WIC participation and the Nutrient Intake of Preschoolers

Jayachandran N Variyam
Economic Research Service, USDA
1800 M Street NW, Room N4082
Washington, DC 20036-5831
Phone: (202) 694-5457
Email: jvariyam@ers.usda.gov

Subject Code: 4

Abstract

Quantile regression is used to evaluate the effect of WIC participation on the nutrient intakes of WIC-eligible preschoolers. Estimates based on 1994-96, 1998 CSFII data show that the WIC effects vary by quantile for iron and zinc while the effects are equal across quantiles for calcium.

Paper prepared for presentation at the 2001 annual meeting of the American Agricultural Economics Association, Chicago, IL August 5-8. The views expressed in this paper are those of the author and do not necessarily reflect the views of the Economic Research Service or the USDA.

WIC participation and the Nutrient Intake of Preschoolers

As the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) has grown rapidly in the 1990's, so have questions about its effectiveness (Besharov and Germanis). Several recent studies have evaluated the impact of WIC, particularly on the nutrient intake of children (Fraker, Long, and Post; Oliveira and Gundersen; Rose, Habicht, and Devaney). These studies show that WIC participants have significantly higher intakes of several nutrients targeted by WIC compared to WIC-eligible nonparticipants. The WIC effects reported in these studies are "average" differences between WIC-participants and eligible nonparticipants, after controlling for the differences in sociodemographic characteristics.[1] However, these conditional mean differences provide only a very limited characterization of distributional differences among population sub-groups such as WIC participants and nonparticipants. They do not account for the possibility that the nutrient intake distributions of WIC participants and eligible nonparticipants may differ in shape and variance. If this is the case, then the estimated WIC-effect at the conditional mean may not be representative of the WIC-effect at other parts of the intake distribution. Since the risk of dietary inadequacy of the nutrient targeted by WIC is greater toward the bottom part of the intake distribution, judging intake difference between participants and nonparticipants by looking at their difference at the conditional mean only, and not the differences at other parts of the intake distribution could lead to incomplete or potentially misleading conclusions.

The purpose of this study is to better evaluate the intake difference between WIC benefit recipients and WIC-eligible nonrecipients among U.S. preschool children. This is achieved by employing the method of quantile regression proposed by Koenker and Bassett (1978). While the classical least squares regression estimates the conditional mean of a dependent variable as a linear function of explanatory variables, the quantile regression enables the estimation of any conditional quantile of the dependent variable as a linear function of explanatory variables. Therefore, using quantile regression allows us to go beyond the conditional mean and evaluate the intake differences between WIC participants and nonparticipants at different parts along the entire conditional distribution of nutrient intakes.

Data

The nutrient intakes of preschoolers for this study were obtained from USDA's 1994-96 CSFII (Tippett and Cypel) and the 1998 Supplemental Children's Survey (U.S. Department of Agriculture). Each year of the 1994-96 CSFII comprised a nationally representative sample of noninstitutionalized persons residing in the United States. Food intake records for selected sample persons from a screened sample of 9,664 households were collected on two nonconsecutive days through in-person interview using 24-hour recalls. For sample persons who were children under six years of age, intake data was collected through proxy interviews with the household members responsible for preparing the children's meals. 15,303 sample persons provided information on food intakes for both days giving a two-day response rate of 76.1%. By combining the food records with a nutrient database, CSFII provides information on the intakes of a variety of macronutrients, vitamins, and minerals of the sample persons.

The Supplemental Children's Survey was conducted to obtain intake data on a larger sample of children than that was available with the 1994-96 CSFII. The design and data collection procedures of the1998 survey were consistent with the 1994-96 survey design so that the two surveys could be combined for analysis. Together, these surveys are referred to as CSFII 1994-96, 1998. The 1998 survey added intake data from 5,559 children from birth to 9 years of age to the intake data collected from 4,253 children of the same age group that participated in the 1994-96 CSFII.

There are five WIC-eligible groups--pregnant women and up to six weeks after delivery, breastfeeding women up to a year after giving birth, postpartum women who are not breastfeeding for up to six month after delivery, infants from birth to a year, and children from 1 up to the age of 5. Among these WIC-eligible groups, children 1 to 4 years of age comprise the majority of WIC participants (51% of all WIC participants as of April 1998). However, relatively little research has been done on the nutritional impact of WIC on children, in comparison to the WIC effect on other eligible groups such as pregnant or breastfeeding women. Therefore, we focused our analysis on the nutrient intakes of 1 to 4 year old preschoolers in CSFII who were determined to be eligible for WIC participation. Since the CSFII did not gather information on the nutrient contribution of breast milk to the nutrient intakes of breastfed children, we excluded such children from the analysis. Further, we based our analysis on children who provided 2 days of intake data.

For WIC participation, those among the eligible groups have to meet income and nutritional risk criteria. An applicant's family income has to be at or below 185 percent of the federal poverty guideline. Those who participate in income-based assistance programs such as Medicaid, TANF (formerly AFDC), and the Food Stamp Program are automatically eligible for WIC participation.

The applicant must also be determined by a health professional to be at nutrition risk, based on guidelines developed by state agencies.

To determine the sample of WIC-eligible preschoolers from CSFII 1994-96, 1998, we followed the guidelines used by Oliveira and Gundersen (who used the 1994-96 CSFII for their analysis). Because WIC income eligibility based on annual income may underestimate actual income eligibility, the required cutoff of an annual household income above 185 percent of the poverty threshold was liberalized to 200 percent to choose the sample of income eligible children for this study. Children from households that received AFDC payments or those who were authorized to receive food stamps were also chosen to be in the WIC-eligible sample. Since information on Medicaid participation was not collected in CSFII, eligibility based on this criterion could not determined. However, children who were not income eligible but who reported participating in the WIC program were included. Based on these criteria, intakes of 2,900 preschoolers were available for analysis from the 1994-96, 1998 CSFII. Of these 1,108 were WIC participants and 1,792 were WIC-eligible nonparticipants.

WIC participants receive supplemental food vouchers that can be redeemed for specific foods that are rich in nutrients considered to be low in the diets of WIC-eligible groups. Food available to children include milk, cheese, eggs, dried beans and peas, peanut butter, breakfast cereal, and fruit or vegetable juice. Nutrients targeted by these foods are protein, iron, calcium, and vitamins A and C. After a 1991 review of the supplemental food packages, WIC program has also been targeting folate, vitamin B6 and zinc.

Previous research has shown that nutritional risk among WIC eligible children is negligible for some of the WIC-targeted nutrients. For example, less than 2% of WIC recipient children failed to meet 100 percent of the Recommended Daily Allowance (RDA) for protein and folate (Oliveira and Gundersen). Since the objective of this study was to take a more detailed look at the entire distribution of intakes, we focused our analysis on three nutrients with the highest percentage of WIC-eligible children failing to meet the RDA. These were iron, zinc, and calcium.

Some Descriptive Results

Table 1 reports the mean and selected percentiles of the iron, zinc, and calcium intakes of preschoolers by WIC participation status. These univariate statistics were estimated using sampling weights. Since the RDA's are higher for 4 year olds compared to 1-3 year olds, the statistics are reported separately for these two age groups (RDA hasn't been established for calcium; therefore, the recommended adequate intakes (AI) are used). Among 4 year old WIC eligibles, participants have significantly higher mean intakes of iron, zinc, and calcium than nonparticipants ($p<.01$). Among 1-3 year olds, only the mean iron intake is significantly higher for WIC participants compared to nonparticipants. For iron and zinc, most of the distribution of intakes lies above the RDA level. A relatively larger proportion of preschoolers has calcium intakes below the AI level. But this is does not signify greater prevalence of calcium inadequacy because the AI levels are, by definition, higher than RDA level (although it is not known by how much).

The statistics in Table 1 illustrate two reasons why it is important to focus on the entire distribution of intakes, rather than only on the mean, to compare intake levels of two population subgroups. First, the mean may be influenced by outlying values at the extremes of the distribution. Estimating the median and other percentiles of intakes gives a more complete picture of the intake distribution than would be provided by the mean alone.

Second, in some cases the intake difference between WIC participants and nonparticipants detected at the mean is not representative of the intake difference at other parts of the distribution. For example, for iron intake among 1-3 year olds, the participant-nonparticipant difference is lower at the 10th and 25th percentiles and higher at the 75th and 90th percentiles compared to the difference at the mean. Therefore, it may be misleading to focus only on the difference at the mean. This is especially so because the risk of inadequacy for these nutrients is greater at the lower end of the distribution. The situation is better depicted in figure 1 where the 10th to the 90th percentiles of intakes at intervals of 5 for 1-3 year olds are graphed. For iron, the distributions for participants and nonparticipants are narrower at the bottom percentiles, with the gap widening toward the upper percentiles. For zinc, the distributions overlap at the bottom percentiles with a slight divergence at the upper end. For calcium, the percentile differences are greater at the bottom than at the top.

The distributional differences between participant and nonparticipant intakes revealed in table 1 and figure 1 are supported by the Kolmogorov-Smirnov tests of the equality of distributions. For both 1-3 year olds and 4 year olds, the distribution of iron intakes for WIC participants and nonparticipants are significantly different from each other ($p<.01$). For zinc, the equality of distributions by WIC status is not rejected for both age groups. For calcium, the equality of intake distributions of WIC and nonWIC 1-3 year olds is rejected at $p<.02$ and for 4 year olds at $p<.01$.

Modeling Approach

The above discussed intake estimates for WIC participant and nonparticipant preschoolers are unconditional estimates that do not take into account various other observable factors that may have influenced the intakes. To estimate the WIC effect on intakes after controlling for such factors, we employed multivariate regression. The WIC effect at the conditional mean was estimated by the traditional ordinary least squares (OLS) regression. The effect of WIC participation at other parts of the conditional distribution of intakes was estimated by using quantile regression. Following the precedence set in earlier studies, we estimated quantile regressions at 0.1, 0.25, 0.5, 0.75, and 0.9 quantiles of intakes to get a good representation of the WIC effects across the distribution. The details of the quantile regression method including estimation and testing procedures are presented in the appendix.

A major statistical issue in estimating the effects of program participation on behavioral outcomes is selection bias and WIC is no exception. As Oliveira and Gundersen note, although multivariate regression controls for the possible confounding effects of other observed variables, unobservable differences between WIC participants and nonparticipants may exist which may influence intakes. Unless the influences of these unobservables are taken into account, the estimated WIC effect may be biased. While this self-selection bias problem is well-known, a satisfactory solution is notoriously difficult due the inability to control for the factors that are, by definition, unobservable. The ideal solution is a randomized experiment in which WIC eligibles are randomly allocated to WIC participation on nonparticipation. Such experiments are, however, difficult due to impracticality of denying benefits to eligibles. Statistical solutions employing instrumental variable methods are potentially useful, provided proper instruments or identifying variables are available in the data being analyzed. However, in most data sets used for WIC evaluation, including the CSFII data used in our analysis, such instruments are not available. This is because most measurable factors that affect the probability of WIC participation by an individual can also arguably influence the nutrient intake of that individual. Due to the paucity of identifying variables, most studies of WIC participation effect that have experimented with statistical selection-bias correction methods have obtained unstable and implausible results which are sensitive to minor changes in the model specification.

Oliveira and Gundersen used an innovative approach to account for selection bias in their study by first identifying the possible sources of bias and then choosing a CSFII subsample that eliminates these sources. However, this approach severely reduced their sample size of eligibles from 1,135 to 180. The proportion of participants increased from 35 percent in the original sample to 61 percent in the reduced sample. It is not clear how this reversal in the relative proportions of participants and eligible nonparticipants may have affected the results. Nevertheless, the results were largely supportive of estimates from the original sample.

Since quantile regression requires at least a few hundred observations for the extreme quantiles to obtain stable results, we did not adopt the Oliveira and Gundersen approach of limiting the sample. Instead, we used an expanded list of variables to account for as much of the observable difference between WIC participants and nonparticipants as possible.

Table 2 lists the explanatory variables used in the regressions, along with their definition and sample means. We included all the explanatory variables used by Oliveira and Gundersen and several additional variables as well. The variables fall into four groups: preschooler characteristics, household characteristics, head of the household characteristics, and a fourth group of fourteen survey-related variables that are listed in the footnote to table 2. After dropping WIC eligible preschoolers who had missing values for these explanatory variables, a sample of 2,509 observations was available for regression analysis.

Thirty eight percent of the WIC eligible preschoolers in the available sample participated in the WIC program. Among other preschooler characteristics, besides sex, age, and race/ethnicity, we included dummy variables to indicate whether a child had food allergies and whether a child went to a child care facility that provided meals or snacks. Household variables included controls for geographic location, income and assets, size, head of the household status, and participation in food stamp program. Besides the education of the head of the household, we controlled for the age of head of the household as well. To account for variations in intake that may be attributable to purely survey-related factors, we included dummy variable for survey year, season, whether the intake was recorded for a weekend day, whether in the respondent's opinion the recorded intake was more than usual or less than usual, and finally whether either the interviewer or the respondent had difficulty with the interview.

Regression Results

The objective of using quantile regressions is to estimate the marginal effects (or the slope coefficients) of explanatory variables at various points along the conditional distribution of the dependent variable. However, if the distribution of the dependent variable is homoskedastic (that is, the conditional variance of dependent variable's distribution is constant by the level of independent variables), the estimated marginal effects will be identical between quantiles as well as with the marginal effects at the conditional mean estimated by OLS. In this case, the quantile slope coefficient estimates do not provide any additional information about the behavior of the dependent variable with respect to the explanatory variables beyond the information conveyed by the OLS slope estimates. Therefore, the first step after estimating quantile regressions is to test whether the estimated slope coefficients are equal across the quantiles. As shown by Koenker and Bassett (1982), such a test for the equality of slope coefficients across quantiles is a robust test for heteroskedasticity.

Estimating regression equations at the five quantiles simultaneously and obtaining the joint variance-covariance matrix allows us to carry out several types of tests of equality of slope coefficients. Table 3 reports the results of these tests. First, we tested for the presence of heteroskedasticity in the data by testing for the equality of slope coefficients at the .1q against the slope coefficients at .9q using the minimum distance chi-square test discussed in the appendix. The resulting chi-square statistics for iron, zinc, and calcium are reported in the last row of table 3. The null hypothesis of homoskedasticity is rejected decisively in all cases. This implies that the intake data for preschoolers is heteroskedastic and that the quantile slope estimates are likely to provide additional information about the behavior of intakes beyond that conveyed by the OLS estimates alone.

The rejection of the joint equality of all coefficients at two quantiles does not imply that the coefficients of individual explanatory variables are not equal across the quantiles. Therefore, next we tested for the equality of the slope coefficients of selected variables across quantiles. While any combination of quantiles could be tested, in table 3 we present test statistics (F-values) for slope equality at symmetrical quantiles (.1q=.9q and .25q=.75q) as well as across all five quantiles. The p-values of the test statistics are reported in parenthesis.

The null hypotheses that the WIC participation coefficients for iron intake are equal across the symmetrical quantiles and across all five quantiles are strongly rejected. For zinc, there is some evidence of discrepancy in quantile effects; slope equality across five quantiles could not be rejected at the 10 percent significance level. However, for calcium, the test results show that the WIC coefficients are statistically equal across the five quantiles. Table 3 also reports test statistics for the equality of sex and age coefficients. While the effect of sex appears to vary by quantiles, the variation in age effects across quantiles seems to diminish by the age level.

Tables 4 to 6 report the estimated regression coefficients of selected explanatory variables at the five quantiles for iron, zinc, and calcium. For comparison with the quantile estimates, the second column in each table presents the OLS estimates. The last column of each table presents restricted coefficient estimates. These are coefficient estimates obtained as a linear combination of the five quantiles coefficients imposing the equality restriction using an optimal minimum distance estimator. When the distribution of the dependent variable is nonnormal or fat-tailed, these estimates have superior statistical properties compared to the OLS estimates. The restricted estimates are especially useful for those variables whose slope coefficients are found to be equal across quantiles by the F-test.

After controlling for other explanatory variables, WIC participants have significantly higher iron intake compared to nonparticipants at all five quantiles ($p<.05$). The effect of WIC participation, however, varies considerably across quantiles from a low of .5mg at .1q to a high of 3.1mg at the .9q. The OLS estimate of a 1.8mg difference is, therefore, not representative of the WIC effect at other parts of the iron intake distribution among WIC eligible preschoolers.

For zinc, the OLS estimate shows a significant WIC effect of .4 mg. However, relying on this estimate alone could be misleading, as shown by the quantile estimates. Notably, there is negligible participant-nonparticipant difference at the bottom quantiles. The only statistically significant effect of WIC participation is at the .75q.

For calcium, the quantile estimates for WIC participation are statistically significant at all quantiles except at .9q. However, recall that the equality of the WIC coefficient across the five quantiles was not rejected for calcium. Notably, there is also no monotonic pattern for the quantile estimates as was evident for iron. Therefore, the restricted coefficient estimate, which is an optimal linear combination of the five quantile coefficients, may be a better estimate of the WIC effect than any individual quantile estimate or the OLS estimate. This is, in fact, borne out by the t-value, which is highest for the restricted estimate.

Among WIC-eligible preschoolers, boys had higher intakes of iron, zinc, and calcium compared to girls, after holding other characteristics similar between them. The difference tend to be larger at the upper quantiles. For both zinc and calcium, the difference in intakes between boys and girls were relatively small and insignificant at the 10th and 25th quantiles. Intakes generally tend to be lower for 1-3 year olds compared to the 4 year olds (the omitted reference group). However, calcium intake is an exception. Children 1 year of age have higher calcium intake than children 2-4 years of age, although as the quantile estimates show, this higher intake is confined to those children with calcium intake at or above the conditional median. The OLS estimate of 102 mg difference (between age 1 and age 4) at the conditional mean is, therefore, misleading.

To get a better view of the change in WIC participation effects across quantiles, we estimated quantiles regressions at all quantiles between .1q and .9q at .05q intervals. The conditional quantiles based on WIC participation status were then predicted at each of these quantiles, holding other explanatory variables, except age and sex, constant at their sample means. Predictions were obtained separately by age and sex. For example, to obtain the predicted intake at the .25q for male, WIC participant preschoolers 4 years of age, we the used the .25q quantile regression coefficient estimates to predict the .25q by setting the dummy variables WIC recipient=1, male=1, age1=0, age2=0, and age3=0, and all other explanatory variables at their sample mean. To obtain the predicted .25 conditional quantile for WIC nonparticipants of the same sex/age combination, we changed WIC recipient=0, and so on. The resulting predicted conditional quantiles for iron, zinc, and calcium are graphed in figures 2 to 4. The predicted values for the five representative quantiles, along with the predicted intake at the conditional mean obtained using the estimated OLS regression for 1-3 year olds are presented in table 7.

WIC participant boys have highest intake levels across all parts of the conditional distribution of intakes. While the largest differences, in general, are between WIC nonparticipant girls and WIC participant boys, the pattern of difference between participants and nonparticipants tend to be specific to each nutrient. For iron and zinc, the difference tend to widen from the bottom quantiles to the top quantiles. However, for zinc there is negligible difference between groups at the very lowest quantiles. Iron intake of participating girls starts to exceed that of nonparticipating boys after .3q. But the zinc intake of participating girls is consistently below that of nonparticipating boys at all quantiles. The difference in calcium intake by WIC status is largely stable across the conditional distribution for both boys and girls. Interestingly, up to about the conditional median, the WIC participant girls have higher calcium intakes than nonparticipant boys. Beyond the median, however, the effect of sex is stronger so that the conditional intake of participating girls and nonparticipating boys tend to converge. Due to the nonconstancy of the effects of the participation, sex, or age variables across parts of the conditional distribution of intakes, these estimates, therefore, convey far more information about the relative intake levels than was evident from the OLS estimate alone.

Among other results based on our sample of WIC-eligible preschoolers, household income does not have influence on zinc and calcium intakes once other characteristics are take into account. Income has a small but significant effect on iron intake at the 10th percentile. This effect needs to be investigated further because of its implications for the potential use of income supplementation programs to combat iron inadequacy. Among the race/ethnicity variables, the most notable effect is the lower intake of calcium by nonhispanic black and nonhispanic other race preschoolers compared to nonhispanic white preschoolers. The effect is relatively stable across quantiles, especially for black, and the restricted estimates have high t-values.

Conclusion

The results of this study suggests that a far more clearer picture of the effect of WIC participation on the nutrient intakes of WIC eligible preschoolers emerges when other parts of the conditional distribution of intakes, in addition to the conditional mean, are studied. This is exemplified by the contrasting results for iron, zinc, and calcium. For iron, the participant-nonparticipant difference at the conditional mean estimated by OLS is 1.8 mg. However, although statistically significant, the difference at the .1q estimated by quantile regression is .5 mg. The estimates at other quantiles show a monotonic pattern with the difference getting larger at the upper quantiles. For zinc, although the OLS estimate shows a significant WIC effect at the conditional mean, the quantile estimates show that the effects are negligible at the first quartile and below.

In contrast, the participant-nonparticipant difference in calcium intake is relatively stable across quantiles. An optimally combined quantile estimates shows that WIC participants have about 54 mg of higher calcium intake compared to WIC nonparticipants. But even for calcium where the OLS estimate of 47 mg is close to the quantile estimates, there is variation in the effects across quantiles of other important demographic variables such as age and sex. When the effects of these variables are taken into account to obtain predicted intakes, the resulting conditional quantile graphs provide a more informative picture of the effects of WIC participation on intakes across age-sex groups.

These results suggest that to fully uncover the extent and nature of the behavioral impact of programs such as WIC, it is essential to look beyond the conditional mean to other parts of the dietary intake distributions. However, as noted earlier, these results have been obtained without applying any methodological corrections for self-selection bias. Therefore, the policy implications of the results should be interpreted and generalized with considerable caution.

Footnotes

1. The recent study of WIC effectiveness by Kramer-LeBlanc et al. is an exception. This study compares the intake of WIC participants and nonparticipants at the median intake as well as at the10th percentile. However, their estimates are unconditional, or estimates that do not adjust for the sociodemographic differences between the two groups.

Appendix

Quantile Regression

Koenker and Bassett (1978) introduced quantile regression as a generalization of the sample quantiles to conditional quantiles expressed as linear functions of explanatory variables. This is analogous to the OLS regression model that expresses the conditional mean in a linear form. However, by permitting conditional functions to be specified at *any* quantile, quantile regression enables one to describe the entire conditional distribution of the dependent variable given a set of regressors. The familiar Least Absolute Deviation (LAD) estimator is a special case of quantile regression that expresses the conditional median as linear function of covariates. Quantile regression's ability to characterize the whole conditional distribution is most potent when there is heteroskedasticity in the data (Deaton). When the data are homoskedastic, the set of slope parameters of conditional quantile functions at each point of the dependent variable's distribution will be identical with each other and with the slope parameters of the conditional mean function. In this case, the quantile regression at any point along the distribution of the dependent variable reproduces the OLS slope coefficients, and only the intercepts will differ.

However, when the data are heteroskedastic (that is, the conditional variance of dependent variable's distribution is not constant but differs by the level of independent variables), the set of slope parameters of the conditional quantile functions will differ from each other as well as from the OLS slope parameters. Therefore, estimating conditional quantiles at various points of the distribution of the dependent variable will allow us to trace out different marginal responses of the dependent variable to changes in the explanatory variables at these points.

Two additional features of the quantile regression model are noteworthy (Buchinsky, 1998). First, the classical properties of efficiency and minimum variance of the least squares estimator are obtained under the restrictive assumption of independently, identically and normally distributed (i.i.d.) errors. When the distribution of errors is non-normal, the quantile regression estimator may be more efficient than the least squares estimator. Second, since the objective function for the quantile regression estimator is a weighted sum of absolute deviations, the parameter estimates are robust to outliers.

Estimation

Let y_i denote intake of a nutrient of the i^{th} sample person, i = 1, ..., N. We assume that the $?^{th}$ quantile (0 < ? < 1) of the conditional distribution of y_i is linear in a K×1 vector of explanatory variables, $\mathbf{x}_i$:

$$Q_?(y_i|\mathbf{x}_i) = \mathbf{x}_i'\mathbf{ß}_?\,,$$

where $Q_?(y_i|\mathbf{x}_i)$ is the conditional quantile function and $\mathbf{ß}_?$ is the unknown vector of parameters. The quantile regression estimator of $\mathbf{ß}_?$ is obtained by solving

$$\min_{\mathbf{ß}_?} \frac{1}{N}\left\{ \sum_{i:y_i \geq \mathbf{x}_i'\mathbf{ß}_?} ?|y_i - \mathbf{x}_i'\mathbf{ß}_?| \quad + \quad \sum_{i:y_i < \mathbf{x}_i'\mathbf{ß}_?} (1-?)|y_i - \mathbf{x}_i'\mathbf{ß}_?| \right\}.$$

This minimization problem has a linear programming representation, which is guaranteed to have a solution in a finite number of simplex iterations (Buchinsky 1998). Several estimators for the asymptotic covariance matrix for $\mathbf{ß}_?$ are available, but for obvious reasons, those that rely on the assumption of i.i.d. errors are of limited value (Deaton). Buchinsky (1995) has shown that the design matrix bootstrap estimator provides a consistent estimator for the covariance matrix under very general conditions. Additional details regarding the estimation of the quantile regression model and the estimation of the asymptotic covariance matrix of the parameters are discussed in Buchinsky's (1998) methodological survey.

Testing

The minimum distance method can be used to test for the equality of slope coefficients of a given dependent variable across any set of estimated quantiles (Buchinsky, 1998). Let $\hat{\boldsymbol{\beta}}_P = (\hat{\boldsymbol{\beta}}'_{?_1}, \ldots, \hat{\boldsymbol{\beta}}'_{?_P})'$ be a KP $\times$ 1 stacked vector of unrestricted parameter estimates from quantile regression at P quantiles. Let $\boldsymbol{\beta}^R = (\beta_{?_1 1}, \ldots, \beta_{?_P 1}, \beta_2, \ldots, \beta_K)'$ be a (K+P−1) $\times$ 1 vector comprising P unrestricted intercepts and K−1 restricted slope parameters. The restricted parameter vector b^R is obtained by minimizing

$$Q(\boldsymbol{\beta}^R) = (\hat{\boldsymbol{\beta}}_P - \mathbf{R}\boldsymbol{\beta}^R)' \mathbf{A}^{-1} (\hat{\boldsymbol{\beta}}_P - \mathbf{R}\boldsymbol{\beta}^R),$$

where **A** is a positive definite matrix and **R** is the appropriate restriction matrix. Under the null hypothesis of equality of slope coefficients, $NQ(b^R)$ is distributed χ^2 with (PK−P−K+1) degrees of freedom. Since the equality of slope parameters will hold if the i.i.d. assumption is valid, this is a general test for heteroskedasticity. The optimal choice for **A** is the variance-covariance matrix of $\hat{\boldsymbol{\beta}}_P$, denoted by L_P. Given L_P, the usual F-statistic for testing liner restrictions can be used to test for the equality of the slope parameters for a specific explanatory variable at symmetrical quantiles such as 0.1q and 0.9q. If the null hypothesis of homoskedasticity or the equality of the slope coefficients is not rejected, the restricted slope estimates b^R give an optimal combination of the quantile slope estimates. Also, given L_P, the variance-covariance matrix of the restricted parameter vector can be obtained as $\mathbf{?}^R = (\mathbf{R}'\mathbf{?}_P^{-1}\mathbf{R})^{-1}$.

References

Besharov, D. J. and P. Germanis. "Is WIC as good as they say?" The Public Interest 134(Winter 1999):21-36.

Buchinsky, M. Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research. The Journal of Human Resources. 33 (1998): 88-126.

Buchinsky, M. Estimating the Asymptotic Covariance Matrix for Quantile Regression Models: A Monte Carlo Study. Journal of Econometrics. 68 (1995):303-338.

Buchinsky, M. Estimating the Asymptotic Covariance Matrix for Quantile Regression Models: A Monte Carlo Study. Journal of Econometrics. 68 (1995):303-338.

Deaton, A. The Analysis of Household Surveys: A Microeconometric Approach to Development Policy. Baltimore, MD: Johns Hopkins University Press, 1997.

Fraker, T., S. K. Long, and C. E. Post. Analyses of the 1985 Continuing Survey of Food Intakes by Individuals, Volume I. USDA, Food and Nutrition Service, Alexandria, VA, 1990

Koenker, R. and G. Bassett. "Regression Quantiles." Econometrica, 46(January 1978):33-50.

Koenker, R. and G. Bassett. "Robust Tests for heteroskedasticity Based on Regression Quantiles." Econometrica, 50(January 1982):43-62.

Kramer-LeBlanc, C. S., A. Mardis, S. Gerrior, and N. Gaston. Review of the Nutritional Status of WIC Participants. CNPP-8, USDA, Center for Nutrition Policy and Promotion, Washington, DC, December 1999.

Oliveira, V., and C. Gundersen. WIC and the Nutrient Intake of Children. Food Assistance and Nutrition Research Report No. 5, USDA, Economic Research Service, Washington, DC, March 2000.

Tippett, K. S., Y. S. Cypel. Design and Operation: The Continuing Survey of Food Intakes by Individuals and the Diet and Health Knowledge Survey, 1994-96. U.S. Department of Agriculture, Agricultural Research Service, NFS Report No. 96-1,1997.

Rose, D., J-P. Habicht, and B. Devaney. "Household Participation in the Food Stamp and WIC Programs Increases the Nutrient Intakes of Preschool Children." Journal of Nutrition. 128(1998):548-555.

U.S. Department of Agriculture, Agricultural Research Service. Food and Nutrient Intakes by Children 1994-96, 1998. Online at the Food Surveys Research Group website <http://www.barc.usda.gov/bhnrc/foodsurvey/home.html>

Table 1. Distribution of Iron, Zinc, and Calcium intakes among WIC and nonWIC Preschoolers

Nutrient	Mean	Percentile				
		10	25	50	75	90
		Milligrams/day				
Age 1-3						
Iron (RDA=7mg/day)						
WIC	12.4	5.9	8.0	11.3	15.6	20.1
Non WIC	11.0	5.5	7.3	9.9	13.5	17.7
Zinc (RDA=3mg/day)						
WIC	8.0	4.4	5.5	7.4	9.7	12.4
Non WIC	7.8	4.4	5.6	7.1	9.3	11.7
Calcium (AI=500mg/day)						
WIC	823.2	399.0	553.1	776.8	1014.2	1337.2
Non WIC	796.0	353.5	521.2	724.0	1001.8	1302.2
Age 4						
Iron (RDA=10mg/day)						
WIC	14.9	8.5	10.5	13.2	18.3	22.5
Non WIC	12.6	7.1	8.9	11.6	15.4	19.6
Zinc (RDA=5mg/day)						
WIC	10.0	5.3	6.9	8.9	12.1	15.7
Non WIC	9.0	4.9	6.6	8.3	10.9	13.6
Calcium (AI=800mg/day)						
WIC	876.2	456.2	636.0	861.1	1054.3	1291.5
Non WIC	803.5	412.8	577.3	764.5	993.0	1220.6

Table 2. Explanatory variables and sample means

Variable	Definition	Mean
Preschooler characteristics		
WIC status	WIC recipient=1; 0 otherwise	.38
Sex	Male=1; 0 otherwise	.50
Age (Age=4 omitted)		
Age 1	Age=1 year; 0 otherwise	.17
Age 2	Age=2 years; 0 otherwise	.19
Age 3	Age=3 years; 0 otherwise	.30
Race/Ethnicity (Nonhispanic white omitted)		
Nonhispanic black	Nonhispanic black=1; 0 otherwise	.21
Nonhispanic other	Nonhispanic other racial groups[1]=1; 0 otherwise	.06
Hispanic	Hispanic national origin=1; 0 otherwise	.25
Food allergy	Child has food allergies=1; 0 otherwise	.05
Child care	Attended child care which gives meals/snacks=1; 0 otherwise	.28
Household characteristics		
Income	Gross household income in previous year ($ '000)	19.3
Size	Count of household members	4.8
Own home	Dwelling owned by household member=1; 0 otherwise	.36
Cash assets	Members have > $5,000 in cash assets=1; 0 otherwise	.09
Food stamp	Any member authorized to receive food stamps=1; 0 otherwise	.36
Dual head	Household has a male and a female head=1; 0 otherwise	.70
Region (Northeast omitted)		
Midwest	Household in the midwest=1; 0 otherwise	.21
South	Household in the south=1; 0 otherwise	.34
West	Household in the west=1; 0 otherwise	.29

Table 2. Explanatory variables and sample means

Variable	Definition	Mean
Urbanization (Central city omitted)		
Suburb	MSA, outside central city=1; 0 otherwise	.40
Nonmetro	Non-MSA	.24
Head of household characteristics[2]		
Education	Years of schooling completed by head of household.	11.6
Age	Age of the head of the household in years	31.2

Note: Sample size = 2509. Fourteen additional dummy variable were used as explanatory variables: three dummy variables representing survey year (1995, 1996, 1998; 1994 omitted), three representing survey season (spring, summer, fall; winter omitted), two indicating whether each of the two-day intake was recorded on a weekend day (day-1 intake on Friday, Saturday, or Sunday; day-2 intake on Friday, Saturday, or Sunday), four indicating the respondent's opinion whether each of the recorded two-day intake was less than or more than the usual intake (day-1 intake less than usual; day-1 intake more than usual; day-2 intake less than usual; day-2 intake more than usual), and two indicating whether the interviewer or the respondent had difficulty with each day's intake interview (day-1 interview difficult; day-2 interview difficult).

[1]Asian, Pacific Islander, American Indian, Alaskan native, or other race.

[2]In the case of dual headed households, values for the female head were used.

Table 3. Tests for Equality of Slope Parameters Across Quantiles

Variable	Iron			Zinc			Calcium		
	$q_{10}=q_{90}$	$q_{25}=q_{75}$	All 5	$q_{10}=q_{90}$	$q_{25}=q_{75}$	All 5	$q_{10}=q_{90}$	$q_{25}=q_{75}$	All 5
WIC recipient	12.27	14.25	5.37	2.33	6.84	2.07	.03	.14	.11
	(.00)	(.00)	(.00)	(.13)	(.01)	(.08)	(.87)	(.71)	(.98)
Male	2.11	3.49	2.72	3.80	6.05	2.25	9.00	1.00	2.91
	(.15)	(.07)	(.03)	(.05)	(.01)	(.06)	(.00)	(.32)	(.02)
Age 1	.01	1.01	1.93	3.73	3.62	2.53	23.96	4.64	6.64
	(.92)	(.32)	(.10)	(.05)	(.06)	(.04)	(.00)	(.03)	(.00)
Age 2	1.72	.71	.74	7.83	5.16	3.05	2.92	.00	1.02
	(.19)	(.40)	(.56)	(.01)	(.02)	(.02)	(.09)	(.99)	(.39)
Age 3	.15	.07	.23	.64	2.77	.92	.17	.04	.51
	(.70)	(.79)	(.92)	(.42)	(.10)	(.45)	(.68)	(.85)	(.73)
?2(37)		86.3			107.91			92.08	

Table 4. Quantile Regression Estimates: Iron Intake of Preschoolers

		Quantile					
Variable	OLS	.10	.25	.50	.75	.90	ß[R]
WIC recipient	1.75	.50	.93	1.51	2.46	3.07	1.01
	(7.14)	(1.99)	(4.18)	(5.80)	(5.98)	(4.33)	(7.16)
Male	1.02	.27	.78	1.02	1.40	1.11	.75
	(4.62)	(1.28)	(3.84)	(4.17)	(4.10)	(1.99)	(6.20)
Age 1	-2.61	-2.31	-2.94	-3.24	-2.31	-2.42	-2.74
	(6.41)	(7.23)	(9.44)	(7.82)	(3.58)	(2.30)	(13.21)
Age 2	-1.95	-1.26	-1.62	-1.87	-2.04	-2.54	-1.37
	(6.04)	(3.57)	(5.51)	(4.76)	(4.06)	(2.61)	(6.96)
Age 3	-.83	-.67	-.84	-.88	-.72	-.37	-.86
	(2.90)	(2.23)	(3.25)	(2.70)	(1.65)	(.50)	(5.23)
Income	-.00	.02	.01	-.00	-.00	-.06	.02
	(.09)	(2.02)	(1.16)	(.25)	(.05)	(1.72)	(2.61)
Black	.08	-.17	-.30	.11	.63	.16	-.08
	(.23)	(.57)	(.92)	(.29)	(1.25)	(.20)	(.40)
Other race	-1.19	-1.42	-.82	-.99	-.78	-1.31	-.65
	(2.87)	(2.47)	(1.82)	(2.11)	(1.12)	(1.31)	(2.27)
Hispanic	.23	-.43	-.17	.05	1.00	.32	-.13
	(.72)	(1.44)	(.64)	(.15)	(2.12)	(.38)	(.75)
R^2	.12	.08	.08	.07	.08	.10	--

Note: Absolute t-values in parenthesis.

Table 5. Quantile Regression Estimates: Zinc Intake of Preschoolers

		Quantile					
Variable	OLS	.10	.25	.50	.75	.90	ß[R]
WIC recipient	.42	.05	-.01	.33	.63	.62	.09
	(2.56)	(.39)	(.07)	(1.82)	(2.54)	(1.76)	(1.04)
Male	.56	.15	.19	.51	.75	.87	.30
	(3.60)	(1.07)	(1.48)	(3.18)	(1.35)	(2.41)	(3.73)
Age 1	-1.70	-.91	-1.35	-1.55	-2.20	-1.93	-1.17
	(7.58)	(4.37)	(7.32)	(5.98)	(4.77)	(3.74)	(9.12)
Age 2	-1.30	-.48	-.86	-1.08	-1.62	-2.07	-.70
	(6.43)	(2.24)	(4.98)	(4.14)	(4.76)	(3.81)	(5.74)
Age 3	-.74	-.51	-.54	-.54	-1.06	-.87	-.47
	(3.73)	(2.63)	(3.34)	(2.30)	(3.26)	(1.93)	(4.61)
Income	-.01	.01	.01	-.00	-.01	-.02	-.01
	(.75)	(.66)	(.72)	(.28)	(.73)	(1.46)	(1.11)
Black	-.04	-.29	-.31	-.15	-.33	.31	-.24
	(.17)	(1.18)	(1.80)	(.52)	(.96)	(.60)	(2.01)
Other race	-.32	-1.02	-.67	-.15	-.05	-.44	-.80
	(1.03)	(3.15)	(1.84)	(.40)	(.09)	(.57)	(4.00)
Hispanic	.11	-.17	-.12	.07	-.43	.14	-.14
	(.52)	(.88)	(.57)	(.30)	(1.35)	(.30)	(1.16)
R^2	.11	.06	.06	.06	.06	.10	--

Note: Absolute t-values in parenthesis.

Table 6. Quantile Regression Estimates: Calcium Intake of Preschoolers

Variable	OLS	Quantile .10	.25	.50	.75	.90	ß^R
WIC recipient	47.36	52.59	57.38	59.28	48.10	58.65	53.55
	(3.01)	(2.79)	(3.38)	(3.28)	(1.98)	(1.79)	(5.54)
Male	44.27	-2.91	20.29	47.17	43.65	104.14	12.48
	(3.05)	(.17)	(1.21)	(2.71)	(1.97)	(3.16)	(1.34)
Age 1	102.36	-29.96	2.57	69.27	111.29	283.06	37.68
	(3.76)	(1.08)	(.07)	(2.36)	(2.37)	(4.55)	(2.34)
Age 2	-56.24	-90.82	-62.82	-56.73	-62.70	-10.76	-59.52
	(2.65)	(3.50)	(2.62)	(2.36)	(1.81)	(.26)	(4.41)
Age 3	-52.27	-37.86	-62.23	-65.95	-67.00	-54.62	-39.23
	(2.96)	(1.81)	(3.34)	(3.30)	(2.70)	(1.46)	(3.31)
Income	.31	.05	.75	-.76	-.45	1.09	.40
	(.42)	(.05)	(1.02)	(.94)	(.40)	(.64)	(.92)
Black	-111.50	-116.18	-116.59	-134.16	-111.35	-85.49	-120.00
	(5.68)	(4.48)	(5.44)	(5.44)	(3.22)	(1.80)	(9.41)
Other race	-81.15	-87.87	-115.64	-96.15	-54.06	-64.66	-112.02
	(2.72)	(2.53)	(3.57)	(2.22)	(1.27)	(.85)	(5.92)
Hispanic	12.83	-10.58	-15.68	6.29	30.60	54.69	-16.60
	(.65)	(.45)	(.74)	(.25)	(.88)	(1.03)	(1.27)
R^2	.08	.06	.05	.06	.05	.08	--

Note: Absolute t-values in parenthesis.

Table 7. Predicted Conditional Quantiles by WIC participation Status for 1-3 year Olds

Variable	Conditional Mean	Conditional Quantile .10	.25	.50	.75	.90
		Milligrams/day				
Iron						
Female, nonWIC	11.2	6.4	7.8	10.1	13.5	17.7
Female, WIC	12.9	6.9	8.7	11.6	16.0	20.8
Male, nonWIC	12.2	6.7	8.6	11.1	14.9	18.9
Male, WIC	14.0	7.2	9.5	12.7	17.4	21.9
Zinc						
Female, nonWIC	8.1	4.8	6.0	7.6	9.7	12.3
Female, WIC	8.5	4.9	6.0	7.9	10.3	12.9
Male, nonWIC	8.7	4.9	6.2	8.1	10.4	13.2
Male, WIC	9.1	5.0	6.2	8.4	11.0	13.8
Calcium						
Female, nonWIC	780.5	414.5	547.0	725.8	973.4	1192.8
Female, WIC	827.9	467.1	604.5	785.1	1021.6	1251.5
Male, nonWIC	824.8	411.6	567.3	772.9	1017.1	1297.0
Male, WIC	872.2	464.2	624.8	832.2	1064.2	1355.6

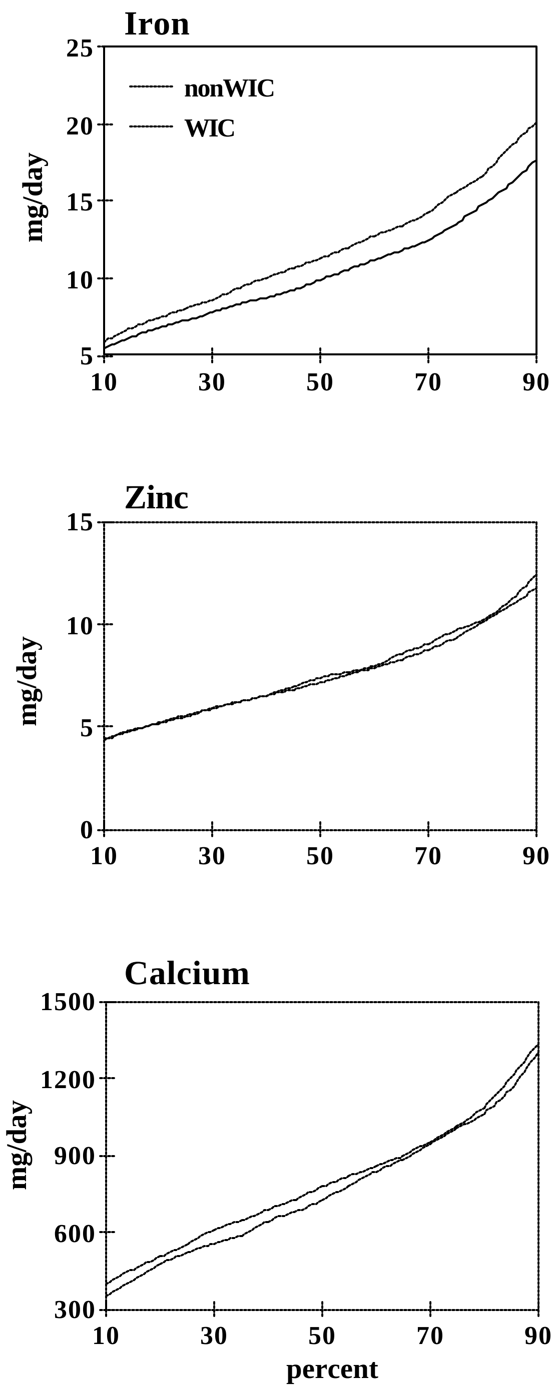
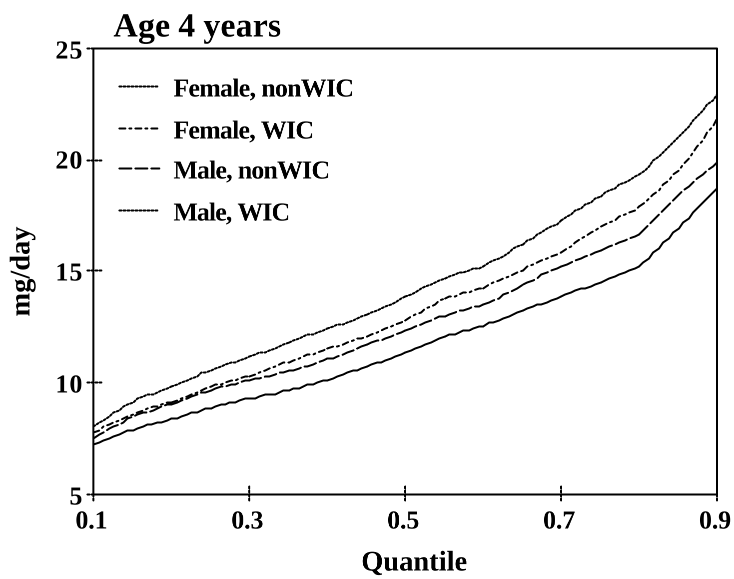


Fig. 1. The percentiles of nutrient intakes among preschoolers



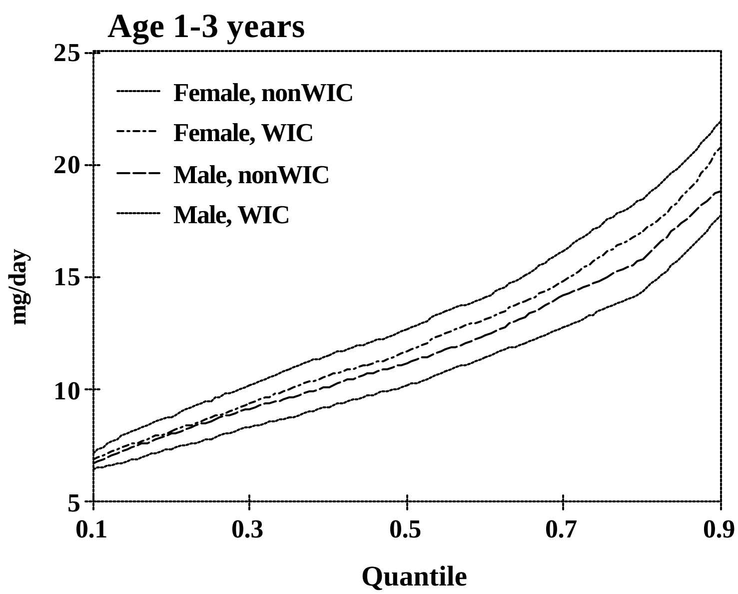


Fig. 2. Conditional quantiles of the iron intake of preschoolers

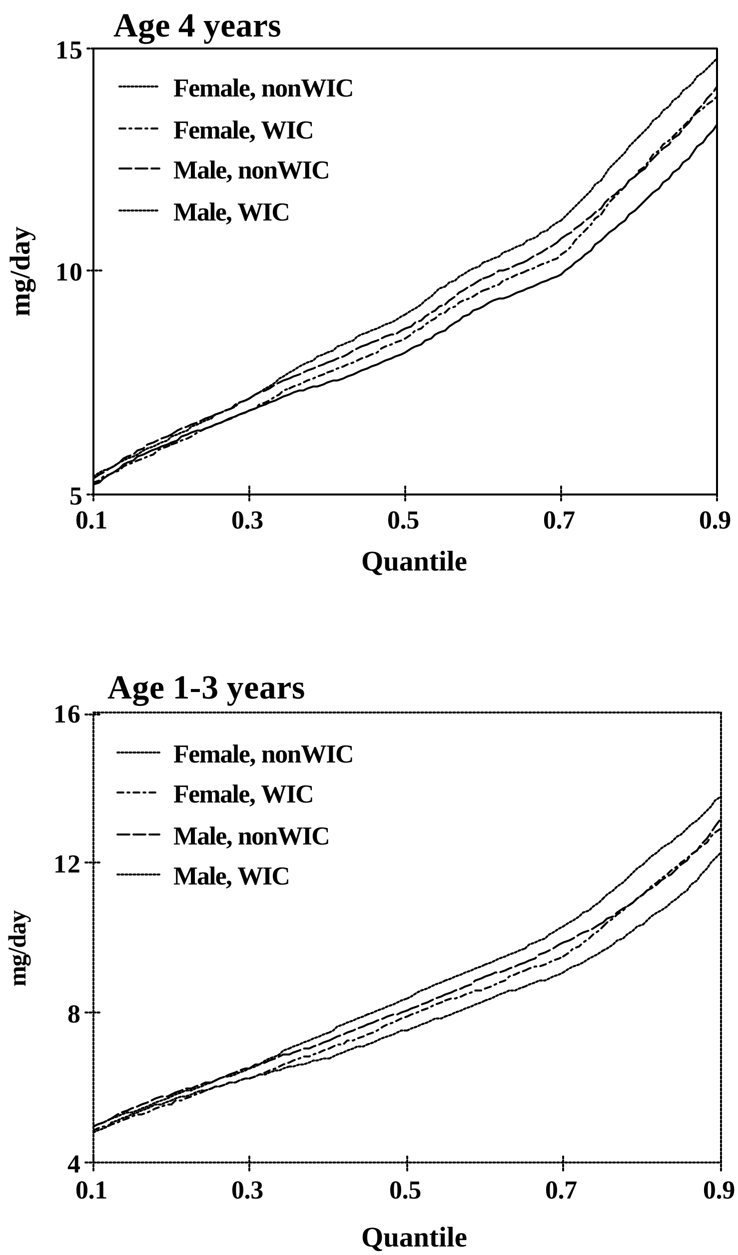
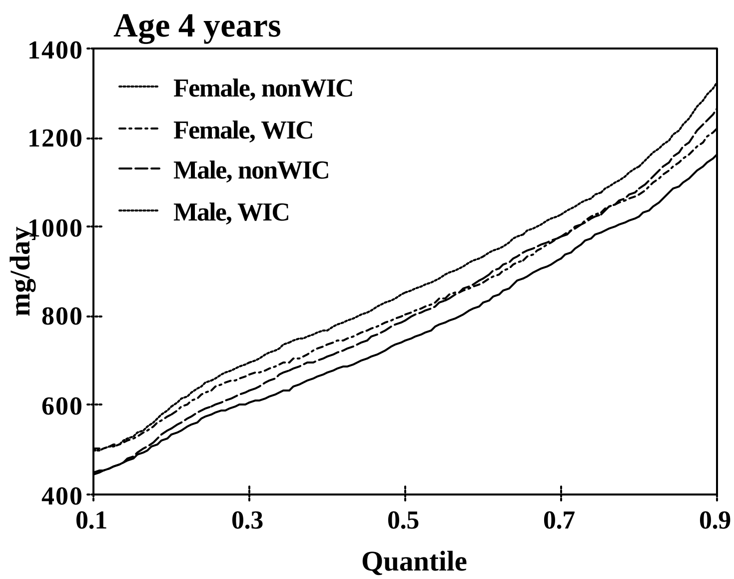


Fig. 3. Conditional quantiles of the zinc intake of preschoolers



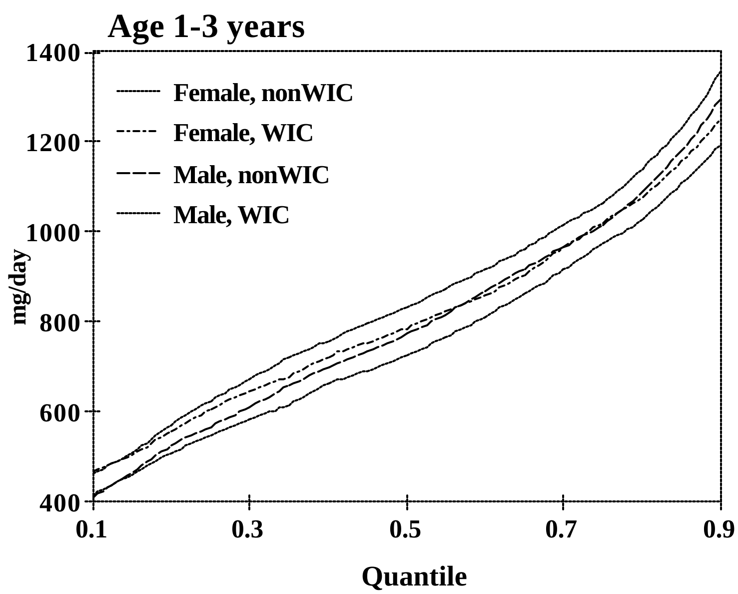


Fig. 4. Conditional quantiles of the calcium intake of preschoolers