

ROBUST INFERENCE ON INFINITE AND GROWING DIMENSIONAL TIME-SERIES REGRESSION

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We develop a class of tests for time-series models such as multiple regression with growing dimension, infinite-order autoregression, and nonparametric sieve regression. Examples include the Chow test and general linear restriction tests of growing rank p . Employing such increasing p asymptotics, we introduce a new scale correction to conventional test statistics, which accounts for a high-order long-run variance (HLV), which emerges as p grows with sample size. We also propose a bias correction via a null-imposed bootstrap to alleviate finite-sample bias without sacrificing power unduly. A simulation study shows the importance of robustifying testing procedures against the HLV even when p is moderate. The tests are illustrated with an application to the oil regressions in Hamilton (2003).

KEYWORDS: Growing number of restrictions, high-order long-run variance, non-parametric regression, infinite-order autoregression.

1. INTRODUCTION

THIS PAPER develops asymptotically valid tests for inference on infinite-order and growing dimensional time-series regression models, revealing the presence of an hitherto undetected *nonlinear serial dependence* or *high-order long-run variance* (HLV) factor. This factor depends on the model error and regressors in a nonlinear fashion, and can appear in limit distributions when the data exhibit dependence and the number of restrictions grows. Chow tests and tests for linear restrictions are both covered. Our theory, simulations, and empirical results show the deleterious effect of ignoring the HLV term, and we propose a testing procedure that is robust to its presence. This is shown to possess desirable finite-sample properties. While the HLV factor is revealed by our increasing dimension asymptotics, it can contaminate inference even in multiple regressions with a moderate number of covariates. Such specifications are ubiquitous in practice. Thus, the findings and recommendations of this paper are important for practitioners wishing to make correct inferences when data are dependent.

Models of infinite or growing dimension have been widely studied in the recent econometric literature, reflecting modern applications with rich sets of variables. For example,

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the asset pricing literature has suggested hundreds of potential risk factors to explain returns; see [Feng, Giglio, and Xiu \(2020\)](#). With a larger number of observations accumulating over time, it is natural to include more of these variables as covariates even without resorting to penalized estimation methods. In fact, an attitude that permits the number of covariates to grow as a function of sample size is tacitly adopted in the literature. In a survey, [Koenker \(1988\)](#) observed that the number of regressors in empirical work increases as the sample size n increases, roughly like $n^{1/4}$, suggesting that practitioners implicitly treat model complexity as a function of sample size. Finally, nonparametric methods such as series estimation have found wide applications in the economics and finance literature; see, for example, [Jordà \(2005\)](#), [Chen \(2007\)](#), [Chen and Christensen \(2015\)](#). These methods involve the approximation of an infinite-order model with a sequence of growing dimensional models. Taken together, this proliferation of models highlights the importance of developing appropriate techniques for their study.

Our approach is to develop tests for null hypotheses that involve a growing number of restrictions p in time-series regression, with p increasing slower than sample size. As a leading example, we consider the Chow test, due to [Chow \(1960\)](#), to test for a structural break at a prescribed time. This has the advantage of being a simple exclusion restriction test with wide applicability. After examining the key issues in this simple context, we present results for the testing of general linear restrictions. This extends specification tests with slowly growing p ; see, for example, [Hong and White \(1995\)](#) and [Gupta \(2018\)](#), to time-series regression. However, our testing problem is distinct from the so-called “many restrictions” setting in, for example, [Calhoun \(2011\)](#), [Anatolyev \(2012, 2019\)](#), [Kline, Saggio, and Sølvssten \(2020\)](#), among others, where the number of restrictions grows proportionally to sample size.

We derive the asymptotic distribution of the Chow test Wald statistic centered by p and normalized by $\sqrt{2p}$. This yields asymptotic normality with an unknown asymptotic variance \mathcal{V} , which we term the HLV, provided that p meets certain growth conditions. The HLV factor \mathcal{V} captures high-order autocovariances of the regressors and disturbances, echoing the long-run variance that appears in fixed dimensional time-series regression, and vanishes under simplifying assumptions that remove these high-order autocovariances. The new HLV factor \mathcal{V} does not appear in fixed p asymptotic regimes, nor does it appear in the independent data setting of [Hong and White \(1995\)](#), who use the same transformation and obtain asymptotic standard normality.

We robustify the Chow test against the HLV by a random scaling because of numerical evidence that asymptotic normal inference based on consistent estimators of HLV performs poorly in finite samples, reported in Section 6. The random scaling is motivated by heteroskedasticity autocorrelation robust (HAR) inference; see, for example, [Kiefer and Vogelsang \(2002\)](#), [Sun \(2014\)](#), and [Lazarus, Lewis, Stock, and Watson \(2018\)](#), just to name a few. The resulting asymptotic distribution is pivotal. However, unlike conventional HAR inference, where the standard Wiener process characterizes mixed normality, our limit distribution is represented by two dependent centered Gaussian processes $W(r)$ and $\bar{W}(r)$ such that $EW(r)^2 = r^2$ and $E\bar{W}(r)^2 = (1-r)^2$. Although pivotal, the asymptotic distribution depends on the location of the hypothesized break date, and thus we provide R code to compute the p-values. Similarly, we robustify the general linear restrictions Wald test to the HLV and provide suitable R code.

Finite sample bias in the Wald statistic, or in quadratic statistics, more generally, is a serious issue when p is large; see, for example, [Kline, Saggio, and Sølvssten \(2020\)](#) for more discussion and a bias correction proposal that works well even when p is proportional to the sample size but under independent sampling. Our simulations document

that the problem is even worse in time-series regression. Thus, we propose a bootstrap bias correction, which imposes the null hypothesis in the resampling so as not to sacrifice power unduly. Even a small number of bootstrap iterations appear sufficient to reduce the bias, making computation easily manageable. Based on these findings, we recommend a bias-corrected and HLV-robust test to practitioners.

In simulations for a range of settings across regression with many covariates, long AR fits and sieve regression, we demonstrate that our statistic exhibits excellent size control without sacrificing power excessively. Failure to correct for the HLV can seriously affect inference, in general leading to overrejection and often severely so. Such a pattern is shown to persist for the two types of tests that we provide: Chow tests and exclusion restrictions. In an empirical example based on Hamilton (2003, 2009), we show that using our bias-corrected and HLV-robust tests can yield inferences that lead to new conclusions when considering the relation between oil prices and economic activity.

The paper is organized as follows. Section 2 introduces the model and the Chow test, along with some basic assumptions and examples. In Section 3, we provide an asymptotic theory while Section 4 introduces our HLV-robust and bias-corrected test statistic. The testing of general linear restrictions is covered in Section 5. Section 6 contains a Monte Carlo study of finite-sample performance, and Section 7 demonstrates our test with real data. All the proofs of theorems and lemmas are collected in two further Appendices, the second of which is available online (Gupta and Seo (2023)). Throughout the paper, cross-referenced items prefixed with “S” can be found in this Online Supplementary Appendix. An R-package to reproduce the simulations and empirical example is available in the replication files.

2. CHOW TEST IN GROWING AND INFINITE-ORDER REGRESSION

We consider the issue of testing for a structural break at a known point in the conditional mean function of y_t given the information available up to $t - 1$, that is, $E(y_t|\mathcal{F}_{t-1})$, where \mathcal{F}_{t-1} denotes the filtration up to time $t - 1$. In nonparametric regression, \mathcal{F}_{t-1} typically consists of a finite number of observable covariates z_t . In the context of the infinite-order autoregressive AR(∞) model, \mathcal{F}_{t-1} is the collection of all the lagged dependent variables, $\{y_{t-j}\}_{j \geq 1}$. Alternatively, it can be viewed as a genuine high-dimensional regression model, which may contain an infinite number of covariates and their lags. We allow for array structure but we do not introduce further notation to denote it unless necessary.

Given a sample of size n , we estimate the unknown regression function via a growing-dimensional (or truncated) linear regression

$$y_t = x'_{nt} \beta_n + e_{nt}, \tag{2.1}$$

where x_{nt} and β_n are p -dimensional vectors and $p \rightarrow \infty$ as $n \rightarrow \infty$ to estimate $E(y_t|\mathcal{F}_{t-1})$ consistently. To be more precise, let

$$\varepsilon_t = y_t - E(y_t|\mathcal{F}_{t-1}),$$

β_n be the best linear predictor of y_t given x_{nt} , and $r_{nt} = E(y_t|\mathcal{F}_{t-1}) - x'_{nt} \beta_n$. Then $e_{nt} = r_{nt} + \varepsilon_t$. Throughout the paper, let C (c) denote a generic positive and finite constant, arbitrarily large (small) but independent of n , and “a.s.” stand for “almost surely.” We introduce the following assumptions.

ASSUMPTION 1: *The martingale difference sequence $\{\varepsilon_t\}$ satisfies $\sigma_t^2 \leq C$, where $E(\varepsilon_t^2|\mathcal{F}_{t-1}) = \sigma_t^2$, and $E(\varepsilon_t^4|\mathcal{F}_{t-1}) \leq C$, a.s.*

The theory presented in the paper may not hold if in fact we only have $E(x_{nt}\varepsilon_t) = 0$ as the long run variance of $x_{nt}\varepsilon_t$ will then appear in the type of quadratic statistics that we consider.

ASSUMPTION 2: For $a = 1, 2$,

$$\sup_t E(r_{nt}^{2a}) = o(n^{-1}). \tag{2.2}$$

We discuss this assumption on the negligibility of the approximation error in more detail in Section 6, where specific examples are introduced. The subscript n will now usually be dropped, although we will emphasize this occasionally to remind the reader of the n -dependence of certain quantities.

Introduce a potential structural break for these models at a given time, say $t = [n\gamma]$, $\gamma \in \Gamma \subset (0, 1)$, with Γ compact and $[\cdot]$ denoting the integer part of the argument. That is, $\beta = \beta_1$ if $t/n \leq \gamma$ and $\beta = \beta_2$ if $t/n > \gamma$. We write the model as

$$y_t = x'_t\beta_1 1\{t/n \leq \gamma\} + x'_t\beta_2 1\{t/n > \gamma\} + e_t = x'_t\delta_1 + x'_t\delta_2 1\{t/n > \gamma\} + e_t, \tag{2.3}$$

where $\delta_1 = \beta_1$, $\delta_2 = \beta_2 - \beta_1$, and $1\{\cdot\}$ denotes the indicator function. Consider the Wald test for the exclusion restriction $\delta_2 = 0$, namely the Chow test for the presence of a structural break at a known date.

Let $\hat{\delta}(\gamma)$ and $\hat{e}_t(\gamma)$ denote the OLS estimate and the OLS residuals, respectively, and $x_t(\gamma) := (x'_t, x'_t 1\{t/n > \gamma\})'$. Also, let $\hat{M}(\gamma) = n^{-1} \sum_{t=1}^n x_t(\gamma)x_t(\gamma)'$, and $\hat{\Omega}(\gamma)$ denote an estimator of $E\varepsilon_t^2 x_t(\gamma)x_t(\gamma)'$. For instance, $\hat{\Omega}(\gamma)$ can be set as $n^{-1} \sum_{t=1}^n x_t(\gamma)x_t(\gamma)'\hat{e}_t(\gamma)^2$ (the Eicker–White formula) or, assuming conditional homoskedasticity, it can be $\hat{\sigma}(\gamma)^2 \hat{M}(\gamma)$, where $\hat{\sigma}^2(\gamma) = n^{-1} \sum_{t=1}^n \hat{e}_t(\gamma)^2$. The choice depends on the case being considered. Then the Wald statistic for the familiar Chow test is defined as

$$W_n(\gamma) := n\hat{\delta}_2(\gamma)'(R\hat{M}(\gamma)^{-1}\hat{\Omega}(\gamma)\hat{M}(\gamma)^{-1}R')^{-1}\hat{\delta}_2(\gamma), \tag{2.4}$$

where $R = (0_{p \times p} : I_p)$ is a selection matrix.

When the dimension p of x_t grows with the sample size n , the Wald statistic diverges as it is approximately chi-squared distributed with p degrees of freedom. Thus, a conventional approach, as used, for example, by **de Jong and Bierens (1994)** and **Hong and White (1995)** in the cross-sectional (independent data) framework is to introduce a new centering and scaling to define

$$Q_n(\gamma) := (W_n(\gamma) - p)/\sqrt{2p}, \tag{2.5}$$

since the mean and variance of a chi-square distribution with p degrees of freedom are p and $2p$, respectively. Furthermore, it has been established that the standard normal approximation of Q_n is valid in their settings. Subsequent sections investigate how this conventional approach fails in the context of growing or infinite-dimensional time-series models, mirroring the failure of time-series inference procedures without heteroscedasticity and autocorrelation correction or robustification.

3. ASYMPTOTIC DISTRIBUTION OF Q_n

This section provides the asymptotic distribution of the Chow test statistic under the null and also shows that the statistic has nontrivial power against local alternatives at an appropriate nonparametric rate.

There has been some recent interest in the so-called many regressor setting where p is allowed to be proportional to n ; see, for example, Cattaneo, Jansson, and Newey (2018) and Kline, Saggio, and Sølvesten (2020). We do not permit such a large p as our hypothesis of interest concerns a p -dimensional restriction and the design matrix of time-series data faces more difficulties in satisfying the rank condition. In this regard, Chen and Lockhart (2001) provide an interesting example from an ANOVA design where the weak convergence of the empirical distribution of residuals from the linear regression with growing dimension fails when the dimension p is of order $n^{1/3}$. They compare various growth conditions for p in the literature and conclude that $p^3 \log^2 p = o(n)$ is nearly necessary for a general stochastic design. Heuristically, a hypothesis represented through the empirical distribution function imposes an infinite number of restrictions, as our structural break testing also does, and valid testing of such a hypothesis demands a tighter control on the growth rate of p .

3.1. Asymptotic Null Distribution

Define $\|A\| = \{\bar{\lambda}(A' A)\}^{1/2}$ for a generic matrix A , where $\underline{\lambda}$ (resp., $\bar{\lambda}$) denotes the smallest (largest) eigenvalue of a symmetric nonnegative definite matrix. Any limit stated as “ $n \rightarrow \infty$ ” is taken as both n and p grow to infinity simultaneously unless specified otherwise. We also introduce the $p \times p$ nonstochastic matrix sequences M and Ω and define

$$M(\gamma) = \begin{bmatrix} M & (1 - \gamma)M \\ (1 - \gamma)M & (1 - \gamma)M \end{bmatrix}, \quad \Omega(\gamma) = \begin{bmatrix} \Omega & (1 - \gamma)\Omega \\ (1 - \gamma)\Omega & (1 - \gamma)\Omega \end{bmatrix}.$$

- ASSUMPTION 3: (i) $\sup_{i,t} E x_{it}^4 < \infty$.
 (ii) For $r \in \Gamma \cup \{1\}$,

$$\begin{aligned} & \left\| n^{-1} \sum_{t=1}^{[nr]} x_t x_t' - rM \right\| + \left\| n^{-1} \sum_{t=1}^{[nr]} x_t x_t' \sigma_t^2 - r\Omega \right\| = O_p(\varkappa_p), \\ & \|\hat{\Omega}(r) - \Omega(r)\| = O_p(v_p), \\ & \underline{\lambda}(M) > \lambda_n, \quad \underline{\lambda}(\Omega) > \lambda_n, \end{aligned}$$

for some positive sequences of numbers \varkappa_p , v_p , and λ_n satisfying

$$\lambda_n^{-4} \sqrt{p} (\lambda_n^{-1} \varkappa_p + v_p) \rightarrow 0 \quad \text{and} \quad \lambda_n^6 p \rightarrow \infty. \tag{3.1}$$

- (iii) $\overline{\lim}_{n \rightarrow \infty} \bar{\lambda}(M) < \infty$, $\overline{\lim}_{n \rightarrow \infty} \bar{\lambda}(\Omega) < \infty$.

Several factors determine the bound \varkappa_p for nonparametric series regression. It is proportional to $\sqrt{p/n}$ or p/\sqrt{n} up to logarithmic factors with iid data, depending on the choice of basis functions. For dependent data, the mixing decay rate also contributes to \varkappa_p . The exact rate v_p depends on a particular example. We formally introduce our examples of multiple linear regression, AR(∞) and nonparametric sieve regression in Section 6. Primitive conditions and expressions for \varkappa_p and v_p are given in Propositions B.1 and B.2 in Appendix B, using the results of Peligrad (1982), Newey (1997), Gonçalves and Kilian (2007), and Chen and Christensen (2015).

Recall that the eigenvalues of the Kronecker product of two symmetric matrices are the products of their eigenvalues, and γ is bounded away from zero and one. Thus, $M(\gamma)$ and $\Omega(\gamma)$ inherit the eigenvalue restrictions on M and Ω in Assumption 3(ii) and (iii), up to positive constants.

To develop the distributional limit of $\mathcal{Q}_n(\gamma)$ where both n and p diverge simultaneously, we introduce more conditions. Now, for convenience we let $\xi_t = \Omega^{-1/2}x_t\varepsilon_t$, \mathcal{G}_t denote a filtration for ξ_t , $Y_t = E(\xi_t\xi_t'|\mathcal{G}_{t-1})$, and $\Xi_s = \sum_{t_1=1}^{s-1} \sum_{t_2=1}^{s-1} \xi_{t_1}\xi_{t_2}'$. The filtration \mathcal{G}_t need not be \mathcal{F}_t but a simpler one as long as it makes ξ_t a mds. Indeed, some conditions may be easier to verify under simpler filtrations. The next assumption introduces the HLV factor \mathcal{V} formally.

ASSUMPTION 4: *Suppose that $\max_{1 \leq t \leq n} \bar{\lambda}(Y_t) = o_p(n^\nu)$, for some $\nu \in [0, 1/3)$, $\max_{1 \leq t \leq n} E((\xi_t'\xi_t)^2|\mathcal{G}_{t-1}) = o_p(n^\omega)$, for some $\omega \in [0, 1 - \nu)$, $\sum_{t=1}^n \sum_{s=1}^{t-1} \text{cov}(\text{tr}(Y_t\Xi_t), \text{tr}(Y_s\Xi_s)) = o(n^4 p^2)$, and there exists \mathcal{V} such that for $l = 0$ or $[n\gamma]$ and for m that is proportional to n ,*

$$\lim_{n \rightarrow \infty} \frac{1}{mp} \text{tr} \sum_{t_1=1}^{m-1} \sum_{t_2=1}^{m-1} E(\xi_{m+t_1}\xi_{m+t_1}'\xi_{t_1+l}\xi_{t_2+l}') = \mathcal{V}. \tag{3.2}$$

The first condition can be met if moments of $\bar{\lambda}(Y_t)$ of an order higher than $1/\nu$ are bounded for all t . The restriction on the summability rate of $\text{cov}(\text{tr}(Y_t\Xi_t), \text{tr}(Y_s\Xi_s))$ is related to the dimension p . To gain some insight, consider the case where the conditional moment Y_t is homogeneous, so that $Y_t = I_p$ for all t . Then some tedious algebra yields that $\text{cov}(\text{tr}(Y_t\Xi_t), \text{tr}(Y_s\Xi_s)) = O(n^2 p)$ uniformly over all s, t with $s < t$. This implies that the double sum of the covariances is $O(n^4 p)$, and thus meets the required condition as $p \rightarrow \infty$. Our assumption says that more generally this double sum over covariances must be $o(n^4 p^2)$ as $n, p \rightarrow \infty$.

Also, note that under the special case where $\{x_t\varepsilon_t\}$ is an iid sequence, we have $\mathcal{V} = \lim_{m,p \rightarrow \infty} m^{-1} \sum_{t=1}^{m-1} p^{-1} \text{tr} E(\xi_m\xi_m')E(\xi_t\xi_t') = 1$; thus \mathcal{V} is an extra factor that appears in the limit due to nonlinear dependence in the data. In particular, it captures a *high-order serial correlation* of ξ_t , while ξ_t itself does not have serial correlation since it is a martingale difference sequence.

For mean zero random variables $a_{1i}, a_{2j}, a_{3k}, a_{4l}$, let $\text{cum}_{ijkl}(a_{1i}, a_{2j}, a_{3k}, a_{4l})$ denote the fourth cumulant.

ASSUMPTION 5: *$\{x_{ti}\varepsilon_i\}_{i \in \mathbb{Z}}$ is fourth-order stationary for all $i = 1, \dots, p$. Furthermore, $\sup_{i,j=1,\dots,p} \sum_{t=-\infty}^{\infty} |c_{ij}(t)| < \infty$, where $c_{ij}(t) = E(x_{r,i}\varepsilon_r x_{r+t,j}\varepsilon_{r+t})$ for integer r , and $\sup_{i,j,k,l=1,\dots,p} \sum_{t_1,t_2,t_3=-n}^n |\text{cum}_{ijkl}(x_{0,i}\varepsilon_0, x_{t_1,j}\varepsilon_{t_1}, x_{t_2,k}\varepsilon_{t_2}, x_{t_3,l}\varepsilon_{t_3})| = O(n^2)$.*

This assumption controls the temporal dependence in $\{x_t\varepsilon_t\}$ and is discussed in Andrews (1991b), for example, wherein sufficient conditions for it to hold are also provided. The following theorem establishes distributional convergence for a given γ .

THEOREM 3.1: *Let Assumptions 1–5 and \mathcal{H}_0 hold. Then $\mathcal{Q}_n(\gamma) \xrightarrow{d} \mathcal{N}(0, \mathcal{V})$, for a given $\gamma \in \Gamma$.*

Theorem 3.1 highlights the distinctive feature of testing growing number of restrictions in time-series regressions. Unlike the independent cross-sectional case, we have to robustify the test against the HLV term \mathcal{V} . The provenance of this term can be illustrated

by some formulae, details of which are contained in the full proofs. These proofs first establish (Theorem SL.B.6) that

$$Q_n(\gamma) := \frac{W_n(\gamma) - p}{\sqrt{2p}} = \frac{\mathcal{R}_n(\gamma) - p}{\sqrt{2p}} + o_p(1), \tag{3.3}$$

where

$$\mathcal{R}_n(\gamma) = [\gamma(1 - \gamma)n]^{-1} \left\| \sum_{t=1}^{[n\gamma]} \xi_t - \gamma \sum_{t=1}^n \xi_t \right\|^2 = \left\| n^{-1/2} \sum_{t=1}^n \psi_t(\gamma) \xi_t \right\|^2, \tag{3.4}$$

and $\psi_t(\gamma) = (1(t/n \leq \gamma) - \gamma) / \sqrt{\gamma(1 - \gamma)}$. Also, note that $n^{-1} \sum_{t=1}^n \psi_t(\gamma)^2 \rightarrow 1$. Thus, just as for the familiar Wald statistic, we have a quadratic form structure for $\mathcal{R}_n(\gamma)$. When p is fixed and there is no approximation error, we note that (3.3) has also been established by Andrews (1993), Cho and Vogelsang (2017), and Sun and Wang (2022).

This then yields the approximation

$$\frac{\mathcal{R}_n(\gamma) - p}{\sqrt{2p}} = S_n(\gamma) + o_p(1), \tag{3.5}$$

where

$$S_n(\gamma) = \frac{2}{\sqrt{2p}} \frac{1}{n} \sum_{t=2}^n \psi_t(\gamma) \xi'_t \sum_{s<t} \psi_s(\gamma) \xi_s = \frac{\sqrt{2}}{\sqrt{n}} \sum_{t=2}^n v_t(\gamma),$$

say, by Lemma SL.B.8. Then $\mathcal{V} = \lim_{n,p \rightarrow \infty} 2n^{-1} \sum_{s,t=2}^n cov(v_s(\gamma), v_t(\gamma))$, that is, the limiting variance of $S_n(\gamma)$. Note that the $v_t(\gamma)$ are defined as products of terms of the type $x_t \varepsilon_t$ and the cumulative sum of their lags, implying that the variances of the $v_t(\gamma)$ themselves contain high-order covariance terms. This explains why we call \mathcal{V} a HLV despite the mds property of the $v_t(\gamma)$, which implies that $\{v_t(\gamma)\}$ is uncorrelated.

The next section establishes that the test based on Q_n has nontrivial local power under suitable sequences of local alternatives, following which we study more detailed characteristics of \mathcal{V} and develop a HLV-robust test.

3.2. Local Alternatives

We consider a sequence of local alternatives that converge to the null at $p^{1/4} / \sqrt{n}$ -rate to study the local power properties of the test. This is slower than the usual $1 / \sqrt{n}$ parametric rate and has been employed by a number of other authors, for example, de Jong and Bierens (1994), Hong and White (1995), Gupta (2018). It is a cost of the growing dimensional nature of the problem. Our sequence of local alternatives is

$$\mathcal{H}_\ell : \delta_{2\ell} = 2^{1/4} \tau p^{1/4} / \sqrt{n}, \tag{3.6}$$

where τ is a unit length $p \times 1$ vector.

THEOREM 3.2: *Suppose that Assumptions 1–5 and \mathcal{H}_ℓ hold and let $\tau_\infty = \lim_{n \rightarrow \infty} \tau' M \Omega^{-1} M \tau$. Then $Q_n(\gamma) \xrightarrow{d} \mathcal{N}(\tau_\infty \gamma(1 - \gamma), \mathcal{V})$.*

Note that the noncentrality term is positive, implying nontrivial power of the test since the critical region is formed by $\mathcal{Q}_n(\gamma)$ being greater than equal to a critical value. Also, $|\tau'M\Omega^{-1}M\tau| \leq \|\tau\| \|M\|^2 \|\Omega^{-1}\| = \bar{\lambda}(M)^2/\underline{\lambda}(\Omega)$ for any n . As Assumption 3 assumes that the numerator $\bar{\lambda}(M)$ is bounded but the denominator may not be bounded away from zero, $\tau_\infty = \lim_{n \rightarrow \infty} \tau'M\Omega^{-1}M\tau$ may diverge to positive infinity to imply more power.

4. ν ROBUST TESTING

In this section, we provide a detailed study of the HLV \mathcal{V} that our analysis has discovered. In particular, we present some alternative representations of \mathcal{V} that shed more light on its structure.

4.1. Discussion

We first examine the relevance of \mathcal{V} . Specifically, we analyze the “pre-limiting” quantity $\mathcal{V}_n = 2 \text{var}(n^{-1} \sum_{t=2}^n \xi'_t p^{-1/2} \sum_{s=1}^{t-1} \xi_s)$. This can be rewritten as

$$\mathcal{V}_n = 2n^{-1} \sum_{i=1}^{n-1} \left(\gamma(i, 0)(n-i)/n + 2 \sum_{j=1}^{n-i} \gamma(i, j)(n-i-j)/n \right),$$

where

$$\gamma(i, j) = p^{-1} E(\xi'_t \xi_{t-i} \xi'_t \xi_{t-i-j}) = p^{-1} E(x'_t \Omega^{-1} x_{t-i} x'_t \Omega^{-1} x_{t-i-j} \varepsilon_t \varepsilon_{t-i} \varepsilon_{t-i-j}).$$

This is a high-order autocovariance and captures a nonlinear serial dependence in the sequence $x_t \varepsilon_t$, which disappears entirely for $j > 0$ in independent cross-sectional data. We encounter $\mathcal{V}_n \rightarrow \mathcal{V} \neq 1$ when $n^{-1} \sum_{i=1}^{n-1} \sum_{j=1}^{n-i} \gamma(i, j)(n-i-j)/n$ has a nonzero limit, with terms arising that are fourth-order cross-moments of the ε_t and x_t . Thus, the behavior of such cross-moments is the key to obtaining nonunity \mathcal{V} . Robinson (1991), studying time-series specification testing, encountered a term of the form $E(\varepsilon_t^2 \varepsilon_{t-i} \varepsilon_{t-i-j})$, somewhat different from ours albeit also of cross-moment type, but imposed conditions that nullify it when $j > 0$.

The Wald statistic is a quadratic form in the moment process. To establish the limit of the Wald statistic when the number of variables (i.e., the number of moments) grows with the sample size, we need to account for the variance of the quadratic form, hence the appearance of fourth-order dependence of a certain type in the moment process. A form of fourth-order dependence has also been encountered in HAR testing; see, for example, Lobato, Nankervis, and Savin (2002). In Section 6, we present some figures to show how \mathcal{V} can vary for various designs and deviate significantly from unity.

4.2. HLV-Robust Test Statistic

This section propose a random scaling approach to robustify our test statistic against the unknown HLV term \mathcal{V} . We opt for this because our numerical experiments in Section 6 (specifically Figure 5 and its discussion therein) reveal poor finite-sample performance of the standard sample variance of $q_t = (np)^{-1/2} x'_t \hat{\Omega}^{-1} \hat{e}_t \sum_{s=1}^{t-1} x_s \hat{e}_s$. The presence of the cumulative sums $\sum_{s=1}^{t-1}$ and the estimated quantities $\hat{\Omega}^{-1}$ and \hat{e}_s in the construction of q_t are likely to contribute to poor finite-sample behavior of its sample variance.

The random scaling approach has been employed when consistent estimators of the asymptotic variance perform poorly in finite samples. For instance, heteroscedasticity and autocorrelation consistent (HAC) estimators, for example, [Newey and West \(1987\)](#), [Andrews \(1991b\)](#), to name but two examples, have been followed by the fixed-bandwidth kernel approach to obtain an asymptotically pivotal and mixed-normal test; see, for example, [Kiefer, Vogelsang, and Bunzel \(2000\)](#) and [Lazarus et al. \(2018\)](#) for a recent review. In the machine learning literature, [Lee, Liao, Seo, and Shin \(2022\)](#) also employ the random scaling approach for computationally efficient online inference based on the stochastic gradient descent algorithm.

While a simple random scaling can be implemented by the integral of the square of the partial sum process of centered q_t , that is, $n^{-2} \sum_{t=1}^n \sum_{s=1}^t (q_t - n^{-1} \sum_{i=1}^n q_i)^2$, we present a class of more general random scaling methods following the heteroscedasticity and autocorrelation robust (HAR) inference literature. We note that the resulting pivotal distributions differ from the HAR literature, however.

Introduce a kernel function $k(\cdot)$ that meets the following conditions.

ASSUMPTION 6: (1) For all $x \in \mathbb{R}$, $k(x) = k(-x)$, and $|k(x)| \leq 1$; $k(0) = 1$; $k(x)$ is continuous at zero and almost everywhere on \mathbb{R} ; $\int_{\mathbb{R}} |k(x)| dx < \infty$. (2) For any $b \in (0, 1]$ and $\rho \geq 1$, $k_b(x) = k(x/b)$ and $k^\rho(x)$ are symmetric, continuous, piecewise monotonic, and piecewise continuously differentiable on $[-1, 1]$. (3) $\int_{[0, \infty)} \bar{k}(x) < \infty$, where $\bar{k}(x) = \sup_{y \geq x} |k(y)|$.

Since ε_t and Ω are not directly observable in practice, we replace them with the least squares estimates as in Section 2 and introduce $q_t = (np)^{-1/2} x_t' \hat{\Omega}^{-1} \hat{e}_t \sum_{s=1}^{t-1} x_s \hat{e}_s$ and its demeaned version, $\bar{q}_t = q_t - n^{-1} \sum_{i=2}^n q_i$. Then define a feasible estimate of \mathcal{V} by

$$\hat{\mathcal{V}} = \frac{2}{n} \sum_{t=2}^n \sum_{s=2}^n k\left(\frac{t-s}{nb}\right) \bar{q}_s \bar{q}_t. \tag{4.1}$$

Thus, we have a seemingly long-run variance estimate, analogous to traditional HAC/HAR inference, of a nonlinear transformation of the primitive variables.

The choice of bandwidth b has been a topic of much discussion in the HAC literature. Since \mathcal{V} captures high-order autocovariances in the growing dimensional vector $x_t \varepsilon_t$, the finite-sample variation in the estimate $\hat{\mathcal{V}}$ is generally larger than in more familiar long-run variances, and the moment condition is more expensive. Motivated by this, we follow a fixed bandwidth approach, as in [Sun \(2014\)](#).

Our estimator is based on the weighting function $K_h(r, s) = k(h(r-s))$, where $h = 1/b$. We present numerical results in this paper with $k(u) = (1 - |u|)^h 1\{|u| < 1\}$, employing the Bartlett kernel case with $h = 1$. [Sun \(2014\)](#) terms this the sharp kernel estimator. Other options include the steep quadratic kernel estimator and the orthonormal series estimator with K basis function, of which [Sun \(2014\)](#) contains a more detailed discussion. [Sun \(2014\)](#) also shows that the centering in \bar{q}_t can be conveniently represented through a centered version of $K_h(\cdot)$, that is, $K_h^*(r, s) = K_h(r, s) - \int_0^1 K_h(\tau, s) d\tau - \int_0^1 K_h(r, \tau) d\tau + \int_0^1 \int_0^1 K_h(\tau_1, \tau_2) d\tau_1 d\tau_2$.

Building on the representation in Lemma 1 of [Sun \(2014\)](#), where the estimate $\hat{\mathcal{V}}$ is not consistent, we characterize the joint weak limit of $\hat{\mathcal{V}}$ and $\mathcal{Q}_n(\gamma)$. For real numbers a and b , let $a \vee b$ ($a \wedge b$) denote their maximum (minimum), and introduce a process

$$\mathcal{Q}(\gamma) = \frac{W(\gamma)}{\gamma} + \frac{\bar{W}(\gamma)}{(1-\gamma)} - W(1), \tag{4.2}$$

where $(W(r), \bar{W}(r))'$, $r \in [0, 1]$, is a bivariate Gaussian process that does not depend on any model parameters including the break point γ , and has covariance kernel

$$C(r_1, r_2) = \begin{pmatrix} (r_1 \wedge r_2)^2 & 1\{r_1 > r_2\}(r_1 - r_2)^2 \\ 1\{r_1 < r_2\}(r_1 - r_2)^2 & (1 - (r_1 \vee r_2))^2 \end{pmatrix}. \tag{4.3}$$

For any given $\gamma \in \Gamma$, the marginal distribution of $Q(\gamma)$ is standard normal. Thus, the conclusion of Theorem 3.1 can be expressed as $Q_n(\gamma) \xrightarrow{d} \sqrt{\hat{V}}Q(\gamma)$, pointwise in $\gamma \in \Gamma$. By taking a suitable ratio, we obtain a pivotal variable as in the following theorem, which is the basis of our test statistic.

THEOREM 4.1: *Let Assumptions 1–6 hold, together with*

$$\lambda_n^{-2} p \left(v_p + \frac{p}{\sqrt{n}} \right) \rightarrow 0 \quad \text{as } n \rightarrow \infty. \tag{4.4}$$

Under \mathcal{H}_0 , we have $\hat{V} \xrightarrow{d} \mathcal{V} \int_0^1 \int_0^1 K_h^*(r, s) dW(r) dW(s)$ and

$$\mathcal{T}_n(\gamma) := \frac{Q_n(\gamma)}{\sqrt{\hat{V}}} \xrightarrow{d} \frac{Q(\gamma)}{\sqrt{\int_0^1 \int_0^1 K_h^*(r, s) dW(r) dW(s)}}.$$

The numerator in the limit becomes $Q(\gamma) + \tau_\infty \gamma(1 - \gamma)$ under \mathcal{H}_t .

The asymptotic null distribution is mixed normal and pivotal. The critical values can be tabulated for each γ via Monte Carlo simulation and the replication files provide R code. Note that the same Gaussian process $W(\cdot)$ occurs in both the limiting numerator and denominator, and this process is different from the Brownian motion in Sun (2014). In fact, it can be represented by the partial sum of $\sqrt{t/n}$ times an iid normal sequence. Since the limit also involves another variable $\bar{W}(\cdot)$, the critical values will be different from those previously tabulated in the literature.

4.3. Bias Correction

The degrees of freedom p provide a correct centering for $W_n(\gamma)$ in first-order asymptotic analysis. However, in the finite-sample experiments given in Section 6, for example, Figure 2 and Figure 6, we find that the bias in $Q_n(\gamma)$ gets bigger for typical values of p in nonparametric regression. Therefore, we propose a bootstrap bias correction of $Q_n(\gamma)$. To estimate the bias, we implement the *null-imposed* wild bootstrap by generating

$$y_t^* = x_t' \hat{\delta}_1(\gamma) + \hat{\epsilon}_t(\gamma) u_t, \quad t = 1, \dots, n, \tag{4.5}$$

where u_t is an iid sequence of centered and normalized variables, for example, the Rademacher variables, to compute $Q_n^*(\gamma)$. It is worthwhile to note that the bootstrap DGP (4.5) imposes the null hypothesis $\delta_2 = 0$, so as not to sacrifice the power of the test. See also Gonçalves and Kilian (2007) for a thorough discussion on the wild bootstrap for infinite-order autoregression. Iterating this B times, we obtain $\bar{Q}_n^*(\gamma) = B^{-1} \sum_j^B Q_n^{*,j}(\gamma)$,

the bootstrap estimate of the bias. In our experiment, $B = 200$ suffices, and thus the bootstrap is not computationally expensive. Therefore, we suggest the following bias corrected test statistic:

$$\mathcal{T}_n^b(\gamma) := \frac{Q_n(\gamma) - \bar{Q}_n^*(\gamma)}{\sqrt{\hat{v}}}. \tag{4.6}$$

The numerical experiments in Section 6 show that the bootstrap bias corrected test controls the type I error reliably without sacrificing power unduly.¹ Now, with the superscript \star indicating the bootstrap analogue, we have the following result.

THEOREM 4.2: *Under Assumptions 1–3 and \mathcal{H}_0 ,*

$$|E^*W_n^*(\gamma) - p| = o_p(p^{1/2}), \tag{4.7}$$

and

$$\mathcal{T}_n^b(\gamma) \xrightarrow{d} \frac{Q(\gamma)}{\sqrt{\int_0^1 \int_0^1 K_h^*(r, s) dW(r) dW(s)}}. \tag{4.8}$$

Theorem 4.2 implies that the bootstrap bias correction is first-order correct but does not imply any higher-order improvement. We demonstrate its merits not analytically but numerically in Section 6, which is common with the wild bootstrap; see, for example, Gonçalves and Kilian (2004) and references therein. Details of the components of $W_n^*(\gamma)$ are left to Section S.C of the Online Supplement.

5. WALD TEST FOR GENERAL LINEAR RESTRICTIONS OF GROWING RANK

For a linear regression model $y_t = x_t' \beta + \varepsilon_t$, we consider testing linear restrictions $\mathcal{H}_0^e : R^e \beta = r$, where R^e is a matrix of rank $p \leq \dim(\beta)$. For the usual Wald statistic

$$W_n^e := n(R^e \hat{\beta} - r)' (R^e \hat{M}^{-1} \hat{\Omega} \hat{M}^{-1} R^e)^{-1} (R^e \hat{\beta} - r), \tag{5.1}$$

$\hat{M} = n^{-1} \sum_t x_t x_t'$ and $\hat{\Omega}$ is an estimator of $E \varepsilon_t^2 x_t x_t'$, define $Q_n^e := (W_n^e - p) / \sqrt{2p}$. Although the test statistic appears to be very similar to the Chow test, the next theorem shows that the numerator and denominator in our corrected test statistic are related differently, calling for different critical values. Furthermore, the HLV is now obtained by replacing Ω^{-1} in Assumption 4 with $L = M^{-1} R^e (R^e M^{-1} \Omega M^{-1} R^e)^{-1} R^e M^{-1}$, and the resulting limit denoted \mathcal{V}^e .

To estimate \mathcal{V}^e and employ bootstrap bias correction, it is convenient to reformulate the restriction as an exclusion restriction of growing dimension, without loss of generality. Indeed, let S be the orthogonal complement of R^e and $Q = (S, R^e)$. Then let $\check{x}_t = Q^{-1} x_t$, $\delta = Q\beta - (0', r)'$ such that $\delta = (\delta_1', \delta_2')$, with $\check{x}_t = (\check{x}_{1t}', \check{x}_{2t}')'$ conformably partitioned, $\delta_2 = R^e \beta - r$ and $\check{y}_t = y_t - \check{x}_{2t}' r$. We can now test the null hypothesis $\mathcal{H}_0^e : \delta_2 = 0$ in the regression of \check{y}_t on \check{x}_t .

¹It is worth noting that the wild bootstrap may not be valid to approximate the quantiles of $Q_n(\gamma)$ as it does not capture the high-order dependence embodied in \mathcal{V} .

This transformation makes it particularly convenient to impose the null in the bootstrap resampling at the bias correction stage. Let \bar{Q}_n^* denote the bootstrap bias correction factor for W_n^e . This yields the bias-corrected statistic $\mathcal{T}_n^{e,b} = (Q_n^e - \bar{Q}_n^*)/\sqrt{\hat{\mathcal{V}}_1}$, where $\hat{\mathcal{V}}^e$ is defined analogously to $\hat{\mathcal{V}}$, but now with $q_t = (np)^{-1/2}\tilde{x}_{2t}'\hat{\Omega}^{e-1}\hat{e}_t\sum_{s=1}^{t-1}\tilde{x}_{2t}\tilde{e}_s$, where \tilde{x}_{2t} denotes the residuals from the regression of \hat{x}_{2t} on \hat{x}_{1t} and $\hat{\Omega}^e = n^{-1}\sum_t\tilde{x}_{2t}\tilde{x}_{2t}'\hat{e}_t^2$. Then, with $W(\cdot)$ defined in (4.3), we have the following theorem.

THEOREM 5.1: *Let Assumptions 1–6 hold with the following modifications: (1) L replacing Ω^{-1} in Assumption 4 and the resulting limit denoted \mathcal{V}^e , (2) The conditions in Assumption 3(ii) hold for $r = 1$. Also, suppose that (4.4) holds. Then, under \mathcal{H}_0^e ,*

$$\mathcal{T}_n^{e,b} = \frac{Q_n^e - \bar{Q}_n^*}{\sqrt{\hat{\mathcal{V}}_1}} \xrightarrow{d} \frac{W(1)}{\sqrt{\int_0^1 \int_0^1 K_h^*(r,s) dW(r) dW(s)}}. \tag{5.2}$$

Under $\mathcal{H}_1^e : R^e\beta - r = 2^{1/4}\tau p^{1/4}/\sqrt{n}$, the numerator in the limit becomes $W(1) + \tau_\infty^e$, where $\tau_\infty^e = \lim_{n \rightarrow \infty} \tau'(R^e M^{-1}\Omega M^{-1}R^e)^{-1}\tau$.

The limiting distribution is mixed normal and pivotal but different from the limit in Theorem 3.1. This is because the Chow test considers a quadratic form in $n^{-1/2}\sum_{t=1}^n\psi_t(\gamma)\xi_t$, which differs from this section by introducing a trend into the regressors via the factor $\psi_t(\gamma)$. Due to this difference, the partial sum processes converge to Gaussian processes with different covariance kernels. An R code to compute the critical values is available in the replication files.

6. MONTE CARLO EXPERIMENTS

This section examines the finite sample properties of our bias corrected HLV-robust test \mathcal{T}_n^b compared to the standard chi-square test W_n , which does not account for growing p , and the unscaled Q_n statistic with standard normal critical values, which does not account for \mathcal{V} , in terms of bias, size, and power.

We will consider the examples below in our Monte Carlo experiments. In Appendix B, we check our assumptions for these settings.

E1—Multiple Regression of Growing Dimension: *Koenker (1988) found through his metastudy that it is common practice in econometrics to increase the number of regressors as the sample size n grows, at a rate of roughly $O(n^{1/4})$. In this case, the approximation error r_t is not explicitly modeled and may be set as zero. Practitioners thus adopt a flexible approach to modeling, where the assumed model becomes richer with more covariates and with more lagged terms to account for the dynamic effect in the spirit of the distributed lag model, as illustrated in, for example, Stock and Watson (2015).*

E2—Infinite-Order Autoregression: *This model is one of the most fundamental models in time-series analysis; see, for example, Brockwell, Davis, and Fienberg (1991) or Hamilton (2020). For the process to be stationary, the coefficients $\{b_j\}$ in the $AR(\infty)$ model $y_t = b_0 + \sum_{j=1}^{\infty} b_j y_{t-j} + \varepsilon_t$ are assumed to obey a certain decay rate. Specifically, the tail sum of the coefficients satisfies Assumption 2 if $\sum_{j=p}^{\infty} |b_j| = o(n^{-1/2})$. While we take p as*

given in our analysis, for practical purposes various methods based on information criteria are available to choose the truncation lag p ; see, for example, [Shibata \(1980\)](#) and references therein. [Wang, Li, and Tsai \(2007\)](#) propose a lasso-based autoregressive-order selection rule while [Lee, Okui, and Shintani \(2018\)](#) propose a lag selection rule in an infinite-order panel autoregression. For expositional ease, we assume that the observations begin from $t = 1 - p$ and $x_1 = (1, y_0, \dots, y_{1-p})$.

E3—Nonparametric Series Regression: *In case of the nonparametric series least squares estimation of $E(y_t|z_t)$, there exists a sequence of transformations of the covariates z_t given by $x_{nt} := x_n(z_t) : \mathbb{R}^k \mapsto \mathbb{R}^p$, and coefficients β_n such that $E(y_t|\mathcal{F}_{t-1}) = f(z_t) = x'_{nt}\beta_n + r_n(z_t)$, where $r_{nt} = r_n(z_t)$ meets Assumption 2 for a broad class of functions f ; see, for example, [Andrews \(1991a\)](#), [Newey \(1997\)](#), [Chen \(2007\)](#), and [Lee and Robinson \(2016\)](#). By Lemma 1 of [Lee and Robinson \(2016\)](#), it is met if $|r_t|_\infty = O(p^\alpha)$ for some $\alpha < 0$ and $p^{2\alpha} \leq n^{-1}$. Depending on the smoothness of the nonparametric function $f(\cdot)$, the regressor support dimension k , and the type of basis functions used, different values of α may be implied; see, for example, [Newey \(1997\)](#), [Chen \(2007\)](#), page 5573, for examples and further references. Often, the condition (2.2) holds under the so-called undersmoothing selection of p . Another closely related example is the partially linear regression model, for example, [Engle, Granger, Rice, and Weiss \(1986\)](#) and [Robinson \(1988\)](#). Again, while we do not consider data-dependent p , for practical purposes the literature proposes methods for the choice of p using cross-validation or information criteria; see, for example, page 5623 of [Chen \(2007\)](#) for a list of references.*

The tests are applied to the setting of the Chow test and testing general linear restrictions. We consider various sample sizes n and dimensions p from the three examples, E1–E3, with the error generated from a bounded ARCH process

$$\varepsilon_t = \sigma_t \eta_t, \quad \sigma_t^2 = (1 - \alpha) + \alpha \phi(\varepsilon_{t-1}), \tag{6.1}$$

where $\phi(x) = x^2 1\{|x| \leq c\} + c^2 1\{|x| > c\}$, $\eta_t = (u_t - Eu_t)/\sqrt{\text{var}(u_t)}$, and $\{u_t\}$ is an iid sequence from the [Marron and Wand \(1992\)](#) normal mixture distributions of type 1–3, which we refer to as errors 1, 2, and 3. Their error 1 is standard normal. For a standard normal vector (Z_1, \dots, Z_k) and multinomial vector (d_1, \dots, d_k) with probability $(1/5, 1/5, 3/5)$, error 2 skewed unimodal variate is $u_t = Z_1 d_1 + (2Z_2/3 + 1/2)d_2 + d_3(5Z_3/9 + 13/12)$, while error 3 strongly skewed variate is $u_t = \sum_{l=0}^7 d_{l+1}(Z_{l+1}(2/3)^l + 3((2/3)^l - 1))$ with equally likely d_i 's. We report results using (6.1) with $\alpha \in \{0.3, 0.4, 0.5, 0.55, 0.57\}$ and $c = 2.5$. Results from $c = 3$ and ∞ are similar and omitted.

More specifically, for multiple regression, E1, the regressors x_t consist of independent AR(1) processes with coefficient α_x and ARCH innovation as in (6.1) and their lags of order up to 3. That is, we consider the distributed lag model with a growing number of variables. The first five elements of β in (2.1) are set as $d_0(5^{-1/2}, \dots, 5^{-1/2})p^{1/4}n^{-1/2}$ and the others as zeros. When there is a break, all the values become zero after the break so that the value d_0 controls the magnitude of the change. We vary $p \in \{5, 9, 13\}$ to examine the effect of the dimension on our tests.

For the infinite-order AR regression, E2, we generate the sample from the MA(1) model $y_t = \varepsilon_t + \theta 1\{t \leq \mu\}\varepsilon_{t-1}$, with $\mu = n$ for the size experiment and $\mu = [n\gamma]$ for the power evaluation, and estimate the AR(p) model with $p = 9$ for $n = 250$ and $p = 13$ for $n = 500$. For the sieve regression, E3, we consider two variables ζ_{1t} and ζ_{2t} and their lags $\zeta_{1,t-1}$ and $\zeta_{2,t-1}$ as regressors, denoted by z_{1t}, \dots, z_{4t} , after transforming them as $2 \arctan(\zeta_{it})/\pi$. Each ζ_{it} follows an AR(1) process with ARCH error. The regression function is set as $f(z_1, \dots, z_4) = d_0(1, z_1, \dots, z_4, z_1^2, \dots, z_4^{p_1})(1^{-2}, \dots, p_2^{-2})' + \sqrt{|z_1|/n}$ with

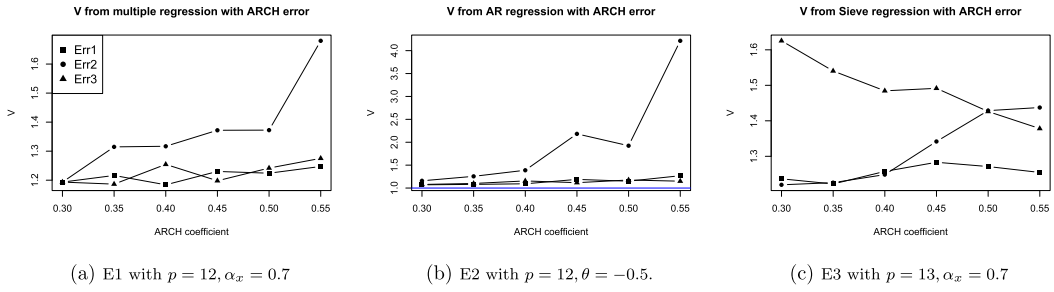


FIGURE 1.—Simulated pre-limit of \mathcal{V} for $n = m = 500$ and $l = 0$. Error 1: square; Error 2: dot; Error 3: triangle.

$p_1 = \lfloor n^{1/4} \rfloor$ and $p_2 = 1 + 4(p_1 - 1)$. To estimate the regression function, we construct x_t from polynomial basis functions and its dimension $p = p_2$.

We first employ these DGPs to simulate pre-limit values of \mathcal{V} in (3.2) with $n = m = 500, l = 0$, and p as described above for each case, which are plotted in Figure 1, reporting averages from 10,000 iterations. This serves as a useful illustration to observe visually that pre-limiting \mathcal{V} deviates from unity for various specifications. A broad observation we make is that the deviation is bigger with larger ARCH coefficients and bigger autocorrelation in x_t , although this feature is not always monotone. To conclude, we observe that the nonlinear serial autocorrelation factor can induce serious distortion in inference without a suitable robustifying treatment, as we provide in Section 4.2.

Also, Appendix B gives the verification of the high-level conditions in Assumptions 1–4 for these examples.

6.1. Chow Test

We consider three candidate break points as proportions of the sample sizes, $\gamma \in \{0.2, 0.3, 0.5\}$. We begin by examining the bias of $Q_n(\gamma)$, conventionally centered by the degrees of freedom p , under the null hypothesis. Note that a severe bias in $Q_n(\gamma)$ also implies that the size of the Wald test $W_n(\gamma)$ can be distorted severely. We report the results in Figure 2, in which the line with dot markers shows the bias in $Q_n(\gamma)$ for $n = 250$ and $n = 500$. For E1, (Figures 2(a), 2(d)) each vertical partition (marked by a dotted vertical line) corresponds to a specific value of p . Within each vertical partition, the DGP parameters change along the horizontal axes as (error type, α), in lexicographic order. As p grows, we observe that the $Q_n(\gamma)$ statistic exhibits severe finite-sample bias for all values of the DGP parameters.

A similar visualization of bias in $Q_n(\gamma)$ for E2 is presented in Figures 2(b), 2(e). Rather than report values for different p , here we focus on the case $p = 9$ for $n = 250$ and $p = 13$ for $n = 500$, and allow the values of α and θ to vary along the horizontal axis lexicographically as (error type, α or θ), as detailed in the caption. A substantial bias in $Q_n(\gamma)$ is observed for all cases, regardless of $n = 250$ or $n = 500$, albeit the biases are generally smaller in the latter case. Finally, Figures 2(c), 2(f) show the bias in $Q_n(\gamma)$ for E3, with the same p as for E2, to mimic the asymptotic regime of a sieve regression, and parameters as in E2. We observe a similar pattern of substantial bias for both sample sizes.

As discussed above, Figures 2(a)–2(f) clearly show that the biases present in $Q_n(\gamma)$ are severe. In these figures, we also plot the bias of the bias-corrected HLV-robust statistic $T_n^b(\gamma)$, shown in black with square markers. The bootstrap bias correction seems to work well for all the cases, substantially alleviating bias. In Figure 2, we observe that $T_n^b(\gamma)$ can

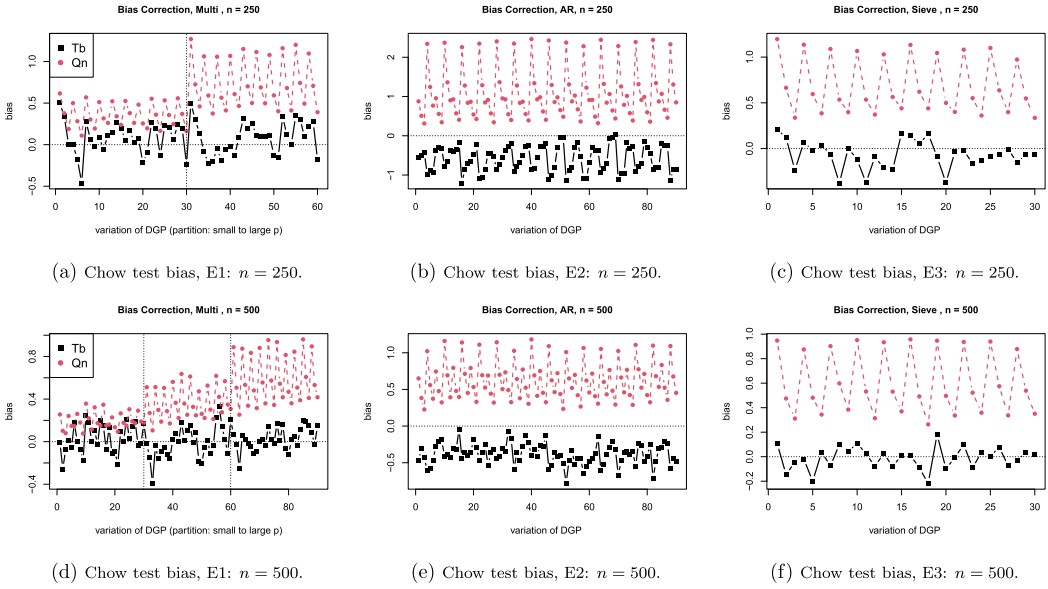


FIGURE 2.—Bias in $Q_n(\gamma)$ (dot) and $T_n^b(\gamma)$ (square, black). For E1, the vertical partitions in (a) and (d) correspond to $p = 5, 9$ and $p = 5, 9, 13$, respectively. Within each vertical partition results are ordered lexicographically as $(\gamma \in \{0.2, 0.3, 0.5\}, \text{error} \in \{1, 2\}, \alpha \in \{0.3, 0.57\})$. E2 and E3: $p = 9$ for $n = 250$ and $p = 13$ for $n = 500$. Results horizontally ordered lexicographically as $(\gamma, \text{error}, \alpha \text{ or } \theta)$.

still exhibit some bias for specific cases but for E1 and E3, unlike the bias of $Q_n(\gamma)$, this is centered around zero, while for E2 it is generally smaller in absolute value. Thus, we recommend the use of the bootstrap bias correction in practice especially when faced with large values of p .

We now study the finite-sample rejection frequencies of four competing tests: $T_n^b(\gamma)$, $T_n(\gamma)$, $Q_n(\gamma)$, and $W_n(\gamma)$, with specific parameter values as given in the respective figure captions. As shown earlier, the unknown HLV scaling factor \mathcal{V} varies along different ARCH parameters. This motivates our approach of experimenting with different α values and innovations. The Monte Carlo sizes resulting from the experiment are plotted in Figure 3, wherein we place a horizontal dotted line to mark the nominal size of 5%. We report results for $\gamma = 0.3$. The vertical partitions in each panel of Figure 3 correspond, as discussed earlier, to increasing values of p from left to right in E1. We cover multiple regression (Figures 3(a), 3(d)), AR fits (Figures 3(b), 3(e)), and sieve regression (Figures 3(c), 3(f)) for $n = 250, 500$.

For all DGPs, the usual Wald statistic $W_n(\gamma)$ (diamond markers) overrejects. Simply standardizing the test statistic $W_n(\gamma)$ to $Q_n(\gamma)$, hence ignoring the HLV \mathcal{V} , does not improve matters. In fact, it usually worsens the problem of overrejection. This can be seen in the lines with triangle markers. Our HLV-robust statistic $T_n(\gamma)$ does much better, as the lines with dot markers indicate. While this shows the importance of the correction for \mathcal{V} that we stress in the paper, there is still a tendency to over-reject. On the other hand, applying the bootstrap bias correction and using the bias corrected HLV-robust statistic $T_n^b(\gamma)$ achieves excellent size control, as can be seen in the line with square markers. The discussion holds regardless of whether $n = 250$ or $n = 500$. Thus, the importance of our proposed testing procedure is clearly visible.

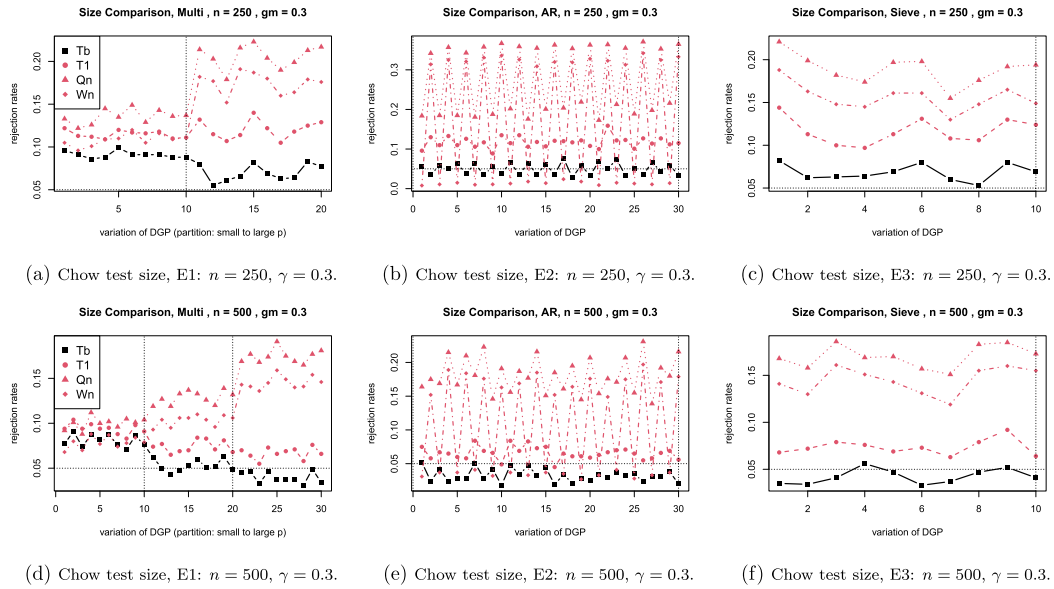


FIGURE 3.—Size of Chow tests with $\gamma = 0.3$: $W_n(\gamma)$ (diamond), $Q_n(\gamma)$ (triangle), $T_n(\gamma)$ (dot), and $T_n^b(\gamma)$ (square, black). Nominal size is 5%. For E1, vertical partitions in (a) correspond to $n = 250$ and $p = 5, 9$ and those in (d) correspond to $n = 500$ and $p = 5, 9, 13$. Within each vertical partition results are ordered lexicographically as (error $\in \{1, 2\}, \alpha \in \{0.3, 0.57\}$). For E2, $p = 9$ for $n = 250$ and $p = 13$ for $n = 500$. Results horizontally ordered lexicographically as (error $\in \{1, 2\}, \alpha \in \{0.3, 0.57\}$ or $\theta \in \{-0.5, -0.1, 0.5\}$). For E3, $p = 9$ for $n = 250$ and $p = 13$ for $n = 500$. Results horizontally ordered lexicographically as (error $\in \{1, 2\}, \alpha \in \{0.3, \dots, 0.57\}$).

We now analyze the power features of the competing test statistics for the proposed DGPs, allowing for breaks of different magnitudes and setting $\gamma = 0.5$. After the break, all the coefficients become zero so that the values of d_0 govern the size of the breaks in E1 and E3, while the values of θ do so for E2. The power performance is plotted in Figure 4, where to conserve space we report results only for $n = 400$. Again, we use $p = 9$ for E2 and E3, while a range of p is employed for E1. The line marker schemes for each of the competing tests are as described earlier. Examining the figure, the power of our HLV-robust statistics $T_n(\gamma)$ (dots) and $T_n^b(\gamma)$ (squares) tracks that of the uncorrected ones as the break size increases for both E2 (center panel) and E3 (right panel). For E1 (left panel), we only report results for $d_0 = 2$ for clarity. We observe that $W_n(\gamma)$ tends to have the highest power but our statistics still perform reasonably well with power in excess of 80% even for large p . Recall that our size experiments earlier indicate that $W_n(\gamma)$ overrejects, a phenomenon of which high power is likely an artefact. Thus, we conclude that our test is able to control size without sacrificing power to an undue extent.

Finally, Figure 5 reports the size distortions when the sample variance of q_t , multiplied by 2 is employed instead of \hat{V} , noting that q_t is a martingale difference array. While we discussed the potential reasons for this severe size distortion in Section 4.2, the investigation on a more precise approximation to the finite-sample distribution of this statistic is an interesting issue but out of the scope of this paper due to the complex nature of the statistic. Nevertheless, Figure 5 provides numerical evidence that the typical scaling by variance is not sufficient to control size. Specifically, define the test statistic $T_n^{b,2}(\gamma)$ exactly like $T_n^b(\gamma)$ but with random scaling replaced by twice the variance of q_t and the

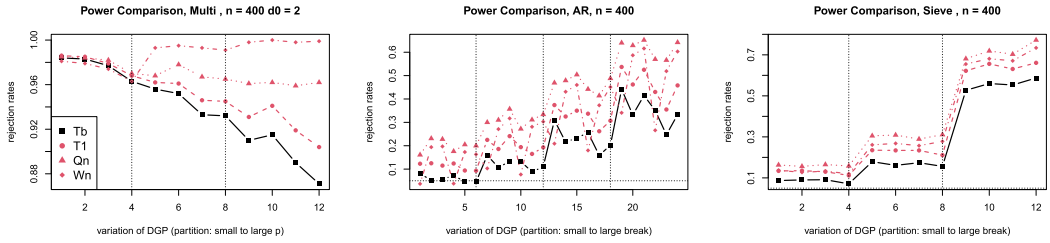


FIGURE 4.—Power of Chow tests, $W_n(\gamma)$ (diamond), $Q_n(\gamma)$ (triangle), $T_n(\gamma)$ (dot) and $T_n^b(\gamma)$ (square, black): E1 (left), E2 (center) and E3 (right), $n = 400$, $\gamma = 0.5$. Vertical partitions correspond to $p = 5, 9, 13$ (left), $\theta = 0.2, 0.4, 0.6, 0.8$ (center) and $\delta = 0.5p^{1/4}/n^{1/2}(1, 5, 10)$ (right). Within each vertical partition results are ordered lexicographically as (error $\in \{1, 2, 3\}, \alpha \in \{0.3, 0.5\}$) for E1 and (error $\in \{1, 2, 3\}, \alpha \in \{0.3, 0.5\}$ or θ) for E2 and E3.

standard normal approximation. It is clear that the test (triangle markers) is oversized relative to our recommended test $T_n^b(\gamma)$.

6.2. Testing Linear Restrictions

This section presents the outcomes of bias, size, and power experiments for testing general linear restrictions, analogous to those for the Chow test in the preceding discussion. We use the reparameterization of the linear restrictions to the exclusion restrictions $\delta_2 = 0$, as discussed in Section 5. We focus on E1 with $n = 400$, $p = 8, 12, 16$, $d_0 = 1$, error 1 and 2 disturbances, and $\alpha = 0.4, 0.55$. The results are displayed in Figure 6, with the same marking scheme as before and three test statistics employed: W_n^e , Q_n^e , and $T_n^{e,b}$. In all three figures, each vertical partition marks a different value of p , increasing from left to right.

The left panel of Figure 6 shows that the bootstrap bias correction indeed improves matters, as was the case for the Chow test. The center panel again demonstrates the importance of our proposed corrections for size control. W_n^e and Q_n^e tend to over-reject, becoming worse as p increases. $T_n^{e,b}$ controls size very well for medium to large p , while still outperforming W_n^e and Q_n^e for smaller p . The right panel shows that $T_n^{e,b}$ sacrifices some power relative to W_n^e and Q_n^e , but not unduly so.

7. EMPIRICAL EXAMPLE

We revisit structural stability in the Hamilton (2003) study of the effect of oil shocks on economic activities. The autoregressive distributed lag model, $ADL(p, p)$, with quarterly

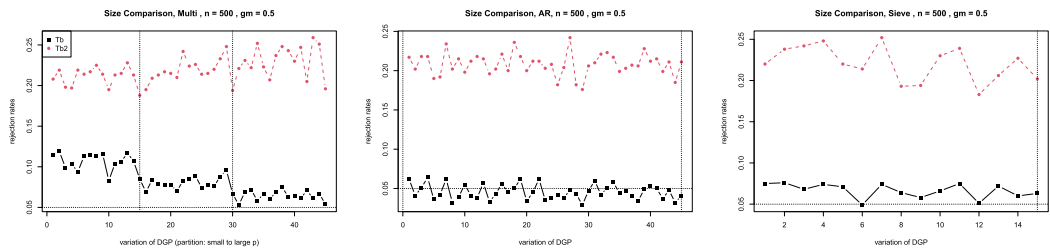


FIGURE 5.—Size distortions in the test based on $T_n^{b,2}(\gamma)$, which is computed exactly like $T_n^b(\gamma)$ except that the scaling is done by the sample variance of q_t along with the standard normal approximation.

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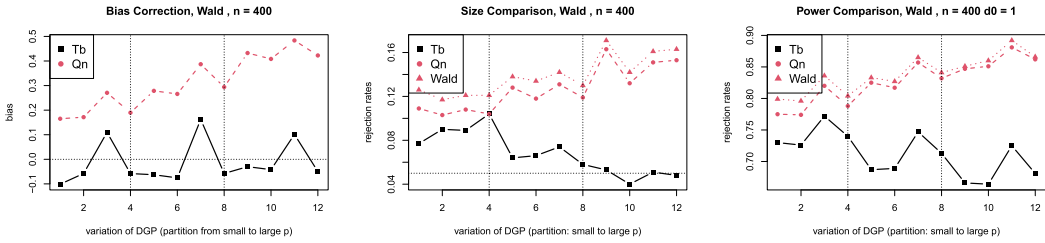


FIGURE 6.—Bias, Size, and Power of Exclusion Tests in E1: Q_n^e (dot) and $T_n^{e,b}$ (square, black). Left to right: vertical partitions correspond to $p = 8, 12, 16$. Within each vertical partition results are ordered lexicographically as (error $\in \{1, 2\}$, $\alpha \in \{0.4, 0.55\}$).

time series of outputs and several oil price measures are employed. For real output, the quarterly growth rate of chain-weighted real GDP is used, while the oil price is the nominal crude oil producer price index, seasonally unadjusted. As in Hamilton, three oil price measures were considered: the growth rate o_t from the previous quarter, the rectified linear unit, $o_t^+ = o_t 1\{o_t > 0\}$, and the net oil price increase, o_t^n , defined as the amount by which log oil prices in quarter t exceed their peak value over the previous 12 months. If it does not exceed the previous peak, then o_t^n is taken to be zero. We extend the original sample using the FRED database at the St. Louis Fed to obtain a sample from January 1949 to October 2019.

First, we reevaluate structural stability of the GDP dynamics using $AR(p)$ fits, and that of the regression function of GDP growth on oil price change using an $ADL(p, p)$ model with the three alternative measures of oil price change. Following Table 4 in Hamilton (2003), we investigate four exogenous disruptions in the world petroleum supply. These are: the Arab–Israel War (November 1973), the Iranian Revolution (November 1978), the Iran–Iraq War (October 1980), and the Persian Gulf War (August 1990).

The p-values of the tests are reported in subtables (a) and (b) in Table I, where for $W(\gamma)$ these are computed using the ordinary Chow test. We observe that in many cases the usual Chow test supports a structural break in both regressions more strongly than our recommended $T_n^b(\gamma)$ test. Thus, the evidence for structural instability is often no longer as strong. In fact, the p-values that we calculate using our test exceed those of the standard Chow test in 22 out of 32 cases.

Second, we explore the relevance of the oil price measures and of the nonlinear transformations (o_t^+, o_t^n) by testing two exclusion restrictions in the $ADL(p, p)$ regression that include all the three oil price measures as covariates. The first exclusion restriction is to set the coefficients of all the measures as zero and the second is to set those of the nonlinear transformations (o_t^+, o_t^n) to zero. This yields 12 and 8 df, respectively, when $p = 4$ and 18 and 12 df, respectively, when $p = 6$. As shown in subtable (c) of Table I, our recommended test $T_n^{e,b}$ produces p-values bigger than 5% for all cases, suggesting the effect of oil price as measured by these transformations is not statistically significant, nor are the nonlinear transformations. The standard Wald test for the exclusion restrictions is more supportive of their inclusion but may lack robustness with large df. Overall, our tests produce larger p-values than the standard Chow or Wald tests in 72% of cases (26 out of 36) cases in Table I.

As another measure of economic activity, we now consider the industrial production (IP) index. This is available at monthly frequency, and thus we consider $ADL(12, 12)$ and $ADL(18, 18)$ to include lags of 1 year and 1.5 years, respectively. With monthly data, the dimensionality becomes more important: the number of restrictions we test varies from

TABLE I

100×P-VALUES OF CHOW TESTS AND EXCLUSION RESTRICTION TESTS FOR FULL SAMPLE. (A) TESTS FOR STABILITY OF GDP DYNAMICS VIA AR(*p*) FITS. (B) TESTS FOR STABILITY OF ADL(*p, p*) REGRESSIONS OF GDP ON *o_t*, *o_t⁺*, OR *o_tⁿ*. (C) TESTS FOR EXCLUSION RESTRICTIONS ON ALL OIL PRICE MEASURES (*o_t*, *o_t⁺*, *o_tⁿ*) OR NONLINEAR OIL PRICE MEASURES (*o_t⁺*, *o_tⁿ*) IN ADL(*p, p*) REGRESSIONS OF GDP ON OIL PRICES.

GDP lags <i>p</i>	Stability Test								Exclusion Test				
	(a) AR(<i>p</i>)		(b) ADL(<i>p, p</i>)						(c) ADL(<i>p, p</i>)				
			<i>o_t</i>		<i>o_t⁺</i>		<i>o_tⁿ</i>		All Oil		NL		
	4	6	4	6	4	6	4	6	4	6	4	6	
Arab–Israel War, November 1973													
$T_n^b(\gamma)$	51.3	43.9	3.5	0.52	1.64	1.33	1.58	0	$T_n^{e,b}$	8.7	26.9	7.6	19
$W_n(\gamma)$	52.9	38	0.5	0	0.58	0	0.7	0	W_n^e	9	4.4	2.8	4.4
Iranian Revolution, November 1978													
$T_n^b(\gamma)$	41.8	52.8	1.04	0.03	7	0.1	0	0					
$W_n(\gamma)$	48.5	53.2	0.6	0	7.57	0	0.1	0					
Iran–Iraq War, October 1980													
$T_n^b(\gamma)$	13.1	28.2	0.3	0.4	0.33	0.64	0.33	0					
$W_n(\gamma)$	10.6	19.7	0	0	0.1	0	0	0					
Persian Gulf War, August 1990													
$T_n^b(\gamma)$	54.6	53.6	73.3	43.7	17.8	31.2	4.53	4.85					
$W_n(\gamma)$	56.2	65	39.5	16	17.1	14.4	1.9	1.17					

13 and 25 in the structural break test for the AR(12) and ADL(12, 12) regressions to 36 and 48 for the exclusion tests in the ADL(18, 18) regression.

The results in Table II illustrate much stronger differences in the conclusions of our test versus the standard Chow test, compared to the GDP study in Table I. The rejection of

TABLE II

100×P-VALUES OF CHOW TESTS AND EXCLUSION RESTRICTION TESTS FOR FULL SAMPLE. (A) TESTS FOR STABILITY OF IP DYNAMICS VIA AR(*p*) FITS. (B) TESTS FOR STABILITY OF ADL(*p, p*) REGRESSIONS OF IP ON *o_t*, *o_t⁺*, OR *o_tⁿ*. (C) TESTS FOR EXCLUSION RESTRICTIONS ON ALL OIL PRICE MEASURES (*o_t*, *o_t⁺*, *o_tⁿ*) OR NONLINEAR OIL PRICE MEASURES (*o_t⁺*, *o_tⁿ*) IN ADL(*p, p*) REGRESSIONS OF IP ON OIL PRICES.

IP lags <i>p</i>	Stability Test								Exclusion Test				
	(a) AR(<i>p</i>)		(b) ADL(<i>p, p</i>)						(c) ADL(<i>p, p</i>)				
			<i>o_t</i>		<i>o_t⁺</i>		<i>o_tⁿ</i>		All Oil		NL		
	12	18	12	18	12	18	12	18	12	18	12	18	
Arab–Israel War, November 1973													
$T_n^b(\gamma)$	20.9	32.9	33.9	28.4	24.9	18.9	10.6	17.8	$T_n^{e,b}$	27	30.9	11.9	18.5
$W_n(\gamma)$	8.46	26.4	5.18	1.71	3.93	0.78	1.23	1.65	W_n^e	1.7	0.8	0.5	0.5
Iranian Revolution, November 1978													
$T_n^b(\gamma)$	11	21.5	1.39	0.74	0.7	0.26	0.15	0.04					
$W_n(\gamma)$	0.96	4.3	0	0	0	0	0	0					
Iran–Iraq War, October 1980													
$T_n^b(\gamma)$	3.31	9.34	1.96	1.87	1.15	1.68	0.08	0.46					
$W_n(\gamma)$	0	0.04	0	0	0	0	0	0					
Persian Gulf War, August 1990													
$T_n^b(\gamma)$	5.82	14.6	3.95	19.4	2.03	12.8	0.94	8.04					
$W_n(\gamma)$	0.08	1.13	0.21	2.98	0.23	2.43	0.02	0.22					

the null of no structural break is now often overturned at reasonable significance levels. For example, for the Arab–Israel War, the ADL(p, p) model fails to reject the null of no structural break for any significance level below 10.6% when using our test $\mathcal{T}_n^b(\gamma)$, in contrast to the standard Chow test $W_n(\gamma)$. Conclusions are likewise overturned for the AR(p) model and the Iranian Revolution and Iran–Iraq War, and indeed for both the ADL(p, p) and AR(p) in several cases for the Persian Gulf War.

The results in Tables I and II are not surprising given our simulation evidence. Indeed, our Monte Carlo simulation illustrates the effect of the degrees of freedom (df) on finite-sample properties of the two tests, $W_n(\gamma)$ tends to have larger p-values in the AR case ($p + 1$ df) than in the ADL case ($2p + 1$ df), while $\mathcal{T}_n^b(\gamma)$ would be the opposite. These are exactly the patterns that we also observe. Finally, subtable (c) of Table II shows even stronger differences than Table I(c), with all conclusions on the exclusion restrictions overturned at significance levels below 11.6%. Overall, our tests produce larger p-values in every single case considered in Table II when compared to the standard Chow or Wald tests.

APPENDIX A: PROOFS OF THEOREMS

We begin with some notation. Let

$$A(\gamma) = (X^*(\gamma)'M_X X^*(\gamma))^{-1} X^*(\gamma)'M_X$$

with $X^*(\gamma)$ having t th row $x_t^*(\gamma)' = x_t'1\{t/n > \gamma\}$, M_X the residual maker for the matrix X with t th row x_t' , and

$$B(\gamma) = RM(\gamma)^{-1}\Omega(\gamma)M(\gamma)^{-1}R'.$$

Also, let $\bar{\Omega}(\gamma) = n^{-1} \sum_{t=1}^n x_t(\gamma)x_t'(\gamma)\sigma_t^2$ and $x_t(\gamma) = (x_t', x_t'^*(\gamma))'$. It is also convenient to recall that $\hat{M} = n^{-1}X'X$ and define $\hat{S}(\gamma) = n^{-1}X'^*(\gamma)X(\gamma)$. Recall that cross-referenced items prefixed with “S” can be found in the Online Supplementary Appendix.

A.1. Proofs for Section 3

PROOF OF THEOREMS 3.1 AND 3.2: For the convenience of exposition, these are combined with the proof of Theorem 4.1 in the next section. *Q.E.D.*

A.2. Proof of Theorem 4.1:

For the result under the null, Section A.2.1 first establishes the asymptotic normality for $\mathcal{Q}_n(\gamma)$, and then Section A.2.2 proves $\hat{V} \xrightarrow{d} \int_0^1 \int_0^1 K_h^*(r, s) dW(r) dW(s)$, where $W(r)$ denotes the same limit Gaussian process as in Theorem ST.B.2. Then the claim follows by Theorem ST.B.2 and the continuous mapping theorem. After completing the proof under the null, we prove convergence under the local alternative in Section A.2.4.

A.2.1. Asymptotic Normality of $\mathcal{Q}_n(\gamma)$ Under \mathcal{H}_0

PROOF: This step is quite involved and we delegate proofs of many intermediate steps to Section S.B. Summarizing these steps, Theorem ST.B.1 therein develops the initial

approximation $\mathcal{Q}_n(\gamma) = (\mathcal{R}_n(\gamma) - p)/\sqrt{2p} + o_p(1)$, where $\mathcal{R}_n(\gamma)$ is defined in (3.4). Then (SB.45) and Lemma SL.B.8 yield the second approximation

$$\frac{\mathcal{R}_n(\gamma) - p}{\sqrt{2p}} = \mathcal{S}_n(\gamma) + o_p(1),$$

where

$$\mathcal{S}_n(\gamma) = \frac{n^{-1} \sum_{s \neq t} g_t(\gamma)' \Omega^{-1} g_s(\gamma) \varepsilon_t \varepsilon_s}{\gamma(1 - \gamma)\sqrt{2p}}, \tag{A.1}$$

and $g_t(\gamma) = x_t 1\{t/n \leq \gamma\} - \gamma x_t$. The claim now follows by a CLT for $\mathcal{S}_n(\gamma)$ established in Theorem ST.B.2. Q.E.D.

A.2.2. Weak Convergence of $\hat{\nu}$

PROOF: First, we establish tightness of the stochastic process

$$\mathcal{A}_n(\gamma) = \frac{1}{n\sqrt{p}} \sum_{s=2}^{[n\gamma]} \sum_{t=1}^{s-1} \xi'_t \xi_s,$$

with $\xi_t = \{\xi_{ti}\}_{i=1}^p = \Omega^{-1/2} x_t \varepsilon_t$ being an mds.

Note that $\mathcal{A}_n(\gamma)$ is a partial sum process of a heterogeneous martingale difference array $w_{ns} = \xi'_s \sum_{t=1}^{s-1} \xi_t / \sqrt{np}$, and thus it is sufficient to show

$$\begin{aligned} E|\mathcal{A}_n(\gamma_1) - \mathcal{A}_n(\gamma_2)|^4 &= E \left| \frac{1}{\sqrt{n}} \sum_{s=[n\gamma_1]+1}^{[n\gamma_2]} w_{ns} \right|^4 \\ &\leq E \left(\sum_s E(w_{ns}^2 | \mathcal{G}_{s-1}) / n \right)^2 + n^{-1} \max_s E|w_{ns}|^4 O(|\gamma_2 - \gamma_1|) \\ &= O(|\gamma_2 - \gamma_1|), \end{aligned} \tag{A.2}$$

where we apply the Rosenthal inequality, for example, Hall and Heyde (1980), for the inequality and a calculation similar to (SB.11) and (SB.14) for the last equality. Specifically,

$$n^{-1} \max_s E|w_{ns}|^4 \leq \max_s E \left(E((\xi'_s \xi_s)^2 | \mathcal{G}_{s-1}) \left(\sum_{t_1, t_2 < s} \xi'_{t_1} \xi_{t_2} \right)^2 \right) n^{-3} p^{-2} = o(1), \tag{A.3}$$

by Assumption 4 and the same reasoning as for (SB.12) and (SB.14).

Having established tightness, by Lemma 1(c) of Sun (2014) weak convergence follows if

$$\hat{\nu} - \tilde{\nu} = o_p(1), \tag{A.4}$$

where $\tilde{\nu} = \frac{2}{n} \sum_{t=2}^n \sum_{s=2}^n k(\frac{t-s}{n/h}) \bar{q}_s^* \bar{q}_t^*$, $q_t^* = (np)^{-1/2} x'_t \Omega^{-1} \varepsilon_t \sum_{s=1}^{t-1} x_s \varepsilon_s$, $\bar{q}_t^* = q_t^* - n^{-1} \sum_{t=2}^n q_t^*$. Strictly speaking, Sun's Lemma 1(c) is stated for the case where the partial sums of q_t are approximated by the partial sums of e_t , which is iid normal, but it also holds when it is

approximated by the partial sums of $a_{nt}e_t$ for any real bounded array a_{nt} by repeating the same argument in the proof. In our case, $a_{nt} = \sqrt{t/n}$.

Let $\varsigma = n/h$, $\hat{\zeta}_t = \hat{h}'_t \sum_{s < t} \hat{h}_s / \sqrt{p} = \sqrt{n}q_t$, $\hat{h}_t = \hat{\Omega}^{-1/2} x_t \hat{e}_t$, $\bar{\zeta}_t / \sqrt{n} = n^{-1} \sum_{t=2}^n q_t = n^{-1} \sum_{t=2}^n \hat{\zeta}_t / \sqrt{n}$, with analogous definitions using Ω and ε_t for ζ_t , h_t , and $\bar{\zeta}$. Then

$$\begin{aligned} \hat{V} - \tilde{V} &= n^{-2} \sum_{j=-(n-1)}^{n-1} k(j/\varsigma) n^{-1} \sum_{t=1+(j \vee 0)}^{n-|j \wedge 0|} \{(\hat{\zeta}_t \hat{\zeta}_{t+|j|} - \zeta_t \zeta_{t+|j|}) + 2\bar{\zeta}(\hat{\zeta}_t - \zeta_t) \\ &\quad + (\bar{\zeta}_t - \bar{\zeta})\hat{\zeta}_t + (\bar{\zeta}^2 - \bar{\zeta}_t^2)\}. \end{aligned} \tag{A.5}$$

We obtain a bound for

$$\hat{\zeta}_t \hat{\zeta}_{t+|j|} - \zeta_t \zeta_{t+|j|} = (\hat{\zeta}_t - \zeta_t)\hat{\zeta}_{t+|j|} + (\hat{\zeta}_{t+|j|} - \zeta_{t+|j|})\hat{\zeta}_t, \tag{A.6}$$

while omitting similar details for the other three terms. To find a bound for (A.6), first note that $\|\hat{h}_t\| = O_p(\|x_t\|) = O_p(\sqrt{p})$, by Assumption 3(ii) and finite fourth moments of x_t components (Assumption 3(i)), and because

$$\hat{e}_t = y_t - x'_t \hat{\delta}_1(\gamma) = x'_t(\hat{\delta}_1(\gamma) - \delta_1) + x'_t 1(t/n > \gamma)\delta_{2\ell} + r_t + \varepsilon_t = O_p(1). \tag{A.7}$$

Hence,

$$\hat{\zeta}_t = \hat{h}'_t \sum_{s < t} \hat{h}_s / \sqrt{p} = O_p(n\sqrt{p}). \tag{A.8}$$

By the same argument, $\|h_t\| = O_p(\sqrt{p})$ and $\zeta_t = O_p(n\sqrt{p})$ as well.

Now recall that $\hat{e}_t - \varepsilon_t = x'_t(\hat{\delta}_1(\gamma) - \delta_1) + x'_t 1(t/n > \gamma)\delta_{2\ell} + r_t$ and $\|\hat{\delta}_1(\gamma) - \delta_1\| = O_p(\|\hat{\delta}(\gamma) - \delta\|) = O_p(\lambda_n^{-1}\sqrt{p}/\sqrt{n})$ implying that

$$\hat{e}_t - \varepsilon_t = O_p(\max\{\lambda_n^{-1} p/\sqrt{n}, p^{3/4}/\sqrt{n}\}). \tag{A.9}$$

Thus, we obtain

$$\begin{aligned} \|\hat{h}_t - h_t\| &= \|\Omega^{-1}(\Omega - \hat{\Omega})\hat{\Omega}^{-1} x_t \hat{e}_t + \Omega^{-1} x_t(\hat{e}_t - \varepsilon_t)\| \\ &= O_p(\lambda_n^{-2}\sqrt{p} \max\{v_p, p/\sqrt{n}\}), \end{aligned} \tag{A.10}$$

using Assumption 3(iii). Using (A.10), we get

$$\begin{aligned} \hat{\zeta}_t - \zeta_t &= (\hat{h}_t - h_t)' \sum_{s < t} \hat{h}_s / \sqrt{p} + \hat{h}'_t \sum_{s < t} (\hat{h}_s - h_s) / \sqrt{p} \\ &= O_p(\lambda_n^{-2} n\sqrt{p} \max\{v_p, p/\sqrt{n}\}). \end{aligned} \tag{A.11}$$

Using (A.8) and (A.11) in (A.6), we obtain $\hat{\zeta}_t \hat{\zeta}_{t+|j|} - \zeta_t \zeta_{t+|j|} = O_p(\lambda_n^{-2} n^2 p \max\{v_p, p/\sqrt{n}\})$. This, along with similarly obtained bounds for the remaining terms in (A.5) and Lemma 1 of Jansson (2002), yield

$$\hat{V} - \tilde{V} = O_p\left(\varsigma \left(\int_{\mathbb{R}} |k(x)| dx\right) \lambda_n^{-2} p \max\{v_p, p/\sqrt{n}\}\right) = O_p(\lambda_n^{-2} \max\{pv_p, p^2/\sqrt{n}\}),$$

which is negligible by (4.4).

Q.E.D.

A.2.3. Characterize the Relationship Between the Numerator and Denominator

For this, we derive the covariance kernel of $(\mathcal{A}_n(\gamma), \bar{\mathcal{A}}_n(\gamma))'$, where

$$\bar{\mathcal{A}}_n(\gamma) = \frac{1}{n\sqrt{p}} \sum_{s=[n\gamma]+1}^n \sum_{t=[n\gamma]+1}^{s-1} \xi'_t \xi_s.$$

Note that $E(\mathcal{A}_n(\gamma_2) - \mathcal{A}_n(\gamma_1))\mathcal{A}_n(\gamma_1) = 0$ for any $\gamma_1 < \gamma_2$. From the proof of Theorem ST.B.2 in the Supplementary Material, we have

$$E|\mathcal{A}_n(\gamma)|^2 = \frac{\gamma^2 \mathcal{V}}{2} + o(1),$$

$$E|\bar{\mathcal{A}}_n(\gamma)|^2 = \frac{(1-\gamma)^2 \mathcal{V}}{2} + o(1),$$

where \mathcal{V} is given in (3.2). Thus,

$$E(\mathcal{A}_n(\gamma_1)\mathcal{A}_n(\gamma_2)) \rightarrow \frac{(\gamma_1 \wedge \gamma_2)^2}{2} \mathcal{V},$$

and, similarly noting that $E(\bar{\mathcal{A}}_n(\gamma_2) - \bar{\mathcal{A}}_n(\gamma_1))\bar{\mathcal{A}}_n(\gamma_1) = 0$ for any $\gamma_1 > \gamma_2$, we have

$$E(\bar{\mathcal{A}}_n(\gamma_1)\bar{\mathcal{A}}_n(\gamma_2)) \rightarrow \frac{(1 - (\gamma_1 \vee \gamma_2))^2}{2} \mathcal{V}.$$

Finally,

$$E(\mathcal{A}_n(\gamma_1)\bar{\mathcal{A}}_n(\gamma_2)) = \frac{1\{\gamma_1 > \gamma_2\}}{n^2 p} \sum_{s=[n\gamma_2]+1}^{[n\gamma_1]} \text{tr}E\left(\xi_s \xi'_s \sum_{t=1}^{s-1} \sum_{u=[n\gamma_2]+1}^{s-1} \xi_t \xi'_u\right)$$

$$= \frac{1\{\gamma_1 > \gamma_2\}}{n^2} \sum_{s=[n\gamma_2]+1}^{[n\gamma_1]} (s-1 - [n\gamma_2]) \mathcal{V} + o(1)$$

$$= \frac{1\{\gamma_1 > \gamma_2\}}{2} (\gamma_1 - \gamma_2)^2 \mathcal{V} + o(1).$$

A.2.4. Under the Alternative

PROOF: We present a general proof where the true break point is γ_0 , and setting $\gamma = \gamma_0$ gives our claim in the paper. Under \mathcal{H}_ℓ , we have $\hat{\delta}_2(\gamma) = A(\gamma)X^*(\gamma_0)\delta_{2\ell} + A(\gamma)\varepsilon + A(\gamma)r$. So that, writing $D(\gamma, \gamma_0) = A(\gamma)X^*(\gamma_0)$ and $\hat{B}(\gamma) = R\hat{M}(\gamma)^{-1}\hat{\Omega}(\gamma)\hat{M}(\gamma)^{-1}R'$, similar algebra to that used in the Online Appendix and Lemmas SL.B.6–SL.B.10 yields

$$\mathcal{Q}_n(\gamma) = S_n(\gamma) + \frac{2n\delta'_{2\ell}D(\gamma, \gamma_0)'\hat{B}(\gamma)^{-1}A(\gamma)\varepsilon}{\sqrt{2p}} + \frac{2n\delta'_{2\ell}D(\gamma, \gamma_0)'\hat{B}(\gamma)^{-1}A(\gamma)r}{\sqrt{2p}}$$

$$+ \frac{n\delta'_{2\ell}D(\gamma, \gamma_0)'(\hat{B}(\gamma)^{-1} - B(\gamma)^{-1})D(\gamma, \gamma_0)\delta_{2\ell}}{\sqrt{2p}} \tag{A.12}$$

$$+ \frac{n\delta'_{2\ell}D(\gamma, \gamma_0)' \hat{B}(\gamma)^{-1}D(\gamma, \gamma_0)\delta_{2\ell}}{\sqrt{2p}} + o_p(1).$$

For the second term on the RHS of (A.12), note that this equals

$$\begin{aligned} & \frac{2n\delta'_{2\ell}D(\gamma, \gamma_0)'B(\gamma)^{-1}A(\gamma)\varepsilon}{\sqrt{2p}} + \frac{2n\delta'_{2\ell}D(\gamma, \gamma_0)'(\hat{B}(\gamma)^{-1} - B(\gamma)^{-1})A(\gamma)\varepsilon}{\sqrt{2p}} \\ &= \frac{2n\delta'_{2\ell}D(\gamma, \gamma_0)'B(\gamma)^{-1}A(\gamma)\varepsilon}{\sqrt{2p}} + O_p(\lambda_n^{-2}n\|\delta_{2\ell}\| \|n^{-1}X'\varepsilon\| \|\hat{B}(\gamma) - B(\gamma)\|/\sqrt{p}) \\ &= \frac{2n\delta'_{2\ell}D(\gamma, \gamma_0)'B(\gamma)^{-1}A(\gamma)\varepsilon}{\sqrt{2p}} + O_p(\lambda_n^{-4}p^{1/4} \max\{\lambda_n^{-1}\varkappa_p, v_p\}), \end{aligned}$$

proceeding like (SB.39), the second stochastic order above being negligible by (3.1). By Assumption 1, the first term has mean zero and variance equal to a constant times

$$\frac{\tau'D(\gamma, \gamma_0)'B(\gamma)^{-1}A(\gamma)A(\gamma)'B(\gamma)^{-1}D(\gamma, \gamma_0)\tau}{\sqrt{p}} = O_p(1/\sqrt{p}),$$

uniformly in γ by Lemmas SL.B.4 and SL.B.5 and the calculations therein.

By Assumption 2, the third term on the RHS of (A.12) is

$$O_p(n\|\delta_{2\ell}\| \|n^{-1}X'r\|/\sqrt{p}) = O_p(p^{-1/4}).$$

The fourth term on the RHS of (A.12) is readily seen to be $O_p(\|\hat{B}(\gamma)^{-1} - B(\gamma)^{-1}\|) = O_p(\lambda_n^{-4} \max\{\lambda_n^{-1}\varkappa_p, v_p\})$, which is negligible by (3.1). Thus, using similar steps to replace $\hat{B}(\gamma)^{-1}$ by $B(\gamma)^{-1}$ in the fifth term on the RHS and by (SB.29), (A.12) becomes

$$\begin{aligned} \mathcal{Q}_n(\gamma) &= \mathcal{S}_n(\gamma) + \frac{n\delta'_{2\ell}D(\gamma, \gamma_0)'B(\gamma)^{-1}D(\gamma, \gamma_0)\delta_{2\ell}}{\sqrt{2p}} + o_p(1) \\ &= \mathcal{S}_n(\gamma) + \gamma(1 - \gamma)\tau'D(\gamma, \gamma_0)'M\Omega^{-1}MD(\gamma, \gamma_0)\tau + o_p(1). \end{aligned}$$

Now, by the definition of its components and steps similar to those elsewhere in the paper, it is readily seen that $\|D(\gamma, \gamma_0) - \{(\gamma + \gamma_0(1 - \gamma) - (\gamma \vee \gamma_0))/\gamma(1 - \gamma)\}I_p\| = o_p(1)$, uniformly on Γ and that $\gamma + \gamma_0(1 - \gamma) - (\gamma \vee \gamma_0) = -\gamma\gamma_0 + (\gamma \wedge \gamma_0)$ as $\gamma + \gamma_0 - (\gamma \vee \gamma_0) = (\gamma \wedge \gamma_0)$. Thus,

$$\mathcal{Q}_n(\gamma) \xrightarrow{d} Q(\gamma) + \frac{(\gamma\gamma_0 - (\gamma \wedge \gamma_0))^2}{\gamma(1 - \gamma)} \lim_{n \rightarrow \infty} \tau'M\Omega^{-1}M\tau, \tag{A.13}$$

by Theorem ST.B.2, which gives the distribution of $\mathcal{Q}_n(\gamma)$ under \mathcal{H}_ℓ . Q.E.D.

PROOF OF THEOREM 4.2: In Section S.C of the online supplement. Q.E.D.

A.3. Proofs for Section 5

PROOF OF THEOREM 5.1: The proof proceeds exactly as that of Theorem 4.1, but without γ . We give a brief summary and omit the details. Because $R^e\hat{\beta} - r =$

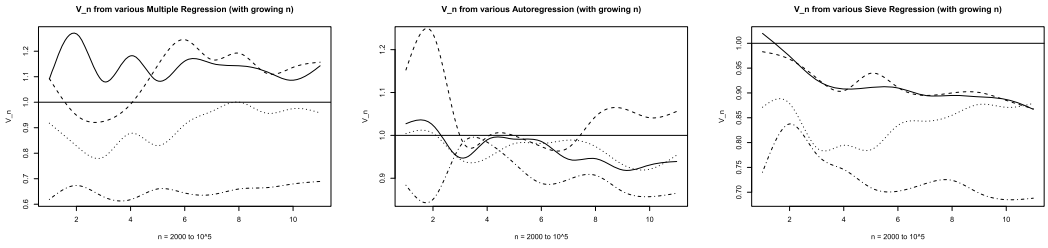


FIGURE B.1.—Simulated v_n for various DGPs with increasing $n = m = 2000, \dots, 10^5$ on a horizontal axis.

$Rn^{-1}\hat{M}^{-1} \sum_{t=1}^n x_t \varepsilon_t$ under \mathcal{H}_0^e , we can obtain the approximation

$$Q_n^e = \frac{n^{-1} \left(\sum_{t=1}^n x_t \varepsilon_t \right)' L \left(\sum_{t=1}^n x_t \varepsilon_t \right) - p}{\sqrt{2p}} + o_p(1).$$

Then the proof of asymptotic normality follows with $w_{ns} = \xi'_s \sum_{t=1}^{s-1} \xi_t / \sqrt{np}$ as in Theorem ST.B.2, but now defining $\xi_t = (R^e M^{-1} \Omega M^{-1} R^e)^{-1/2} R^e M^{-1} x_t \varepsilon_t$. From this, it is readily seen that $E(\sum_{s=1}^n w_{ns})^2 = \mathcal{V}^e + o(1)$. *Q.E.D.*

APPENDIX B: VERIFICATION OF HIGH-LEVEL CONDITIONS FOR EXAMPLES E1, E2, AND E3

This section verifies some of the high-level conditions for our examples analytically, while others are verified numerically.

First, we show that Assumptions 1 and 2 are satisfied for all the examples. For this, note that the innovations η_t in the DGPs are mixed-normal with finite moments of all order. Recall that an AR(1) or MA(1) process with bounded ARCH innovations whose AR or MA coefficients satisfy $|\alpha| < 1$ and $|\alpha_x| < 1$ (as in our DGP for x_{it}) is strictly stationary and β -mixing; see, for example, Theorem 15.0.1 of *Meyn and Tweedie (1993)*. Thus, x_{it} is strictly stationary and β -mixing with a finite moment generating function. This implies that Assumptions 1 and 2 are met for all the examples.

E1: Multivariate Regression

The regressor x_t is a collection of independent centered stationary AR(1) processes x_{it} and their lags up to order 3. Thus, Assumption 3(i) is trivially satisfied. For (ii), we note that M and Ω are block diagonal, implying that the minimum eigenvalues are bounded away from zero. As for Assumption 3(iii), the usual maximal inequality for mixing, as in, for example, Lemma 7 in *Linton, Seo, and Whang (forthcoming)*, holds to yield the bounds $O_p(pn^{-1/2} \log n)$ on $\|n^{-1} \sum_{t=1}^{[nr]} x_t x'_t - rM\|$ and $\|n^{-1} \sum_{t=1}^{[nr]} x_t x'_t \sigma_t^2 - r\Omega\|$.

Turning to Assumption 4, first recall that the maximum of n random variables is $O_p(\log n)$ if the moment generating function of each random variable exists. Thus,

$$E \max_{1 \leq t \leq n} \bar{\lambda}(\xi_t, \xi'_t) \leq E \max_{1 \leq t \leq n} (\xi'_t \xi_t) \leq \sum_{i=1}^p E \max_{1 \leq t \leq n} \xi_{it}^2 = pO(\log n), \tag{B.1}$$

as desired for $p = o(n^{1/3}/\log n)$, and similarly we can deduce the bound for $E|E(\max_{1 \leq t \leq n} (\xi'_t \xi_t)^2 | \mathcal{G}_{t-1})|$, which equals $E(\max_{1 \leq t \leq n} (\xi'_t \xi_t)^2) = p^2 O(\log n)$, due to the nonnegativity of the square and the law of iterated expectations.

Next, the two conditions on convergence in Assumption 4 are difficult to derive analytically, so we present some numerical evidence in Figure B.1 and Table S.Tab.D.1 in the Online Appendix. The coefficient α is chosen from 0, 0.3, or 0.8 for the experiments. The AR coefficient in E1 is set as -0.5 or 0.5 , the MA coefficient in E2 as -0.5 or -0.1 , and the AR coefficient in E3 as 0.3, 0.5, or 0.7. The expectations in (3.2) are approximated by the average of 10,000 iterations. For each coefficient combination, we experiment with growing sample sizes from $n = m = 2000$ to 10^5 , $l = 0$, and $p = n^{1/3}$ for E1 and E2 and $p = 2n^{1/4}$ for E3. The results are plotted as lines in the figure. We note that the values do not diverge even for the most persistent case of $\alpha = 0.8$ and tend to stabilize for larger n . On the other hand, the degeneracy of $(n^4 p^2)^{-1} \sum_{t=1}^n \sum_{s=1}^{t-1} cov(\text{tr}(Y_t \Xi_t), \text{tr}(Y_s \Xi_s))$ in Assumption 4 is given in Table S.Tab.D.1 for various parameter vales and error types. The table shows clear evidence of decaying covariances.

Finally, Assumption 5 is rather trivially met given that ε_t is mds and all the moments exist for ε_t and x_{it} for all $i = 1, \dots, p$.

E2: Infinite-Order AR

A set of primitive conditions is given in the next Proposition. Gonçalves and Kilian (2007) has emphasized the empirical relevance of allowing for conditional heteroscedasticity in autoregressive models, which is allowed below by relaxing Berk (1974)'s condition of an iid error to an mds process. Let L be the lag operator and $b(L) = \sum_{j=1}^{\infty} b_j L^j$ denote the lag polynomial. The MA(1) with the coefficient less than the unity in modulus satisfies the conditions in the next proposition.

PROPOSITION B.1: *Suppose that (1) $b(z) \neq 0$ for any $|z| \leq 1$ and $b^{-1}(e^{i\lambda})$ exists and is nonzero for $-\pi < \lambda \leq \pi$. (2) $\{\varepsilon_t\}$ is a stationary mds that possesses a density of bounded variation, $E\varepsilon_t = 0$ and $E|\varepsilon_t|^\kappa < C$ for some $\kappa \geq 4$ and $E(\varepsilon_t^2 | \mathcal{F}_{t-1})$ is bounded and bounded away from zero. (3) $p^3 = o(n)$. (4) $\sum_{j=p}^{\infty} |b_j| = o(n^{-1/2})$. (5) (σ_t, y_{t-1}) is ρ -mixing with $\sum_{j=1}^{\infty} \rho(2^j) < \infty$. Then Assumptions 1–3 are satisfied with $\varkappa_p = v_p = o(p^{-1/2})$.*

PROOF: Berk (1974) established that the minimum eigenvalue of the limiting autocovariance matrix M is bounded away from zero; see its equation (2.7), and the deviation bound for its sample autocovariance is $o(p^{-1/2})$ in its Lemma 3. As for Ω , note that for some $c > 0$, which is an a.s. lower bound of $E(\varepsilon_t^2 | \mathcal{F}_{t-1})$, and any $|a| = 1$,

$$a' \Omega a = E(a' x_t)^2 \varepsilon_t^2 = E(a' x_t)^2 E(\varepsilon_t^2 | \mathcal{F}_{t-1}) \geq c E(a' x_t)^2,$$

to conclude that the minimum eigenvalue of Ω is also bounded away from zero.

Lemma 3.4 of Peligrad (1982) yields $E|\sum_{i=1}^n (z_i^2 - E z_i^2)| \leq n \sum_i \rho(2^i) E z_i^4$ for a ρ -mixing sequence z_i . Since $z_i = \sigma_i y_{i-j}$ for $j = 1, \dots, p$ in the current case and (σ_t, y_{t-1}) is ρ -mixing, the bound may be set as $n \sum_i \rho(0 \vee (2^i - p)) E z_i^4 \leq n(\sum_i \rho(2^i) + \log p) E \sigma_i^4 y_{i-j}^4$ for any $j \leq p$. Then $\|\bar{\Omega}(\gamma) - \Omega(\gamma)\| = O_p(n^{-1} p^2 \log p)$. The rest of the proof is given in Lemma SL.B.1. Q.E.D.

The same comments as in E1 apply for Assumptions 4 and 5.

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E3: Sieve Regression

Let $\mathbb{Z} \subseteq \mathbb{R}^k$ denote the support of z_t in E3. The following proposition provides some more primitive conditions for E3 as given by Chen and Christensen (2015) and the dgp in our Monte Carlo simulation satisfies them with a bounded support by construction and geometric mixing rate due to Meyn and Tweedie (1993) as discussed above.

PROPOSITION B.2: *Suppose that the following hold: (1) The sequence $\{z_t\}$ is strictly stationary and β -mixing with β -mixing coefficient $\beta(\cdot)$. Let $q = q(n)$ be a sequence of integers satisfying $\beta(q)n/q \rightarrow 0$ as $n \rightarrow \infty$ and $q \leq n/2$; (2) \mathbb{Z} is compact and rectangular, and $\sup_{z \in \mathbb{Z}} \|x_{nt}(z)\| = O(\vartheta_p)$; (3) The x_t are tensor-products of power series, univariate polynomial spline, trigonometric polynomial wavelet, or orthogonal polynomial bases. Then Assumptions 1–3 are met with $\varkappa_p = \vartheta_p \sqrt{q(\log p)/n}$ and $v_p = \min\{p^3/n, \vartheta_p^2 p/n\}$.*

PROOF: We prove that Assumption 3 is met for the partial sum only, with the result for the full sum following from Corollary 4.2 of Chen and Christensen (2015). By Assumption 3, we can normalize the x_t so that $E(x_t x_t') = I_p$ without loss of generality. The result then follows by Corollary SC.A.1 by taking $\Xi_{t,n} = n^{-1}(x_t x_t' - I_p)$, which implies that the terms in Theorem ST.A.1 have bounds: $R_n \leq n^{-1}(C\vartheta_p^2 + 1)$ and $s_n^2 \leq n^{-2}(C\vartheta_p^2 + 1)$. The second claim follows similarly. The rest of the proof is given in Lemma SL.B.1. *Q.E.D.*

The permissible mixing decay rate depends on the dimension p of x_t : larger p requires faster mixing decay. Both exponential and geometric decays are allowed. See the discussions of Assumption 4 and Remark 2.3 in Chen and Christensen (2015) for more detailed discussion in relation to the sieve basis functions. The sequence q depends on the mixing decay rate. For instance, if $\beta(q)$ decays at an exponential rate, q can be set as $\log n$. If all elements of $x_t(\cdot)$ are bounded, then $\vartheta_p = p^{1/2}$. Under suitable conditions, it can be shown that $\vartheta_p = p$ for power series or orthogonal polynomials and $\vartheta_p = p^{1/2}$ for univariate polynomial splines, trigonometric polynomials, or wavelets; see Newey (1997), Chen and Christensen (2015).

The same comments as in E1 apply for Assumptions 4 and 5.

REFERENCES

- ANATOLYEV, STANISLAV (2012): "Inference in Regression Models With Many Regressors," *Journal of Econometrics*, 170, 368–382. [1334]
- (2019): "Many Instruments and/or Regressors: A Friendly Guide," *Journal of Economic Surveys*, 33, 689–726. [1334]
- ANDREWS, DONALD W. K. (1991a): "Asymptotic Normality of Series Estimators for Nonparametric and Semiparametric Regression Models," *Econometrica*, 59, 307–345. [1345]
- (1991b): "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation," *Econometrica*, 59, 817–858. [1338,1341]
- (1993): "Tests for Parameter Instability and Structural Change With Unknown Change Point," *Econometrica*, 61, 821–856. [1339]
- BERK, KENNETH N. (1974): "Consistent Autoregressive Spectral Estimates," *Annals of Statistics*, 2, 489–502. [1358]
- BROCKWELL, PETER J., RICHARD A. DAVIS, AND STEPHEN E. FIENBERG (1991): *Time Series: Theory and Methods*. Springer Science & Business Media. [1344]
- CALHOUN, GRAY (2011): "Hypothesis Testing in Linear Regression When k/n Is Large," *Journal of Econometrics*, 165, 163–174. [1334]
- CATTANEO, MATIAS D., MICHAEL JANSSON, AND WHITNEY K. NEWEY (2018): "Inference in Linear Regression Models With Many Covariates and Heteroscedasticity," *Journal of the American Statistical Association*, 113, 1350–1361. [1337]

- CHEN, GEMAI, AND RICHARD A. LOCKHART (2001): "Weak Convergence of the Empirical Process of Residuals in Linear Models With Many Parameters," *Annals of Statistics*, 29, 748–762. [1337]
- CHEN, XIAOHONG (2007): "Large Sample Sieve Estimation of Semi-Nonparametric Models," in *Handbook of Econometrics, Volume 6B, Chapter 76*, ed. by J. Heckman and E. Leamer. North Holland, 5549–5632. [1334, 1345]
- CHEN, XIAOHONG, AND TIMOTHY M. CHRISTENSEN (2015): "Optimal Uniform Convergence Rates and Asymptotic Normality for Series Estimators Under Weak Dependence and Weak Conditions," *Journal of Econometrics*, 188, 447–465. [1334,1337,1359]
- CHO, CHEOL KEUN, AND TIMOTHY J. VOGELSANG (2017): "Fixed- b Inference for Testing Structural Change in a Time Series Regression," *Econometrics*, 5, 1–26. [1339]
- CHOW, GREGORY C. (1960): "Tests of Equality Between Sets of Coefficients in Two Linear Regressions," *Econometrica*, 28, 591–605. [1334]
- DE JONG, ROBERT M., AND HERMAN J. BIERENS (1994): "On the Limit Behavior of a chi-Square Type Test if the Number of Conditional Moments Tested Approaches Infinity," *Econometric Theory*, 10, 70–90. [1336, 1339]
- ENGLE, ROBERT F., CLIVE W. J. GRANGER, JOHN RICE, AND ANDREW WEISS (1986): "Semiparametric Estimates of the Relation Between Weather and Electricity Sales," *Journal of the American Statistical Association*, 81, 310–320. [1345]
- FENG, GUANHAO, STEFANO GIGLIO, AND DACHENG XIU (2020): "Taming the Factor Zoo: A Test of New Factors," *Journal of Finance*, 75, 1327–1370. [1334]
- GONÇALVES, SILVIA, AND LUTZ KILIAN (2004): "Bootstrapping Autoregressions With Conditional Heteroskedasticity of Unknown Form," *Journal of Econometrics*, 123, 89–120. [1343]
- (2007): "Asymptotic and Bootstrap Inference for AR(∞) Processes With Conditional Heteroskedasticity," *Econometric Reviews*, 26, 609–641. [1337,1342,1358]
- GUPTA, ABHIMANYU (2018): "Nonparametric Specification Testing via the Trinity of Tests," *Journal of Econometrics*, 203, 169–185. [1334,1339]
- GUPTA, ABHIMANYU, AND MYUNG HWAN SEO (2023): "Supplement to 'Robust Inference on Infinite and Growing Dimensional Time-Series Regression'," *Econometrica Supplemental Material*, 91, <https://doi.org/10.3982/ECTA17918>. [1335]
- HALL, PETER, AND CHRISTOPHER C. HEYDE (1980): *Martingale Limit Theory and Its Application*. Academic Press. [1353]
- HAMILTON, JAMES D. (2003): "What Is an Oil Shock?" *Journal of Econometrics*, 113, 363–398. [1333,1335,1349, 1350]
- (2009): "Causes and Consequences of the Oil Shock of 2007–08," *Brookings Papers on Economic Activity SPRING*, 215–261. [1335]
- (2020): *Time Series Analysis*. Princeton University Press. [1344]
- HONG, YONGMIAO, AND HALBERT WHITE (1995): "Consistent Specification Testing via Nonparametric Series Regression," *Econometrica*, 63, 1133–1159. [1334,1336,1339]
- JANSSON, MICHAEL (2002): "Consistent Covariance Matrix Estimation for Linear Processes," *Econometric Theory*, 18, 1449–1459. [1354]
- JORDÀ, OSCAR (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182. [1334]
- KIEFER, NICHOLAS M., AND TIMOTHY J. VOGELSANG (2002): "Heteroskedasticity-Autocorrelation Robust Standard Errors Using the Bartlett Kernel Without Truncation," *Econometrica*, 70, 2093–2095. [1334]
- KIEFER, NICHOLAS M., TIMOTHY J. VOGELSANG, AND HELLE BUNZEL (2000): "Simple Robust Testing of Regression Hypotheses," *Econometrica*, 68, 695–714. [1341]
- KLINE, PATRICK, RAFFAELE SAGGIO, AND MIKKEL SØLVSTEN (2020): "Leave-out Estimation of Variance Components," *Econometrica*, 88, 1859–1898. [1334,1337]
- KOENKER, ROGER (1988): "Asymptotic Theory and Econometric Practice," *Journal of Applied Econometrics*, 3, 139–147. [1334,1344]
- LAZARUS, EBEN, DANIEL J. LEWIS, JAMES H. STOCK, AND MARK W. WATSON (2018): "HAR Inference: Recommendations for Practice," *Journal of Business & Economic Statistics*, 36, 541–559. [1334,1341]
- LEE, JUNGYOON, AND PETER M. ROBINSON (2016): "Series Estimation Under Cross-Sectional Dependence," *Journal of Econometrics*, 190, 1–17. [1345]
- LEE, SOKBAE, YUAN LIAO, MYUNG HWAN SEO, AND YOUNGKI SHIN (2022): "Fast and Robust Online Inference With Stochastic Gradient Descent via Random Scaling," in *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 36, 7381–7389. [1341]
- LEE, YOON-JIN, RYO OKUI, AND MOTOTSUGU SHINTANI (2018): "Asymptotic Inference for Dynamic Panel Estimators of Infinite Order Autoregressive Processes," *Journal of Econometrics*, 204, 147–158. [1345]

- LINTON, OLIVER, MYUNG HWAN SEO, AND YOON-JAE WHANG (forthcoming): "Testing Stochastic Dominance With Many Conditioning Variables," *Journal of Econometrics*. [1357]
- LOBATO, IGNACIO N., JOHN C. NANKERVIS, AND N. EUGENE SAVIN (2002): "Testing for Zero Autocorrelation in the Presence of Statistical Dependence," *Econometric Theory*, 18, 730–743. [1340]
- MARRON, JAMES STEPHEN, AND MATTHEW P. WAND (1992): "Exact Mean Integrated Squared Error," *Annals of Statistics*, 20, 712–736. [1345]
- MEYN, SEAN P., AND RICHARD L. TWEEDIE (1993): *Markov Chains and Stochastic Stability*. London: Springer. [1357,1359]
- NEWBY, WHITNEY K. (1997): "Convergence Rates and Asymptotic Normality for Series Estimators," *Journal of Econometrics*, 79, 147–168. [1337,1345,1359]
- NEWBY, WHITNEY K., AND KENNETH D. WEST (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708. [1341]
- PELIGRAD, MAGDA (1982): "Invariance Principles for Mixing Sequences of Random Variables," *Annals of Probability*, 10, 968–981. [1337,1358]
- ROBINSON, PETER M. (1988): "Root- n -Consistent Semiparametric Regression," *Econometrica*, 56, 931–954. [1345]
- (1991): "Testing for Strong Serial Correlation and Dynamic Conditional Heteroskedasticity in Multiple Regression," *Journal of Econometrics*, 47, 67–84. [1340]
- SHIBATA, RITEI (1980): "Asymptotically Efficient Selection of the Order of the Model for Estimating Parameters of a Linear Process," *Annals of Statistics*, 8, 147–164. [1345]
- STOCK, JAMES H., AND MARK W. WATSON (2015): *Introduction to Econometrics*. Pearson. [1344]
- SUN, YIXIAO (2014): "Fixed-Smoothing Asymptotics in a Two-Step GMM Framework," *Econometrica*, 82, 2327–2370. [1334,1341,1342,1353]
- SUN, YIXIAO, AND XUOXIN WANG (2022): "An Asymptotically F-Distributed Chow Test in the Presence of Heteroscedasticity and Autocorrelation," *Econometric Reviews*, 41, 177–206. [1339]
- WANG, HANSHENG, GUODONG LI, AND CHIH-LING TSAI (2007): "Regression Coefficient and Autoregressive Order Shrinkage and Selection via the Lasso," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 69, 63–78. [1345]

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