IV QUANTILE REGRESSION FOR GROUP-LEVEL TREATMENTS, WITH AN APPLICATION TO THE DISTRIBUTIONAL EFFECTS OF TRADE

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Abstract. We present a methodology for estimating the distributional effects of an endogenous treatment that varies at the group level when there are group-level unobservables, a quantile extension of Hausman and Taylor (1981). Because of the presence of group-level unobservables, standard quantile regression techniques are inconsistent in our setting even if the treatment is independent of unobservables. In contrast, our estimation technique is consistent as well as computationally simple, consisting of group-by-group quantile regression followed by two-stage least squares. Using the Bahadur representation of quantile estimators, we derive weak conditions on the growth of the number of observations per group that are sufficient for consistency and asymptotic zero-mean normality of our estimator. As in Hausman and Taylor (1981), micro-level covariates can be used as internal instruments for the endogenous group-level treatment if they satisfy relevance and exogeneity conditions. Our approach applies to a broad range of settings including labor, public finance, industrial organization, urban economics, and development; we illustrate its usefulness with several such examples. Finally, an empirical application of our estimator finds that low-wage earners in the US from 1990–2007 were significantly more affected by increased Chinese import competition than high-wage earners.

Keywords: quantile regression, instrumental variables, panel data, income inequality, import competition

JEL Classification: C21, C31, C33, C36, F16, J30

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1. Introduction

In classical panel-data models for mean regression, fixed effects are commonly used to obtain identification when time-invariant unobservables are correlated with included variables. While this approach yields consistent estimates of the coefficients on time-varying variables, it precludes identification of the coefficients of any time-invariant variables, as these variables are eliminated by the within-group transformation. In an influential paper, Hausman and Taylor (1981) demonstrated that exogenous between variation of time-varying variables can help to identify the coefficients of time-invariant variables after their within variation has been used to identify the coefficients on time-varying variables, thus yielding identification of the whole model without external instruments. Our paper provides a quantile extension of the Hausman and Taylor (1981) classical linear panel estimator.

We present our model in Section 2. To clarify the range of potential applications of our estimator, we depart in the model from the usual panel-data terminology and refer to panel units as groups (instead of as individuals; groups might be states, cities, schools, etc.) and to within-group observations as individuals or micro-level observations (instead of as time observations; individuals might be students, families, firms, etc.).\footnote{Similar terminology is used, for example, by Altonji and Matzkin (2005).} The model is of practical significance when the researcher has data on a group-level endogenous treatment and has microdata on the outcome of interest within each group. For example, a researcher may be interested in the effect of a policy which varies across states and years (a “group”) on the within-group distribution of micro-level outcomes. In Section 2, we also explain how the problem we solve differs from others in the quantile regression literature, and we demonstrate that, as in Hausman and Taylor (1981), micro-level covariates can be used as internal instruments for the endogenous group-level treatment if they satisfy relevance and exogeneity conditions. This last feature of the model is especially appealing because in practice it may be difficult to find external instruments.

In Section 3 we introduce our estimation approach, which we refer to as grouped IV quantile regression. The estimator is computationally simple to implement and consists of two steps: (i) perform quantile regression within each group to estimate effects of micro-level covariates, or, if no micro-level covariates are included, calculate the desired quantile for the outcome within each group; and (ii) regress the estimated group-specific effects on group-level covariates using either 2SLS, if the group-level covariates are endogenous, or OLS, if the group-level covariates are exogenous, either of which cases would render standard quantile regression (e.g. Koenker and Bassett 1978) inconsistent.\footnote{Even in the absence of endogeneity, the Koenker and Bassett (1978) estimator will be inconsistent in our setting because of group-level unobservables, akin to left-hand side measurement error; see Section 2 for details on our setting. While posing no problems for linear models, left-hand side errors-in-variables can bias quantile estimation (see Hausman (2001) and Hausman, Luo, and Palmer (2014)).} Section 3 also discusses Monte Carlo simulations (found in Section
A of the Supplemental Appendix) that demonstrate that our estimator has much lower bias than that of the standard quantile regression estimator when the group-level treatment is endogenous, even in small samples, and at larger sample sizes our estimator outperforms quantile regression even when the treatment is exogenous. Section 3 also highlights additional computational benefits of our estimator.

Section 4 provides a variety of examples illustrating the use of the grouped IV quantile regression estimator. In particular, we use examples from Angrist and Lang (2004), Larsen (2014), Palmer (2011), and Backus (2014) to illustrate applicability of our estimator. In addition to these examples, the grouped quantile approach can apply to a wide range of settings in labor, industrial organization, trade, public finance, development, and other applied fields.

We derive theoretical properties of the estimator in Section 5. The results are based on asymptotics where both the number of groups and the number of observations per group grow to infinity. While linear panel models, including Hausman and Taylor (1981), admit a simple unbiased fixed effects estimator and hence do not require asymptotics in the number of observations per group, quantile estimators are biased in finite samples leading to inconsistency of our estimator if the number of observations per group remains small as the number of groups increases, and making the estimator inappropriate in the settings with a small number of observations per group and a large number of groups. However, since quantile estimators are asymptotically unbiased, we are able to employ Bahadur’s representation of quantile estimators to derive weak conditions on the growth of the number of observations per group that are sufficient for the consistency and asymptotic zero-mean normality of our estimator. Importantly, the attractive theoretical properties of the estimator remain valid even if the number of observations per group is relatively small in comparison with the number of groups. We demonstrate that standard errors for the proposed estimator can be obtained using traditional heteroskedasticity-robust variance estimators for 2SLS, making inference particularly simple. In the Supplemental Appendix, we also discuss clustered standard errors, and we show how to construct confidence bands for the coefficient of interest which hold uniformly over a set of quantiles via multiplier bootstrap procedure.

Section 6 presents an empirical application which studies the effect of trade on the distribution of wages within local labor markets. We build on the work of Autor, Dorn, and Hanson (2013), who studied the effect of Chinese import competition on average wages in local labor markets.

Using the grouped IV quantile regression approach developed here, we find that Chinese import competition reduced the wages of low-wage earners (individuals at the bottom quartile of the conditional wage distribution) more than high-wage earners, particularly for females, heterogeneity which is missed by focusing on traditional 2SLS estimates.

To the best of our knowledge, our paper is the first to present a framework for estimating distributional effects as a function of group-level covariates. There is, however, a large literature studying quantile models for panel data when the researcher wishes to estimate distributional effects

Throughout the paper, we use the following notation. The symbol $\| \cdot \|$ denotes the Euclidean norm. The symbol $\Rightarrow$ signifies weak convergence, and $l^\infty(U)$ represents the set of bounded functions on $U$. With some abuse of notation, $\ell^\infty(U)$ also denotes the set of component-wise bounded vector-valued functions on $U$. All equalities and inequalities concerning random variables are implicitly assumed to hold almost surely. All proofs and some extensions of our results are contained in the Supplemental Appendix.

2. Model

We study a panel data quantile regression model for a response variable $y_{ig}$ of individual $i$ in group $g$. We first present a simple version of the model, which we consider as most appealing in empirical work, and then present the general version of our model, which allows for more flexible distributional effects. Our estimator and theoretical results apply to both the general and simple versions of the model.

In the simple version of the model, we assume that the $u$th quantile of the conditional distribution of $y_{ig}$ is given by

$$Q_{y_{ig}|\bar{z}_{ig},x_{g},\varepsilon_{g}}(u) = \bar{z}_{ig}'\gamma(u) + x_{g}'\beta(u) + \varepsilon_{g}(u), \quad u \in U,$$

(1)

where $Q_{y_{ig}|\bar{z}_{ig},x_{g},\varepsilon_{g}}(u)$ is the $u$th conditional quantile of $y_{ig}$ given $(\bar{z}_{ig}, x_{g}, \varepsilon_{g})$, $\bar{z}_{ig}$ is a $(d_{z}-1)$-vector of observable individual-level covariates (which we sometimes refer to as micro-level covariates), $x_{g}$ is a $d_{x}$-vector of observable group-level covariates ($x_{g}$ contains a constant), $\gamma(u)$ and $\beta(u)$ are $(d_{z}-1)$- and $d_{x}$-vectors of coefficients, $\varepsilon_{g} = \{\varepsilon_{g}(u), u \in U\}$ is a set of unobservable group-level random scalar shifters, and $U$ is a set of quantile indices of interest. Here, $\gamma(u)$ and $\beta(u)$ represent the effects of individual- and group-level covariates, respectively. In this paper, we are primarily interested in estimating $\beta(u)$, although we also provide some new results on estimating $\gamma(u)$.

One interpretation of the term $\varepsilon_{g}(u)$ in (1) is that it accounts for all unobservable group-level covariates $\eta_{g}$ that affect the distribution of $y_{ig}$ but are not included in $x_{g}$. In this case, $\varepsilon_{g}(u) = \varepsilon(u, \eta_{g})$. Note that we do not impose any parametric restrictions on $\varepsilon(u, \eta_{g})$, and so we allow for arbitrary nonlinear effects of the group-level unobservable covariates that can affect different quantiles in different ways.
In the more general version of the model, of which (1) is a special case, we assume that the $u$th quantile of the conditional distribution of $y_{ig}$ is given by

$$Q_{y_{ig}|z_{ig},x_{g},\alpha_{g}}(u) = z_{ig}'\alpha_{g}(u), \ u \in U \quad (2)$$

$$\alpha_{g,1}(u) = x_{g}'\beta(u) + \varepsilon_{g}(u), \ u \in U, \quad (3)$$

where $Q_{y_{ig}|z_{ig},x_{g},\alpha_{g}}(u)$ is the $u$th conditional quantile of $y_{ig}$ given $(z_{ig}, x_{g}, \alpha_{g})$, $z_{ig}$ is a $d_{z}$-vector of observable individual-level covariates, $\alpha_{g} = \{\alpha_{g}(u), u \in U\}$ is a set of (random) group-specific effects with $\alpha_{g,1}(u)$ being the first component of the vector $\alpha_{g}(u) = (\alpha_{g,1}(u), \ldots, \alpha_{g,d_{z}}(u))'$, and all other notation is the same as above. In this model, we assume that the response variable $y_{ig}$ satisfies the quantile regression model in (2) with group-specific effects $\alpha_{g}(u)$. We are primarily interested in studying how these effects depend on the group-level covariates $x_{g}$, and, without loss of generality, we focus on $\alpha_{g,1}(u)$, the first component of the vector $\alpha_{g}(u)$. To make the problem operational, we assume that $\alpha_{g,1}(u)$ satisfies the linear regression model (3), in which we are interested in estimating the vector of coefficients $\beta(u)$.

Observe that the model (1) is a special case of the model (2)-(3). Indeed, setting $z_{ig} = (1, z_{ig}')'$ and assuming that $(\alpha_{g,2}(u), \ldots, \alpha_{g,d_{z}}(u))' = \gamma(u)$ for some non-stochastic $(d_{z} - 1)$-vector $\gamma(u)$ and all $g = 1, \ldots, G$ in the model (2)-(3) gives the model (1) after substituting (3) into (2). The model (2)-(3) is more general, however, because it allows all coefficients of individual-level covariates to vary across groups via group-specific effects $\alpha_{g}(u)$, and it also allows to study not only location shift effects of the group-level covariates $x_{g}$ but also their interaction effects. Therefore, throughout this paper, we study the model (2)-(3).

As an example of where the above modeling framework is useful, consider a case in which a researcher wishes to model the effects of a policy, contained in $x_{g}$, which varies at the state-by-year level (a “group” in this setting) on the distribution of micro-level outcomes (such as individuals’ wages within each state-by-year combination), denoted $y_{ig}$, conditional on micro-level covariates, such as education level, denoted $z_{ig}$. The framework in (1) would model the location-shift effect of the policy on conditional quantiles of wages within a group, given by $\beta(u)$. The additional flexibility of (2)-(3) would also allow for interaction effects. For example, a policy $x_{g}$ may have differential effects on lower wage quantiles for the less-educated than for the higher-educated; model (2) would capture this idea by allowing the researcher to specify a linear regression model of the form of (3) for the component of $\alpha_{g}$ that is the coefficient on education level, allowing the researcher to study how the effect of education level on the wage distribution varies as a function of $x_{g}$, the policy.\(^4\)

In many applications, it is likely that the group-level covariates $x_{g}$ may be endogenous in the sense that $E[x_{g}\varepsilon_{g}(u)] \neq 0$, at least for some values of the quantile index $u \in U$. Therefore, to

\(^4\)If the researcher is interested in modeling several effects, for example location-shift and some interaction effects, she can specify a linear regression model of the form (3) for each effect.
increase applicability of our results, we assume that there exists a $d_u$-vector of observable instruments $w_g$ such that $E[w_g \varepsilon_g(u)] = 0$ for all $u \in \mathcal{U}$, $E[w_g x_g']$ is nonsingular, and $y_{ig}$ is independent of $w_g$ conditional on $(z_{ig}, x_g, \alpha_g)$. The first two conditions are familiar from the classical linear instrumental variable regression analysis, and the third condition requires the distribution of $y_{ig}$ to be independent of $w_g$ once we control for $z_{ig}, x_g,$ and $\alpha_g$. It implies, in particular, that $Q_{y_{ig}|z_{ig},x_g,\alpha_g,w_g}(u) = z'_{ig} \alpha_g(u)$ for all $u \in \mathcal{U}$.

We assume that a researcher has data on $G$ groups and $N_g$ individuals within group $g = 1, ..., G$. Thus, the data consist of observations on $\{(z_{ig}, y_{ig}), i = 1, \ldots, N_g\}$, $x_g$, and $w_g$ for $g = 1, \ldots, G$. Throughout the paper, we denote $N_G = \min_{1 \leq g \leq G} N_g$. For our asymptotic theory in Section 5, we will assume that $N_G$ gets large as $G \to \infty$. Specifically, for the asymptotic zero-mean normality of our estimator $\hat{\beta}(u)$ of $\beta(u)$, we will assume that $G^{2/3}(\log N_G)/N_G \to 0$ as $G \to \infty$; see Assumption 3 below. Thus, our results are useful when both $G$ and $N_G$ are large, which occurs in many empirical applications, but we also note that our results apply even if the number of observations per group is relatively small in comparison with the number of groups.

We also emphasize that, like in the original panel data mean regression model of Hausman and Taylor (1981), an important feature of our panel data quantile regression model is that it allows for internal instruments. Specifically, if some component of the vector $z_{ig}$, say $z_{ig,k}$, is exogenous in the sense that $E[z_{ig,k} \varepsilon_g(u)] = 0$ for all $u \in \mathcal{U}$, we can use, for example, $N_g^{-1/2} \sum_{i=1}^{N_g} z_{ig,k}$ as an additional instrument provided it is correlated with $x_g$, including it into the vector $w_g$. Since in practice it is often difficult to find an appropriate external instrument, allowing for internal instruments greatly increases the applicability of our results.

Our problem in this paper is different from that studied in Koenker (2004), Kato, Galvao, and Montes-Rojas (2012), and Kato and Galvao (2011). Specifically, they considered the panel data

5The assumption that $E[w_g \varepsilon_g(u)] = 0$ holds jointly for all $u \in \mathcal{U}$ should not be confused with requiring quantile crossing. To understand it, assume, for example, that $\varepsilon_g(u) = \varepsilon(u, \eta_g)$ where $\eta_g$ is a vector of group-level omitted variables in regression (3). Then a sufficient condition for the assumption $E[w_g \varepsilon_g(u)] = E[w_g \varepsilon(u, \eta_g)] = 0$ is that $E[\varepsilon(u, \eta_g)|w_g] = 0$. In turn, the restriction of the condition $E[\varepsilon(u, \eta_g)|w_g] = 0$ is that $E[\varepsilon(u, \eta_g)|w_g]$ does not depend on $w_g$, which occurs (for example) if $\eta_g$ is independent of $w_g$. Once we assume that $E[\varepsilon(u, \eta_g)|w_g]$ does not depend on $w_g$, the further restriction that $E[\varepsilon(u, \eta_g)|w_g] = 0$ is a normalization of the component of the vector $\beta(u)$ corresponding to the constant in the vector $x_g$.

6The setting we model differs from other IV quantile settings, such as Chernozhukov and Hansen (2005, 2006, 2008). Consider, for simplicity, our model (1) and assume that $\mathcal{U} = [0, 1]$. Then the Skorohod representation implies that $y_{ig} = \tilde{z}_{ig}'(u_{ig}) + x'_g \beta(u_{ig}) + \varepsilon_g(u_{ig})$ where $u_{ig}$ is a random variable that is distributed uniformly on $[0, 1]$ and is independent of $(\tilde{z}_{ig}, x_g, \varepsilon_g)$. Here, one can think of $u_{ig}$ as unobserved individual-level heterogeneity. In this model, the unobserved group-level component $\varepsilon_g(\cdot)$ is modeled as an additively separable term. In contrast, the model in Chernozhukov and Hansen (2005, 2006, 2008) assumes that $\varepsilon_g(u) = 0$ for all $u \in [0, 1]$ and instead assumes that $u_{ig}$ is not independent of $(\tilde{z}_{ig}, x_g)$. Thus, these two models are different and require different analysis.

7Our paper is also related to but different from Graham and Powell (2012) who studied the model that in our notation would take the form $y_{ig} = z'_{ig}\alpha_g(u_{ig})$ where $u_{ig}$ represents (potentially multi-dimensional) random unobserved heterogeneity, and developed an interesting identification and estimation strategy for the parameter $E[\alpha_g(u_{ig})]$. 

quantile regression model  
\[ Q_{y_i|z_{i,g},g}(u) = z_{i,g}'\gamma(u) + \alpha_g(u), \quad u \in \mathcal{U}, \tag{4} \]
and developed estimators of \( \gamma(u) \). Building on Koenker (2004), Kato, Galvao, and Montes-Rojas (2012) suggested estimating \( \gamma(u) \) in this model by running a quantile regression estimator of Koenker and Bassett (1978) on the pooled data, treating \{\alpha_g(u), g = 1, \ldots, G\} as a set of parameters to be estimated jointly with the vector of parameters \( \gamma(u) \) (the same technique can be used to estimate \( \gamma(u) \) in our model (1) by setting \( \alpha_g(u) = x_g'\beta(u) + \varepsilon_g(u) \)). They showed that their estimator is asymptotically zero-mean normal if \( G^2(\log G)^3/N_G \to 0 \) as \( G \to \infty \). Making further progress, Kato and Galvao (2011) suggested an interesting smoothed quantile regression estimator of \( \gamma(u) \) that is asymptotically zero-mean normal if \( G/N_G \to 0 \).\(^8\) These papers do not provide a model for our estimator of \( \beta(u) \), our primary object of interest, but instead focus solely on \( \gamma(u) \).

Our model is also different from that studied in Hahn and Meinecke (2005), who considered an extension of Hausman and Taylor (1981) to cover non-linear panel data models. Formally, they considered a non-linear panel data model defined by the following equation:
\[ E \left[ \varphi(y_{ig}, z_{ig}'\gamma + x_g'\beta + \varepsilon_g) \right] = 0 \]
where \( \varphi(\cdot, \cdot) \) is a vector of moment functions and \( x_g'\beta + \varepsilon_g \) is the group-specific effect. As in this paper, the authors were interested in estimating the effect of group-level covariates (coefficient \( \beta \)) without assuming that \( \varepsilon_g \) is independent (or mean-independent) of \( x_g \) but assuming instead that there exists an instrument \( w_g \) satisfying \( E[w_g \varepsilon_g] = 0 \). Importantly, however, they assumed that \( \varphi(\cdot, \cdot) \) is a vector of smooth functions, so that their results do not apply immediately to our model.

In addition, Hahn and Meinecke (2005) required that \( N_G/G > c \) for some \( c > 0 \) uniformly over all \( G \) to prove that their estimator is asymptotically zero-mean normal. In contrast, as emphasized above, we only require that \( G^{2/3}(\log N_G)/N_G \to 0 \) as \( G \to \infty \), with the improvement coming from a better control of the residuals in the Bahadur representation.

Achieving identification when the number of observations per group remains small as the number of groups gets large and, under certain conditions, allowing \( \alpha_g(\cdot) = \alpha_g(\cdot) \) to depend on \( i \).

\(^8\)To clarify the difference between the growth condition in our paper, which is \( G^{2/3}(\log N_G)/N_G \to 0 \), and the growth condition, for example, in Kato, Galvao, and Montes-Rojas (2012), which is \( G^2(\log G)^3/N_G \to 0 \), assume, for simplicity, that \( d_s = 1, d_s = 2 \), and \( x_g \) and the second component of \( z_{ig} \) are constants, that is, \( x_g = 1 \) and \( z_{ig} = (z_{ig}, 1)' \). Then our model (2)-(3) reduces to \( Q_{y_{ig}|z_{ig},e_g,\alpha_g}(u) = z_{ig}(\beta(u) + \varepsilon_g(u)) + \alpha_g(u) \), which is similar to the model (4) studied in Kato, Galvao, and Montes-Rojas (2012) with the exception that we allow for additional group-specific random shifter \( e_g(u) \). When \( e_g(u) \) is present, our estimator \( \hat{\beta}(u) \) of \( \beta(u) \) satisfies \( G^{1/2}(\hat{\beta}(u) - \beta(u)) \Rightarrow N(0, V_1) \) for some non-vanishing variance \( V_1 \); see Section 5. When \( e_g(u) \) is set to zero, however, \( V_1 \) vanishes, making the limiting distribution degenerate and leading to faster convergence rate of the estimator \( \hat{\beta}(u) \). In fact, when \( V_1 \) vanishes, one obtains \( G^{1/2}(\hat{\beta}(u) - \beta(u)) \Rightarrow N(0, V_2) \) for some non-vanishing variance \( V_2 \). An additional \( N_G^{1/2} \) factor in turn appears in the residual terms of the Bahadur representation of the estimator \( \hat{\beta}(u) \), which eventually lead to stronger requirements on the growth of the number of observations per group \( N_G \) relative to the number of groups, explaining the difference between the growth condition in Kato, Galvao, and Montes-Rojas (2012) and our growth condition.
3. Estimator

In this section we develop our estimator, which we refer as grouped IV quantile regression. Our main emphasis is to derive a computationally simple, yet consistent, estimator. The estimator consists of the following two stages.

Stage 1: For each group \( g \) and each quantile index \( u \) from the set \( \mathcal{U} \) of indices of interest, estimate \( u \)th quantile regression of \( y_{ig} \) on \( z_{ig} \) using the data \( \{(y_{ig}, z_{ig}) : i = 1, \ldots, N_g\} \) by the classical quantile regression estimator of Koenker and Bassett (1978):

\[
\hat{\alpha}_g(u) = \arg \min_{a \in \mathbb{R}^{d_g}} \sum_{i=1}^{N_g} \rho_u(y_{ig} - z_{ig}'a),
\]

where \( \rho_u(x) = (u - 1\{x < 0\})x \) for \( x \in \mathbb{R} \). Denote \( \hat{\alpha}_g(u) = (\hat{\alpha}_{g,1}(u), \ldots, \hat{\alpha}_{g,d_g})' \).

Stage 2: Estimate a 2SLS regression of \( \hat{\alpha}_{g,1}(u) \) on \( x_g \) using \( w_g \) as an instrument to get an estimator \( \hat{\beta}(u) \) of \( \beta(u) \), that is,

\[
\hat{\beta}(u) = (X'P_WX)^{-1}X'P_W\hat{A}(u)
\]

where \( X = (x_1, \ldots, x_G)' \), \( W = (w_1, \ldots, w_G)' \), \( \hat{A}(u) = (\hat{\alpha}_{1,1}(u), \ldots, \hat{\alpha}_{G,1}(u))' \), and \( P_W = W(W'W)^{-1}W' \).

Intuitively, as the number of observations per group increases, \( \hat{\alpha}_{g,1} - \alpha_{g,1} \) shrinks to zero uniformly over \( g = 1, \ldots, G \), and we obtain a classical instrumental variables problem. The theory presented below provides a mild condition on the growth of the number of observations per group that is sufficient to achieve consistency and asymptotic zero-mean normality of \( \hat{\beta}(u) \).

Several special cases of our estimator are worth noting. First, when the model is given by equation (1), the steps of our estimator consist of (i) group-by-group quantile regression of \( y_{ig} \) on \( z_{ig} \) and on a constant, saving the estimated coefficient \( \hat{\alpha}_{g,1}(u) \) corresponding to the constant, \( \alpha_{g,1}(u) = x_g'\beta(u) + \varepsilon_g(u) \), in each group; and (ii) regressing those saved coefficients \( \hat{\alpha}_{g,1}(u) \) on \( x_g \) via 2SLS using \( w_g \) as instruments. Second, if \( z_{ig} \) contains only a constant, the first stage simplifies to selecting the \( u \)th quantile of the outcome variable \( y_{ig} \) within each group. Third, if \( x_g \) is exogenous, that is, \( E[x_g\varepsilon_g(u)] = 0 \), OLS of \( \hat{\alpha}_{g,1}(u) \) on \( x_g \) may be used rather than 2SLS in the second stage. In this latter case, the grouped quantile estimation approach provides the advantage of handling group-level unobservables (or, alternatively, left-hand-side measurement error), which would bias the traditional Koenker and Bassett (1978) estimator. When \( z_{ig} \) only includes a constant and \( x_g \) is

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9The use of a 2SLS regression on the second stage of our estimator is dictated by our assumption that \( \varepsilon_g(u) \) is (mean)-uncorrelated with \( w_g \): \( E[w_g\varepsilon_g(u)] = 0 \). If, instead, we assumed that \( \varepsilon_g(u) \) is median-uncorrelated with \( w_g \), a concept developed in Komarova, Severini, and Tamer (2012), the second stage of our estimator would be an IV quantile regression developed in Chernozhukov and Hansen (2006). In this case, our method would be a quantile-after-quantile estimator.
exogenous, the grouped IV quantile regression estimator $\hat{\beta}(u)$ simplifies to the minimum distance estimator described in Chamberlain (1994) (see also Angrist, Chernozhukov, and Fernandez-Val 2006).

This estimator has several computational benefits relative to alternative methods. First, note that when the model is given by equation (1), another approach to perform the first stage of our estimator would be to denote $\alpha_{g,1}(u) = x_g^\prime \gamma(u) + \varepsilon_g(u)$ and estimate parameters $\gamma(u)$ and $\{\alpha_{g,1}(u), g = 1, \ldots, G\}$ jointly from the pooled dataset as in Kato, Galvao, and Montes-Rojas (2012). This would provide an efficiency gain given that in this case, individual-level effects $\gamma(u)$ are group-independent. Although the method we use is less efficient, it is computationally much less demanding since only few parameters are estimated in each regression, which can greatly reduce computation times in large datasets with many fixed effects.\(^\text{10}\) Second, even if no group-level unobservables exist (consider model (1) with $\varepsilon_g(u) = 0$ for all $g = 1, \ldots, G$), the grouped estimation approach can be considerably faster than the traditional Koenker and Bassett (1978) estimator (though both estimators will be consistent). This computational advantage occurs when the dimension of $x_g$ is large: standard quantile regression estimates $\beta(u)$ in a single, nonlinear step, whereas the grouped quantile approach estimates $\beta(u)$ in a linear second stage.\(^\text{11}\)

Monte Carlo simulations in Section A of the Supplemental Appendix highlight the performance of our estimator for $\beta(u)$ in (1) relative to the traditional Koenker and Bassett (1978) estimator (which ignores endogeneity of $x_g$ as well as the existence of $\varepsilon_g(u)$). Even when $N_G$ and $G$ are both small, the grouped IV quantile approach has lower bias than traditional quantile regression when $x_g$ is endogenous. When $x_g$ is exogenous but group-level unobservables $\varepsilon_g(u)$ are still present, the bias of the grouped quantile approach shrinks quickly to zero as $N_G$ grows but the bias of traditional quantile estimator does not. When no group-level unobservables are present, and hence both the grouped estimation approach and traditional quantile regression should be consistent, our estimator still has small bias, although traditional quantile regression outperforms our method in this case.

As we demonstrate below, standard errors for our estimator $\hat{\beta}(u)$ may be obtained using standard heteroskedasticity-robust (Section 5) or clustering (Section E of the Supplemental Appendix) approaches for 2SLS or OLS as if there were no first stage. Note that clustering in the second stage refers to dependence across groups, not within groups. For example, if a group is a state-by-year combination, the researcher may wish to use standard errors which are clustered at the state level.

\(^{10}\)In Monte Carlo experiments in Section A of the Supplemental Appendix, we find that jointly estimating group-level effects can take over 150 times as long as the grouped quantile approach when $G = 200$. With $G > 200$, the computation time ratio drastically increases further, with standard optimization packages often failing to converge appropriately.

\(^{11}\)One such example would be a case where a group is a state-by-year combination, and $x_g$ contains many state and year fixed effects, in addition to the treatment of interest, as in Example 2 of Section 4.
4. Examples of Grouped IV Quantile Regression

To help the reader envision applications of our estimator, in this section, we provide several motivating examples of settings for which our estimator may be useful. Each of the following examples involves estimation of a treatment effect that varies at the group level with all endogeneity concerns also existing only at the group level.\(^{12}\)

**Example 1: Peer Effects of School Integration.** Angrist and Lang (2004) studied how suburban student test scores were affected by the reassignment of participating urban students to suburban schools through Boston’s Metco program. Before estimating their main instrumental variables model, the authors tested for a relationship between the presence of urban students in the classroom and the second decile of student test scores by estimating

\[
Q_{y_{gjt}|x_{gjt}}(0.2) = \alpha_g(0.2) + \beta_j(0.2) + \gamma_t(0.2) + \delta(0.2)m_{gjt} + \lambda(0.2)s_{gjt} + \xi_{gjt}(0.2) \tag{5}
\]

where the left-hand side represents the second decile of student test scores within a group, \(x_{gjt} = (m_{gjt}, s_{gjt}, \xi_{gjt}, \alpha_g, \beta_j, \gamma_t)\), and a group is a grade \(g\) \(\times\) school \(j\) \(\times\) year \(t\) cell. The variables \(s_{gjt}\) and \(m_{gjt}\) denote the class size and the fraction of Metco students within each \(g \times j \times t\) cell, and \(\alpha_g, \beta_j, \text{ and } \gamma_t\) represent grade, school, and year effects, respectively. The unobserved component \(\xi_{gjt}\) is analogous to \(\varepsilon_g(0.2)\) in our model (1).

Angrist and Lang (2004) estimated equation (5) by OLS, which is equivalent to the non-IV application of our estimator with no micro-level covariates. Similar to their OLS results on average test scores, they found that classrooms with higher proportions of urban students have lower second decile test scores. Once they instrumented for a classroom’s level of Metco exposure, the authors found no effect on average test scores. However, by not estimating model (5) by 2SLS, they were unable to address the causal distributional effects of Metco exposure.

In estimating (5), Angrist and Lang (2004) used heteroskedasticity-robust standard errors, which we demonstrate in Section 5 is valid. The extension in Section E of the Supplemental Appendix implies that the authors could have instead allowed for clustering across groups in computing standard errors (for example, clustering at the school level given a sufficient number of schools).

**Example 2: Occupational Licensing and Quality.** Larsen (2014) applied the estimator developed in this paper to study the effects of occupational licensing laws on the distribution of quality within the teaching profession. Similar to Example 1, the explanatory variable of interest is treated as exogenous and the researcher is concerned that there may be unobserved group-level disturbances. In this application, a group is a state-year combination \((s, t)\), and micro-level data consists

\(^{12}\)This is in contrast to settings where the endogeneity exists at the individual level, i.e. when the individual unobserved heterogeneity is correlated with treatment. Such situations require a different approach than the one presented here, e.g. Chernozhukov and Hansen (2005), Abadie, Angrist, and Imbens (2002), or the other approaches referenced in Section 1.
of teachers within a particular state in a given year. The conditional $u$th quantile of teacher quality among teachers who began teaching in state $s$ in year $t$ is modeled as

$$Q_{qist}|Law_{st},\sigma_{st}(u) = \gamma_s(u) + \lambda_t(u) + Law'\delta(u) + \varepsilon_{st}(u)$$

(6)

where $Law_{st}$ is a vector of dummies capturing the type of certification tests required for licensure in state $s$ and year $t$, $\gamma_s(u)$ and $\lambda_t(u)$ are state and year effects, and $\varepsilon_{st}(u)$ represents group-level unobservables.

Because no micro-level covariates are included, the first stage of the grouped quantile estimator is obtained by simply selecting the $u$th quantile of quality in a given state-year cell. The second stage is obtained via OLS. Larsen (2014) found that, for first-year teachers, occupational licensing laws requiring teachers to pass a subject test lead to a small but significant decrease in the upper tail of quality, suggestive that these laws may drive some highly qualified candidates from the occupation.

In this setting, if micro-level covariates, $z_{ist}$, were included in the first stage of estimation, the researcher could also estimate interaction effects of the group-level treatment and a micro-level covariate, such as the percent of minority students at the teacher’s school. This would be done by (i) estimating quantile regression of $q_{ist}$ on a vector $z_{ist}$ (which would include a measure of the percent minority students) separately for each $(s, t)$ group and saving each group-level estimate for the coefficient corresponding to the percent minority variable; and (ii) estimating a linear regression of these coefficients on $Law_{st}$ and on the state and year fixed effects.

This example highlights another useful feature of grouped IV quantile regression. Including many variables in a standard quantile regression can drastically increase the computational time (see Koenker (2004), Lamarche (2010), Galvao and Wang (2013), and Galvao (2011) for further discussion) and, in our experience, can often lead standard optimization packages to fail to converge.

The grouped quantile approach, on the other hand, can handle large numbers of variables easily when these variables happen to be constant within group, as in the case of state and year fixed effects in this example, because the coefficients corresponding to these variables can be estimated in the second-stage linear model, greatly reducing the number of parameters to be estimated in the nonlinear first stage and hence reducing the computational burden significantly.\footnote{Note also that this specific computational advantage of the grouped quantile regression estimator exists even in cases where both standard quantile regression and the grouped approach are valid (i.e. when no group-level unobservables are present). Larsen (2014) found that estimating (6) using the grouped approach was significantly faster than estimating (6) in a single standard quantile regression. See also Section A of the Supplemental Appendix for further discussion of computational advantages of the grouped quantile approach.}

**Example 3: Distributional Effects of Suburbanization.** Palmer (2011) applied the grouped quantile estimator to study the effects of suburbanization on resident outcomes. This application illustrates the use of our estimator in an IV setting. In this application, a group is a metropolitan statistical area (MSA), and individuals are MSA residents. As an identification strategy, Palmer...
Baum-Snow (2007) instrumented for actual constructed highways with planned highways and estimated that each highway ray emanating out of a city caused an 18% decline in central-city population.
Backus (2014) reported standard errors clustered at the market level, which we demonstrate are valid in Section E of the Supplemental Appendix.

5. Asymptotic Theory

In this section, we formulate our assumptions and present our main theoretical results.

5.1. Assumptions. Let \( c_M, c_f, C_M, C_f, C_L \) be strictly positive constants whose values are fixed throughout the paper. Recall that \( N_G = \min_{g=1,...,G} N_g \). We start with specifying our main assumptions.

\textbf{A1} (Design). (i) Observations are independent across groups. (ii) For all \( g = 1, \ldots, G \), the pairs \((z_{ig}, y_{ig})\) are i.i.d. across \( i = 1, \ldots, N_g \) conditional on \((x_g, \alpha_g)\).

\textbf{A2} (Instruments). (i) For all \( u \in \mathcal{U} \) and \( g = 1, \ldots, G \), \( E[w_g z_g(u)] = 0 \). (ii) As \( G \to \infty \), \( G^{-1} \sum_{g=1}^{G} E[w_g w'_g] \to Q_{xx} \) and \( G^{-1} \sum_{g=1}^{G} E[w_g w'_g] \to Q_{ww} \) where \( Q_{xx} \) and \( Q_{ww} \) are matrices with singular values bounded in absolute value from below by \( c_M \) and from above by \( C_M \). (iii) For all \( g = 1, \ldots, G \) and \( i = 1, \ldots, N_g \), \( y_{ig} \) is independent of \( w_g \) conditional on \((z_{ig}, x_g, \alpha_g)\). (iv) For all \( g = 1, \ldots, G \), \( E[\|w_g\|^4] \leq C_M \).

\textbf{A3} (Growth Condition). As \( G \to \infty \), we have \( G^{2/3}(\log N_G)/N_G \to 0 \).

Assumption 1(i) holds, for example, if groups are sampled randomly from some population of groups. This assumption precludes the possibility of clustering across groups (for example, if a group is a state-by-year combination, there may be clustering on the state level). Since clustered standard errors are important in practice, however, we derive an extension of our results relaxing the independence across groups condition and allowing for clustering in Section E of the Supplemental Appendix. Assumption 1(ii) allows for inter-dependence (clustering) within groups but imposes the restriction that the inter-dependence between observations within the group \( g \) is fully controlled for by the group-level covariates \( x_g \) and the group-specific effect \( \alpha_g \). Assumption 2 is our main identification condition. Note that Assumption 2 allows for internal instruments. In particular, if \( w_g = N_g^{-1/2} \sum_{i=1}^{N_g} z_{ig,k} \) for some \( k \), then Assumption 2(iii) automatically follows from Assumption 1(ii). Assumption 3 implies that the number of observations per group grows sufficiently fast as \( G \) gets large, and gives a particular growth rate that suffices for our results. Note that our growth condition is rather weak and, most importantly, allows for the case when the number of observations per group is small relative to the number of groups.\(^{15}\)

Next, we specify technical conditions that are required for our analysis. Let \( E_g[\cdot] = E[\cdot|x_g, \alpha_g] \), and let \( f_g(\cdot) \) denote the conditional density function of \( y_{1g} \) given \((z_{1g}, x_g, \alpha_g)\) (dependence of \( f_g(\cdot) \)

\(^{15}\)Using the more common notation of panel data models, where \( N \) is the number of individuals (groups) and \( T \) is the number of time periods (individuals within the group), Assumption 3 would take the form: \( N^{2/3}(\log T)/T \to 0 \) as \( N \to \infty \).
on \((z_g, x_g, \alpha_g)\) is not shown explicitly for brevity of notation). Also denote \(B_g(u, c) = (z_{1g}' \alpha_g(u) - c, z_{1g}' \alpha_g(u) + c)\) for \(c > 0\). We will assume the following regularity conditions:

\[\text{A4 (Covariates).} \ (i) \text{ For all } g = 1, \ldots, G \text{ and } i = 1, \ldots, N_g, \text{ random vectors } z_{ig} \text{ and } x_g \text{ satisfy } \|z_{ig}\| \leq C_M \text{ and } \|x_g\| \leq C_M. \ (ii) \text{ For all } g = 1, \ldots, G, \text{ all eigenvalues of } E_g[z_{1g}' z_{1g}'] \text{ are bounded from below by } c_M.\]

\[\text{A5 (Coefficients).} \ \text{For all } u_1, u_2 \in U \text{ and } g = 1, \ldots, G, \|\alpha_g(u_2) - \alpha_g(u_1)\| \leq C_L |u_2 - u_1|.\]

\[\text{A6 (Noise).} \ (i) \text{ For all } g = 1, \ldots, G, \ E[\sup_{u \in U} |\varepsilon_g(u)|^{4+c_M}] \leq C_M. \ (ii) \text{ For some (matrix-valued) function } J : U \times U \to \mathbb{R}^{d_w \times d_w}, \ G^{-1} \sum_{g=1}^G E[\varepsilon_g(u_1)\varepsilon_g(u_2)w_g w_g'] \to J(u_1, u_2) \text{ uniformly over } u_1, u_2 \in U. \ (iii) \text{ For all } u_1, u_2 \in U, \ |\varepsilon_g(u_2) - \varepsilon_g(u_1)| \leq C_L |u_2 - u_1|.\]

\[\text{A7 (Density).} \ (i) \text{ For all } u \in U \text{ and } g = 1, \ldots, G, \text{ the conditional density function } f_g(\cdot) \text{ is continuously differentiable on } B_g(u, c_f) \text{ with the derivative } f_g'(\cdot) \text{ satisfying } |f_g'(y)| \leq C_f \text{ for all } y \in B_g(u, c_f) \text{ and } |f_g'(z_{1g}' \alpha_g(y))| \geq c_f. \ (ii) \text{ For all } u \in U \text{ and } g = 1, \ldots, G, \ f_g(y) \leq C_f \text{ for all } y \in B_g(u, c_f) \text{ and } f_g(z_{1g}' \alpha_g(y)) \geq c_f.\]

\[\text{A8 (Quantile indices).} \ \text{The set of quantile indices } U \text{ is a compact set included in } (0, 1).\]

Assumption 4(i) requires that both individual and group-level observable covariates \(z_{ig}\) and \(x_g\) are bounded. Assumption 4(ii) is a familiar identification condition in regression analysis. Assumption 5 is a mild continuity condition. Assumption 6(i) requires sufficient integrability of the noise \(\varepsilon_g(u)\), which is a mild regularity condition. In fact, under Assumption 6(iii), which is also a mild continuity condition, Assumption 6(i) is satisfied as long as \(E[|\varepsilon_g(u)|^{4+c_M}] \leq C_M\) for some \(u \in U\) (with a possibly different constant \(C_M\)). Assumption 6(ii) is trivially satisfied if the pairs \((w_g, \varepsilon_g)\) are i.i.d. across \(g\). Assumption 7 is a mild regularity condition that is typically imposed in the quantile regression analysis. Finally, Assumption 8 excludes quantile indices that are too close to either 0 or 1 (when the quantile index \(u\) is close to either 0 or 1, one obtains a so-called extremal quantile model, which requires a rather different analysis; see, for example, Chernozhukov (2005) and Chernozhukov and Fernández-Val (2011)).

5.2. Results. We now present our main results. In Theorem 1, we derive the asymptotic distribution of our estimator. In Theorem 2, we show how to estimate the asymptotic covariance of our estimator. For brevity of the paper, further results are relegated to Sections C-E of the Supplemental Appendix. In particular, in Section C, we describe a multiplier bootstrap method for constructing uniform over \(u \in U\) confidence intervals for \(\beta(u)\) and prove its validity relying on results from Chernozhukov, Chetverikov, and Kato (2013). In Section D, we present an approach for uniform inference on \(\{\alpha_{g,1}(u), g = 1, \ldots, G\}\) in the model (2)–(3) by constructing the confidence bands \([\hat{\alpha}_{g,1}^l(u), \hat{\alpha}_{g,1}^r(u)]\) that cover the true group-specific effects \(\alpha_{g,1}(u)\) for all \(g = 1, \ldots, G\) simultaneously with probability approximately \(1 - \alpha\). In Section E, we consider clustered standard errors.
The first theorem derives the asymptotic distribution of our estimator.

**Theorem 1 (Asymptotic Distribution).** Let Assumptions 1-8 hold. Then

\[
\sqrt{G}(\hat{\beta}(\cdot) - \beta(\cdot)) \Rightarrow \mathcal{G}(\cdot), \quad \text{in } \ell^\infty(U)
\]

where \(\mathcal{G}(\cdot)\) is a zero-mean Gaussian process with uniformly continuous sample paths and covariance function \(C(u_1, u_2) = SJ(u_1, u_2)S'\) where \(S = (Q_{xx}Q_{ww}^{-1}Q_{ww}')^{-1}Q_{xx}Q_{ww}^{-1}\), \(Q_{xx}\) and \(Q_{ww}\) appear in Assumption 2, and \(J(u_1, u_2)\) in Assumption 6.

**Remark 1.** (i) This is our main convergence result that establishes the asymptotic behavior of our estimator. Note that we provide the joint asymptotic distribution of our estimator for all \(u \in U\). In addition, Theorem 1 implies that for any \(u \in U\),

\[
\sqrt{G}(\hat{\beta}(u) - \beta(u)) \Rightarrow N(0, V)
\]

where \(V = SJ(u, u)S'\), which is the asymptotic distribution of the classical 2SLS estimator.

(ii) In order to establish the joint asymptotic distribution of our estimator for all \(u \in U\), we have to deal with \(G\) independent quantile processes \(\{\hat{\alpha}_{g,1}(u) - \alpha_{g,1}(u), u \in U\}\). Since \(G \to \infty\), classical functional central limit theorems do not apply. Therefore, we employ a non-standard but powerful Bracketing by Gaussian Hypotheses Theorem; see Theorem 2.11.11 in Van der Vaart and Wellner (1996).

(iii) Since quantile regression estimators are biased in finite samples, our estimator \(\hat{\alpha}_{g,1}(u)\) of \(\alpha_{g,1}(u)\) does not necessarily satisfy \(E[(\hat{\alpha}_{g,1}(u) - \alpha_{g,1}(u))w_g] = 0\). For this reason, our estimator \(\hat{\beta}(u)\) of \(\beta(u)\) is not consistent if \(N_g\) is bounded from above uniformly over \(g = 1, \ldots, G\) and \(G \geq 2\). We note, however, that quantile estimators are asymptotically unbiased, and so we use the Bahadur representation of quantile estimators to derive weak condition on the growth of \(N_G = \min_{1 \leq g \leq G} N_g\) relative to \(G\), so that consistent estimation of \(\beta(u)\) is indeed possible. Specifically, we prove consistency and asymptotic zero-mean normality under Assumption 3 that states that \(G^{2/3}(\log N_G)/N_G \to 0\) as \(G \to \infty\), which is a mild growth condition. In principle, it is also possible to consider bias correction of the quantile regression estimators. This would further relax the growth condition on \(N_G\) relative to \(G\) at the expense of stronger side assumptions and more complicated estimation procedures.

(iv) The requirement that \(N_G \to \infty\) as \(G \to \infty\) is in contrast with the classical results of Hausman and Taylor (1981) on estimation of panel data mean regression model. The main difference is that the fixed effect estimator in the panel data mean regression model is unbiased even in finite samples leading to consistent estimators of the effects of group-level covariates with the number of observations per group being fixed.

The result in Theorem 1 derives asymptotic behavior of our estimator. In order to perform inference, we also need an estimator of the asymptotic covariance function. We suggest using an
estimator $\hat{C}(\cdot, \cdot)$ that is defined for all $u_1, u_2 \in U$ as

$$
\hat{C}(u_1, u_2) = \hat{S}\hat{J}(u_1, u_2)\hat{S}',
$$

where

$$
\hat{J}(u_1, u_2) = \frac{1}{G} \sum_{g=1}^{G} \left( (\hat{\alpha}_{g,1}(u_1) - x'_g \hat{\beta}(u_1)) (\hat{\alpha}_{g,1}(u_2) - x'_g \hat{\beta}(u_2)) w_g w'_g \right),
$$

$$
\hat{S} = (\hat{Q}_{ww}^{-1} \hat{Q}_{ww}^{-1})^{-1} \hat{Q}_{ww}^{-1} \hat{Q}_{ww}, \quad \hat{Q}_{ww} = X'W/G, \quad \text{and} \quad \hat{Q}_{ww} = W'W/G. \quad \text{In the theorem below, we show that } \hat{C}(u_1, u_2) \text{ is consistent for } C(u_1, u_2) \text{ uniformly over } u_1, u_2 \in U.
$$

**Theorem 2** (Estimating $C$). Let Assumptions 1-8 hold. Then $\|\hat{C}(u_1, u_2) - C(u_1, u_2)\| = o_p(1)$ uniformly over $u_1, u_2 \in U$.

**Remark 2.** Theorems 1 and 2 can be used for hypothesis testing concerning $\beta(u)$ for a given quantile index $u \in U$. In particular, we have that

$$
\sqrt{G} \hat{C}(u, u)^{-1/2} (\hat{\beta}(u) - \beta(u)) \Rightarrow N(0, 1). \quad (8)
$$

Importantly for applied researchers, Theorems 1 and 2 demonstrate that heteroskedasticity-robust standard errors for our estimator can be obtained by the traditional White (1980) standard errors where we proceed as if $\hat{\alpha}_{g,1}(u)$ were equal to $\alpha_{g,1}(u)$, that is, as if there were no first-stage estimation error. Traditional approaches to clustered standard errors are also valid in this setting; extending Theorems 1 and 2 to apply to settings with clustering is straightforward, but requires additional notation, and therefore we present these results in Section E of the Supplemental Appendix. As highlighted above, clustering in this context refers to clustering across groups. For example, if a group is state-by-year cell, the researcher could cluster at the state level.

6. **The effect of Chinese import competition on the local wage distribution**

6.1. **Background on wage inequality.** Over the past 40 years, wage inequality within the United States has increased drastically.\(^{16}\) Economists have engaged in heated debates about the primary causes of the rising wage inequality—such as globalization, skill-biased technological change, or the declining real minimum wage—and how the importance of these factors has changed over the years.\(^{17}\) Recent work in Autor, Dorn, and Hanson (2013) (hereafter ADH) focused on import competition and its effects on wages and employment in US local labor markets. ADH studied the period 1990–2007, when the share of US spending on Chinese imports increased dramatically from 0.6% to 4.6%. For identification, the authors used spatial variation in manufacturing concentration,

\(^{16}\) Autor, Katz, and Kearney (2008) documented that, from 1963 to 2005, the change in wages for the 90\textsuperscript{th} percentile earner was 55% higher than for the 10\textsuperscript{th} percentile earner.

\(^{17}\) See, for example, Leamer (1994), Krugman (2000), Feenstra and Hanson (1999), Katz and Autor (1999), as well as many other papers cited in Feenstra (2010) or in Haskel, Lawrence, Leamer, and Slaughter (2012).
showing that localized US labor markets which specialize in manufacturing were more affected by increased import competition from China. The authors found that those markets which were more exposed to increased import competition in turn had lower employment and lower wages.

We contribute to this debate by studying the effect of increased trade, in the form of increased import competition, on the distribution of local wages (rather than on the average local wages as in ADH). Given that we exploit the same variation in import competition as in ADH, we first describe the ADH framework below and then present our results.

6.2. Framework of Autor, Dorn, and Hanson (2013). To study the effect of Chinese import competition on average domestic wages, ADH used Census microdata to calculate the mean wage within each Commuting Zone (CZ) in the United States.\textsuperscript{18} The authors then estimated the following regression:

\[
\Delta \ln w_g = \beta_1 \Delta IPW^U_g + X'_g \beta_2 + \varepsilon_g
\]  

(9)

where $\Delta \ln w_g$ is the change in average individual log weekly wage in a given CZ in a given decade, $X_g$ are characteristics of the CZ and decade, including indicator variables for each decade. Note that we have changed the notation slightly from that in ADH in order to improve clarity for our application—a “group” $g$ in this setting is a given CZ in a given decade. The variable of interest is $\Delta IPW^U_g$, which represents the decadal change in Chinese imports per US worker for the CZ and decade corresponding to group $g$.\textsuperscript{19}

To address endogeneity concerns (i.e. that imports from China may be correlated with unobserved labor demand shocks), the authors instrumented for imports per last-period worker using $\Delta IPW^O_g$, a measure of import exposure that replaces the change in Chinese imports to the US in a given industry with the change in Chinese imports to other similarly developed nations for the same industry and uses one decade lagged employment shares in calculating the weighted average. Using this 2SLS approach, the authors found that a $1,000 increase in Chinese imports per worker in a CZ decreases average log weekly wage by -0.76 log points, corresponding to decrease in wages for the average CZ of 0.9% from 1990–2000 and 1.4% from 2000–2007. When estimated separately by gender, the effect was more negative for males (-0.89 log points) and less so for females (-0.61 log points).\textsuperscript{20}

\textsuperscript{18}The United States is covered exhaustively by 722 Commuting Zones (Tolbert and Sizer 1996), each roughly corresponding to a local labor market.

\textsuperscript{19}Due to data limitations, ADH proxy for the change in actual local imports per worker with the weighted average of industry-level changes in the value of Chinese imports to the US with the weights corresponding to the beginning of decade employment share of each industry in each CZ.

\textsuperscript{20}As discussed by ADH, the existence of an extensive-margin labor supply response—imports affecting whether individuals are employed—makes these results likely a lower-bound for the effect on all workers because we don’t observe wages for the unemployed population.
6.3. Distributional effects of increased import competition. We build on the ADH framework to analyze whether low-wage earners were more adversely affected than high-wage earners by Chinese import competition. To apply the grouped IV quantile regression estimator to this setting, we replace $\Delta \ln w_g$, the change in the average log weekly wage in equation (9) with $\Delta u_{g}^{\text{w}}$, the change in the $u$-quantile of log wages in the CZ and decade corresponding to group $g$. We calculate these quantiles using micro-level observations from the Census Integrated Public Use Micro Samples for 1990 and 2000 and the American Community Survey for 2006-2008, matching these observations to CZs following the strategy described in ADH.\textsuperscript{21} We instrument for $\Delta IPW_{g}^{U}$ using $\Delta IPW_{g}^{O}$ as described above. Recall that existing methods for handling endogeneity in quantile models are suited for the case where the individual-level unobserved conditional quantile itself is correlated with the treatment and would be inconsistent in this setting because the endogeneity consists of a group-level treatment being correlated with the group-level unobservable additive term.

Figures 1, 2, and 3 display the results of the grouped IV quantile regression estimator for the full sample, for females only, and for males only. Each figure displays $u$-quantile estimates for $u \in \{0.05, 0.1, ..., 0.95\}$, along with pointwise 95% confidence bands about each estimate. The figures also display the 2SLS effect found in ADH and 95% confidence intervals corresponding to their IV estimate of Chinese import penetration on the change in CZ-level average wages.

Each figure provides evidence that Chinese import competition affected the wages of low-wage earners more than high-wage earners, demonstrating how increases in trade can causally exacerbate local income inequality. For all three samples, the magnitude of the estimated causal effect of Chinese import penetration is much larger for lower quantiles of the conditional wage distribution. The point estimates suggest that the average negative effect of Chinese import penetration estimated by ADH is primarily driven by large negative effects for those in the bottom tercile, where the effect is twice as large as the average effect.\textsuperscript{22} Wages not in the bottom tercile were less affected than the average—Figure 1 shows that for most wage-earners (from the 0.35 quantile and above) the effect of Chinese import competition was one-third smaller in magnitude than the effect on the average estimated by ADH. Comparing the pattern of the coefficients across two gender subsamples in Figures 2 and 3, there is more distributional heterogeneity for females than males, a finding that additional testing shows is even more pronounced for non-college educated females.

\textsuperscript{21}The thought experiment behind the asymptotics in this application is that the estimator is consistent as the number of groups ($G = 722$ CZs \times two decades) and the number of individuals within each group ($N_G = 543$, the size of the smallest group) both grow large. We follow ADH by clustering at the state level and weighting by start-of-decade CZ population in the second stage of our estimator. To cluster, we are relying on Section E of the Supplemental Appendix, which relaxes Assumption 1 to allow for observations to be dependent across groups. We also follow the ADH individual weighting procedure in the first stage given that not all individuals can be mapped to a unique CZ.

\textsuperscript{22}A coefficient of -1.4 log points, e.g. for the lower quantiles of Figure 1, corresponds to a 2.6% decrease in wages from 2000–2007 for the average commuting zone’s change in Chinese import exposure.
For each sample, we can reject an effect size of zero for almost all quantiles below the median but cannot for all quantiles above the median.

7. Conclusion

In this paper, we present a quantile extension of Hausman and Taylor (1981), modeling the distributional effects of an endogenous group-level treatment. We develop an estimator, which we refer to as grouped IV quantile regression, and show that the estimator, as well as its standard errors, are easy to compute. We demonstrate that, in contrast to standard quantile regression, this estimator is asymptotically unbiased in the presence of the group-level shocks that are ubiquitous in applied microeconomic models. We illustrate the model and estimator with examples from labor, education, industrial organization, and urban economics. An empirical application to the setting of Autor, Dorn, and Hanson (2013) highlights the usefulness of our approach by estimating the effects of Chinese import competition on the distribution of wages—insights which would be missed by focusing on average effects alone. We believe the estimator has the potential for widespread practical use in applied microeconomics.
References


Figure 1. Effect of Chinese Import Competition on Conditional Wage Distribution: Full Sample

Notes: Figure plots grouped IV quantile regression estimates of the effect of a $1,000 increase in Chinese imports per worker on the conditional wage distribution ($\beta_1$ in equation (9) in the text when the change in average log wages for the commuting zone and decade corresponding to group $g$, $\Delta \ln w_g$, is replaced with the change in the $u$-quantile of log wages $\Delta \ln w_u^g$). The dashed horizontal line is the ADH estimate of $\beta_1$ in equation (9). 95% pointwise confidence intervals are constructed from robust standard errors clustered by state and observations are weighted by CZ population, as in ADH. Units on the vertical axis are log points.
Figure 2. Effect of Chinese Import Competition on Conditional Wage Distribution: Females Only

Notes: Figure plots grouped IV quantile regression estimates for the female-only sample of the effect of a $1,000 increase in Chinese imports per worker on the female conditional wage distribution ($\beta_1$ in equation (9) in the text when the change in average log wages for the commuting zone and decade corresponding to group $g$, $\Delta \ln w_g$, is replaced with the change in the $u$-quantile of log wages $\Delta \ln w_u$). The dashed horizontal line is the ADH estimate of $\beta_1$ in equation (9). 95% pointwise confidence intervals are constructed from robust standard errors clustered by state and observations are weighted by CZ population, as in ADH. Units on the vertical axis are log points.
**Figure 3.** Effect of Chinese Import Competition on Conditional Wage Distribution: Males Only

Notes: Figure plots grouped IV quantile regression estimates for the male-only sample of the effect of a $1,000 increase in Chinese imports per worker on the male conditional wage distribution ($\beta_1$ in equation (9) in the text when the change in average log wages for the commuting zone and decade corresponding to group $g$, $\Delta \ln w_g$, is replaced with the change in the $u$-quantile of log wages $\Delta \ln w^u_g$). The dashed horizontal line is the ADH estimate of $\beta_1$ in equation (9). 95% pointwise confidence intervals are constructed from robust standard errors clustered by state and observations are weighted by CZ population, as in ADH. Units on the vertical axis are log points.