Do Maternal Health Problems Influence Child's Worrying Status? Evidence from the British Cohort Study

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Abstract

Conventional methods apply symmetric prior distributions such as a normal distribution or a Laplace distribution for regression coefficients, which may be suitable for median regression and exhibit no robustness to outliers. This work develops a quantile regression on linear panel data model without heterogeneity from a Bayesian point of view, i.e., upon a location-scale mixture representation of the asymmetric Laplace error distribution, and provides how the posterior distribution is summarized using Markov chain Monte Carlo methods. Applying this approach to the 1970 British Cohort Study data, it finds that a different maternal health problem has different influence on child's worrying status at different quantiles. In addition, applying stochastic search variable selection for maternal health problems to the 1970 British Cohort Study data, it finds that maternal nervous breakdown, among the 25 maternal health problems, contributes most to influence the child's worrying status.

Key words: British Cohort Study data; Bayesian inference; Quantile regression; Asymmetric Laplace error distribution; Markov chain Monte Carlo; Stochastic Search Variable selection.

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1 Introduction

In many applications, conventional regression analysis focuses on the mean effect or optimal forecasting in a mean squared error sense. Since a set of quantiles often provides more complete description of the response distribution than the mean, or classical mean regression, quantile regression not only quantifies the relationship between quantiles of the response distribution and covariates, but also exhibits robustness to outliers and has a wide application (Buchinsky, 1998; Yu et al., 2003; and Koenker, 2005), for example, to calculate Value at Risk and expected shortfall for financial risk management (Taylor, 2008), to study the relationship between GDP and population (Schnabel and Eilers, 2009), to study the correlation of the wage and the level of education (Härdle and Song, 2010), and to estimate the volatility of temperatures (Guo and Härdle , 2012).

For classical quantile regression, the error distribution is often assumed to have the q-th quantile equal to zero, see, for example, Yu and Stander (2003), and classical quantile regression parameters depend on asymptotic normality which is assumed unbiased and normal. In addition, confidence intervals depend on the density function of model error which is difficult to estimate reliability. On the contrary, credible intervals from Bayesian inference can avoid these problems, whichever sample sizes. Aside from these, Bayesian inference can take historical information or expert opinion easily via prior information. Therefore Bayesian quantile regression is naturally motivated.

Quantile regression is attempted in Bayesian framework in both theoretical and applied econometric analysis, for example, Walker and Mallick (1999), Kottas and Gelfand (2001), and Hanson and Johnson (2002) on median regression (one special quantile regression), and Yu and Moyeed (2001), Tsionas (2003) and Kozumi and Kobayashi (2010) on general quantile regression with the asymmetric Laplace density for the errors. In addition, on infinite mixture model, Kottas and Krnjajic (2009) on Bayesian semi-parametric approach, Yu (2002), Taddy and Kottas (2010) and Yue and Rue (2011) on Bayesian nonparametric approach. However, few studies have been on Bayesian quantile regression for panel data (Yuan and Yin, 2010; Reich et al., 2010).

This paper explores a Bayesian quantile regression for linear panel data without heterogeneity. For posterior inference, upon a location-scale mixture representation of the asymmetric Laplace error distribution, we propose a Gibbs sampling algorithm and develop Markov chain Monte Carlo (MCMC) methods (see, e.g., Chib 2001; Liu 2001; Gamerman and Lopes 2006). All posterior densities are fully tractable and easy to sample, making the Gibbs sampler appealing when several quantile regressions are required at one time. In addition, the proposed Gibbs sampler can be applied for the calculation of the marginal likelihood and the variable selection.

For variable selection, several criteria have been proposed (see, for example, Zwick and Velicer (1986)), though no agreement has emerged in the literature on optimal criterion. Aside from the classical literature, Bayesian approach focuses on an unknown number of variables (Frühwirth-Schnatter and Lopes (2009), Conti, et al. (2014)). Variable selection in modeling with Bayesian quantile regression is difficult due to the computational efficiency. This work applies stochastic search variable selection based on Markov chain Monte Carlo method.

We apply Bayesian approach to the 1970 British Cohort Study (BCS) to analyze the influence of maternal health problems on child's worrying status. This is the first instance, as we know, in which the influences of the maternal health problems are estimated to account for child's worrying status. We find that the different maternal health problems have different influence on child's worrying status at different quantiles, moreover, maternal nervous breakdown, among the 25 maternal health problems, contributes most to influence the child's worrying status. Indeed Bayesian approach may be applied to empirical study of optimal taxation under prospect theory, or predictive asset return, see, for example, Kanbur, pirttila and Tuomala (2008) and Dai (2011) for optimal taxation under prospect theory, and Campbell and Yogo (2006) and Dai, Li and Wang (2013) for predictive asset return.

This paper joins the literature in health economics and personality psychology. While it is established in psychology on their importance (see, for example, Roberts et al.(2006, 2007), Hampson and Friedman (2008)), and in economics for the influence of personality traits on health (Kaestner and Callison, 2011; Conti et al., 2014) and health-related behaviors (Heckman et al., 2006; Cutler and Lleras-Muney, 2010; Conti, et al., 2014), it is less recognized in economics on the influence of maternal health problems on child's worrying status.

Using principal component analysis, a few economic result from the BCS data, for example, psychological and behavioral development influences education and labor market outcomes (Feinstein, 2000), intergenerational income persistence rises across the 1958 and the 1970 cohorts (Blanden et al., 2007), and the standardized raw scores from the locus of control and self-esteem scales significantly predict self-reported poor health at age 30 (Murasko, 2007). Other data may be explored, see, for example, Dai and Heckman (2013). This work goes beyond those studies, since Bayesian inference is explored to examine the influence of maternal health problems on child's worrying status.

The remain of the paper is structured as follows. In the next section, we describe the BCS data. Section 3 outlines the basic model, while Section 4 develops MCMC method for quantile regression model and explains how the MCMC output may be used to compute the marginal likelihoods and for variable selection. Empirical implementation and results for our Bayesian approach are shown in Section 5. Section 6 concludes.

2 Data: The British Cohort Study

The data, we use in this work, are from the BCS, a survey of all babies born (alive or dead) after the 24-th week of gestation from 0.01 hours on Sunday, 5th April to 24.00 hours on Saturday, 11 April, 1970 in places including England, Scotland, Wales and Northern Ireland. Seven surveys, in detail, respectively in 1975, 1980, 1986, 1996, 2000, 2004 and 2008, are followed up so far to trace all members of the birth cohort. In this work, information on background characteristics is drawn from the survey in 1975 and 1980 on maternal health problems, and on child's worrying status from the survey in 1980 and 1986. Samples from the family of multiple children are excluded, and samples for the respondents with any missing information on those background characteristics are also excluded. A sample of size 3,426 is left for our analysis in this paper.

2.1 Rutter Score Derived Variable for Child

Applying the Rutter Behaviour Scale question "Often worried?" for child, the Rutter score derived variable, Y, was derived, where the question was completed by the cohort member's parent (usually the mother) in the BCS 1980 and 1986 follow-up data sets. In the BCS, the Rutter score derived, and thus the response variable, is discrete choice. For our case, the response results are 1 (Does not worried), 2 (Somewhat worried), and 3 (Certainly worried).

2.2 Mother Malaise Score Derived Variables

Applying the Malaise Inventory ("How you feel") completed by the cohort member's parent (usually the mother), the mother malaise score derived variables were derived on behalf of the cohort member and included in the BCS 1975 and 1980 follow-up data sets. These 25 variables were named in the Mother Malaise data sets as follows:

(1) Do you often have backache? (X_1)

(2) Do you feel tired most of the time? (X_2)

(3) Do you often feel depressed? (X_3)

(4) Do you often have bad headaches? (X_4)

(5) Do you often get worried about things? (X_5)

(6) Do you usually have great difficulty in falling or staying asleep? (X_6)

(7) Do you usually wake unnecessarily early in the morning? (X_7)

(8) Do you wear yourself out worrying about your health? (X_8)

(9) Do you often get into a violent rage? (X_9)

(10) Do people annoy and irritate you? (X_{10})

(11) Have you at times had a twitching of the face, head or shoulders? (X_{11})

(12) Do you suddenly become scared for no good reason? (X_{12})

(13) Are you scared to be alone when there are not friends near you? (X_{13})

(14) Are you easily upset or irritated? (X_{14})

(15) Are you frightened of going out alone or of meeting people? (X_{15})

(16) Are you constantly keyed up and jittery? (X_{16})

(17) Do you suffer from indigestion? (X_{17})

(18) Do you suffer from an upset stomach? (X_{18})

(19) Is your appetite poor? (X_{19})

(20) Does every little thing get on your nerves and wear you out? (X_{20})

(21) Does your heart often race like mad? (X_{21})

(22) Do you often have bad pain in eyes? (X_{22})

(23) Are you troubled with rheumatism or fibrosis? (X_{23})

(24) Have you ever had a nervous breakdown? (X_{24})

(25) Do you have other health problems? (X_{25})

3 Potential Outcome Model

Let Y_{it+1} be the Rutter score derived variable for the i-th cohort member surveyed at the $(t+1)$-th sweep, and $X_{1,it}$, $X_{2,it}$,..., $X_{25,it}$ the mother malaise score derived variables for the i-th cohort member's parent (usually the mother) surveyed at the t-th sweep. We introduce the linear panel data model without heterogeneity as follows.

$$Y_{it+1} = \beta_0 + \sum_{j=1}^{25} \beta_j X_{j,it} + \varepsilon_{it}. \tag{1}$$

for $i = 1, 2, ..., 3426$, and $t = 1, 2$, where $\beta_{.}$ is unknown parameter, and ε_{it} is is an idiosyncratic error term assumed to be independent of the Rutter score derived variable and mother malaise score derived variables.

4 Bayesian Inference and Variable Selection

In this study, we consider quantile regression to estimate β from

$$\min \sum_{i=1}^{3426} \sum_{t=1}^{2} \rho_q(Y_{it} - \sum_{j=1}^{25} \beta_j X_{j,it} - \beta_0), \tag{2}$$

where $\rho_q(.)$ in (2) is the check function defined by

$$\rho_q(u) \equiv \{q - I(u < 0)\} \cdot u, \tag{3}$$

for $0 < q < 1$, where $I(.)$ is the indicator function. Instead of classical approach, a Bayesian approach and MCMC algorithm will be developed for posterior inference.

4.1 Asymmetric Laplace Distribution

For Bayesian inference of (2), an assumption on the data distribution is required to construct a likelihood function. The error term ε_{it} is assumed, following Yu and Moyeed (2001), to follow the asymmetric Laplace distribution (ALD) with density

$$f_{AL}(\varepsilon_{it}) = \frac{q(1-q)}{\sigma} \exp\{-\rho_q(\frac{\varepsilon_{it}}{\sigma})\}, \tag{4}$$

where σ is the scale parameter. For the properties of this distribution, see, for example, Yu and Moyeed (2001), and Yu and Zhang (2005). Note that the q-th quantile of ε_{it} is zero, $\mathrm{E}(\varepsilon_{it}) = \frac{1-2q}{q(1-q)}$, and $\mathrm{Var}(\varepsilon_{it}) = \frac{1-2q+2q^2}{q^2(1-q)^2}$.

To develop MCMC algorithm for the quantile regression, a location scale mixture representation is applied, i.e.,

$$\varepsilon_{it} = \theta v_{it} + \tau\sqrt{\sigma v_{it}} u_{it}, \tag{5}$$

where $\theta = \frac{1-2q}{q(1-q)}$, $\tau^2 = \frac{2}{q(1-q)}$, $v_{it} \sim \varepsilon(\sigma)$ and $u_{it} \sim \mathrm{N}(0,1)$ are mutually independent random variables, and $\varepsilon(\sigma)$ is the exponential distribution with mean σ (Kozumi and Kobayashi, 2010). Thus the panel data model without heterogeneity can be represented as follows.

$$Y_{it} = \beta_0 + \sum_{j=1}^{25} \beta_j X_{j,it} + \theta v_{it} + \tau\sqrt{\sigma v_{it}} u_{it}, \tag{6}$$

where $v_{it} \sim \varepsilon(\sigma)$ and $u_{it} \sim \mathrm{N}(0,1)$ are mutually independent random variables.

To begin posterior inference, some prior distributions are supposed as follows: (1) $\beta \sim \mathrm{N}(\beta_0, B_0)$, where $\beta \equiv (\beta_0, \beta_1, ..., \beta_{25})$, and β_0 and B_0 are specified parameters; (2) $\sigma \sim \mathrm{IG}(\frac{n_0}{2}, \frac{s_0}{2})$, where $\mathrm{IG}(a,b)$ is the inverse Gamma distribution with the parameters a and b, and n_0 and s_0 are specified parameters. These priors are chosen for computational reasons, but are flexible enough when analyzing BCS to represent various prior beliefs about the parameters. Next to construct a MCMC algorithm with those prior distributions.

4.2 Markov Chain Monte Carlo Algorithm

A MCMC algorithm (see, for example, Chib (2001), Liu (2001) and Gamerman and Lopes (2006)) for the quantile regression is constructed by sampling $\{v_{it}\}$, β, and σ from their full conditional distributions applying the data augmentation techniques as Chib (1992). A tractable and efficient Gibbs sampler is proposed for general $i = 1, 2, ..., N$ and $t = 1, T$ as follows. In the empirical part, $N = 3426$, and $T = 2$.

1. Sample v_{it} $(i = 1, 2, ..., N;\ t = 1, T)$ from GIG$(\frac{1}{2}, \hat{c}_{it}^2, \hat{d}_{it}^2)$, where

$$\hat{c}_{it}^2 = \frac{(Y_{it+1} - \beta^\top X_{it})^2}{\tau^2\sigma}, \tag{7}$$

$$\hat{d}_{it}^2 = \frac{\theta^2}{\tau^2\sigma} + \frac{2}{\sigma}, \tag{8}$$

and GIG(ν, c, d) is the generalized inverse Gaussian distribution with the probability density function

$$f_{GIG}(x|\nu, c, d) = \frac{(\frac{d}{c})^\nu}{2K_\nu(cd)} x^{\nu-1} \exp\{-\frac{1}{2}(c^2 x^{-1} + d^2 x)\}, \tag{9}$$

for $x > 0$, $-\infty < \nu < \infty$, and $c, d > 0$, where $K_\nu(.)$ is a modified Bessel function of the third kind (Barndorff-Nielsen and Shephard, 2001).

2. Sample β from $\mathrm{N}(\hat{\beta}, \hat{B})$, where

$$\hat{\beta} = \hat{B}\{\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{(Y_{it+1} - \theta v_{it})X_{it}}{\tau^2\sigma v_{it}} + B_0^{-1}\beta_0\}, \tag{10}$$

$$\hat{B}^{-1} = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{X_{it}X_{it}^{\top}}{\tau^2\sigma v_{it}} + B_0^{-1}. \tag{11}$$

3. Sample σ from $\mathrm{IG}(\frac{\hat{n}}{2}, \frac{\hat{s}}{2})$, where

$$\hat{n} = 3NT + n_0, \tag{12}$$

$$\hat{s} = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{(Y_{it+1} - \beta^{\top}X_{it} - \theta v_{it})^2}{\tau^2 v_{it}} + 2\sum_{i=1}^{N}\sum_{t=1}^{T} v_{it} + s_0. \tag{13}$$

The MCMC algorithm for the quantile regression model is constructed applying the data augmentation technique as Chib (1992). From (5), (6) and the assumptions for some prior distributions, a tractable and efficient Gibbs sampler can be proposed as above. In addition, the proposed Gibbs sampler sample v_{it} from the generalized inverse Gaussian distribution. Efficient algorithms to simulate from the generalized inverse Gaussian distribution exist, see, for example, Dagpunar (1989) and Hörman et al. (2004), but our proposed Gibbs sampler is implemented easily without any further need for tuning. Similar to Alhamzawi and Yu (2013), all those similar results and our assumptions can, applying Ghosh et al.(2006) and Sriram et al.(2011), guarantee the rationality of the MCMC algorithm mentioned above.

4.3 Marginal Likelihood

The marginal likelihood, $m(Y)$, of the panel data model is defined as

$$m(Y) = \int f(Y|\eta)\pi(\eta)d\eta, \tag{14}$$

where $f(Y|\eta)$ is the sampling density of the data $\{Y\}$ and $\pi(\eta)$ is the prior of the model specific parameter η.

The marginal likelihood, $m(Y)$, can be reformulated as

$$m(Y) = \frac{f(Y|\eta)\pi(\eta)}{\pi(\eta|Y)}, \tag{15}$$

from which Chib (1995) suggests to estimate the marginal likelihood as follows.

$$\log m(Y) = \log f(Y|\eta^*) + \log \pi(\eta^*) - \log \pi(\eta^*|Y), \tag{16}$$

where η^* is a particular high density point, typically the posterior mean or mode.

For $\eta \equiv \{\beta, \sigma\}$ and $Y \equiv \{Y_{it}\}$ in the panel data model, the posterior ordinate $\pi(\eta^*|Y)$ is estimated by the following decomposition.

$$\pi(\eta^*|Y) = \pi(\sigma^*|Y)\pi(\beta^*|\sigma^*, Y), \tag{17}$$

marginalized over the latent variable $v \equiv \{v_{it}\}$, since the ordinates $\pi(\sigma^*|Y)$, and $\pi(\beta^*|\sigma^*, Y)$ can be estimated according to Chib (1995). The likelihood ordinate, $f(Y|\eta^*)$, can be estimated by Chib method.

4.4 Variable Selection

To perform the variable selection for the quantile regression, an indicator vector is defined as follows. $\gamma \equiv (\gamma_0, \gamma_1, ..., \gamma_{25})$, where $\gamma_0 = 1$, and $\gamma_i = 1$ for $i \geq 1$ if β_i is included in the model (i.e., $\beta_i \neq 0$), and $\gamma_i = 0$ for $i \geq 1$ if β_i is excluded in the model (i.e., $\beta_i = 0$).

Given the indicator γ, k_γ denote the size of the γ-th subset model, $k_\gamma = \gamma^\top 1$, and β_{k_γ} and $X_{k_\gamma,it}$ are $k_\gamma \times 1$ vectors corresponding to all the components of β and X_{it} such that the corresponding γ_i's are equal to 1. Given γ, the following prior assumptions are supposed.

1. $\beta_{k_\gamma}|\sigma, \nu \sim \mathrm{N}(\beta_0, 2\sigma(X_{k_\gamma}^\top V X_{k_\gamma})^{-1})$, where $p(\sigma) \propto \sigma^{-1}$ and each $\nu_i \sim \varepsilon(\frac{\sigma}{p(1-p)})$.
2. A prior distribution over model space γ is given by $p(\gamma|\pi) \propto \pi^{k_\gamma}(1-\pi)^{k-k_\gamma}$.
3. $\pi \sim beta(a_0, b_0)$.

Given γ and the prior assumptions above, there are several ways to develop, for examples, (a) a tractable and efficient Gibbs sampler can be proposed applying the data augmentation technique as Chib (1992), similarly to section 4.2, then compare the posterior model probabilities for different γ; (b) following Smith and Kohn (1996), Kuo and Mallick (1998), Krishna et al. (2008), Zou and Yuan (2008), Wu and Liu (2009), Alhamzawi and Yu (2013), or Yu et. al. (2013), an efficient Gibbs sampler can be proposed for computing posterior model probabilities in quantile regression, which we will follow next.

Under the prior assumptions, a MCMC algorithm can be developed to compute posterior model probabilities in the quantile regression by running the Gibbs sampler, and the marginal likelihood of Y under model γ can be obtained by integrating out β_{k_γ} and σ,

$$p(Y|\gamma, \nu, X) \propto \int p(\sigma)d\sigma \int p(Y|\beta_{k_\gamma}, \gamma, \sigma, \nu, X)p(\beta_{k_\gamma}|\gamma, \sigma, \nu)p(\nu|\sigma)d\beta_{k_\gamma}. \tag{18}$$

Integrating out β_{k_γ} and σ as a normal integral and an inverse gamma integral,

$$Y|\gamma, \nu, X \sim t_{(2n)}\{X_{k_\gamma}\beta_0 + \xi\nu, \frac{1}{2}(V + VX_{k_\gamma}(X_{k_\gamma}^\top VX_{k_\gamma})^{-1}X_{k_\gamma}^\top V)\}. \tag{19}$$

Then, the Gibbs sampler can be implemented (Smith and Kohn, 1996; Krishna et al., 2008) to generate samples of

$$p(Y|\gamma, \nu, X) \propto p(Y, \gamma, \nu, X)p(\gamma|\pi). \tag{20}$$

5 Real Data Application

In this section, the Bayesian quantile regression is applied to analysis the British Cohort study data. This data set was extensively investigated for many sorts of topics, but this paper examines the influence of maternal health problems on child's worrying status. There are 3426 observations, 25 predictor variables, and one response variable. We assume the quantile regression model between the response variable and the 25 covariates, plus an intercept.

In Table 1, upon the Bayesian quantile regression applying the MCMC package in R (R Development Core Team, 2011), the model is evaluated at three different quantiles 0.05, 0.50 and 0.95. The maternal health problems have different influence on child's worrying status at different quantiles, through MCMC quantile regression iteration 50001 of 51000, in detail, β_i have different estimates at different quantiles for each $i = 0, ..., 25$. β_{24} and β_{25} have the biggest absolute value for the three quantiles, except for β_0.

Upon the Bayesian quantile regression applying the MCMC package in R (R Development Core Team, 2011), iterations = 1001 : 50991, thinning interval = 10, number of chains = 1, sample size per chain = 5000. Table 2 summarizes the empirical mean and standard deviation for each variable X_i ($i = 1, ..., 25$), and standard error of the mean for the model at the quantile 0.05. In this case, X_{24} has the biggest standard deviation, and X_{25} has the next biggest standard deviation. Table 3 summarizes the quantiles for each variable X_i ($i = 1, ..., 25$).

Tables 4-5 summarizes the same contents for the quantile 0.50, and Tables 6-7 for the quantile 0.95.

Applying the stochastic search variable selection (R Development Core Team, 2011), quantreg iteration 50001 of 51000, the top models and the posterior model probabilities are summarized in Table 8-10 for the different quantiles 0.05, 0.50, and 0.95. From the posterior model probabilities applying the stochastic search variable selection, SSVSquantreg, the top models picked have significantly different posterior model probabilities, and, in particular, the maternal nervous breakdown, X_{24}, and the other health problems, X_{25}, are the first two important to influence child's worrying status. This indicates that the maternal nervous breakdown and the other health problems need be made enough attention to intervene early for the influence on child's worrying status.

6 Conclusions

In this paper, we developed a Bayesian quantile regression for linear panel data model without heterogeneity, in particular, upon a location-scale mixture representation of the asymmetric Laplace error distribution, this paper provides how the posterior distribution can be sampled and summarized by a MCMC method.

In addition, the influence of maternal health problems on child's worrying status was explored by this method to the 1970 BCS data, and we find that different maternal health problem has different influence on child's worrying status at different quantiles, also that maternal nervous breakdown and the other maternal health problem, by our method, are the first two important to influence the child's worrying status.

Our findings have high policy relevance in terms of the importance of the intervention of maternal nervous breakdown early for the influence on child's worrying status.

	q=0.05	q=0.50	q=0.95
β_0	1126.80	2909.93	6219.29
β_1	5.13	0.56	0.95
β_2	-3.30	0.05	-8.85
β_3	0.23	-0.41	-0.30
β_4	-1.11	0.25	-3.58
β_5	-4.88	-0.09	0.93
β_6	-0.10	-0.20	-2.80
β_7	2.20	-0.55	-3.76
β_8	-1.81	2.09	1.86
β_9	-0.41	-1.19	-5.94
β_{10}	2.22	0.28	0.06
β_{11}	-14.86	-3.09	-7.68
β_{12}	-13.23	-0.79	-2.01
β_{13}	13.86	0.79	6.21
β_{14}	0.96	0.27	5.51
β_{15}	6.42	1.49	-6.35
β_{16}	2.87	0.41	-5.71
β_{17}	2.75	0.54	3.07
β_{18}	-0.85	-0.38	3.42
β_{19}	-3.20	0.32	2.77
β_{20}	6.24	-1.07	1.86
β_{21}	4.43	0.74	3.21
β_{22}	1.31	0.50	0.54
β_{23}	-3.54	0.10	-5.09
β_{24}	-194.69	63.94	317.94
β_{25}	79.96	-40.22	-289.67

Table 1: β for the quantile q=0.05, 0.50, 0.95 (all figures e-3 units)

	Mean	SD	Naive SE	Time-series SE
(Intercept)	80960.000	71879.300	1017.000	1106.000
X_1	261.900	213.400	3.018	3.491
X_2	-149.800	237.600	3.360	3.822
X_3	185.400	340.400	4.814	5.271
X_4	-75.700	245.800	3.476	3.877
X_5	-254.900	257.300	3.638	4.211
X_6	-157.500	267.900	3.789	3.952
X_7	163.800	273.500	3.868	4.166
X_8	-186.800	461.000	6.519	7.460
X_9	-6554.000	335.300	4.742	5.084
X_{10}	1507.000	290.300	4.106	4.513
X_{11}	-313.300	557.300	7.881	8.479
X_{12}	-329.200	533.100	7.539	8.646
X_{13}	38.260	472.600	6.684	7.343
X_{14}	-4.005	288.400	4.079	4.303
X_{15}	237.800	352.400	4.984	5.331
X_{16}	49.760	423.700	5.992	6.617
X_{17}	-163.300	379.400	5.365	6.031
X_{18}	4.134	425.900	6.023	6.681
X_{19}	188.400	383.400	5.423	5.706
X_{20}	200.100	429.500	6.074	6.698
X_{21}	511.500	445.400	6.298	7.015
X_{22}	-145.200	456.700	6.459	6.873
X_{23}	50.030	266.600	3.771	3.990
X_{24}	8781.000	29472.100	416.800	449.800
X_{25}	894.100	15204.000	215.000	225.300

Table 2: Empirical mean and standard deviation for each variable, and standard error of the mean for the quantile q=0.05 (all figures e-3 units)

	2.5%	25%	50%	75%	97.5%
X_1	-1.34700	1.13700	2.54300	3.98620	6.93500
X_2	-6.33800	-3.02200	-1.45200	0.12610	3.02100
X_3	-4.75700	-0.49200	1.84600	4.15660	8.71300
X_4	-5.81500	-2.35300	-0.73510	0.89110	3.99100
X_5	-7.70100	-4.26700	-2.55100	-0.78220	2.43500
X_6	-6.94900	-3.34100	-1.56900	0.25070	3.75800
X_7	-3.83500	-0.13280	1.64700	3.46200	7.04700
X_8	-10.26800	-5.08700	-2.13500	1.18830	7.48600
X_9	-7.25500	-2.92700	-0.70160	1.57420	6.00400
X_{10}	-5.59700	-1.81500	0.23440	2.10240	5.73600
X_{11}	-13.57600	-6.94100	-3.33700	0.59920	8.25000
X_{12}	-13.38400	-6.96400	-3.31500	0.28870	7.30000
X_{13}	-8.44000	-2.85800	0.24870	3.44650	10.18400
X_{14}	-5.73800	-1.93200	-0.06721	1.90910	5.67600
X_{15}	-3.93900	-0.09158	2.16200	4.58360	9.75500
X_{16}	-7.83700	-2.42900	0.44340	3.29010	8.77200
X_{17}	-9.35300	-4.09600	-1.53500	0.91150	5.69400
X_{18}	-8.17500	-2.86500	-0.01683	2.89110	8.58500
X_{19}	-5.68900	-0.60500	1.91100	4.39410	9.39800
X_{20}	-6.46200	-0.87610	1.97500	4.88770	10.38500
X_{21}	-3.12100	2.08200	4.94800	7.97480	14.39400
X_{22}	-10.27300	-4.54000	-1.46500	1.52430	7.74900
X_{23}	-4.87600	-1.25900	0.54290	2.24970	5.87200
X_{24}	-475.64400	-100.40000	74.99000	264.89090	698.47500
X_{25}	-292.12600	-91.20000	7.40400	108.54190	310.32500

Table 3: Quantiles for each variable when the quantile q=0.05 (all figures e-3 units)

	Mean	SD	Naive SE	Time-series SE
(Intercept)	29510.00000	1917.03100	27.11000	27.11000
X_1	0.66020	4.70700	0.06656	0.06889
X_2	0.42350	4.45500	0.06300	0.06300
X_3	2.91500	7.11300	0.10060	0.10060
X_4	-1.09500	4.83300	0.06835	0.06898
X_5	-1.02500	4.17200	0.05899	0.05899
X_6	-0.02617	6.51800	0.09217	0.09471
X_7	-1.56800	6.86200	0.09704	0.09704
X_8	2.16700	12.10100	0.17110	0.17110
X_9	-1.96000	7.36500	0.10420	0.10420
X_{10}	-45.60000	5.74800	0.08129	0.08129
X_{11}	-5.42100	13.93300	0.19700	0.19700
X_{12}	-6.85000	12.46000	0.17620	0.17250
X_{13}	2.50500	12.51200	0.17700	0.17700
X_{14}	-1.28200	6.02300	0.08517	0.08517
X_{15}	1.26500	9.32900	0.13190	0.13190
X_{16}	1.27600	9.62700	0.13610	0.13810
X_{17}	-0.27990	7.54500	0.10670	0.10670
X_{18}	2.56600	9.28200	0.13130	0.13130
X_{19}	1.81300	11.09900	0.15700	0.15350
X_{20}	-4.30400	10.52200	0.14880	0.14880
X_{21}	2.18700	11.71400	0.16570	0.16950
X_{22}	3.21700	9.07700	0.12840	0.11980
X_{23}	1.50600	6.13100	0.08671	0.08671
X_{24}	489.50000	832.31100	0.11770	11.77000
X_{25}	-172.10000	360.37700	5.09600	5.09600

Table 4: Empirical mean and standard deviation for each variable, and standard error of the mean for the quantile q=0.50 (all figures e-4 units)

	2.5%	25%	50%	75%	97.5%
(Intercept)	25445.4100	28376.7290	29630.0000	30743.89190	33003.4600
X_1	-8.6250	-2.4480	0.5838	3.6300	10.1710
X_2	-8.5120	-2.4630	0.4258	3.2990	9.3610
X_3	-10.8590	-1.7350	2.7430	7.4820	17.5130
X_4	-11.0650	-4.2140	-1.1040	2.0350	8.1710
X_5	-9.8440	-3.6330	-0.8936	1.6830	7.0560
X_6	-12.7880	-4.2380	-0.0366	4.2310	12.7960
X_7	-15.3660	-5.8820	-1.4430	3.0750	11.6360
X_8	-21.2970	-5.3980	2.0210	9.5740	26.5670
X_9	-16.9570	-6.6250	-1.9170	3.0030	12.1740
X_{10}	-12.1040	-4.0950	-0.2667	3.3190	10.6870
X_{11}	-33.8050	-14.5850	-4.8640	3.8510	21.6330
X_{12}	-34.0110	-14.3300	-6.1220	1.5110	16.1080
X_{13}	-22.5280	-5.1120	2.2030	9.8840	27.8070
X_{14}	-13.8990	-5.0690	-1.1530	2.6480	10.1430
X_{15}	-16.8440	-4.6930	1.0780	7.0880	20.4560
X_{16}	-17.3840	-5.0210	1.0840	7.3910	20.8090
X_{17}	-15.8120	-4.9400	-0.2400	4.6070	14.7560
X_{18}	-15.0820	-3.3770	2.3710	8.3070	21.7620
X_{19}	-19.4420	-5.2890	1.5910	8.5320	25.0950
X_{20}	-26.2960	-11.1120	-4.0050	2.6800	15.8220
X_{21}	-21.3700	-5.5090	2.1500	9.5880	25.7640
X_{22}	-14.1720	-2.7470	3.0950	9.0090	21.8540
X_{23}	-10.5890	-2.4880	1.3630	5.4100	13.9490
X_{24}	-968.4610	-48.3330	402.5000	955.8340	2391.5660
X_{25}	-927.5700	-399.4760	-156.6000	68.2750	502.9410

Table 5: Quantiles for each variable when the quantile q=0.50 (all figures e-4 units)

	Mean	SD	Naive SE	Time-series SE
(Intercept)	543695.460	89426.900	1265.000	1526.000
X_1	-26.660	263.000	3.720	4.410
X_2	-315.410	285.900	4.044	5.278
X_3	56.890	380.900	5.387	6.252
X_4	-272.060	277.500	3.924	4.794
X_5	-188.940	267.000	3.776	4.756
X_6	209.250	330.700	4.677	5.667
X_7	-219.800	321.400	4.546	5.336
X_8	114.880	493.900	6.985	7.819
X_9	-323.280	383.700	5.426	6.256
X_{10}	-23.130	344.300	4.869	5.876
X_{11}	107.880	587.300	8.305	9.311
X_{12}	-288.510	506.800	7.167	7.714
X_{13}	-182.250	502.800	7.111	7.820
X_{14}	-119.030	348.300	4.925	5.872
X_{15}	-180.200	426.800	6.036	7.686
X_{16}	45.020	449.200	6.353	7.070
X_{17}	46.290	382.700	5.412	6.318
X_{18}	40.220	451.800	6.389	7.439
X_{19}	-283.000	463.500	6.555	7.313
X_{20}	-340.210	457.600	6.472	7.280
X_{21}	5380.900	451.000	6.378	7.051
X_{22}	596.060	476.700	6.742	7.828
X_{23}	-69.550	327.200	4.627	5.620
X_{24}	11901.210	32910.100	465.400	526.100
X_{25}	-17966.530	18277.500	258.500	324.300

Table 6: Empirical mean and standard deviation for each variable, and standard error of the mean for the quantile q=0.95 (all figures e-5 units)

	2.5%	25%	50%	75%	97.5%
(Intercept)	3783.021000	4822.000000	5411.142900	6011.000000	7310.987000
X_1	-5.526000	-2.044000	-0.182300	1.547000	4.797000
X_2	-8.516000	-5.127000	-3.207600	-1.260000	2.565000
X_3	-7.097000	-2.014000	0.679300	3.184000	7.869000
X_4	-8.036000	-4.580000	-2.731600	-79.930000	2.706000
X_5	-7.234000	-3.644000	-1.910700	-705.400000	3.189000
X_6	-4.811000	-0.073560	2.210700	4.391000	8.246000
X_7	-8.675000	-4.335000	-2.161400	0.007187	3.938000
X_8	-8.859000	-2.114000	1.186400	4.435000	10.403000
X_9	-10.886000	-5.801000	-3.227300	-0.648600	4.243000
X_{10}	-7.099000	-2.538000	-0.192100	2.090000	6.376000
X_{11}	-11.012000	-2.672000	1.329400	5.071000	11.764000
X_{12}	-13.181000	-6.219000	-2.721400	0.581100	6.605000
X_{13}	-12.166000	-5.053000	-1.754700	1.648000	7.593000
X_{14}	-8.183000	-3.535000	-1.173300	1.203000	5.571000
X_{15}	-10.492000	-4.647000	-1.685700	1.147000	6.205000
X_{16}	-8.687000	-2.559000	0.555000	3.577000	8.928000
X_{17}	-7.463000	-2.024000	0.643100	3.161000	7.391000
X_{18}	-8.881000	-2.501000	0.658700	3.484000	8.691000
X_{19}	-12.285000	-5.818000	-2.713800	0.417100	5.652000
X_{20}	-12.563000	-6.433000	-3.268300	-0.329300	5.214000
X_{21}	-4.353000	2.590000	5.707900	8.514000	13.439000
X_{22}	-3.864000	2.872000	6.214400	9.278000	14.778000
X_{23}	-7.358000	-2.825000	-0.538400	1.571000	5.350000
X_{24}	-90.350000	-88.010000	147.516800	49.500000	696.594000
X_{25}	-555.750000	-300.300000	-172.533700	-49.340000	153.451000

Table 7: Quantiles for each variable when the quantile q=0.95 (all figures e-3 units)

Models	Probability
(Intercept)	0.9278
X_{24}	0.0502
(Intercept), X_{24}	0.0142
(Intercept), X_{25}	0.0052
(Intercept), X_3	0.0004

Table 8: Variable Selection for the quantile q=0.05

Models	Probability
(Intercept)	0.9954
(Intercept), X_{24}	0.0040
(Intercept), X_{25}	0.0004
(Intercept), X_2	0.0002

Table 9: Variable Selection for the quantile q=0.50

Models	Probability
(Intercept)	0.9274
(Intercept), X_{24}	0.0486
(Intercept), X_{25}	0.0146
(Intercept), X_{20}	0.0012
(Intercept), X_2	0.0010

Table 10: Variable Selection for the quantile q=0.95

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