



Finite sample inference for quantile regression models

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ABSTRACT

Under minimal assumptions, finite sample confidence bands for quantile regression models can be constructed. These confidence bands are based on the “conditional pivotal property” of estimating equations that quantile regression methods solve and provide valid finite sample inference for linear and nonlinear quantile models with endogenous or exogenous covariates. The confidence regions can be computed using Markov Chain Monte Carlo (MCMC) methods. We illustrate the finite sample procedure through two empirical examples: estimating a heterogeneous demand elasticity and estimating heterogeneous returns to schooling. We find pronounced differences between asymptotic and finite sample confidence regions in cases where the usual asymptotics are suspect.

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1. Introduction

Quantile regression (QR) methods, initiated largely in the seminal work of Koenker and Bassett (1978), provide useful tools for examining the effects of covariates on an outcome variable of interest. Perhaps the most appealing feature of QR methods is that they allow estimation of the effect of covariates on many points of the outcome distribution, including the tails as well as the center of the distribution. While the central effects are useful summary statistics of the impact of a covariate, they do not capture the full distributional impact of a variable unless the variable affects all quantiles of the outcome distribution in the same way. Due to its ability to capture heterogeneous effects and its interesting theoretical properties, QR has been used in many empirical studies and has been studied extensively in theoretical econometrics; see Koenker and Bassett (1978), Portnoy (1991), Buchinsky (1994), and Chamberlain (1994), among others. Koenker (2005) provides an excellent introduction to QR methods.

In this paper, we contribute to the existing literature by considering finite sample inference for quantile regression models. We show that valid finite sample confidence regions can be constructed for parameters of a model defined by quantile restrictions under minimal assumptions. These assumptions do not

require the imposition of distributional assumptions and will be valid for both linear and nonlinear conditional quantile models and for models which include endogenous as well as exogenous variables. The approach makes use of the fact that the estimating equations that correspond to conditional quantile restrictions are conditionally pivotal; that is, conditional on the exogenous regressors and instruments, the estimating equations are pivotal in finite samples. Thus, valid finite sample tests and confidence regions can be constructed based on these estimating equations.

The approach we pursue is related to early work on finite sample inference for the sample (unconditional) quantiles. The existence of finite sample pivots is immediate for unconditional quantiles as illustrated, for example, in Walsh (1960) and MacKinnon (1964). We extend the results from the unconditional case to the estimation of regression quantiles by noting that, conditional on the exogenous variables and instruments, the estimating equations solved by QR methods are pivotal in finite samples. This property suggests that tests based on these quantities can be used to obtain valid finite sample inference statements. The resulting approach is similar in spirit to the rank-score methods and related “pivotal” resampling methods, see e.g. Gutenbrunner and Jurečková (1992) and Parzen et al. (1994), but, in sharp contrast to these approaches, it does not require asymptotics or homoskedasticity (in the case of the rank score methods) for its validity.

The finite sample approach that we develop has a number of appealing features. The approach will provide valid inference statements under minimal assumptions, requiring only weak independence assumptions on the sampling mechanism and continuity of quantile functions in the probability index. In

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endogenous settings, the finite sample approach will remain valid in cases of weak identification or set identification (e.g. as in Haile and Tamer (2003) and Chernozhukov et al. (2007a)). In this sense, the finite sample approach usefully complements asymptotic approximations and can be used in situations where the validity of the assumptions necessary to justify these approximations is questionable.

The chief difficulty with the finite sample approach is computational. In general, implementing the approach will require inversion of an objective function-like quantity, which may be quite difficult if the number of parameters is large. To help alleviate this computational problem, we explore the use of Markov Chain Monte Carlo (MCMC) methods for constructing joint confidence regions. The use of MCMC methods allows us to draw an adaptive set of grid points which offers potential computational gains relative to more naive grid based methods. We also consider a simple combination of search and optimization routines for constructing marginal confidence bounds. When interest focuses on a single parameter, this approach may be computationally convenient and may be more robust in nonregular situations than an approach aimed at constructing the joint confidence region.

Another potential disadvantage of the proposed finite sample approach is that one might expect that minimal assumptions would lead to wide confidence intervals. We show that this concern is unwarranted for joint inference: the finite sample tests have correct size and good asymptotic power properties. However, conservativeness may be induced by going from joint to marginal inference by projection methods. In this case, the finite sample confidence bounds may not be sharp.

We consider the use of finite sample inference in two empirical examples. In the first, we consider estimation of a demand curve in a small sample; and in the second, we estimate the returns to schooling in a large sample. In the demand example, we find modest differences between the finite sample and asymptotic intervals when we estimate conditional quantiles not instrumenting for price and large differences when we instrument for price. In the schooling example, the finite sample and asymptotic intervals are almost identical in models in which we treat schooling as exogenous, and there are large differences when we instrument for schooling. These results suggest that the identification of the structural parameters in the instrumental variables models in both cases is weak.

The remainder of this paper is organized as follows. In the next section, we formally introduce the modelling framework we are considering and the basic finite sample inference results. Section 3 presents results from the empirical examples, and Section 4 concludes. Asymptotic properties of the finite sample procedure that include asymptotic optimality results are contained in an Appendix.

2. Finite sample inference

2.1. The model

We consider finite sample inference in the quantile regression model characterized below.

Assumption 1. Let there be a probability space (Ω, \mathcal{F}, P) and a random vector (Y, D', Z', U) defined on this space, with $Y \in \mathbb{R}$, $D \in \mathbb{R}^{\dim(D)}$, $Z \in \mathbb{R}^{\dim(Z)}$, and $U \in (0, 1)P$ -a.s., such that

- A1.** $Y = q(D, U)$ for a function $q(d, u)$ that is measurable.
- A2.** $q(d, u)$ is strictly increasing in u for each d in the support of D .
- A3.** $U \sim \text{Uniform}(0, 1)$ and is independent from Z .
- A4.** D is statistically dependent on Z .

When $D = Z$, the model in A1–A4 corresponds to the conventional quantile regression model with exogenous covariates, see Koenker (2005), where Y is the dependent variable, D is the regressor, and $q(d, \tau)$ is the τ -quantile of Y conditional on $D = d$ for any $\tau \in (0, 1)$. In this case, A1, A3, and A4 are not restrictive and provide a representation of Y , while A2 restricts Y to have a continuous distribution function. The exogenous model was introduced in Bhattacharya (1963), Doksum (1974), Hogg (1975), Koenker and Bassett (1978) and Matzkin (2003), as discussed in more detail in Koenker (2005). It usefully generalizes the classical linear model $Y = D'\gamma_0 + \gamma_1(U)$ by allowing for quantile specific effects of covariates D . Estimation and asymptotic inference for the linear version of this model, $Y = D'\theta(U)$, were developed in Koenker and Bassett (1978), and estimation and inference results have been extended in a number of useful directions by subsequent authors. Matzkin (2003) provides many economic examples that fall in this framework and considers general nonparametric methods for asymptotic inference.

When $D \neq Z$ but Z is a set of instruments that are independent of the structural disturbance U , the model A1–A4 provides a generalization of the conventional quantile model that allows for endogeneity. See Chernozhukov and Hansen (2001, 2005, 2006, 2008) for discussion of the model as well as for semi-parametric estimation and inference theory under strong and weak identification. See Chernozhukov et al. (2007b) for a nonparametric analysis of this model and Chesher (2003) for a related nonseparable model. The model A1–A4 can be thought of as a general nonseparable structural model that allows for endogenous variables as well as a treatment effects model with heterogeneous treatment effects. In this case, D and U may be jointly determined, rendering the conventional quantile regression invalid for making inference on the structural quantile function $q(d, \tau)$. This model generalizes the conventional instrumental variables model with additive disturbances, $Y = D'\alpha_0 + \alpha_1(U)$, where $U | Z \sim U(0, 1)$, to cases where the impact of D varies across quantiles of the outcome distribution. Note that, in this case, A4 is necessary for identification. However, the finite sample inference results presented below will remain valid even when A4 is not satisfied.

Under Assumption 1, we state the following result, which provides the basis for the finite sample inference results that follow.

Proposition 1 (Main Statistical Implication). Suppose A1–A3 hold, then

$$1. P[Y \leq q(D, \tau) | Z] = \tau, \quad (2.1)$$

$$2. \{Y \leq q(D, \tau)\} \text{ is Bernoulli}(\tau) \text{ conditional on } Z. \quad (2.2)$$

Proof. $\{Y \leq q(D, \tau)\}$ is equivalent to $\{U \leq \tau\}$, which is independent of Z . The results then follow from $U \sim U(0, 1)$. \square

Eq. (2.1) provides a set of moment conditions that can be used to identify and estimate the quantile function $q(d, \tau)$. When $D = Z$, these are the standard moment conditions used in quantile regression which have been analyzed extensively, starting with Koenker and Bassett (1978), and when $D \neq Z$, the identification and estimation of $q(d, \tau)$ from (2.1) is considered in Chernozhukov and Hansen (2005).

Eq. (2.2) is the key result from which we obtain the finite sample inference results. The result states that the event $\{Y \leq q(D, \tau)\}$ conditional on Z is distributed exactly as a Bernoulli(τ) random variable regardless of the sample size. This random variable depends only on τ , which is known, and so is pivotal in finite samples. These results allow the construction of exact finite sample confidence regions and tests conditional on the observed data, Z .

2.2. Model and sampling assumptions

In the preceding section, we outlined a general heterogeneous effect model and discussed how the model relates to quantile regression. We also showed that the model implies that $\{Y \leq q(D, \tau)\}$ conditional on Z is distributed exactly as a Bernoulli(τ) random variable in finite samples. In order to operationalize the finite sample inference, we also impose the following conditions.

Assumption 2. Let $\tau \in (0, 1)$ denote the quantile of interest. Suppose that there is a sample $(Y_i, D_i, Z_i, i = 1, \dots, n)$ on probability space (Ω, \mathcal{F}, P) (possibly dependent on the sample size), such that A1–A4 hold for each $i = 1, \dots, n$, and the following additional conditions hold:

A5 (Parameterization): There exists $\theta_0 \in \Theta_n \subset \mathbb{R}^{K_n}$ such that $q(D, \tau) = q(D, \theta_0, \tau)$, with equality holding up to a numerically negligible error, where the function $q(D, \theta, \tau)$ is known, but θ_0 is not.

A6 (Conditionally Independent Sampling): (U_1, \dots, U_n) are i.i.d. Uniform(0, 1), conditional on (Z_1, \dots, Z_n) .

We will use the letter \mathcal{P} to denote the collection of all probability laws P on the measure space (Ω, \mathcal{F}) that satisfy conditions A1–A6.

Conditions A5–A6 restrict the model A1–A4 sufficiently to allow finite sample inference. A5 requires that the τ -quantile function $q(d, \tau)$ can be approximated by a finite-dimensional model $q(d, \tau, \theta_0)$ (where θ_0 may vary with τ), up to a negligible numerical error. The finite sample inference results of this paper in principle apply to any parameter space, including a function space. However, from a practical point of view, we should require that each element of the function space can be approximated in a suitable norm by a finite-dimensional model, and the approximation error can be made arbitrarily small. In this sense, we can allow flexible (approximating) functional forms for $q(D, \theta_0, \tau)$ such as linear combinations of B-splines, trigonometric, power, and spline series. Of course, the usual parametric assumptions are permitted. A5 allows the model to depend on the sample size in the Pitman sense and allows the dimension of the model, K_n , to increase with n in the sense of Huber (1973) and Portnoy (1985), where $K_n \rightarrow \infty$ as $n \rightarrow \infty$. Condition A6 is obviously satisfied if $(Y_i, X_i, Z_i, i = 1, \dots, n)$ are i.i.d., but in principle should allow for some dynamics, e.g. of the kinds considered in Koener and Xiao (2004a,b).

2.3. The finite sample inference procedure

Using the conditions discussed in the previous sections, we are able to provide the key results on finite sample inference. We start by noting that Eq. (2.1) in Proposition 1 justifies the following generalized method-of-moments (GMM) function for estimating θ_0 :

$$L_n(\theta) = \frac{1}{2} \left[\frac{1}{\sqrt{n}} \sum_{i=1}^n m_i(\theta) \right]' W_n \left[\frac{1}{\sqrt{n}} \sum_{i=1}^n m_i(\theta) \right], \quad (2.3)$$

where $m_i(\theta) = [\tau - 1(Y_i \leq q(D_i, \theta, \tau))]g(Z_i)$. In this expression, $g(Z_i)$ is a known vector of functions of Z , and W_n is a positive semi-definite weight matrix which is fixed conditional on Z_1, \dots, Z_n . One would typically choose $g(Z)$ such that $\dim(g(Z)) \geq \dim(\theta_0)$, though this is not required for validity of the approach. A convenient and natural choice of W_n is given by $W_n = \frac{1}{\tau(1-\tau)} \left[\frac{1}{n} \sum_{i=1}^n g(Z_i)g(Z_i)'\right]^{-1}$, which equals the inverse of the variance of $n^{-1/2} \sum_{i=1}^n m_i(\theta_0)$ conditional on Z_1, \dots, Z_n . Since this conditional variance does not depend on θ_0 , the GMM function with W_n defined above also corresponds to the continuous-updating estimator of Hansen et al. (1996). In all examples in this paper, we use the identity function for $g(\cdot)$.

We focus on the GMM function $L_n(\theta)$ for defining the key results for finite sample inference. The GMM function provides an intuitive statistic for performing inference given its close relation to standard estimation and asymptotic inference procedures. In addition, we show in the Appendix that testing based on $L_n(\theta)$ may have useful asymptotic optimality properties.

We now state the key finite sample results.

Proposition 2. Under A1–A6, statistic $L_n(\theta_0)$ is conditionally pivotal:

$L_n(\theta_0) \stackrel{d}{=} \mathcal{L}_n$, conditional on (Z_1, \dots, Z_n) , where

$$\mathcal{L}_n = \frac{1}{2} \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n (\tau - B_i) \cdot g(Z_i) \right)' \times W_n \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n (\tau - B_i) \cdot g(Z_i) \right),$$

and (B_1, \dots, B_n) are i.i.d. Bernoulli random variables with $EB_i = \tau$, which are independent of (Z_1, \dots, Z_n) .

Proof. Implication 2 of Proposition 1 and A6 imply the result. \square

Proposition 2 states the finite sample distribution of the GMM function $L_n(\theta)$ at $\theta = \theta_0$. Conditional on (Z_1, \dots, Z_n) , the distribution does not depend on any unknown parameters, and appropriate critical values from the distribution may be obtained allowing finite sample inference on θ_0 .

Given the finite sample distribution of $L_n(\theta_0)$, a $1 - \alpha$ -level test of the null hypothesis that $\theta = \theta_0$ is given by the rule that rejects the null if $L_n(\theta) > c_n(\alpha)$, where $c_n(\alpha)$ is the α -quantile of \mathcal{L}_n . By inverting this test-statistic, one obtains confidence regions for θ_0 .

Let $CR(\alpha)$ be the $c_n(\alpha)$ -level set of the function $L_n(\theta)$: $CR(\alpha) \equiv \{\theta : L_n(\theta) \leq c_n(\alpha)\}$. It follows immediately from the previous results that $CR(\alpha)$ is a valid α -level confidence region for θ_0 . This result is stated formally in Proposition 3.

Proposition 3. Fix an $\alpha \in (0, 1)$. $CR(\alpha)$ is a valid α -level confidence region for inference about θ_0 in finite samples: $\Pr_P(\theta_0 \in CR(\alpha)) \geq \alpha$. $CR(\alpha)$ is also a valid critical region for obtaining a $1 - \alpha$ -level test of $\theta = \theta_0$: $\Pr_P(\theta_0 \notin CR(\alpha)) \leq 1 - \alpha$. Moreover, these results hold uniformly in $P \in \mathcal{P}$, $\inf_{P \in \mathcal{P}} \Pr_P(\theta_0 \in CR(\alpha)) \geq \alpha$ and $\sup_{P \in \mathcal{P}} \Pr_P(\theta_0 \notin CR(\alpha)) \leq 1 - \alpha$.

Proof. $\theta_0 \in CR(\alpha)$ is equivalent to $\{L_n(\theta_0) \leq c_n(\alpha)\}$ and $\Pr_P\{L_n(\theta_0) \leq c_n(\alpha)\} \geq \alpha$, by the definition of $c_n(\alpha) := \inf\{l : P\{\mathcal{L}_n \leq l\} \geq \alpha\}$ and $L_n(\theta_0) \stackrel{d}{=} \mathcal{L}_n$. \square

Proposition 3 demonstrates how one may obtain valid finite sample confidence regions and tests for the parameter vector θ characterizing the quantile function $q(D, \theta_0, \tau)$. Thus, this result generalizes the approach of Walsh (1960) from the sample quantiles to the regression case. It is also apparent that the pivotal nature of the finite sample approach is similar to the asymptotically pivotal nature of the rank-score method, see Gutenbrunner and Jurečková (1992) and Gutenbrunner et al. (1993), and the pivotal bootstrap method of Parzen et al. (1994). In contrast to the pivotal bootstrap and the rank-score method, the finite sample approach does not rely on asymptotics for its validity and is valid in finite samples. Moreover, the rank-score method relies on a homoskedasticity assumption, while the finite sample approach does not.

It is worth emphasizing the distinction between the finite sample approach and some other inferential procedures. The pivotal bootstrap produces a “fiducial” distribution, whose support is a finite set of points that generically does not contain the true parameter θ_0 . Therefore, the pivotal bootstrap does not possess formal finite sample validity. Furthermore, Parzen et al. (1994) establish its asymptotic validity under conditions of strong

identifiability and asymptotic normality for the QR estimator. We conjecture that the asymptotic validity of the pivotal bootstrap does not hold in more nonstandard settings such as cases with weak instruments, under set identification, or for extreme quantiles. In contrast, the finite sample approach is shown to work under all such conditions. The finite sample method should not be confused with the Gibbs bootstrap proposed in He and Hu (2002), which may be viewed as a computationally attractive alternative to Parzen et al. (1994). The method is also different from specifying the finite sample density of quantile regression as in Koenker and Bassett (1978). The finite sample density of QR is not pivotal and it cannot be used for finite sample inference unless the nuisance parameters (the conditional density of the outcome given the regressors) are specified.

Finally, we note that, while the statement of Proposition 3 is for joint inference about the entire parameter vector, one can define a confidence region for a real-valued functional $\psi(\theta_0, \tau)$ as

$$CR(\alpha, \psi) = \{\psi(\theta, \tau) : \theta \in CR(\alpha)\}.$$

Since the event $\{\theta_0 \in CR(\alpha)\}$ implies the event $\{\psi(\theta_0, \tau) \in CR(\alpha, \psi)\}$, it follows that $\inf_{P \in \mathcal{P}} \Pr_P(\psi(\theta_0, \tau) \in CR(\alpha, \psi)) \geq \alpha$ by Proposition 3. For example, if one is interested in inference about a single component of θ , say $\theta_{[1]}$, a confidence region for $\theta_{[1]}$ may be constructed as the set $\{\theta_{[1]} : \theta \in CR(\alpha)\}$. That is, the confidence region for $\theta_{[1]}$ is obtained by first taking all vectors of θ in $CR(\alpha)$ and then extracting the element from each vector corresponding to $\theta_{[1]}$. Confidence bounds for $\theta_{[1]}$ may be obtained by taking the infimum and supremum over this set of values for $\theta_{[1]}$.

2.4. Primary properties of the finite sample inference

The finite sample tests and confidence regions obtained in the preceding section have a number of interesting and appealing features. Perhaps the most important feature of the proposed approach is that it allows for finite sample inference under weak conditions. Working with a model defined by quantile restrictions makes it possible to construct exact joint inference in a general nonlinear, nonseparable model with heterogeneous effects that allows for endogeneity.

The approach is valid without imposing distributional assumptions and allows for general forms of heteroskedasticity and some forms of dynamics. The result is obtained without relying on asymptotic arguments and essentially requires only that Y has a continuous conditional distribution function given Z . In contrast with conventional asymptotic approaches to inference in quantile models, the validity of the finite sample approach does not depend upon having a well-behaved density for Y : it does not rely on the density of Y given $D = d$ and $Z = z$ being continuous or differentiable in y or having connected support around $q(d, \tau)$, as required for example in Chernozhukov and Hansen (2006).

In addition to these features, the finite sample inference procedure will remain valid in situations where the parameters of the model are only set-identified. The confidence regions obtained from the finite sample procedure will provide valid inference about $q(D, \tau) = q(D, \theta_0, \tau)$ even when θ_0 is not uniquely identified by $P[Y \leq q(D, \theta_0, \tau) | Z] = \tau$. This builds on the point made in Hu (2002). In addition, since the inference is valid for any n , it follows trivially that it remains valid under the asymptotic formalization of “weak instruments”, as defined for example in Stock and Wright (2000).

As noted previously, inference statements obtained from the finite sample procedure will also remain valid in models where the dimension of the parameter space K_n is allowed to increase with future increases of n since the statements are valid for any given n . Thus, the results of the previous section remain valid in the asymptotics of Huber (1973) and Portnoy (1985), where $K_n/n \rightarrow 0$,

$K_n \rightarrow \infty, n \rightarrow \infty$. These rate conditions are considerably weaker than those required for conventional inference using Wald statistics, as described in Portnoy (1985) and Newey (1997), which require $K_n^2/n \rightarrow 0, K_n \rightarrow \infty, n \rightarrow \infty$.

Inference statements obtained from the finite sample procedure will be valid for inference about extremal quantiles where the usual asymptotic approximation may perform quite poorly. One alternative to using the conventional asymptotic approximation for extremal quantiles is to pursue an approach explicitly aimed at performing inference for extremal quantiles, for example as in Chernozhukov (2005). The extreme value approach improves upon the usual asymptotic approximation but requires a regular variation assumption on the tails of the conditional distribution of $Y | D$, that the tail index does not vary with D , and also relies heavily on linearity and exogeneity. None of these assumptions are required in the finite sample approach, so the inference statements apply more generally than those obtained from the extreme value approach.

It is also worth noting that while the approach presented above is explicitly finite sample, it will remain valid asymptotically. Under conventional assumptions and asymptotics the inference approaches conventional GMM based joint inference, as for example in Pakes and Pollard (1989), Abadie (1995) and Chernozhukov et al. (2003).

Finally, it is important to note that inference is simultaneous on all components of θ and that for joint inference the approach is not conservative. Inference about subcomponents of θ may be made by projections, as illustrated in the previous section, and may be conservative.

2.5. Computation

The main difficulty with the approach introduced in the previous sections is computing the confidence regions. The distribution of $L_n(\theta_0)$ is not standard, but its critical values can be easily constructed by simulation. The more serious problem is that inverting the function $L_n(\theta)$ to find joint confidence regions may pose a significant computational challenge. One possible approach is to simply use a naive grid-search, but as the dimension of θ increases, this approach becomes intractable. To help alleviate this problem, we explore the use of MCMC methods. MCMC methods seem attractive in this setting because they generate an adaptive set of grid points and so should explore the relevant region of the parameter space more quickly than performing a conventional grid search. We also consider a marginalization approach that combines a one-dimensional grid search with optimization for estimating a confidence bound for a single parameter which may be computationally convenient in some cases.

2.5.1. Computation of the critical value

The computation of the critical value $c_n(\alpha)$ may proceed by simulating the distribution \mathcal{L}_n . We outline a simulation routine below.

Algorithm 1 (Computation of $c_n(\alpha)$). Given $(Z_i, i = 1, \dots, n)$, for $j = 1, \dots, J$: 1. Draw $(U_{i,j}, i \leq n)$ as i.i.d. Uniform, and let $(B_{i,j} = 1(U_{i,j} \leq \tau), i \leq n)$. 2. Compute $\mathcal{L}_{n,j} = \frac{1}{2}(\frac{1}{\sqrt{n}} \sum_{i=1}^n (\tau - B_{i,j}) \cdot g(Z_i))' W_n (\frac{1}{\sqrt{n}} \sum_{i=1}^n (\tau - B_{i,j}) \cdot g(Z_i))$. 3. Obtain $c_n(\alpha)$ as the α -quantile of the sample $(\mathcal{L}_{n,j}, j = 1, \dots, J)$, for a large number J .

2.5.2. Computation of confidence regions

Finding the confidence region requires computing the $c_n(\alpha)$ -level set of the function $L_n(\theta)$, which involves inverting a nonsmooth, nonconvex function. For even moderately sized problems, the use of a conventional grid search is impractical due to the computational curse of dimensionality.

To help resolve this problem, we consider the use of a generic random walk Metropolis–Hastings MCMC algorithm. Of course, other MCMC algorithms or stochastic search methods could also be employed. The idea is that the MCMC algorithm will generate a set of adaptive grid-points that are placed in relevant regions of the parameter space only. By focusing more on relevant regions of the parameter space, the use of MCMC methods may alleviate the computational problems associated with a conventional grid search.

To implement the MCMC algorithm, we treat $f(\theta) \propto \exp(-L_n(\theta))$ as a quasi-posterior density and feed it into a random walk MCMC algorithm. The idea is similar to that in Chernozhukov et al. (2003), except that we use it here to get level sets of the objective function rather than pseudo-posterior means and quantiles. A related suggestion would be to use $f(\theta) \propto \exp(-\max[L_n(\theta), c_n(\alpha)])$ as a quasi-posterior density. This choice of $f(\theta)$ samples the confidence region uniformly.

Given f , the basic random walk MCMC algorithm is implemented as follows:

Algorithm 2 (Random Walk MCMC). For a symmetric proposal density $h(\cdot)$ and given $\theta^{(t)}$, 1. Generate $\theta_{prop}^{(t)} \sim h(\theta - \theta^{(t)})$. 2. Take $\theta^{(t+1)} = \theta_{prop}^{(t)}$ with probability $\min\{1, f(\theta_{prop}^{(t)})/f(\theta^{(t)})\}$ and $\theta^{(t)}$ otherwise. 3. Store $(\theta^{(t)}, \theta_{prop}^{(t)}, L_n(\theta^{(t)}), L_n(\theta_{prop}^{(t)}))$. 4. Repeat Steps 1–3 J times replacing $\theta^{(t)}$ with $\theta^{(t+1)}$ as the starting point for each repetition.

At each step, the MCMC algorithm considers two potential values for θ and obtains the corresponding values of the objective function. Step 3 above differs from a conventional random walk MCMC algorithm in that we are interested in every value considered not just those accepted by the procedure.

The implementation of the MCMC algorithm requires the user to specify a starting value for the chain and a transition density $h(\cdot)$. The choice of both quantities can have important practical implications, and implementation in any given example will typically involve some fine tuning in both the choice of $h(\cdot)$ and the starting value.¹ Robert and Casella (1998) provide an excellent overview of these and related issues.

As illustrated above, the MCMC algorithm generates a set of grid points $\{\theta^{(1)}, \dots, \theta^{(k)}\}$ and, as a by-product, a set of values for the objective function $\{L_n(\theta^{(1)}), \dots, L_n(\theta^{(k)})\}$. Using this set of evaluations of the objective function, we can construct an estimate of the critical region by taking the set of draws for θ where the value of $L_n(\theta) \leq c_n(\alpha)$: $\hat{CR}(\alpha) = \{\theta^{(i)} : L_n(\theta^{(i)}) \leq c(\alpha)\}$.

2.5.3. Computation of confidence bounds for individual regression parameters

The MCMC approach outlined above may be used to estimate joint confidence regions. If one is interested solely in inference about an individual regression parameter, there may be a computationally more convenient approach. In particular, for constructing a confidence bound for a single parameter, knowledge of the entire joint confidence region is unnecessary, which suggests that we may collapse the d -dimensional search to a one-dimensional search.

For concreteness, suppose we are interested in constructing a confidence bound for a particular element of θ , denoted $\theta_{[1]}$, and let $\theta_{[-1]}$ denote the remaining elements of the parameter vector. We note that a value of $\theta_{[1]}$, say $\theta_{[1]}^*$, will lie inside the confidence

bound as long as there exists a value of θ with $\theta_{[1]} = \theta_{[1]}^*$ that satisfies $L_n(\theta) \leq c_n(\alpha)$. Since only one such value of θ is required to place $\theta_{[1]}^*$ in the confidence bound, we may restrict consideration to θ^* , the point that minimizes $L_n(\theta)$ conditional on $\theta_{[1]} = \theta_{[1]}^*$. If $L_n(\theta^*) > c_n(\alpha)$, we may conclude that there will be no other point that satisfies $L_n(\theta) \leq c_n(\alpha)$, and exclude $\theta_{[1]}^*$ from the confidence bound. On the other hand, if $L_n(\theta^*) \leq c_n(\alpha)$, we have found a point that satisfies $L_n(\theta) \leq c_n(\alpha)$ and can include $\theta_{[1]}^*$ in the confidence bound.

This suggests that a confidence bound for $\theta_{[1]}$ can be constructed using the following simple algorithm that combines a one-dimensional grid search with optimization.

Algorithm 3 (Marginal Approach). 1. Define a suitable set of values for $\theta_{[1]}$, $\{\theta_{[1]}^j, j = 1, \dots, J\}$. 2. For $j = 1, \dots, J$, find $\theta_{[-1]}^j = \arg \inf_{\theta_{[-1]}} L_n((\theta_{[1]}^j, \theta_{[-1]}^j)')$. 3. Calculate the confidence region for $\theta_{[1]}$ as $\{\theta_{[1]}^j : L_n((\theta_{[1]}^j, \theta_{[-1]}^j)') \leq c_n(\alpha)\}$.

In addition to its being computationally convenient for finding confidence bounds for individual parameters in high-dimensional settings, we also anticipate that this approach will perform well in some irregular cases. Since the marginal approach focuses on only one parameter, it will typically be easy to generate a tractable and reasonable search region. The approach will have some robustness to multimodal objective functions and potentially disconnected confidence sets because it considers all values in the grid search region and will not be susceptible to getting stuck at a local mode.

3. Empirical examples

In the preceding section, we presented an inference procedure for quantile regression that provides exact finite sample inference for joint hypotheses and discussed how confidence bounds for subsets of quantile regression parameters may be obtained. In the following, we further explore the properties of the proposed finite sample approach through two simple case studies.² In the first, we consider estimation of a demand model in a small sample; and in the second, we consider estimation of the impact of schooling on wages in a rather large sample. In both cases, we find that the finite sample and asymptotic intervals are similar when the variables of interest, price and years of schooling, are treated as exogenous. However, when we use instruments, the finite sample and asymptotic intervals differ significantly. In each of these examples, we consider specifications that include only a constant and the covariate of interest. In these two-dimensional situations, computation is relatively simple, so we consider estimating the finite sample intervals using a simple grid search, MCMC methods, and the marginal inference approach suggested in the previous section. We find that all methods result in similar confidence bounds for the parameter of interest in the demand example, but there are some discrepancies in the schooling example.

3.1. Demand for fish

In this section, we present estimates of demand elasticities which may potentially vary with the level of demand. The data contain observations on price and quantity of fresh whiting sold

¹ In our applications, we use estimates of θ and the corresponding asymptotic distribution obtained from the quantile regression of Koenker and Bassett (1978) in exogenous cases and from the inverse quantile regression of Chernozhukov and Hansen (2006) in endogenous cases as starting values and transition densities.

² Simulation results are available in a previous working paper version of this paper, Chernozhukov et al. (2006). In the simulations, we find that tests about the entire parameter vector based on the finite sample method have the correct size and that tests about individual parameters based on the finite sample method have correct size in the sense that the size is less than the nominal level but may be conservative. In both cases, conventional asymptotic procedures have large size distortions in situations where the asymptotic approximations may be suspect. The results also suggest the finite sample procedure has nontrivial power.

