

A New Quantile Treatment Effect Model for Studying Smoking Effect on Birth Weight During Mother's Pregnancy^{*†}

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Abstract: This paper proposes a new quantile regression model to characterize the heterogeneity for distributional effects of maternal smoking during pregnancy on infant birth weight across different sub-populations defined by the mother's age. By imposing a parametric restriction on the quantile functions of the potential outcome distributions conditional on the mother's age, we estimate the quantile treatment effects of maternal smoking during pregnancy on her baby's birth weight across different age groups of mothers. The results show strongly that the quantile effects of maternal smoking on infant birth weight are negative and substantially heterogenous across different ages.

Keywords: Birth weight; Heterogeneity; Quantile regression; Smoking; Treatment effect.

JEL classification: C12; C13; C14; C23

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1 Introduction

There is an increasing number of interests in estimating causal effect of a treatment, program or policy on economic or other outcomes, which is important in comparing different medical treatments, social programs and intervention policies. A conventional approach is to assume that the treatment variable is unconfounded after conditioning on a set of observable covariates, which leads to regression, matching or inverse probability weighting based methods, among others, for estimating the average treatment effects¹. However, although the average treatment effects are interesting and critical measures in determining a treatment or policy's effect, they might not be sufficient to fully capture the impact of the treatment or policy except under very restrictive conditions. In particular, when the treatment effect is heterogeneous, the average treatment effects can not provide enough information about the effect of the treatment or policy on other points in the outcome distribution which the researcher may be more interested in. Such distributional aspects beyond simple averages can be of fundamental interest and arise naturally in many areas of empirical economic research². To characterize the heterogeneous effects along with the outcome distribution, quantile treatment effect (QTE), originally introduced by Doksum (1974) and Lehmann (1975), provides an effective and intuitive tool to document such heterogeneity. The importance of QTE has motivated researchers to consider its identification and estimation under common identifying assumptions such as selection on observables (see Assumption 2.1(i) later) as in Firpo (2007) and Donald and Hsu (2014). Recently, Tang (2019) provided a comprehensive survey on recent developments in modeling methods for the quantile treatment effect.

It has been explicitly recognized in program evaluation literature that the effect of a treatment can be heterogeneous across different individuals (Heckman and Robb (1985), Heckman et al. (1997)). Therefore, except for the treatment effect for the entire population, it may also be of interest to estimate the treatment effect in various sub-populations defined by some covariates of interest. Some of this interest in treatment effect heterogeneity has been extensively considered in the recent literature. For example, to characterize the heterogeneous effect across different sub-populations, Abrevaya et al. (2015) and Lee, Okui and Whang (2017) considered the partially conditional average treatment effect.

In this paper, we propose a parametric quantile treatment effect model to characterize

¹For example, Heckman et al. (1998), Hahn (1998), Hirano, Imbens and Ridder (2003), Abrevaya, Hsu and Lieli (2015), Abadie and Imbens (2006, 2016), and the references therein.

²For example, in trying to understand the effect of a government-subsidized training program, the effect of the program on the lower tail of the savings distribution is of central interest for welfare analysis; see LaLonde (1995) and Abadie et al. (2002) for more details. Similarly, when evaluating effects of unionization on wage inequality, distributional effect is also of central interest for welfare analysis; see Freeman (1980) and Card (1996) for more discussions.

the heterogeneously distributional effect of treatment variable on outcome of interest across different sub-populations defined by the covariates of interest. More specifically, a polynomial restriction is proposed to specify the quantile functions of the potential outcome distributions conditional on the covariates of interest. The rationale for using a polynomial model is that the notation is simple and the estimator is computationally convenient and the resulting estimator simplifies to a linear quantile regression as in Koenker and Bassett (1978). Different from Koenker and Bassett (1978), there are missing data in the potential outcomes. Hence, the unknown parameters in the conditional quantile functions can not be estimated directly by the quantile regression estimator as in Koenker and Bassett (1978). To this end, we provide conditions (see Assumption 2.1 later) under which the conditional quantiles of the potential outcome distributions can be recovered from the distribution of the observable data.

In our empirical study, the proposed model is applied to reexamine the quantile treatment effect of a first-time mother's smoking during pregnancy on the birth weight of her baby conditional on the mother's age. Some previous work has been investigated the effect of maternal smoking during pregnancy on infant birth weight; see for example, Abrevaya (2006), Abrevaya and Dahl (2008), Abrevaya et al. (2015), Lee et al. (2017), and the reference therein. In particular, Abrevaya et al. (2015) and Lee et al. (2017) investigated the average effect of mother's smoking during pregnancy on infant birth weight across different age groups of mothers. However, Cai, Fang, Lin and Tang (2019) argued that the heterogeneity of the effect of mother's smoking on infant birth weight exists so that it might not be enough to consider the average treatment effect. Instead, they explored the nonparametric quantile effects of maternal smoking during pregnancy on her baby's birth weight across different age groups of mothers. In this paper, we apply the proposed parametric model to re-investigate the quantile treatment effect of mother's smoking during pregnancy on infant birth weight across different sub-populations defined by the mother's age. It is worth stressing that our goal is not to provide another estimate of the quantile treatment effect of mother's smoking on the birth weight of her child per se, but rather to illustrate how the proposed parametric model can be easily used to explore the heterogeneity of the quantile treatment effect across different sub-populations defined by the mother's age.

The structure of the paper is as follows. In the next section, we introduce the model framework and the estimation procedure. Section 3 presents an empirical application and Section 4 concludes.

2 Econometric Model

2.1 Framework

The focus of our interest is to estimate the causal effect of a binary treatment, represented by the binary variable D , on some scalar outcome variable, denoted by Y . More specifically, $D = 1$ denotes that some individual in a large sample receives the active treatment, while $D = 0$ denotes the same individual receives the control treatment. Following Rubin (1974) and Imbens and Rubin (2015), treatment effects are defined in terms of potential outcomes. Specifically, $Y(1)$ denotes the potential outcome for the individual under treatment and $Y(0)$ stands for the potential outcome under control. For each individual, the treatment variable D and the outcome Y are observed, which has the following relationship with the potential outcomes $Y(1)$ and $Y(0)$ as $Y = D \cdot Y(1) + (1 - D)Y(0)$. In addition, a vector of pretreatment variables or covariates, denoted by X are observed too, which are predetermined relative to the treatment assignment and oftentimes contain characteristics of the units measured before the treatment assignment is known.

Recently, the quantile treatment effect has been popularly studied and extensively applied in the economics literature and real applications³. Specifically, for $j = 0$ and 1, let $F_{Y(j)}(y)$ be the distribution function of the potential outcome $Y(j)$. Then, for a given quantile level $\tau \in (0, 1)$, the QTE is defined as $F_{Y(1)}^{-1}(\tau) - F_{Y(0)}^{-1}(\tau)$, where for $j = 0$ and 1, $F_{Y(j)}^{-1}(\tau)$ is the τ th quantile function of the distribution $F_{Y(j)}(y)$, given by $F_{Y(j)}^{-1}(\tau) = \inf\{y \in \mathbb{R} : F_{Y(j)}(y) \geq \tau\}$. The quantile treatment effect can be used to characterize the heterogeneously distributional effect of a treatment or policy on outcome of interest. However, as stated in the introduction, in many applications, except for the population quantile treatment effect, researchers may also be interested in estimating the heterogeneously distributional effect of a treatment or policy on outcome of interest across different sub-populations defined by certain covariates of interest. To this end, the focus in this paper is on the quantile treatment effect conditional on a subset of the pretreatment variables, termed as the partially conditional quantile treatment effect. Specifically, let $W = (W_1, \dots, W_k) \in \mathbb{R}^k$ be a sub-vector of $X \in \mathbb{R}^p$, where $1 \leq k < p$. Similarly, let $F_{Y(j)|W}(y|w)$ denote the distribution function of $Y(j)$ conditional on $W = w$ for $j = 0$ and 1. Then, the quantile regression model for treatment effect is defined as

$$\delta_\tau(w) = Q_{1,\tau}(w) - Q_{0,\tau}(w),$$

where $Q_{j,\tau}(w)$ is the τ th quantile function of the distribution of $Y(j)$ conditional on W , given by $Q_{j,\tau}(w) = \inf\{y \in \mathbb{R} : F_{Y(j)|W}(y|w) \geq \tau\}$ and $\tau \in (0, 1)$ is the quantile level.

³See, for example, Firpo (2007), Donald and Hsu (2014), Chernozhukov and Hansen (2005, 2006), Frölich and Melly (2013), and the references therein.

It is easy to see that estimation of quantile treatment effect is complicated by the fact that for each individual in the population, we observe at most one of the potential outcomes $Y(1)$ and $Y(0)$. Therefore, the parameter of interest can not be identified without further restrictions. To solve the identification problem, it is assumed in this paper that assignment to treatment is unconfounded as in Rubin (1980) and Rosenbaum and Rubin (1983), and that the probability of assignment is bounded away from 0 and 1. Formally, the following assumptions are imposed.

Assumption 2.1. *For almost every $x \in \mathcal{X}$, where \mathcal{X} is the support of X ,*

(i) $(Y(0), Y(1))$ *is independent of D conditional on $X = x$;*

(ii) $0 < \underline{c} \leq p(x) = P(D = 1|X = x) \leq \bar{c} < 1$ *for some $0 < \underline{c} < \bar{c} < 1$, where $p(x)$ is the so-called propensity score function.*

Assumption 2.1(i) is often referred to as unconfoundedness or "selection on observables" and it states that when a vector of measured covariates are controlled, the treatment variable is independent of the potential outcomes. It rules out the existence of unobserved factors that affect treatment assignment and are also correlated with the potential outcomes. Assumption 2.1(ii) implies that, for almost all values of X , the population includes treated and untreated units. Clearly, it is easy to show that indeed, $\delta_\tau(w)$ can be identified under Assumption 2.1 so that Assumption 2.1 holds true through the whole paper.

2.2 Model Specification and Estimation Procedure

In this paper, our focus is on estimating $\delta_\tau(w)$ based on a linear model for the conditional quantile functions of the potential outcome distributions. Formally, a linear restriction for the conditional quantile functions is given by

$$Q_{j,\tau}(w) = \alpha_{j,\tau} + \beta'_{j,\tau}w \tag{2.1}$$

for $j = 0$ and 1 , where $\alpha_{j,\tau} \in \mathbb{R}$ and $\beta_{j,\tau} \in \mathbb{R}^k$ are the unknown parameters. Based on the specification in (2.1), it is easy to see that the treatment effect parameter of interest $\delta_\tau(w)$ has the form of

$$\delta_\tau(w) = (\alpha_{1,\tau} - \alpha_{0,\tau}) + (\beta_{1,\tau} - \beta_{0,\tau})'w.$$

Note that the particular form of the conditional quantile functions specified in (2.1) can be easily extended to nonlinear parametric models, since identification does not depend on the particular specification adopted for the conditional quantile functions.

According to the approach proposed by Bassett and Koenker (1982), the parameters of

the conditional quantile functions in (2.1) can be expressed as

$$(\alpha_{j,\tau}, \beta_{j,\tau}) = \arg \min_{(\alpha, \beta) \in \mathbb{R}^{k+1}} E[\rho_\tau(Y(j) - \alpha - \beta'W)] \quad (2.2)$$

for $j = 0$ and 1 , where $\rho_\tau(u)$ is the check function, defined as $\rho_\tau(u) = u \cdot (\tau - I\{u < 0\})$. It is important to note that the potential outcomes $Y(1)$ and $Y(0)$ are not observed simultaneously. Therefore, the minimization problem in (2.2) can not be solved directly. To overcome this problem, the following weight functions of D and X are defined

$$\kappa_1(X, D) = D/p(X), \quad \text{and} \quad \kappa_0(X, D) = (1 - D)/[1 - p(X)].$$

Then, it follows by the unconfoundedness assumption and the law of iteration expectation that

$$(\alpha_{j,\tau}, \beta_{j,\tau}) = \arg \min_{(\alpha, \beta) \in \mathbb{R}^{k+1}} E[\kappa_j(X, D) \cdot \rho_\tau(Y - \alpha - \beta'W)] \quad (2.3)$$

for $j = 0$ and 1 . It should be noted that the weights $\kappa_1(X, D)$ and $\kappa_0(X, D)$ are non-negative, so both the population objective function in (2.3) and its sample analogy are globally convex in (α, β) and hence the global optimum can be obtained in a finite number of iterations. Following the analogy principle in Manski (1988), a natural estimator of $(\alpha_{j,\tau}, \beta_{j,\tau})$ is the sample counterpart of (2.3).

To be specific, it is assumed that a random sample of n observations on $\{Y_i, X_i, D_i\}_{i=1}^n$ is observed. If the weight function $\kappa_j(X_i, D_i)$ for $j = 0$ and 1 would be known, then the estimation problem becomes a weighted quantile regression as discussed in Newey and Powell (1990). Unfortunately, the propensity score function $p(x)$ is unknown in general in practice, so these two weight functions are also unknown. Therefore, to estimate the unknown parameters $\alpha_{j,\tau}$ and $\beta_{j,\tau}$, one needs an estimation in two steps. First, one can use some standard parametric or nonparametric techniques to estimate the unknown function $p(x)$. Since the treatment variable D is binary, a logistic or probit regression model can be used to estimate $p(x)$ in the parametric case⁴.

Once the estimator $\hat{p}(x)$ of $p(x)$ is obtained, the fitted values $\{\hat{\kappa}_j(X_i, D_i)\}$ can be used to estimate $(\alpha_{j,\tau}, \beta_{j,\tau})$ in the second step as follows, for $j = 0$ and 1 ,

$$(\hat{\alpha}_{j,\tau}, \hat{\beta}_{j,\tau}) = \arg \min_{(\alpha, \beta) \in \mathbb{R}^{k+1}} \frac{1}{n} \sum_{i=1}^n \hat{\kappa}_j(X_i, D_i) \rho_\tau(Y_i - \alpha - \beta'W_i). \quad (2.4)$$

⁴Of course, one can use a nonparametric procedure to estimate $p(x)$, and several approaches have been proposed in the treatment effect literature. Examples include the series logit estimator (SLE) as in Hirano et al. (2003) and Firpo (2007), local polynomial regression estimation as in Ichimura and Linton (2005) and higher order kernel regression estimation as in Abrevaya et al. (2015). The reader is referred to the original references for details.

3 Empirical Application

In this section, the proposed parametric quantile regression model for treatment effect is applied to the analysis of the quantile treatment effect of maternal smoking during pregnancy on infant birth weight while allowing for arbitrary treatment effect heterogeneity conditional on the mother’s age.

3.1 Data description

We use the same dataset as in Abrevaya et al. (2015), collected by the North Carolina State Center Health Services. Similar to Abrevaya et al. (2015), our focus is on the sample for the first-time pregnant white mothers with 433,558 observations.

It is well documented that there are many factors to cause low birth weight and maternal smoking during pregnancy has been labeled the most important preventable negative cause of low birth weight; see Kramer (1987) for the detailed discussion. Although it is well understood that there is a negative relationship between maternal smoking during pregnancy and infant birth weight, it is not an easy task to accurately estimate the causal effect of maternal smoking during pregnancy on infant birth weight. Actually, there were some previous attempts to estimating the causal effect of maternal smoking on infant birth weight by using an instrumental variable strategy or panel data approach; see, for example, Evans and Lien (2005), Abrevaya (2006), Abrevaya and Dahl (2008), and the references therein. Recently, the program evaluation approach is successfully employed to estimating this effect; see, for example, Almond, Chay, and Lee (2005), Walker, Tekin, and Wallace (2009), Abrevaya et al. (2015), and Lee et al. (2017). In particular, both Abrevaya et al. (2015) and Lee et al. (2017) explored how the average effect of maternal smoking on infant birth weight changes across different age groups of mothers. They found different degrees of heterogeneity by age and the main qualitative finding is that smoking has a more severe impact at higher ages. As discussed in Abrevaya and Dahl (2008), the costs associated with birth weight have been found to exist primarily at the low end of the infant birth weight distribution (with costs increasing significantly at the very low end). Therefore, researchers may be more interested in understanding the distributional effect of maternal smoking on baby’s birth weight. This motivates us to consider the estimation of the quantile treatment effect of maternal smoking on infant birth weight. To be specific, our interest is to estimate how the quantile effect of smoking changes across different age groups of mothers. To this end, the proposed model is used to estimate the quantile effect of maternal smoking during pregnancy on infant birth weight conditional on the mother’s age.

Since our interest is to estimating how the quantile effect of maternal smoking during

pregnancy changes across different age groups of mothers, the conditional variable W is the mother's age. In addition, D denotes the treatment variable which is equal to one if the mother smokes and zero otherwise. The outcome of interest Y is the baby's birth weight measured in grams. In this example, $Y(1)$ denotes the infant birth weight for the treated (smoking) group and $Y(0)$ stands for the infant birth weight for the untreated (no-smoking) group. Figure 1 depicts the kernel density estimations of infant birth weight for the untreated (solid line) and treated (dotted line) groups, respectively. It looks that the density estimations of infant birth weight both for the treated and untreated groups are asymmetric and fat-tailed in the left side. To further confirm these findings, the skewness and kurtosis of the distributions of infant birth weight are computed and also, a symmetry test is conducted to see if the distributions are symmetry. The results are reported in Table 1, which support the findings observed from Figure 1. Based on the discussions above, it gives us a strong motivation to consider the distributional effect of maternal smoking during pregnancy on infant birth weight.

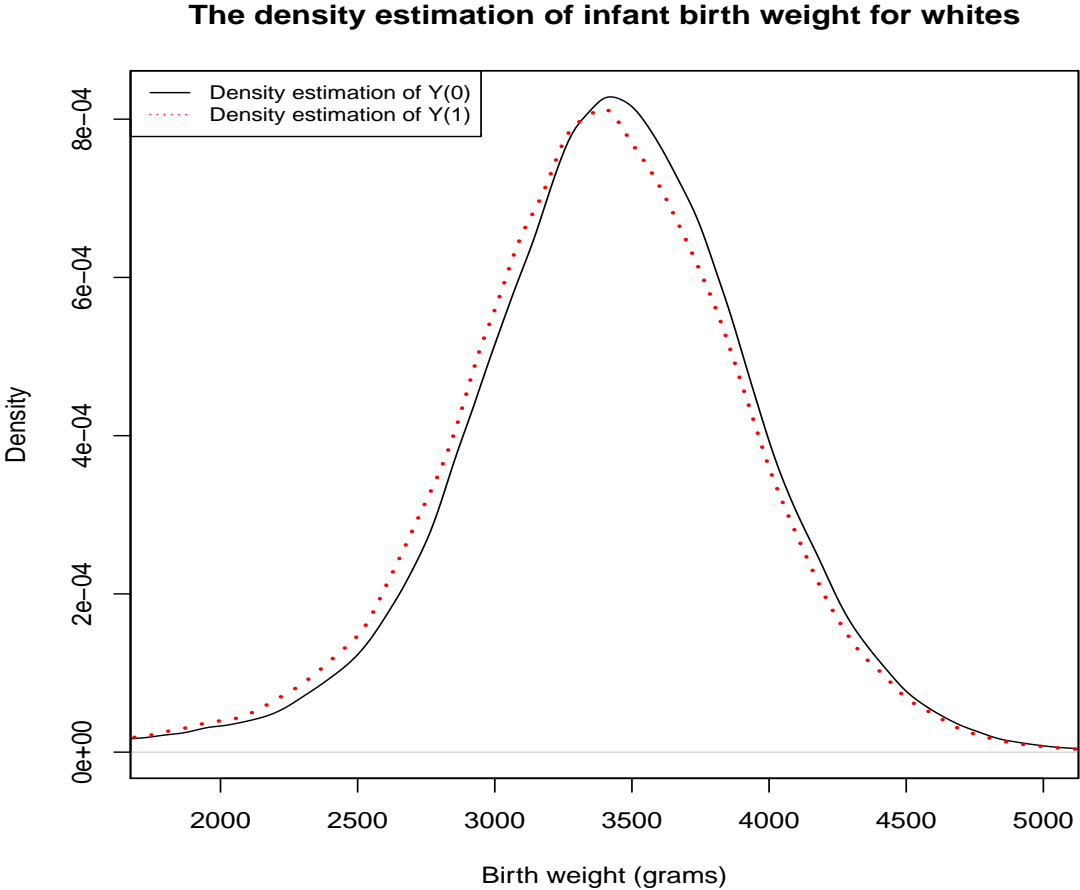


Figure 1: The kernel density estimation of infant birth weight for white. The solid line is for $Y(0)$ and the dotted line for $Y(1)$.

Table 1: Descriptive statistics and symmetry testing results.

	$Y(0)$	$Y(1)$
Mean	3398.68	3346.85
Skewness	-0.846	-0.840
Kurtosis	5.931	5.734
Symmetry test (p-value)	0.000	0.000
Number of observations	359172	74386

To estimate the causal effect of maternal smoking on infant birth weight using program evaluation procedure, the main difficulty is to find certain baseline covariates such that the potential birth weight outcomes are independent of the smoking decision conditional on the baseline covariates. Several studies have been conducted in the literature by using variants of the unconfoundedness assumption to identify the average effect of smoking on infant birth weight; see, for example, Almond et al. (2005), Da Veiga and Wilder (2008), and Walker et al. (2009) for details. In this paper, the same set of covariates X as in Abrevaya et al. (2015) are used, including certain parents' background information and the mothers' medical and health records as well as other variables. Specifically, Table 2 summarizes the pre-treatment covariates used in the dataset.

Another practical problem is how to estimate the unknown propensity score function $p(x)$. Following Abrevaya et al. (2015), a logit model for the propensity score function is considered and the explanatory variables used in the logit model consist of all the elements of X displayed in Table 2, the square of the mother's age, and the interaction terms between the mother's age and all other elements of X . Finally, the conditional quantile treatment effect, $\delta_\tau(w)$, is estimated for mother's ages in the interval from 20 to 30.

Table 2: Variable description

	Variable name	Variable type	Description	
<i>Outcome of interest</i>	bweight	continuous variable	Infant birth weight measured in grams	
<i>Treatment variable</i>	smoke	binary	Whether mother smokes or not during pregnancy?	
	mage	continuous variable	Mother's age	
	fage	continuous variable	Father's age	
Certain parents' background information	meduc	integer	Mother's years of schooling	
	feduc	integer	Father's years of schooling	
	fagemiss	integer	Whether or not father's age is missing?	
	married	binary	Whether or not mother is married?	
<i>Pre-treatment covariates (X):</i>	prenatal	integer	Month of first prenatal visit which is equal to 10 if prenatal care is foregone	
	prenatal-visits	integer	Number of prenatal visits	
	Mothers' medical and health records	hyperpr	binary	Whether or not mother suffered from hypertension?
		terms	integer	Previous (terminated) pregnancies
		anemia	binary	Whether or not mother suffered from anemia?
		ultra	binary	Whether or not mother took ultra sound exams?
		diabetes	binary	Whether or not mother suffered from gestational diabetes?
		amnio	binary	Whether or not mother took amniocentesis?
Other variables	male	binary	Whether or not baby is male?	
	drink	binary	Whether or not mother used alcohol?	

3.2 Empirical Results

As stated above, since the costs associated with birth weight exist primarily at the low end of the birth weight distribution, we consider three quantile levels: $\tau = 0.1$, 0.25 and $\tau = 0.5$. First, a polynomial model is explored and it turns out that the following models $Q_{0,\tau}(w)$ and $Q_{1,\tau}(w)$ are suitable

$$Q_{j,\tau}(w) = \alpha_{j,\tau} + \beta_{j,\tau} \cdot \text{age} + \gamma_{j,\tau} \cdot \text{age}^2$$

for $j = 0$ and 1 . Therefore,

$$\delta_\tau(w) = (\alpha_{1,\tau} - \alpha_{0,\tau}) + (\beta_{1,\tau} - \beta_{0,\tau}) \cdot \text{age} + (\gamma_{1,\tau} - \gamma_{0,\tau}) \cdot \text{age}^2,$$

which is a quadratic form of age. Table 3 summarizes the estimation results from the computer output in the package *quantreg* in **R**⁵. It can be seen from Table 3 that all the estimated coefficients are statistically significant at the 1% level. In particular, $\hat{\gamma}_{j,\tau}$ is significant too for three values of τ (0.1, 0.25 and 0.50). Based on these estimated coefficients, $\hat{\delta}_\tau(w)$ can be computed easily and it is displayed in Figure 2, plotting the estimation results for the par-

⁵The command *rq()* in the package *quantreg* in **R** with the weights $\{\hat{\omega}_{j,i}\}$ as in (2.4) is employed to obtain the estimated coefficients $\hat{\alpha}_{j,\tau}$, $\hat{\beta}_{j,\tau}$, and $\hat{\gamma}_{j,\tau}$.

tially conditional quantile treatment effect, $\widehat{\delta}_\tau(w)$ at three quantile levels $\tau = 0.1$, $\tau = 0.25$ and $\tau = 0.5$, respectively. For example,

$$\widehat{\delta}_{0.10}(w) = -57.222 - 8.951 \cdot \text{age} + 0.067 \cdot \text{age}^2.$$

However, since $\widehat{\gamma}_{1,\tau} - \widehat{\gamma}_{0,\tau} = 0.067$ for $\tau = 0.10$ (-0.043 for $\tau = 0.25$ and -0.025 for $\tau = 0.50$) is too small, the linear term in the estimated curve $\widehat{\delta}_\tau(w)$ dominates the whole curve in the range of (20, 30) (look like a linear), which can be seen in Figure 2.

From Table 3 and Figure 2, one can see clearly that the results exhibit a number of striking features. First, one can observe that there is a significant negative effect of smoking on infant birth weight across all ages and quantile levels considered. Second, the estimation results show substantial heterogeneity across different ages. For example, the estimated effect ranges from about $-200g$ to $-250g$ at the quantile level $\tau = 0.1$ and about $-185g$ to $-235g$ at the quantile level $\tau = 0.25$. Another interesting feature of the results is that for a given age, the numerical values of the quantile treatment effect point estimates at lower quantiles are bigger than those at the higher quantiles, and for a given quantile level, the estimated quantile treatment effects become stronger (more negative) at higher ages. These findings are new in the literature, different from those in Abrevaya et al. (2015) and Lee et al. (2017).

Table 3: Estimation results of the coefficients

Coefficients	Quantile regressions		
	10%	25%	50%
α_0	1850.455*** (51.755)	2414.536*** (31.466)	2819.315*** (24.092)
β_0	71.734*** (4.283)	52.741*** (2.616)	46.288*** (1.976)
γ_0	-1.378*** (0.086)	-0.984*** (0.053)	-0.845*** (0.039)
α_1	1793.233*** (119.690)	2299.294*** (91.859)	2679.412*** (75.539)
β_1	63.283*** (9.791)	50.057*** (7.638)	44.556*** (6.286)
γ_1	-1.311*** (0.190)	-1.027*** (0.152)	-0.870*** (0.125)

Note: The dependent variable is infant birth weight (in grams). *: significant at 10% level; **: 5% level; ***: 1% level. Standard errors of the estimates are reported in the parentheses.

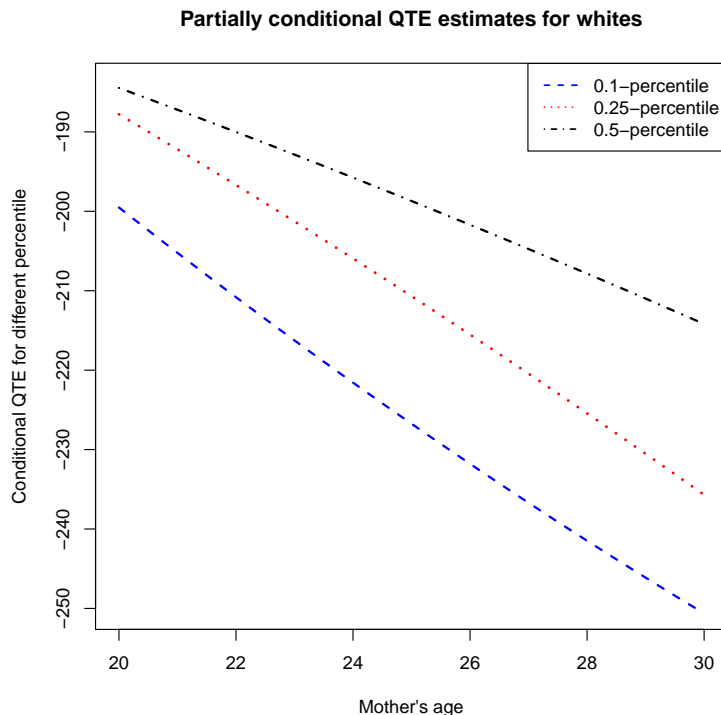


Figure 2: Estimation results for the partially conditional quantile treatment effects

4 Conclusion

In this paper, a parametric quantile regression model for treatment effect is proposed to analyze the data from the North Carolina State Center Health Services, which have previously been used by Abrevaya et al. (2015), Lee et al. (2017) and Cai et al. (2019), to examine the quantile effect of maternal smoking during pregnancy on infant birth weight across different age groups of mothers. The estimated results suggest that the quantile effect of maternal smoking on infant birth weight is quite heterogeneous across different age groups of mothers. The results also indicate that for a given quantile level, the effect is monotonically decreasing in the mother's age and for a given mother's age, the numerical values of the effect at lower quantiles are bigger than those at the higher quantiles. These results demonstrate that estimates of treatment effect which focus on a single feature of the outcome distribution, for example, the average treatment effect, may fail to capture the full impact of the treatment variable on the outcome of interest and that examining additional features may provide more information about the relationships between the treatment variable and the outcome of interest.

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