP s1 but not in DGP s2-s3.

It is worth mentioning that our tests are based on the local polynomial quantile estimates, which typically require compact support of the conditioning variables. That is why the way we generate \( X_t \) seems awkward. On the other hand, according to the central limit theorem we can treat \( \zeta_{2t} \) as being nearly standard normal random variables but with compact support \([-12,12]\).

To construct the test statistics, we choose the normalized Epanechnikov kernel (with variance 1),

\[
K(u) = \frac{3}{4} \left( 1 - \frac{1}{5} u^2 \right) I \left( |u| \leq \sqrt{5} \right).
\]

Since there is no data-driven procedure to choose the bandwidth for quantile regression, to estimate the \( \tau \)th conditional quantile of \( Y_t \) given \( X_t \), we may choose a preliminary bandwidth according to the rule of thumb recommended by Yu and Jones (1998):

\[
h_{0\tau} = s_X n^{-1/5} \left\{ \tau (1-\tau) |\phi \left( \Phi^{-1}(\tau) \right) |^{-2} \right\}^{1/5},
\]

where \( s_X \) is the standard deviation of \( X_t, \phi \) and \( \Phi \) are the standard normal p.d.f. and c.d.f., respectively. Since undersmoothing is required for our test, we modify the above choice of bandwidth to

\[
h_{0\tau} = s_X n^{-1/\gamma} \left\{ \tau (1-\tau) |\phi \left( \Phi^{-1}(\tau) \right) |^{-2} \right\}^{1/5},
\]

where \( 3 < \gamma < 4 \). We may study the behavior of our tests with different choices of \( \lambda \) in order to examine the sensitivity of our test to the bandwidth sequence. Robinson (1991, p.448) and Lee
(2003, p.16) propose very similar devices. Note that these choices for $h_{0r}$ and the kernel function meet the requirements for our test. Through a preliminary study, we find our bootstrap-based test is not sensitive to the choice of $\gamma$ when we restrict $\gamma \in (3, 4)$. So we fix $\gamma = 3.5$ below when we report the simulation results. We choose $G(\cdot)$ to be the standard normal c.d.f.. For the block bootstrap, we generate $\{z_j\}$ independently from $N(0,1/l)$.

Table 1 reports the empirical rejection frequencies of our tests at the 5% nominal level. We use 1000 replications for sample sizes $n = 100, 200$, and 500 replications for sample size $n = 400$. To obtain the simulated $p$-values, we use 199 simulation paths for each replication. To see how our tests are sensitive to the choice of block size $l$ and the smoothing parameter $\lambda_n$, we set $\lambda_n = 0, 0.001, 0.01$, and choose $l = [cn^{1/4}]$ for three choices of $c$: 0.5, 1, 2. When $\lambda_n = 0$, we effectively replace the approximating function $G_{\lambda_n}(-\tilde{u}_{tr})$ by the indicator function $1(\tilde{u}_{tr} \leq 0)$. Table 1 shows that: (a) our tests are robust to different choices of smoothing parameter values $\lambda_n$ but is a little bit sensitive to the choice of block size $l$ (or equivalently $c$ in the table); (b) when the sample size is small ($n = 100, 200$) our tests tend to be undersized for large values of block sizes; (c) as the sample size increases, the empirical level approaches the nominal level quickly; (d) the behavior of the $CM_n$ test is quite similar to the $KS_n$ test, but the former is slightly less sensitive to the choice of block size.
### 4.2 Finite sample power

To consider the finite sample power performance of the tests, we consider the following three alternatives:

- DGP p1. \( Y_t = g_t(X_t) + v_t, \quad v_t = \sqrt{0.1 + 0.5X_t^2(1 + 1(t \geq \lfloor n\pi_0 \rfloor))}\zeta_{1t}, \)
- DGP p2. \( Y_t = g_t(X_t) + v_t, \quad v_t = \sqrt{\sigma}\zeta_{1t}, \quad \sigma_t = 0.05 + (0.95 - 0.4\delta_2)1(t < \lfloor n\pi_0 \rfloor))\zeta_{t-1} + 0.025\nu_{t-1}^2, \)
- DGP p3. \( Y_t = g_t(X_t) + v_t, \quad v_t = \sqrt{\sigma}\zeta_{1t}, \quad \sigma_t = 0.05 + (0.95 - 0.4\delta_2)1(t < \lfloor n\pi_0 \rfloor))\zeta_{t-1} + 0.025\nu_{t-1}^2, \)

where \( g_t(X_t) = X_t - 0.5X_t^2 + \delta_11(t \geq \lfloor n\pi_0 \rfloor), \) and \( X_t \) and \( \zeta_{1t} \) in DGPs p1-p3 are generated as in DGPs s1-s3, respectively.

We consider different values of \((\delta_1, \delta_2)\) to evaluate the finite sample performance of our tests under the alternatives. Obviously, when \( \delta_1 = \delta_2 = 0 \), DGPs p1-p3 reduce to DGPs s1-s3. As the values of \( \delta_1 \) and \( \delta_2 \) move away from zero, we have increasing magnitude of structural break. We consider two different break ratios, \( \pi_0 = 0.25, 0.5 \), to examine whether the tests are sensitive to the timing of the break. Also, we consider six different break sizes, \((\delta_1, \delta_2) = (1, 0), (2, 0), (0, 1), (0, 2), (1, 1), (2, 2)\) to see how the test is sensitive to the size of the breaks. Note that when \( \delta_2 = 0 \) and \( \delta_1 \) is nonzero, we have structural change in the location only. Similarly, when \( \delta_1 = 0 \) and \( \delta_2 \) is nonzero, we have structural change in the scale only.

Tables 2-4 report the finite sample performance of our tests under the alternatives. To save computing time, here we use 500 replications for each case. Some of the main findings from Tables 2-4 are: (a) The power of the KS and \( CM_n \) tests are sensitive to the choice of block size \( l \) but not that of \( \lambda_n \). The large value of \( l \) tends to decrease the power of the tests. (b) As the break size \( \delta_1 \) or \( \delta_2 \) increases, the powers of both tests increase. But for DGP p1, the breaks in the scale may have adverse effect on the detection of the breaks in the location. (c) Other things being equal, the \( CM_n \) test tends to be a little bit more powerful than the KS test. (d) As expected, it is easiest to detect a break when it occurs at the halfway point, \( \pi_0 = 0.5 \). (e) For DGP p1, it is much easier for our tests to detect breaks in the location than the scale of the distribution. But this is not the case for DGPs p2 and p3.

### 4.3 A Comparison with Linear Quantile Regression-Based Tests

We compare our test with Qu’s (2008) linear quantile regression-based test where a linear conditional quantile model is specified. To be specific, we focus on the following linear DGP

\[
Y_t = \beta_{0t} + \beta_{1t}X_t + (1 + \beta_{2t}X_t)\nu_t, \tag{4.2}
\]

where the process \( \{\nu_t, t \geq 1\} \) is independent of the process \( \{X_t, t \geq 1\} \). So the \( \tau \)th conditional quantile function of \( Y_t \) given \( X_t \) is linear in \( X_t \):

\[
m_t(\tau, X_t) = \beta_{0t}(\tau) + \beta_{1t}(\tau)X_t, \tag{4.3}
\]

where \( \beta_{0t}(\tau) = \beta_{0t} + F_{\nu_t}^{-1}(\tau), \beta_{1t}(\tau) = \beta_{1t} + \beta_{2t}F_{\nu_t}^{-1}(\tau), \) and \( F_{\nu_t}^{-1}(\cdot) \) is the inverse of the distribution function of \( \nu_t \). Let \( \beta_t(\tau) = (\beta_{0t}(\tau), \beta_{1t}(\tau))^t \). Qu was interested in testing the null hypothesis

\[
H_0^* : \beta_t(\tau) = \beta_0(\tau) \quad \text{for all} \ t \geq 1 \ \text{and for all} \ \tau \in \mathcal{T}. \tag{4.4}
\]
Table 2: Finite sample power at 0.05 nominal level (DGP p1: n=200)

<table>
<thead>
<tr>
<th>Tests</th>
<th>Break point size</th>
<th>$\lambda_n = 0$</th>
<th>Block size: $l = \lfloor cn^{1/4} \rfloor$</th>
<th>$\lambda_n = 0.001$</th>
<th>$\lambda_n = 0.01$</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$\pi_0$</td>
<td>$c=0.5$</td>
<td>$c=1$</td>
<td>$c=2$</td>
<td>$c=0.5$</td>
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<td>$KS_n$</td>
<td>0.25</td>
<td>(1,0)</td>
<td>0.722</td>
<td>0.640</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(2,0)</td>
<td>0.988</td>
<td>0.984</td>
<td>0.914</td>
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<tr>
<td></td>
<td></td>
<td>(0,1)</td>
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<tr>
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<td></td>
<td>(0,2)</td>
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<tr>
<td></td>
<td></td>
<td>(1,1)</td>
<td>0.634</td>
<td>0.578</td>
<td>0.454</td>
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<tr>
<td></td>
<td></td>
<td>(2,2)</td>
<td>0.924</td>
<td>0.896</td>
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<tr>
<td></td>
<td>0.50</td>
<td>(1,0)</td>
<td>0.930</td>
<td>0.894</td>
<td>0.832</td>
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<td></td>
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<td>1</td>
<td>1</td>
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<tr>
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<tr>
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<td></td>
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<td>0.908</td>
<td>0.882</td>
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<tr>
<td></td>
<td></td>
<td>(2,2)</td>
<td>0.996</td>
<td>1</td>
<td>0.994</td>
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<tr>
<td>$CM_n$</td>
<td>0.25</td>
<td>(1,0)</td>
<td>0.748</td>
<td>0.702</td>
<td>0.626</td>
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<tr>
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<td>0.612</td>
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<td></td>
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<tr>
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<td></td>
<td>(1,1)</td>
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<td>0.910</td>
<td>0.904</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2,2)</td>
<td>1</td>
<td>0.998</td>
<td>1</td>
</tr>
</tbody>
</table>

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Table 3: Finite sample power at 0.05 nominal level (DGP p2: n=200)

| Tests | Break point | Break size: \( l = |cn^{1/4}| \) | \( \lambda_n = 0 \) | \( \lambda_n = 0.001 \) | \( \lambda_n = 0.01 \) |
|-------|-------------|----------------------------------|----------------|----------------|----------------|
|       | \( \pi_0 \) | \( (\delta_1,\delta_2) \) | \( c = 0.5 \) | \( c = 1 \) | \( c = 2 \) | \( c = 0.5 \) | \( c = 1 \) | \( c = 2 \) | \( c = 0.5 \) | \( c = 1 \) | \( c = 2 \) |
| \( KS_n \) 0.25 | (1,0) | 0.752 | 0.690 | 0.512 | 0.756 | 0.684 | 0.484 | 0.762 | 0.694 | 0.468 |
| | (2,0) | 0.998 | 0.998 | 0.990 | 0.996 | 0.990 | 0.998 | 0.998 | 0.998 | 0.988 |
| | (0,1) | 0.818 | 0.684 | 0.336 | 0.820 | 0.650 | 0.266 | 0.816 | 0.652 | 0.290 |
| | (0,2) | 0.938 | 0.834 | 0.412 | 0.946 | 0.814 | 0.320 | 0.946 | 0.810 | 0.340 |
| | (1,1) | 0.996 | 0.996 | 0.988 | 0.996 | 0.996 | 0.984 | 0.996 | 0.994 | 0.978 |
| | (2,2) | 0.998 | 0.998 | 0.996 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 |
| | 0.50 | (1,0) | 0.942 | 0.916 | 0.866 | 0.954 | 0.934 | 0.850 | 0.952 | 0.942 | 0.834 |
| | (2,0) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | (0,1) | 0.904 | 0.794 | 0.500 | 0.922 | 0.754 | 0.340 | 0.920 | 0.772 | 0.352 |
| | (0,2) | 0.988 | 0.914 | 0.500 | 0.992 | 0.892 | 0.422 | 0.990 | 0.914 | 0.426 |
| | (1,1) | 1 | 0.998 | 0.996 | 1 | 0.998 | 0.996 | 0.998 | 0.998 | 0.998 |
| | (2,2) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| \( CM_n \) 0.25 | (1,0) | 0.810 | 0.774 | 0.720 | 0.810 | 0.786 | 0.698 | 0.806 | 0.782 | 0.694 |
| | (2,0) | 1 | 1 | 0.998 | 1 | 1 | 0.992 | 1 | 0.998 | 0.996 |
| | (0,1) | 0.938 | 0.884 | 0.640 | 0.944 | 0.842 | 0.585 | 0.928 | 0.842 | 0.568 |
| | (0,2) | 0.986 | 0.952 | 0.806 | 0.984 | 0.950 | 0.712 | 0.988 | 0.954 | 0.704 |
| | (1,1) | 0.996 | 0.996 | 0.986 | 0.996 | 0.996 | 0.984 | 0.996 | 0.996 | 0.984 |
| | (2,2) | 0.998 | 0.998 | 0.996 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 |
| | 0.50 | (1,0) | 0.958 | 0.950 | 0.932 | 0.978 | 0.958 | 0.926 | 0.974 | 0.958 | 0.926 |
| | (2,0) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | (0,1) | 0.972 | 0.926 | 0.736 | 0.964 | 0.896 | 0.642 | 0.974 | 0.896 | 0.638 |
| | (0,2) | 0.994 | 0.982 | 0.866 | 0.996 | 0.972 | 0.796 | 0.996 | 0.976 | 0.774 |
| | (1,1) | 1 | 0.998 | 0.998 | 1 | 0.998 | 0.994 | 1 | 1 | 0.998 |
| | (2,2) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Tests | Break point size \((\delta_1, \delta_2)\) \(\pi_0\) \(\lambda_n = 0\) \(c = 0.5\) \(c = 1\) \(c = 2\) \(\lambda_n = 0.001\) \(c = 0.5\) \(c = 1\) \(c = 2\) \(\lambda_n = 0.01\) \(c = 0.5\) \(c = 1\) | Block size: \(l = \lfloor cn^{1/4}\rfloor\) |
|-------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| \(K_{Sn}\) | \(0.25\) | \((1,0)\) | 0.680 | 0.610 | 0.436 | 0.736 | 0.676 | 0.510 | 0.746 | 0.678 | 0.508 |
| & | | \((2,0)\) | 0.998 | 0.998 | 0.988 | 0.998 | 0.994 | 0.998 | 0.998 | 0.998 | 0.992 |
| & | | \((0,1)\) | 0.820 | 0.730 | 0.458 | 0.818 | 0.712 | 0.390 | 0.828 | 0.710 | 0.396 |
| & | | \((0,2)\) | 0.938 | 0.882 | 0.560 | 0.948 | 0.862 | 0.480 | 0.952 | 0.868 | 0.492 |
| & | | \((1,1)\) | 0.998 | 0.998 | 0.990 | 0.998 | 0.994 | 0.998 | 0.998 | 0.998 | 0.998 |
| & | | \((2,2)\) | 1 | 1 | 1 | 1 | 1 | 0.998 | 1 | 1 | 0.998 |
| \(C_{Mn}\) | \(0.25\) | \((1,0)\) | 0.856 | 0.812 | 0.722 | 0.878 | 0.852 | 0.766 | 0.874 | 0.844 | 0.770 |
| & | | \((2,0)\) | 1 | 1 | 0.998 | 1 | 1 | 0.998 | 1 | 1 | 0.998 |
| & | | \((0,1)\) | 0.890 | 0.814 | 0.556 | 0.896 | 0.778 | 0.480 | 0.898 | 0.802 | 0.468 |
| & | | \((0,2)\) | 0.976 | 0.912 | 0.666 | 0.968 | 0.904 | 0.568 | 0.964 | 0.904 | 0.562 |
| & | | \((1,1)\) | 0.998 | 0.996 | 0.988 | 0.998 | 0.994 | 0.998 | 0.998 | 0.998 | 0.982 |
| & | | \((2,2)\) | 1 | 1 | 0.998 | 1 | 0.998 | 0.998 | 1 | 1 | 0.998 |
| \(0.50\) | \((1,0)\) | 0.714 | 0.682 | 0.592 | 0.788 | 0.748 | 0.658 | 0.772 | 0.740 | 0.646 |
| & | | \((2,0)\) | 1 | 1 | 0.988 | 1 | 0.998 | 0.992 | 1 | 1 | 0.994 |
| & | | \((0,1)\) | 0.948 | 0.918 | 0.806 | 0.942 | 0.890 | 0.712 | 0.930 | 0.900 | 0.710 |
| & | | \((0,2)\) | 0.992 | 0.970 | 0.890 | 0.990 | 0.970 | 0.810 | 0.994 | 0.954 | 0.824 |
| & | | \((1,1)\) | 0.998 | 0.998 | 0.988 | 0.998 | 0.998 | 0.976 | 0.998 | 0.998 | 0.988 |
| & | | \((2,2)\) | 1 | 1 | 0.998 | 1 | 0.998 | 0.998 | 1 | 1 | 0.998 |
| \(C_{Mn}\) | \(0.50\) | \((1,0)\) | 0.896 | 0.882 | 0.832 | 0.930 | 0.912 | 0.880 | 0.938 | 0.916 | 0.888 |
| & | | \((2,0)\) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| & | | \((0,1)\) | 0.964 | 0.900 | 0.794 | 0.952 | 0.878 | 0.714 | 0.942 | 0.884 | 0.726 |
| & | | \((0,2)\) | 0.996 | 0.988 | 0.894 | 0.992 | 0.978 | 0.840 | 0.992 | 0.978 | 0.838 |
| & | | \((1,1)\) | 0.994 | 0.992 | 0.988 | 0.994 | 0.994 | 0.982 | 0.992 | 0.990 | 0.982 |
| & | | \((2,2)\) | 1 | 1 | 0.998 | 1 | 1 | 0.998 | 1 | 1 | 0.998 |
Qu (2008) considered two tests for structural changes across quantiles. The first test is based on
the subgradient:

\[ H_{nx}(\tilde{\beta}(\tau)) = (X'X)^{-1/2} \sum_{i=1}^{[np]} X_i \psi_\tau(Y_i - \tilde{\beta}_n(\tau)), \]

where \( X_t = (1, X_t')', X = (X_1, \cdots X_n)', \) and \( \tilde{\beta}(\tau) \) is the linear quantile regression estimate of \( \beta_0(\tau) \)
under \( H_0^\tau \) by using the full sample. The test statistic is defined as

\[ DQ_n = \sup_{\tau \in \mathcal{T}} \sup_{\pi \in [0,1]} \| H_{nx}(\tilde{\beta}(\tau)) - \pi H_{nx}(\tilde{\beta}(\tau)) \|_\infty \]

where \( \| \cdot \|_\infty \) is the sup norm, i.e., for a generic vector \( a = (a_1, \cdots, a_k) \), \( \| a \|_\infty = \max(|a_1|, \cdots, |a_k|) \).

Qu’s second test statistic is of Wald type. Let \( \hat{\beta}_1(\pi, \tau) \) denote the quantile regression
estimate of \( \beta_0(\tau) \) using observations up to \([np]\) for \( \pi \in (0,1) \). Let \( \hat{\beta}_2(\pi, \tau) \) denote the quantile regression
estimate of \( \beta_0(\tau) \) using the remaining observations. Then the Wald test for no structural change
across quantiles is given by

\[ DW_n = \sup_{\tau \in \mathcal{T}} \sup_{\pi \in \Pi_\epsilon} n \Delta \hat{\beta}(\pi, \tau) \hat{V}(\pi, \tau)^{-1} \Delta \hat{\beta}(\pi, \tau) \]

where \( \Pi_\epsilon = [\epsilon, 1 - \epsilon] \) for some small \( \epsilon \in (0,1/2) \), \( \Delta \hat{\beta}(\pi, \tau) = \hat{\beta}_2(\pi, \tau) - \hat{\beta}_1(\pi, \tau) \), and \( \hat{V}(\pi, \tau) \) is a
consistent estimate of the limiting variance of \( \sqrt{n} \Delta \hat{\beta}(\pi, \tau) \) under \( H_0^\tau \), i.e.,

\[ \text{plim}_{p \to \infty} \hat{V}(\pi, \tau) = \tau (1 - \tau) \left\{ \frac{1}{\pi} + \frac{1}{1 - \pi} \right\} \Omega_0 \tau, \quad \Omega_0 \tau = H_0^{-1} J_0 H_0^{-1}, \]

where \( H_0 = \text{plim}_{n \to \infty} n^{-1} \sum_{i=1}^{n} f_t(F_i^{-1}(\tau)) X_i X_i' \), \( J_0 = \text{plim}_{n \to \infty} n^{-1} \sum_{i=1}^{n} X_i X_i' \), and \( f_t(F_i^{-1}(\tau)) \)
is the conditional density function of \( Y_i \) evaluated at the \( \tau \)th conditional quantile. The difficult part
in implementing Qu’s \( DW_n \) test is to estimate \( f_t(F_i^{-1}(\tau)) \). We follow Qu’s advice and estimate it
by the difference quotient

\[ \Delta_{nt} = \frac{2b_n}{X_t \hat{\beta}(\tau + b_n) - X_t \hat{\beta}(\tau - b_n)}, \]

where \( b_n = n^{-1/5} \left\{ 4.5\phi^4(\Phi^{-1}(\tau))/[2\Phi^{-1}(\tau)^2 + 1] \right\}^{1/5} \) as recommended by Bofinger (1975).

To avoid division by 0 [which may occur when \( n \) is small and \( \tau \) is close to 0 or 1], we replace the
denominator in (4.5) by 1e-6 when it is 0.

The asymptotic null distributions of the \( DQ_n \) and \( DW_n \) test statistics are asymptotically pivotal
and Qu (2008) tabulated their critical values for conventional 1%, 5% and 10% tests. Since Qu’s
\( DW_n \) test needs to split the sample into two parts and one cannot estimate the coefficients well in
the quantile regression when the sample size is too small, we follow his advice and choose \( \Pi_\epsilon = \mathcal{T} = [0.15, 0.85] \) to implement his parametric tests. The number of replications is 1000.

We first evaluate the performance of Qu’s test in the case of functional form misspecification.
We consider the scenario when the data are generated from nonlinear quantile processes in DGPs
s1-s3, but test for the presence of structural change in the conditional distributions using Qu’s linear
quantile regression test. Table 5 reports the finite sample “level” of these tests. From Table 5, we see
that under functional misspecification, the size of the Qu’s test tends to be highly distorted and the
Table 5: Finite sample level of Qu’s test for DGP s1-s3

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<tr>
<th>n</th>
<th>DGP\nominal level</th>
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<th>(DQ_n) 0.05</th>
<th>(DQ_n) 0.10</th>
<th>(DW_n) 0.01</th>
<th>(DW_n) 0.05</th>
<th>(DW_n) 0.10</th>
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<td>0.069</td>
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<td>0.322</td>
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<td>0.864</td>
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<tr>
<td></td>
<td>s2</td>
<td>0.761</td>
<td>0.917</td>
<td>0.958</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>s3</td>
<td>0.933</td>
<td>0.976</td>
<td>0.987</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>400</td>
<td>s1</td>
<td>0.017</td>
<td>0.082</td>
<td>0.156</td>
<td>0.064</td>
<td>0.146</td>
<td>0.239</td>
</tr>
<tr>
<td></td>
<td>s2</td>
<td>0.828</td>
<td>0.941</td>
<td>0.968</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>s3</td>
<td>0.988</td>
<td>0.998</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

distortion tends to increase as \(n\) increases. Exception occurs when the data are generated via DGP s1. For DGP s1, the empirical level of the \(DQ_n\) test is also distorted, but is much less severe than the other cases. This may be due to fact that the m.d.s. condition on \(\{\psi_r(\xi_r), F_r\}\) is satisfied in this case. On the other hand, the empirical level of the \(DW_n\) tests improve as the sample size doubles or quadruples. We conjecture this is due to the fact that the \(DW_n\) test demands sample splitting and it cannot be well behaved with as small sample sizes as \(n = 100\) or 200. Similar observations are found even if the underlying conditional quantile function is linear.

Due to the level distortion of Qu’s test in the case of functional misspecification, it is inappropriate to compare the power performance of his test to that of our test. In addition, it is difficult, if possible at all, to calculate the level-adjusted empirical power.

Nevertheless, if we stick to linear conditional quantile functions, we can compare the power performance of the two sets of tests. For simplicity, we consider the following DGP:

\[
Y_t = 1 + \{1 + \delta_1 \mathbf{1}(t \geq \lceil n/2 \rceil)\} X_t + \{1 + [1 + \delta_2 \mathbf{1}(t \geq \lceil n/2 \rceil)] X_t\} \varepsilon_t, \tag{4.6}
\]

where the \(\varepsilon_t\)’s are i.i.d. \(t(3)\) (\(t\) distribution with 3 degrees of freedom) and \(X_t\) are generated as in DGP s1. Clearly, when \(\delta_1 = \delta_2 = 0\), there is no structural change in the conditional quantile or distribution function. Any nonzero value of \(\delta_1\) indicates a location change in the conditional distribution. Similarly, any nonzero value of \(\delta_2\) indicates a scale change in the conditional distribution.

Table 6 compares Qu’s test of \(H^*_0\) with our test of \(H_0\). To save space, for our nonparametric test, we only report the empirical rejection frequencies for \(\lambda_n = 0\). The total number of replications is 1000 for each scenario. When \(\delta_1 = \delta_2 = 0\), Table 6 reports the level behavior of both types of tests. Clearly, the levels of both Qu’s \(DQ_n\) test and our tests behave reasonably well. Like the nonlinear case, the level of Qu’s \(DW_n\) test is highly distorted for the sample sizes under investigation. When \(\delta_1 \neq 0\) or \(\delta_2 \neq 0\), Table 6 reports the power behavior of both types of tests. Surprisingly, our nonparametric test performs almost as well as, if not better, than the Qu’s \(DQ_n\) test except for the case when \(n\) is too small and the block size is too large (\(n = 100\) and \(c = 2\)).
### Table 6. Finite sample rejection frequencies under linear DGP in (4.2) (nominal level: 0.05)

<table>
<thead>
<tr>
<th>n</th>
<th>$(\delta_1, \delta_2)$</th>
<th>Qu’s test $DQ_n$</th>
<th>Our test: $c = 0.5$</th>
<th>$KS_n$ $c = 1$</th>
<th>$c = 2$</th>
<th>$c = 0.5$</th>
<th>$CM_n$ $c = 1$</th>
<th>$c = 2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>(0,0)</td>
<td>0.036</td>
<td>0.278</td>
<td>0.062</td>
<td>0.048</td>
<td>0.025</td>
<td>0.057</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>(1,0)</td>
<td>0.194</td>
<td>0.372</td>
<td>0.324</td>
<td>0.264</td>
<td>0.186</td>
<td>0.366</td>
<td>0.337</td>
</tr>
<tr>
<td></td>
<td>(2,0)</td>
<td>0.734</td>
<td>0.658</td>
<td>0.832</td>
<td>0.778</td>
<td>0.644</td>
<td>0.872</td>
<td>0.852</td>
</tr>
<tr>
<td></td>
<td>(0,1)</td>
<td>0.040</td>
<td>0.403</td>
<td>0.087</td>
<td>0.073</td>
<td>0.045</td>
<td>0.087</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td>(0,2)</td>
<td>0.077</td>
<td>0.570</td>
<td>0.173</td>
<td>0.143</td>
<td>0.093</td>
<td>0.135</td>
<td>0.138</td>
</tr>
<tr>
<td></td>
<td>(1,1)</td>
<td>0.163</td>
<td>0.456</td>
<td>0.298</td>
<td>0.243</td>
<td>0.172</td>
<td>0.297</td>
<td>0.272</td>
</tr>
<tr>
<td></td>
<td>(2,2)</td>
<td>0.490</td>
<td>0.684</td>
<td>0.674</td>
<td>0.615</td>
<td>0.474</td>
<td>0.663</td>
<td>0.642</td>
</tr>
<tr>
<td>200</td>
<td>(0,0)</td>
<td>0.026</td>
<td>0.100</td>
<td>0.047</td>
<td>0.052</td>
<td>0.037</td>
<td>0.049</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>(1,0)</td>
<td>0.466</td>
<td>0.317</td>
<td>0.613</td>
<td>0.585</td>
<td>0.052</td>
<td>0.647</td>
<td>0.641</td>
</tr>
<tr>
<td></td>
<td>(2,0)</td>
<td>0.985</td>
<td>0.966</td>
<td>0.991</td>
<td>0.988</td>
<td>0.973</td>
<td>0.999</td>
<td>0.998</td>
</tr>
<tr>
<td></td>
<td>(0,1)</td>
<td>0.059</td>
<td>0.218</td>
<td>0.143</td>
<td>0.127</td>
<td>0.113</td>
<td>0.106</td>
<td>0.111</td>
</tr>
<tr>
<td></td>
<td>(0,2)</td>
<td>0.155</td>
<td>0.476</td>
<td>0.380</td>
<td>0.354</td>
<td>0.317</td>
<td>0.333</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>(1,1)</td>
<td>0.398</td>
<td>0.379</td>
<td>0.594</td>
<td>0.568</td>
<td>0.506</td>
<td>0.579</td>
<td>0.582</td>
</tr>
<tr>
<td></td>
<td>(2,2)</td>
<td>0.908</td>
<td>0.872</td>
<td>0.968</td>
<td>0.956</td>
<td>0.940</td>
<td>0.968</td>
<td>0.959</td>
</tr>
</tbody>
</table>

### 5 Concluding Remarks

In this paper we propose a test for structural change in conditional distributions. It is based upon the local polynomial quantile regression, and thus does not need to specify any conditional mean, variance, or quantile regression model. Moreover, it has non-trivial power to detect deviations from the null at the parametric rate $n^{-1/2}$. To implement our test, one needs to choose the block size to obtain the simulated $p$-values. It is important to derive a data-driven procedure to select the block size, which requires the study of the trade-off between size and power under a sequence of local alternatives. Another potential extension of our test is to allow fixed breaks in the distribution of the conditioning variable. We leave these for future research.

### References


Su, L., and White, H., 2009b. Local polynomial quantile regression under nonstationary data: uniform Bahadur representation with applications to testing conditional independence. Working paper, School of Economics, Singapore Management Univ.


