

# Quantile Regression Analysis for Statin Effects on Body mass Index

April 30, 2021

## **Abstract**

My abstract

## **Contents**

<b>1</b>	<b>introduction</b>	<b>2</b>
<b>2</b>	<b>Quantile Regression</b>	<b>6</b>
2.1	Quantile Regression Technique . . . . .	10
2.2	splines . . . . .	10
<b>3</b>	<b>Methods</b>	<b>12</b>
<b>4</b>	<b>Numerical Example</b>	<b>13</b>
4.1	Data . . . . .	13
<b>5</b>	<b>Results</b>	<b>18</b>
<b>6</b>	<b>Conclusion</b>	<b>25</b>
<b>7</b>	<b>References</b>	<b>27</b>

# 1 introduction

High BMI has negative impact on public health. Due to high cost of obesity, it is crucial to get better understanding of the underlying risk factor for obesity. This can help decision makers to create a new regulation that help to prevent and to stop the dramatic increase in the BMI index.

Body Mass Index (BMI) plays an important role in predicting heart disease risk(Katzmarzyk et al. 2012). Approximately, 18 million deaths annually per year are caused by cardiovascular diseases(CVD), and similar to this number of nonfatal cardiovascular events (Hay et al. 2017). In 2011, annual costs for CVD and stroke were \$320.1 billion, which is more than cancer cost. This cost includes \$195.6 billion in direct costs (healthcare costs), and the cost of future productivity loss is \$124.5 (Mozaffarian et

al. 2015). Important factors associated with CVD are high body mass index (BMI) and

abnormal lipid ratio (Yusuf et al. 2004), (Anderson et al. 1991). Lowering low-density

lipoprotein (LDL) by using statin or other drugs reduces the risk of cardiovascular diseases

even with a population with no CVD (Yusuf et al. 2016). Ferrieres et al. (Ferrières et al.

2018) studied the effect of BMI on the choice of lipid-lowering treatment. It is been found

that statin intensity increases with the high level of BMI( $\rho = 0.13$ ).

Taking cholesterol drug medication associates with a high risk of elevating BMI level. It

is been shown that statin users consume 192 additional calories per day which causes gaining

a 6 lb to 11 lb. in a year. Statin users gain 1.3 units in the BMI measure while non-staining

users gain 0.4 unit. Moreover, consumption of fat in statin users raised by 14.4%(Sugiyama

et al. 2014).

Logistic regression helps us to find out the group that has a higher odd of obesity, and

ordinary least squares (OLS) regression helps us to study the effects of predictors on the

average mean of the response. For example, estimating the association of different factors

like a lipid-lowering drug with the conditional mean of BMI using OLS or logistic regression

model(Ferrières et al. 2018). Both of these approaches do not give us insight into the

predictor's effects on different quantiles of the responses.

Quantile regression is used to investigate the heterogeneity in the association of the  $\tau$ th

quantile of BMI with a set of independent predictors, that is investigate the effects of a

specific predictors on the various quantiles of the BMI. BMI departs normality because

of the skewness on the right and left tails (Flegal 1999). Estimation of underweight and

overweight can be affected by the violation of normality. Quantile regression is a crucial tool

used to estimate BMI with the dispersion of the association with predictors.

Quantile regression has many successful applications in ecology where different factors

interact in a complicated way that produces different variations of one factor for different

levels of another variable (Cade and Noon 2003). The association between BMI and the set

of predictors; low childhood socioeconomic position, high maternal weight, low childhood

general cognition is stronger in the upper end of BMI quantile. This trend is found in the

UK population(Bann, Fitzsimons, and Johnson 2020). One cause of this heterogeneity is

that risk factors may have stronger effect on patients with worse health, and these effects

may diminishes when conditional mean of the BMI is studied.

We found that spline regressions produce a different estimate than polynomial regressions.

Polynomial regression using the quadratic term of predictors forces the response to take

convex or concave shape, see Figure 1.12 (Koenker 2005). This is because the limit of

quadratic functions approach  $\pm\infty$  as  $x \rightarrow \pm\infty$ . However, when we model the predictor

as splines the response is not forced to take a specific shape. In the latter case, different

polynomials are constructed for the different regions in the range of predictors.

## 2 Quantile Regression

Quantile regression is a tool used to regress the dependent variable with high variance over

the independent variables. QR is developed to study the relationships between variables

that have weak or no-relationships between their means. One of the advantages of using QR

over OLS is QR is robust for outliers.

For a random variable  $X$ , the cumulative distribution function (CDF) is

$$F(X) = P(X \leq x),$$

and the  $\tau$ th quantile of  $X$  is defined by

$$F^{-1}(\tau) = \inf\{x : F(x) \geq \tau\}$$

where  $0 < \tau < 1$ . Let the loss function is defined by

$$\rho_\tau(u) = u(\tau - I_{(u<0)})$$

where  $I$  is the indicator function (Koenker 2005). The quantile estimator is the value that

minimizes the expected loss function

$$E\rho_\tau(X - \hat{x}) = (\tau - 1) \int_{-\infty}^{\hat{x}} (x - \hat{x}) dF(x) + \tau \int_{\hat{x}}^{-\infty} (x - \hat{x}) dF(x).$$

Differentiating with respect to  $\hat{x}$ , we get

$$0 = (\tau - 1) \int_{-\infty}^{\hat{x}} dF(x) + \tau \int_{\hat{x}}^{-\infty} dF(x) = F(\hat{x}) - \tau.$$

Due to the monotonicity of the cumulative distribution function, any solution that satisfies

$\{x : F(x) = \tau\}$  is a minimizing for the expected loss function.

Least square method expresses conditional mean of y given x as  $\mu(x) = x^T \beta$  and it solves

$$\min_{\beta \in \mathcal{R}^p} \sum_{i=1}^n (y_i - x_i^T \beta)^2.$$

Quantile regression expresses conditional quantile function  $Q_y(\tau|x) = x^T \beta(\tau)$  and solve

$$\min_{\beta \in \mathcal{R}^p} \sum_{i=1}^n \rho_\tau(y_i - x_i^T \beta)^2.$$

This minimization problem can be reformulated to a linear programming problem

$$\min_{\beta \in \mathcal{R}^p}$$

## 2.1 Quantile Regression Technique

## 2.2 splines

A continuous predictor can be modeled as linear, say  $X$ , or nonlinear term, say  $X^2$  depends

on the relationship with the response variable. Most of the relations between the responses

and predictors variables are complicated to the point that linear regressions are not suitable

to model these relationships(Bruce, Bruce, and Gedeck 2020). For example, the response to

different levels of drug doses is not a linear relationship. Linear regressions can be generalized

to deal with nonlinear effects. One approach is through including polynomial terms in the

regression equation. This approach is called Polynomial regression. The mathematical model

for  $n$  degree polynomial regression is shown in the Eq(1)

$$y = \beta_0 + \beta_1 X + \beta_2 X^2 + \cdots + \beta_n X^n. \quad (1)$$

One of the limitations of using polynomial regression is the curvature that can be captured is limited with low order terms. However, including higher-order terms has a negative impact on the model by introducing undesirable “wigginess” in the regression equation. Another robust approach to model nonlinear relationships is splines. It is similar to a technique used by draftsmen in plotting curves. The spline is a process of constructing a set of piece-wise continuous polynomials that are smoothly connected at a set of points in the range of the predictor variable. The connection points are called knots i.e. splines are used to smoothly interpolate between certain points. Let  $a, b$ , and  $c$  are the endpoints of the  $x$ -axis intervals.

A smooth cubic spline function is defined by the following equation.

$$f(X) = X\beta = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \beta_4 (X - a)_+^3 + \beta_5 (X - b)_+^3 + \beta_6 (X - c)_+^3, \quad (2)$$

where

$$(u)_+ = \begin{cases} u & \text{if } u > 0 \\ 0 & \text{if } u \leq 0 \end{cases}$$

### 3 Methods

A multivariate quantile regression model is used to assess the characteristics of the association

variability in different quantiles of the conditional distribution of the body mass index.

The independent variables in our model are gender, race, age, total cholesterol, cholesterol

drug use (yes or no). All types of cholesterol drugs are used including statins. The included

races are non-Hispanic white, non-Hispanic black, Hispanic, or other.

## 4 Numerical Example

### 4.1 Data

The data used in this study is National Health and Nutrition Examination Survey data

(NHANES)(Disease Control and (CDC) 2018). The survey examines a nationally repre-

sentative sample of the U.S. population. It focuses on a variety of health and nutrition

measurements. The survey data are released every two years cycle. In this study, we ac-

cumulated 6 cycles of NHANES data (2007–2018). We used two data files: One contains

demographic variables, such as age, sex, race, income, etc., and the other contains data that

are related to body measurements, such as BMI, head circumference, etc. These files are

merged by using the respondent sequence number (SEQN) There are around 12,000 records.

We selected a population age between 20 and 80. BMI are classified into different categories

according to underweight, 18.5 kg/m<sup>2</sup>; normal weight, 18.5 to 25 kg/m<sup>2</sup>; overweight, 25 to

30 kg/m<sup>2</sup>; obese, 30 to 35 kg/m<sup>2</sup>; and very obese more than 35 kg/m<sup>2</sup>.

---

Syntax	Male	Female
--------	------	--------

---

count	5990	6416
-------	------	------

Mean of Age	49.9	49.73
-------------	------	-------

BMI	28.549	29.379
-----	--------	--------

TC		
----	--	--

Statin use (ratio)	0.198	0.181
--------------------	-------	-------

---

base\_box\_plot

## BMI for Colesterol drug users and who are not

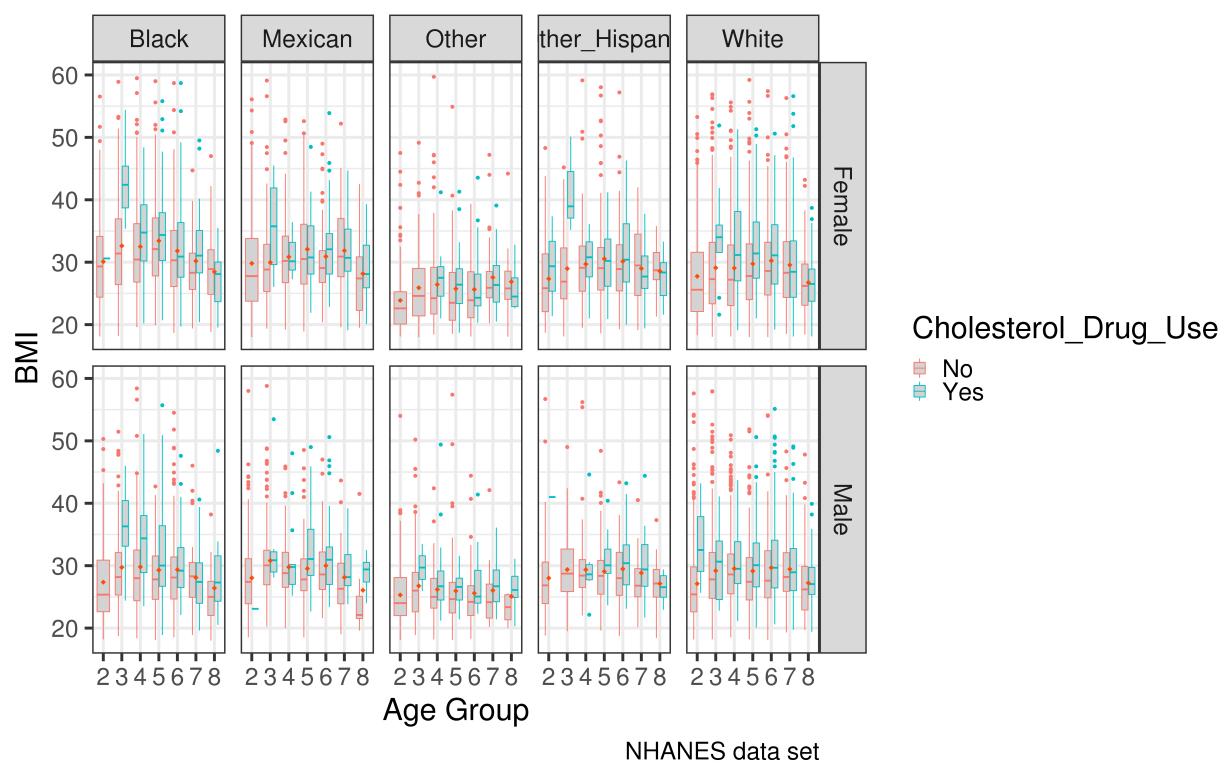


Figure 1: Illustration of data distribution using a box plot. The plot compares cholesterol drug users vs non-cholesterol drug users

Figure 1 shows the association between age and BMI with respect to cholesterol drug

is inconsistent. At the early age, the correlation is positive while at the middle age the

correlation is almost flat, and at the old age the correlation is negative. Moreover, at low

age cholesterol medications are described only for a population with high BMI, but at a higher

age, the difference in term of the BMI for a population that takes cholesterol medication and

without cholesterol medication decreases until it diminishes as in the white population. The

heterogeneity can also be seen in gender ?, for the Hispanic female population, the cholesterol

medication is taken by the population with lower BMI if compared to the population that

does not take cholesterol medication.

So,

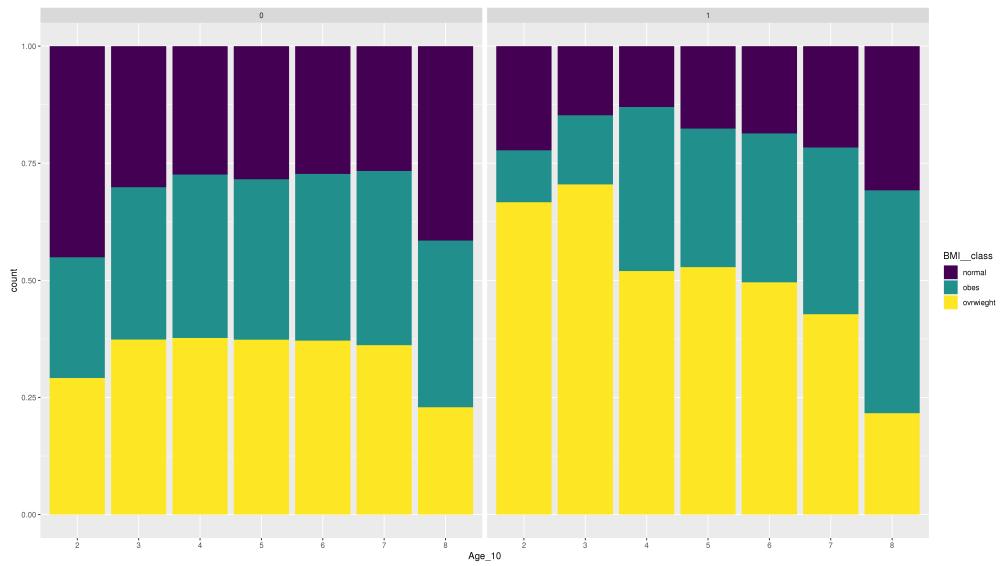


Figure 2: A better figure caption

Figure 3: A better figure caption

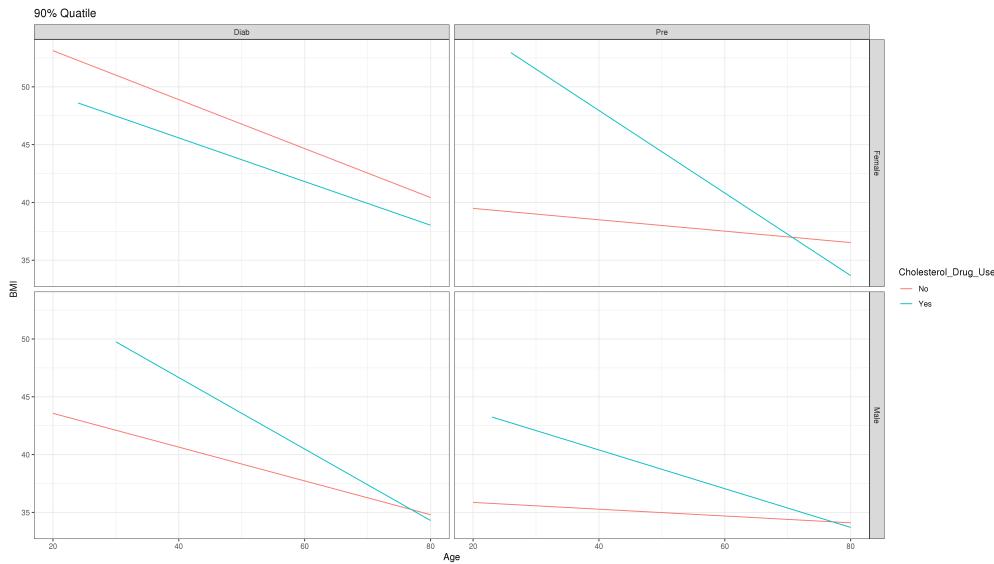


Figure 4: A 90th quantile of BMI plotted with respect to age. The population grouped with respect to gender and fasting blood glucose level: prediabetes nad diabetes

## 5 Results

The resulting estimate of effects on conditional mean of BMI level may not reflect the size and

nature of these effects on lower or upper quantile. For example, in Figure 5, the conditional

mean effect of gender on BMI level is about -1, that is on average male's BMI is less than

a female's BMI by one unit. However, the disparity of the gender effects on lower tails is

much larger which is about 1, but the disparity is lower for the upper tail of the distribution

somewhat around -3 unit.

From the OLS it is obvious cholesterol drug users have on average higher BMI levels if compared to non-cholesterol drug users which are around 1.75. The disparity in BMI level for cholesterol drug users vs non-cholesterol drug users is almost the same for different Quantiles. cholesterol drug use seems to be associated with rather large effects on BMI levels somewhat around 1.5 to 1.7.

So,

Age effect modeled as a quadratic factor. The age effect is concave in general, see Figure 7. At the lower quantile, BMI increases from age 20 to around age 50, and it starts to decrease after that. In the 55th quantile, the concavity is stronger at age 50 if compared to the left or right tail. The quadratic effect of age is reflected in the hyperbolic shape.

However, the age effect modeled as b spline behaves in a different way. Age effect on BMI increases from age 20 to around age 36 and then start to decrease up to around age 63

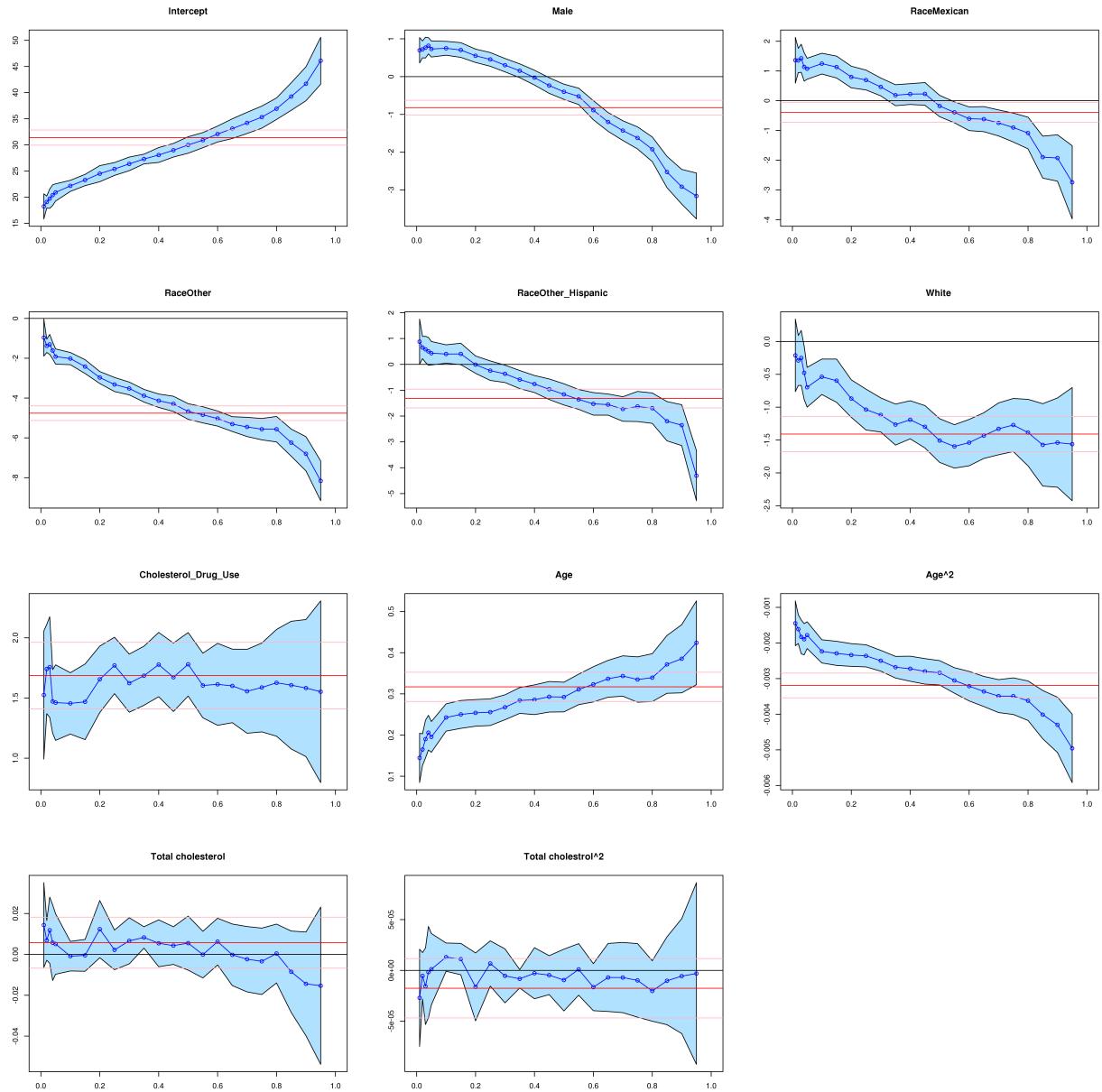


Figure 5: Quantile regression of BMI plotted f for different marginal effects. The predictors modeled using quadratic terms

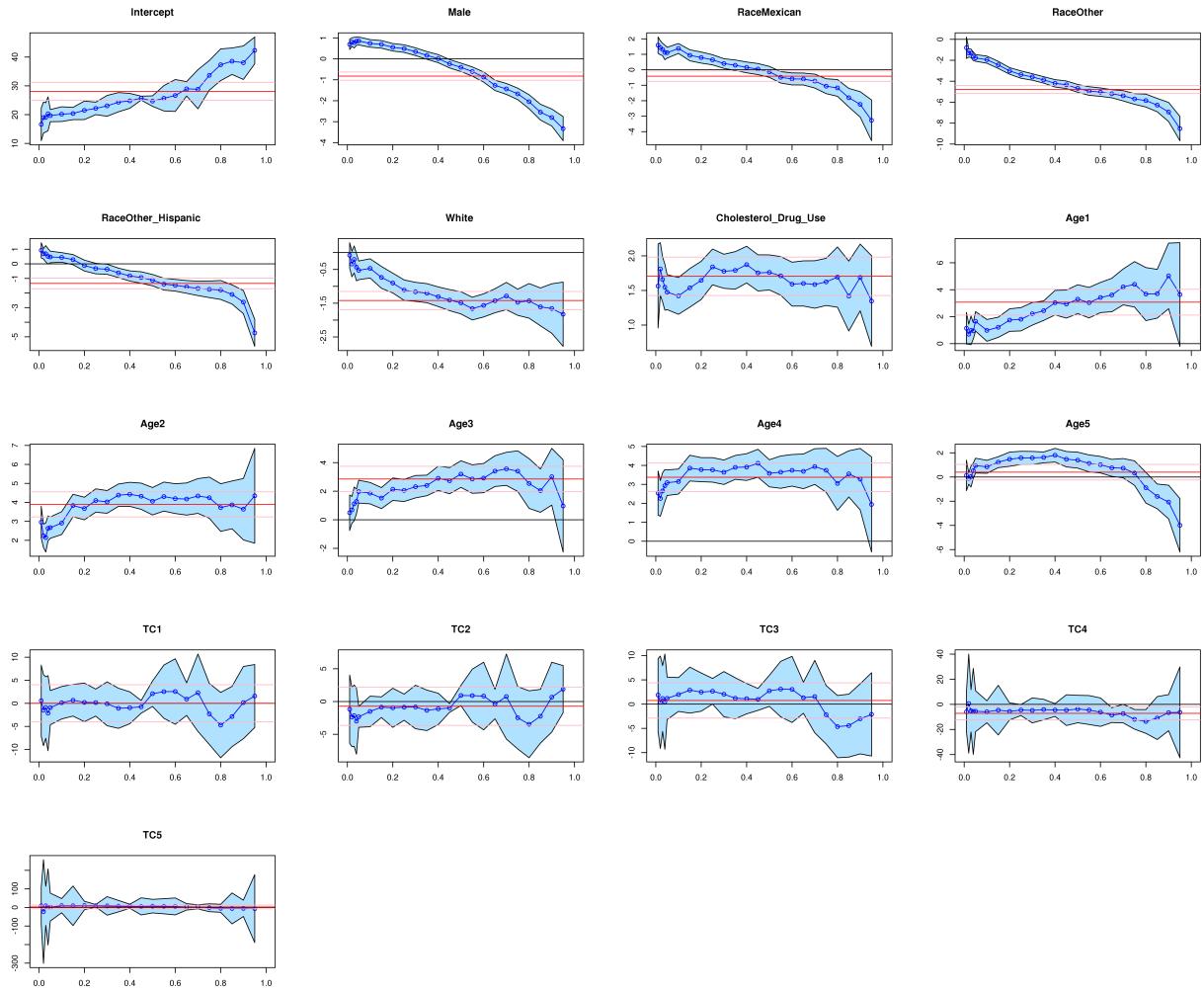


Figure 6: Quantile regression of BMI plotted f for different marginal effects. The predictors modeled using splines

then move up again and then decreases up to age 80, see Fig.8. The BMI trend in this

modeling is close to the trend shown in (Chen 2005) by using a complicated polynomial and

log transformation for the response.

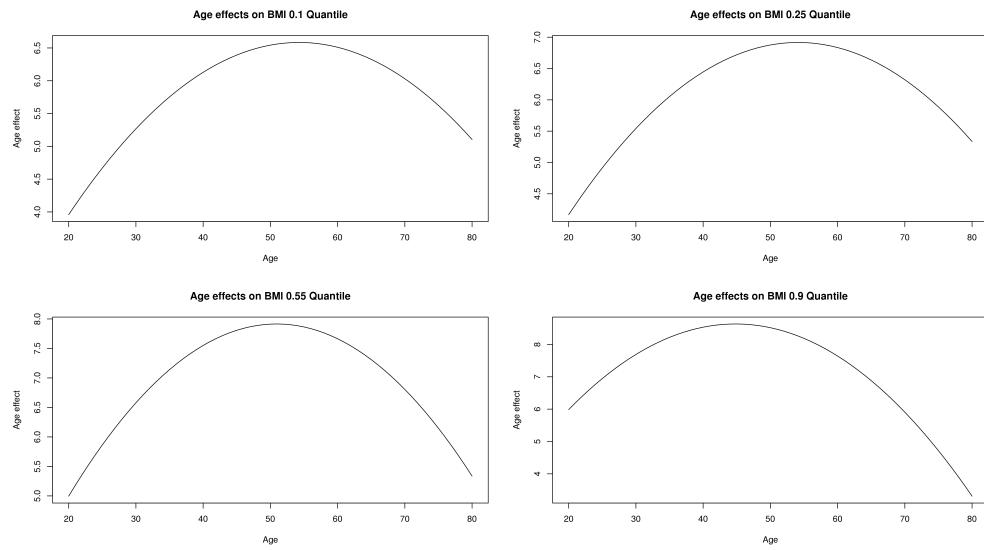


Figure 7: Illustration of the quadratic age effect on BMI levels for four different quantiles of the conditional BMI distribution. The

Using splines

Marginal quadratic cholesterol effect

Splines modeling

The quadratic effect of total cholesterol on the conditional distribution of BMI is convex.

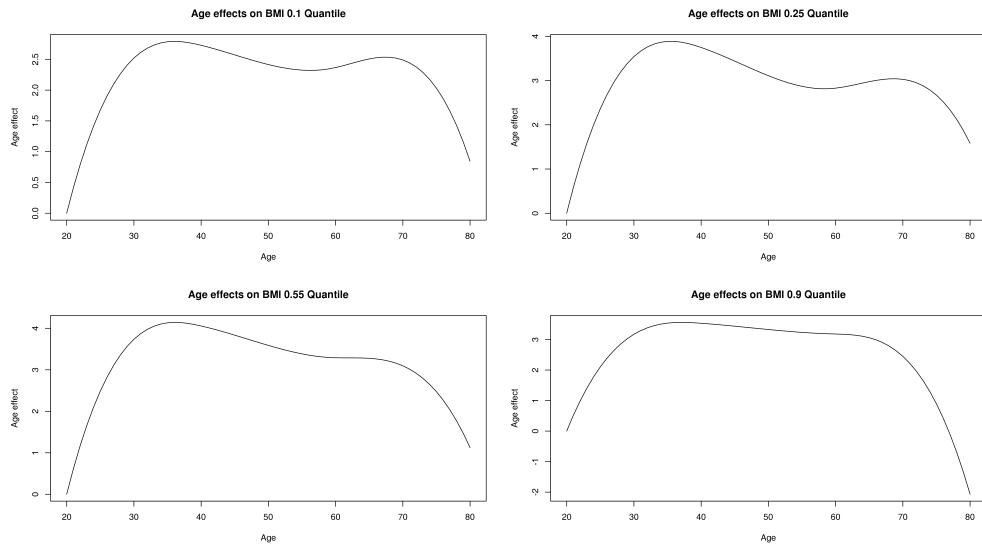


Figure 8: Age effect modeled using bsplines

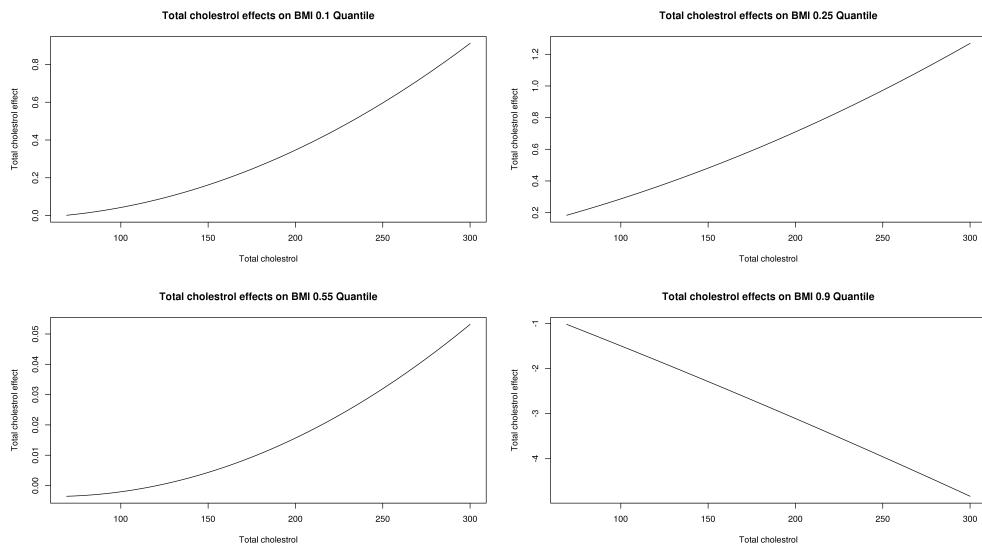


Figure 9: Illustration of the quadratic cholesterol effect on BMI leveles for four different quantiles of the conditional BMI distribution. The

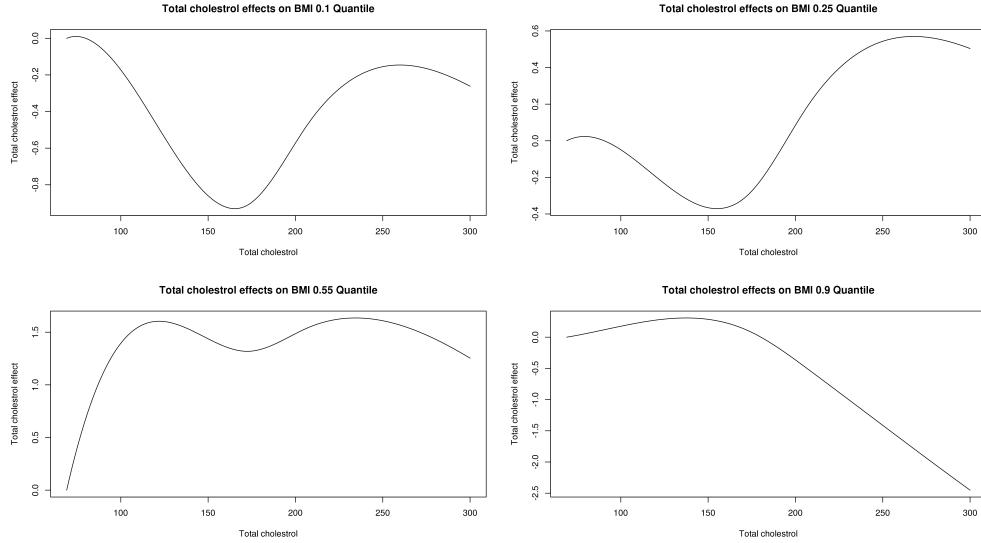


Figure 10: Illustration of marginal cholesterol effect modeled as B splines. The

At the lower tail, the correlation is positive that is as cholesterol increases the BMI increases.

decreasing glucose level by somewhat around 1.4 up to around 180 Cholesterol level. How-

ever, at higher quantile the association become negative that is as cholesterol level increases

the BMI decreases, see Figure 9. The relation between total cholesterol and fasting glucose

has been studied in (Tsaousis 2014),(Chang et al. 2011). They found that there is a positive

correlation between the two groups on average.

On the other hand, when we use splines to modeled the total cholesterol, there is a

huge difference in the shape of the association expect at the higher quantile there is some

similarity. At the lower quantile, there is negative correlation between total cholesterol and

BMI for total cholesterol in the range less than 160, then the correlation becomes positive for

total cholesterol in the range of (170, 250). at the 55th quantile, the correlation is positive

for low cholesterol level and then becomes almost flat for the rest cholesterol values. At a

higher qunatile, the correlation becomes negative at cholesterol level in the range (160,300),

see Figure ??.

## 6 Conclusion

Multivariate quantile regression is used to study the effects of different risk factors on the BMI

levels. Cholesterol drug effects on BMI is negligible at low quantile but at higher quantile

cholesterol medication effects on BMI is larger. This study showed that the association

between BMI and total cholesterol is varying with respect to different quantile.

total people who have TC levels around 190 mg/dL have the lowest fasting glucose levels

for the lowest quantile, for the second quantile optimal cholesterol level is around 220mg/dL,

and for the upper quantile, the optimal cholesterol level is around 200 mg/dL. Moreover,

It is recommended to investigate why the effect estimates are varying across different

BMI quantiles.

## 7 References

Anderson, Keaven M, Patricia M Odell, Peter WF Wilson, and William B Kannel. 1991.

“Cardiovascular Disease Risk Profiles.” *American Heart Journal* 121 (1): 293–98.

Balkau, Beverley, Gang Hu, Qing Qiao, Jaakko Tuomilehto, Knut Borch-Johnsen, K

Pyorala, DECODE Study Group, European Diabetes Epidemiology Group, and others. 2004.

“Prediction of the Risk of Cardiovascular Mortality Using a Score That Includes Glucose as

a Risk Factor. The Decode Study.” *Diabetologia* 47 (12): 2118.

Bann, David, Emla Fitzsimons, and William Johnson. 2020. “Determinants of the

Population Health Distribution: An Illustration Examining Body Mass Index.” *International*

*Journal of Epidemiology* 49 (3): 731–37.

Bruce, Peter, Andrew Bruce, and Peter Gedeck. 2020. *Practical Statistics for Data*

*Scientists: 50+ Essential Concepts Using R and Python.* O'Reilly Media.

Cade, Brian S, and Barry R Noon. 2003. "A Gentle Introduction to Quantile Regression for Ecologists." *Frontiers in Ecology and the Environment* 1 (8): 412–20.

Castro, M Regina, Gyorgy Simon, Stephen S Cha, Barbara P Yawn, L Joseph Melton, and Pedro J Caraballo. 2016. "Statin Use, Diabetes Incidence and Overall Mortality in Normoglycemic and Impaired Fasting Glucose Patients." *Journal of General Internal Medicine* 31 (5): 502–8.

Chang, Jin-Biou, Nain-Feng Chu, Jhu-Ting Syu, An-Tsz Hsieh, and Yi-Ren Hung. 2011. "Advanced Glycation End Products (Ages) in Relation to Atherosclerotic Lipid Profiles in Middle-Aged and Elderly Diabetic Patients." *Lipids in Health and Disease* 10 (1): 228.

Chen, Colin. 2005. "Growth Charts of Body Mass Index (Bmi) with Quantile Regression." *AMCS* 5: 114–20.

Disease Control, Centers for, and Prevention (CDC). 2018. “National Health and Nutrition Examination Survey Data (Nhanes.”

Ferrières, Jean, Dominik Lautsch, Anselm K Gitt, Gaetano De Ferrari, Hermann Toplak,

Moses Elisaf, Heinz Drexel, et al. 2018. “Body Mass Index Impacts the Choice of Lipid-

Lowering Treatment with No Correlation to Blood Cholesterol—Findings from 52 916 Patients

in the Dyslipidemia International Study (Dysis).” *Diabetes, Obesity and Metabolism* 20 (11):

2670–4.

Flegal, Katherine M. 1999. “The Obesity Epidemic in Children and Adults: Current

Evidence and Research Issues.” *Medicine and Science in Sports and Exercise* 31 (11 Suppl):

S509–14.

Hay, Simon I, Sudha P Jayaraman, Alejandra G Contreras Manzano, Anoushka Millear,

Laura Kemmer, Brent Bell, Juan Jesus Carrero, et al. 2017. “GBD 2015 Risk Factors Col-

laborators. Global, Regional, and National Comparative Risk Assessment of 79 Behavioural,

Environmental and Occupational, and Metabolic Risks or Clusters of Risks, 1990-2015: A

Systematic Analysis for the Global Burden of Disease Study 2015 (Vol 388, Pg 1659, 2016)."

*Lancet* 389 (10064): E1–E1.

Katzmarzyk, Peter T, Bruce A Reeder, Susan Elliott, Michel R Joffres, Punam Pahwa,

Kim D Raine, Susan A Kirkland, and Gilles Paradis. 2012. "Body Mass Index and Risk

of Cardiovascular Disease, Cancer and All-Cause Mortality." *Canadian Journal of Public*

*Health* 103 (2): 147–51.

Koenker, Roger. 2005. "Quantile Regression, Volume 38 of." *Econometric Society Mono-*

*graphs.*

Mozaffarian, Dariush, Emelia J Benjamin, Alan S Go, Donna K Arnett, Michael J Blaha,

Mary Cushman, Sarah De Ferranti, et al. 2015. "Executive Summary: Heart Disease and

Stroke Statistics—2015 Update: A Report from the American Heart Association.” *Circulation* 131 (4): 434–41.

Pandya, Ankur, Stephen Sy, Sylvia Cho, Milton C Weinstein, and Thomas A Gaziano. 2015. “Cost-Effectiveness of 10-Year Risk Thresholds for Initiation of Statin Therapy for Primary Prevention of Cardiovascular Disease.” *Jama* 314 (2): 142–50.

Ridker, Paul M, Aruna Pradhan, Jean G MacFadyen, Peter Libby, and Robert J Glynn. 2012. “Cardiovascular Benefits and Diabetes Risks of Statin Therapy in Primary Prevention: An Analysis from the Jupiter Trial.” *The Lancet* 380 (9841): 565–71.

Sugiyama, Takehiro, Yusuke Tsugawa, Chi-Hong Tseng, Yasuki Kobayashi, and Martin F Shapiro. 2014. “Different Time Trends of Caloric and Fat Intake Between Statin Users and Nonusers Among Us Adults: Gluttony in the Time of Statins?” *JAMA Internal Medicine* 174 (7): 1038–45.

Tsaousis, Konstantinos T. 2014. "Blood Glucose and Cholesterol Concentrations in a Mediterranean Rural Population of Andros Island, Greece." *International Journal of Preventive Medicine* 5 (11): 1464.

Van de Kassteele, Jan, RT Hoogenveen, PM Engelfriet, PHM Van Baal, and HC Boshuizen. 2012. "Estimating Net Transition Probabilities from Cross-Sectional Data with Application to Risk Factors in Chronic Disease Modeling." *Statistics in Medicine* 31 (6): 533–43.

Yusuf, Salim, Jackie Bosch, Gilles Dagenais, Jun Zhu, Denis Xavier, Lisheng Liu, Prem Pais, et al. 2016. "Cholesterol Lowering in Intermediate-Risk Persons Without Cardiovascular Disease." *New England Journal of Medicine* 374 (21): 2021–31.

Yusuf, Salim, Steven Hawken, Stephanie Ôunpuu, Tony Dans, Alvaro Avezum, Fernando Lanas, Matthew McQueen, et al. 2004. "Effect of Potentially Modifiable Risk Factors

Associated with Myocardial Infarction in 52 Countries (the Interheart Study): Case-Control

Study." *The Lancet* 364 (9438): 937–52.