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Research Article

Retirement Consumption Puzzle in Malaysia: Evidence from Bayesian Quantile Regression Model

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The objective of this study is to use the Bayesian quantile regression for studying the retirement consumption puzzle, which is defined as the drop in consumption upon retirement, using the cross-sectional data of the Malaysian Household Expenditure Survey (HES) 2009/2010. Three different measures of consumption, namely, total expenditure, work-related expenditure, and nonwork-related expenditure, are suggested for studying the retirement consumption puzzle. The results show that the drop in consumption upon retirement is significant and has a regressive distributional effect as indicated by larger drops at lower percentiles and smaller drops at higher percentiles. The smaller drops among higher consumption retirees (or higher income retirees) may imply that they have more savings and/or retirement benefits than the smaller consumption retirees (or lower income retirees). Comparison between the three types of consumption shows that the work-related expenditure has a uniform drop across the distribution. The drop under the nonwork-related expenditure varies across the distribution, implying that it is the source behind the variation of the consumption drop.

1. Introduction

A life cycle theory is a major economic theory that relates consumption and saving behavior, which states that individuals desire to maintain their level of consumption in their entire lifetime [1]. The marginal utility consumption should remain smooth throughout retirement transition because the change in income during retirement should be predictable [2]. On the contrary, a number of previous studies found a one-time significant drop in consumption in the early years of retirement, a situation which is known as retirement consumption puzzle.

Over the past three decades, several studies focusing on the smoothing or stable path of consumption have been carried out. Hamermesh [3], who was among the first to study retirement consumption puzzle in the United States, showed that an individual was unable to sustain the level of real consumption prior to retirement due to inadequate retirement savings. Later, several more studies have been conducted in other countries such as Banks et al. [4], Hurd and Rohwedder [5], Schwerdt [6], Wakabayashi [7], and Battistin et al. [8]. A review on several studies related to the retirement consumption puzzle can be found in Attanasio and Weber [9]. There are a number of studies which found that the decline in consumption upon retirement is due to several reasons. As examples, Haider and Stephens [10], Smith [11], and Blau [12] found that the consumption drop is due to the unexpected retirement which resulted from illnesses, disabilities, or involuntarily unemployment. Blau [12] also developed a modified life cycle model which incorporated the uncertainty in the timing of retirement.

In terms of consumption measures, several studies utilized food expenditure as a prominent substitution for the actual consumption during retirement. However, Aguiar and Hurst [13] found that food expenditure is a poor proxy for the actual consumption because retirees consumed the

same quantity of food, as well as its quality, even when food expenditure has declined. The main reason is that the retirees consumed home production food in their retirement since they have more time to prepare their meal and survey for cheaper food. Later, Hurst et al. [14] and Fisher et al. [15] proposed a broader measure of consumption which can be categorized according to several different types of expenditure and showed that a broader consumption measure can be used to eliminate retirement consumption puzzle.

Previous studies on the drop in retirement consumption were mostly concentrated at the mean distribution, which covered only certain parts of distribution, and may lead to poor estimation of parameters especially in long-tailed distributions. The traditional mean model estimates only the average effects of the whole data and do not allow for an understanding of any potential distributional impacts (or heterogeneity potential). Furthermore, the mean regression model is based on least squares estimation and thus has a significant sensitivity (or is not robust) to outliers. Several studies have been carried out to study the distributional aspects of retirement consumption puzzle, including Bernheim et al. [16] who estimated the retirement consumption drop using subgroups of wealth and income replacement rate and Aguila et al. [17] who used low and high consumption households to examine the drop in retirement expenditures. Recently, Fisher and Marchand [18] used the quantile regression model to investigate the drop in consumption upon retirement.

Quantile regression model is different from the traditional mean regression model as it uses the Least Absolute Deviation (LAD), instead of the least square error, which is able to rectify the weaknesses prevalent in the usual regression framework. Quantile regression model also allows the impact of each regression parameter to be analysed based on different selected quantiles. In short, quantile regression model has several advantages; it is a distribution-free model which does not adhere to any distributional assumptions, it is robust to outliers, it does not require independence assumption, and it allows the analysis of regression parameters to be extended beyond central locations.

Quantile regression model is based on the works of Koenker and Bassett [19] and Koenker and Hallock [20] and is gaining rapid interests by other researchers. The model has been developed for linear models with continuous responses and has been applied in various fields such as finance and economics [21], ecology [22], environmental epidemiology [23], criminology [24], and climate change [25]. Several extensions to the quantile regression model have been suggested and applied in other areas, such as Yu and Moyeed [26] who proposed Bayesian quantile regression model, Machado and Silva [27] who proposed quantile regression model for discrete data, Hewson and Yu [28] who suggested quantile regression model for binary data within the Bayesian framework, Reich et al. [25] who introduced Bayesian spatial quantile regression model, and Fuzi et al. [29] who applied Bayesian quantile regression model for claim count data in insurance area.

In this paper, we use the Bayesian quantile regression model to examine the drop in consumption upon retirement. The Bayesian quantile regression has the combined advantages of both the quantile regression and the Bayesian approach. The quantile regression is a distribution-free model and robust to data, while the Bayesian approach allows the complete univariate and joint posterior distribution of each parameter to be generated by the MCMC simulations. Several motivational examples are worth mentioning here. For instance, in the field of environmental study, the quantile regression model allows the investigation of whether the effects of environmental exposure change depending on the level of respiratory health of the population [23], while in the area of insurance pricing and ratemaking, the Bayesian quantile regression models handle the parameters of covariates (or the risk factors) as random variables [29]. We use a cross-sectional data of Household Expenditure Survey (HES) 2009/2010 in Malaysia to investigate the changes in consumption drop across the population. We also expand the consumption measure into three categories, namely, total expenditure (TE), work-related expenditure (WRE), and nonwork-related expenditure (NWRE), to identify the source behind the variation of consumption drop.

2. Materials and Methods

2.1. Mean Regression. In our study, the drop in mean consumption upon retirement is estimated using the ordinary least square (OLS):

$$\ln(C_i) = \alpha + \beta \cdot Retired_i + \mathbf{x}_i^T \boldsymbol{\gamma} + \varepsilon_i \tag{1}$$

where $\ln(C_i)$ is the log of response variable (consumption measures), $Retired_i$ is the binary variable which equals one for retirees and zero for working households, and $\mathbf{x}_i$ is the vector of control variables consisting of demographic and socioeconomic variables (gender, marital status, ethnic, etc.). The regression parameter, β, represents the mean consumption difference between working and retired households.

2.2. Frequentist Quantile Regression. The frequentist quantile regression model from Koenker and Bassett [19] is used in our study for comparison purposes. The same equation shown in (1) is used, but the quantile regression is now fitted to the conditional differences in the log of consumption between working households (preretirement) and retirees (postretirement) at the θth quantile.

Let $\mathbf{Y}$ be the vector of continuous response variables, which in our case can be represented by the three different consumption measures, and $\mathbf{x}_i$ be the associated row-vector of covariates consisting of demographic and socioeconomic characteristics of households. The classical regression model focuses on the expectation of variable Y, conditional on the values of variables $\mathbf{X}$, which can be summarized as $E(Y_i \mid \mathbf{x}_i) = \mathbf{x}_i^T \boldsymbol{\beta}$. On the other hand, the quantile regression model extends this approach to $Q_{Y_i}(\theta \mid \mathbf{x}_i) = \mathbf{x}_i^T \boldsymbol{\beta}_\theta$, where the quantile θ are fixed values between 0 and 1, allowing us to study the conditional distribution of Y on $\mathbf{X}$ at different locations.

The regression parameter, β_θ, can be obtained using

$$\min_{\boldsymbol{\beta}_\theta} \sum p_\theta \left[\ln(C_i) - \mathbf{x}_i^T \boldsymbol{\beta}_\theta\right] \tag{2}$$

where the loss function $p_\theta(u) = u(\theta - I[u < 0])$ is a piecewise linear function and $I[\cdot]$ is the indicator function. Equivalently, the loss function can be written as

$$p_\theta(u) = u(\theta I[u > 0] - (1-\theta) I[u < 0]). \quad (3)$$

Equation (3) can be minimized using linear programming, while the confidence interval can be obtained using bootstrap method. R statistical program with *quantreg* package [30] is used in this study to fit the frequentist quantile regression model.

2.3. Bayesian Quantile Regression. The Bayesian approach for quantile regression model was introduced by Yu and Moyeed [26] who formed the likelihood function using the asymmetric Laplace distribution (ALD). A random variable Y follows the ALD when the density function is given by

$$f_\theta(y \mid \mu, \sigma) = \frac{\theta(1-\theta)}{\sigma} \exp\left\{-p_\theta\left(\frac{y-\mu}{\sigma}\right)\right\} \quad (4)$$

where $0 < \theta < 1$ and $p_\theta(\cdot)$ is the loss function in equation (3). Under the Bayesian approach, the MCMC can be used to obtain the posterior distributions of the unknown parameters. The posterior distribution of parameter $\boldsymbol{\beta}$ is given by

$$\pi(\boldsymbol{\beta} \mid \mathbf{y}) \alpha L(\mathbf{y} \mid \boldsymbol{\beta}) p(\boldsymbol{\beta}) \quad (5)$$

where $p(\boldsymbol{\beta})$ is the prior distribution of $\boldsymbol{\beta}$ and $L(\mathbf{y} \mid \boldsymbol{\beta})$ is the likelihood function which is formed by joining the independently distributed ALD. The joint likelihood function can be written as

$$L(\mathbf{y} \mid \boldsymbol{\beta}) = \frac{\theta^n (1-\theta)^n}{\sigma(\theta)^n} \exp\left\{-\sum_{i=1}^{n} \rho_\theta\left(\frac{y_i - \mathbf{x}_i^T \boldsymbol{\beta}(\theta)}{\sigma(\theta)}\right)\right\}. \quad (6)$$

Since there is no specific conjugate prior distribution for generating the posterior distribution, we use the uniform prior distribution for all $\boldsymbol{\beta}(\theta)$ in our study. The prior distribution for the scale parameter is the inverse-gamma distribution, or $\sigma(\theta) \sim$inverse-gamma(a, b), which allows the Gibbs sampling algorithm in the MCMC to update and tune $\sigma(\theta)$ for obtaining good acceptance rates.

3. Results and Discussion

3.1. Sample Data. The sample data from Household Expenditure Survey (HES) 2009/2010 is used in our study. The data contains information on monthly expenditure, together with demographic and socioeconomic characteristics of each household. The selected sample is a cross-sectional data consisting of 6480 household heads.

Three different measures of consumption are used for the response variable, namely, total expenditure (TE), work-related expenditure (WRE), and nonwork-related expenditure (NWRE). TE consists of food at home, alcohol and cigarettes, home appliances and furniture, clothing, education, entertainment and recreation, health, insurance, outside food (restaurant and café), transportation (own vehicle and public transport), personal care, rental, utility, and other services (such as legal services, tax services, and government agency). WRE and NWRE are constructed using the definitions in Aguiar and Hurst [31] and Fisher and Marchand [18]. WRE consists of outside food, personal care, public transport, and clothing, whereas NWRE contains food at home, alcohol, utilities, and entertainment.

3.2. Model Development. The MCMC simulations via Gibbs sampling algorithm are used to generate 5,000 posterior samples of each regression parameter. The first 1,000 runs of posterior samples are discarded as burn-ins to lessen the effect of initial simulations, and the process resulted in 4,000 final posterior samples for each regression parameter. The values of $\boldsymbol{\beta}$ are initialized at zero, while the inverse-gamma parameters are set at $a = 0.01$ and $b = 0.01$.

3.3. Summary Statistics. Table 1 provides the summary statistics for the sample. More than half of household heads (69%) are located in urban areas, a large majority (78%) are married, and more than half (64%) belongs to Bumiputera ethnic. In terms of educational attainment, 14% of household heads are university or college graduates, 35% are high school graduates, and the balances are below high school education (16%), and others (35%) (attend informal or religious education). For occupational groups, almost 13% of household heads are professionals, while 19% and 13% are administrative supports and technicians, respectively. In terms of employment type, almost half of household heads are private sector employees, followed by self-employed (19%) and government employees (13%). The proportions of age group are quite equally divided, with the exception of younger household heads (age less than 25). With regard to the status of living quarters, more than half (67%) are homeowners, followed by renters (24%).

3.4. Mean Regression. Table 2 provides the estimate, β, for the mean regression model, which can be used to show the difference (in mean consumption) between working and retired households. Three response variables are considered, namely, total expenditure (TE), work-related expenditure (WRE), and nonwork-related expenditure (NWRE).

The mean consumption among retirees is lower compared to the working households for all expenditure measures as shown by the negative coefficient. The regression estimate for TE is significant and indicates that the consumption for retirees is 14% lower than the working households. The estimates for WRE and NWRE are also significant, showing that the retirees' consumptions are 39% and 5% lower than the working households, respectively. As expected, the WRE has a relatively larger drop than the NWRE, indicating that retirees are no longer involved in employment. The results also agree with studies from Fisher and Marchand [18] and Fisher et al. [15] who found that the WRE has the highest consumption drop. The results indicate that a broader measure of consumption may diminish the retirement consumption puzzle, as indicated by the smaller drop in the NWRE.

Table 1: Summary statistics for HES Sample 2009.

Variable	Proportion of households (%)
Region	
1 (Kelantan, Pahang, Terengganu)	15
2 (Johor, Melaka, Negeri Sembilan)	16
3 (Kedah, Perak, Perlis)	20
4 (P.Pinang, Selangor, Kuala Lumpur, Putrajaya)	27
5 (Sabah, Sarawak)	22
Strata	
Urban	69
Rural	31
Marital status	
Married	78
Single Female	12
Single Male	10
Ethnic	
Bumiputera	64
Non Bumiputera	36
Educational level	
College/University	14
High School Grad	35
Less than High School	16
Others (not attending formal education, religious education, not finishing school)	35
Occupational group	
Professionals and Legislators	13
Administrative Supports	19
Technicians	13
Agriculture and Fishery	10
Craft and Repair	9
Elementary Occupations	10
Operators	11
Others (housewife, unemployed, disabled)	15
Employment type	
Employer	2.8
Government Professional and Administrative	7.0
Government Technicians and below	6.3
Private Professional and Administrative	16.4
Private Technicians and below	33.4
Self-employed	19.0
Others (e.g. pensioners)	15.1
Subjective life expectancy	
live ≤ 25	4
$25 \leq$ live ≤ 34	18
$35 \leq$ live ≤ 44	26
$45 \leq$ live ≤ 54	26
$55 \leq$ live	26
Status living quarters	
Owned	67
Rented	24
Quarters	5
Others (e.g. squatters owned, squatters rented)	4

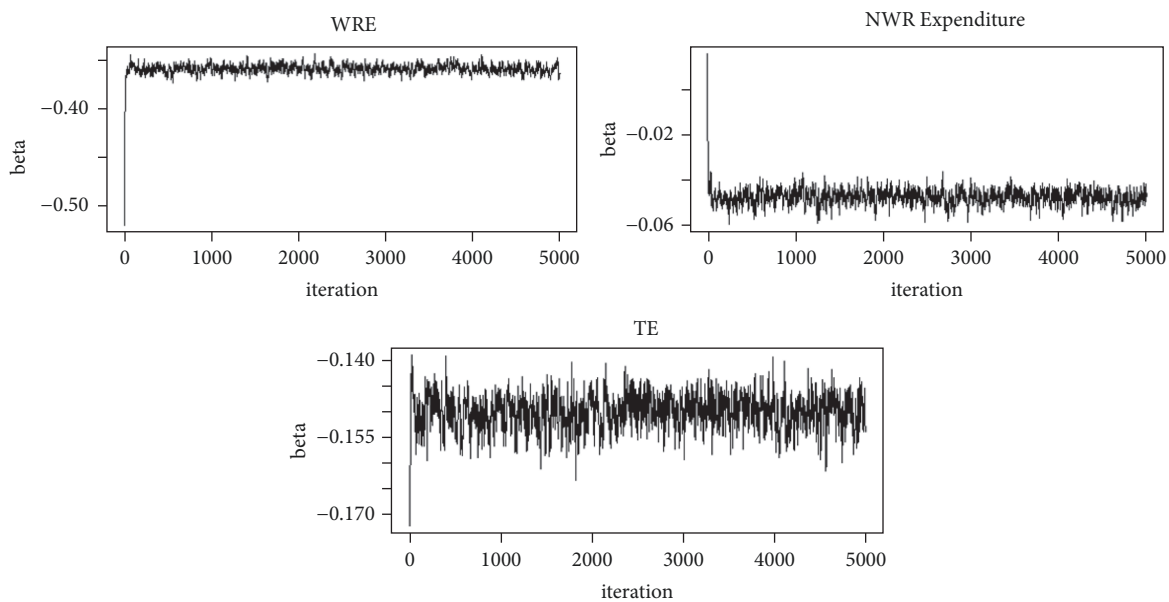

Figure 1: Trace plots for regression estimate under Bayesian median regression ($\theta = 0.5$).

Table 2: Regression estimate for mean regression model.

Expenditure Measure	Estimate	SE
Work-Related Expenditures (WRE)	-0.385	0.026
Non Work-Related Expenditures (NWRE)	-0.050	0.017
Total Expenditures (TE)	-0.139	0.018

3.5. Bayesian Quantile Regression. The trace plots for the regression estimate under the Bayesian median regression ($\theta = 0.5$) are provided in Figure 1. The trace plots for other quantiles are also obtained but are not shown here. The trace plots show that the MCMC simulations mix well, the convergence of the posterior distributions took place, and there were no significant problems in the chain simulations.

Table 3 shows the regression estimates (and standard deviations) under the Bayesian quantile regression. It can be seen that the estimates for the three consumption measures are significant at all quantiles. The drops in consumption also differ across the distribution. All three consumption measures show larger drops at lower percentiles and smaller drops at higher percentiles (regressive trend), where the smallest and highest drops are at the highest and lowest percentiles respectively. The regressive trend disagrees with the results of Fisher and Marchand [18] who found that the estimates are more negative (progressive trend) when moving towards the upper distribution. However, the regressive trend is consistent with the results of Aguila et al. [17] who found that the retirement consumption has larger drops at lower percentiles.

The TE displays the largest drop (22%) at the 10th percentile, a drop of 15% at the median, and the smallest drop (3%) at the 90th percentile. Similar patterns are also seen in the WRE and NWRE: 60%, 36%, and 17% drops, respectively, at the 10th, median, and 90th percentiles for the WRE and 11%, 5%, and 2% drops, respectively, at the 10th, median, and 90th percentiles for the NWRE. In terms of magnitude, the WRE shows the largest drop at all quantiles, and the result agrees with the mean model which shows that the largest drop is from the WRE. As expected, the consumption drops under the Bayesian median model (θ=0.50) that is quite comparable to the OLS model. The drops for TE, WRE, and NWRE are 14%, 39%, and 5%, respectively, under the OLS and 15%, 36%, and 5%, respectively, under the Bayesian median model, indicating that the median model can be used as an alternative to the mean model (OLS).

It can be observed that the drop in WRE follows a uniform trend across the distribution, while the NWRE has more variations at lower percentiles (from 0.10 to 0.50). The variations show that the NWRE is the source behind the variation in the consumption drop. Our result agrees with Fisher and Marchand [18] who found that the WRE displays a uniform drop across the distribution, and the NWRE is the source behind the variation of the consumption drop.

Figure 2 exhibits the plots of regression estimates with their respective 95% credible intervals under the Bayesian quantile regression. For comparison purpose, the estimates from the OLS are also included, represented by the dashed horizontal line. It can be seen that the estimates under the NWRE have more variations in the lower percentiles (from 0.10 to 0.50), while the estimates under the WRE are uniformly increasing. The consistently small widths of the credible intervals throughout the quantiles indicate that the estimates for the three consumption measures are significant throughout the distribution.

3.6. Frequentist Quantile Regression. For comparison purpose, Table 4 shows the estimates (and standard errors) under the frequentist quantile regression model for the three different measures of consumption. Comparison between

Table 3: Regression estimate for Bayesian quantile regression model.

Consumption Measure	$\theta = 0.10$				$\theta = 0.25$				$\theta = 0.50$			
	Est	LB	UB	SD	Est	LB	UB	SD	Est	LB	UB	SD
WRE	-0.596	-0.608	-0.584	0.006	-0.480	-0.491	-0.470	0.005	-0.359	-0.367	-0.352	0.004
NWRE	-0.112	-0.123	-0.101	0.006	-0.044	-0.051	-0.035	0.004	-0.047	-0.054	-0.041	0.003
TE	-0.223	-0.234	-0.211	0.006	-0.150	-0.157	-0.143	0.004	-0.150	-0.157	-0.145	0.003
Consumption Measure	$\theta = 0.75$				$\theta = 0.90$							
	Est	LB	UB	SD	Est	LB	UB	SD				
WRE	0.004	-0.281	-0.289	-0.273	0.004	-0.167	-0.185	-0.151				
NWRE	0.003	-0.021	-0.029	-0.014	0.004	-0.016	-0.007	-0.027				
TE	0.003	-0.123	-0.130	-0.115	0.004	-0.029	-0.044	-0.016				

Table 4: Regression estimate for frequentist quantile regression model.

Consumption measures	$\theta = 0.1$		$\theta = 0.25$		$\theta = 0.5$		$\theta = 0.75$		$\theta = 0.9$	
	Est	SE	Est	SE	Est	SE	θ Est	SE	Est	SE
WRE	-0.595	0.060	-0.483	0.041	-0.361	0.033	-0.281	0.032	-0.162	0.045
NWRE	-0.108	0.030	-0.043	0.023	-0.047	0.019	-0.020	0.021	-0.020	0.032
TE	-0.222	0.036	-0.150	0.022	-0.148	0.020	-0.124	0.025	-0.024	0.036

Tables 3 and 4 shows that the estimates under the Bayesian and frequentist quantile regression models are similar for all quantiles. The main difference between both models is shown by the standard deviations and standard errors; the standard deviations under the Bayesian model are different from the standard errors under the frequentist model. The differences are expected since the estimates under both approaches are obtained under different estimation methods; the frequentist intervals are estimated via bootstrap method, whereas the Bayesian intervals are obtained from the MCMC simulation.

The smaller standard deviations under the Bayesian regression suggest that the model has more significant estimates. The estimates are statistically significant at all quantiles for all three consumption measures under the Bayesian model, while the frequentist model has several insignificant estimates at several quantiles.

Similar to the Bayesian quantile regression, all three consumption measures under the frequentist quantile regression show larger drops at lower percentiles and smaller drops at higher percentiles (regressive trend). The TE displays the largest drop (22%) at the 10th percentile and the smallest drop (12%) at the 75th percentile. The drop at the 90th percentile is insignificant. The WRE displays the largest drop (60%) at the 10th percentile and the smallest drop (16%) at the 90th percentile, while the NWRE displays the largest drop (11%) at the 10th percentile and the smallest drop (5%) at the median. The drops after the median are insignificant. The drop in WRE also follows a uniform trend, while the drop in NWRE has more variations.

4. Conclusions

In this study, we applied the Bayesian quantile regression to investigate the consumption drop upon retirement which is an area where, currently, the quantile regression model is of limited utilization. The Bayesian quantile regression has the combined advantages of both quantile regression and Bayesian approach. In particular, the quantile regression is a distribution-free model and robust to data, while the Bayesian approach allows the complete univariate and joint posterior distribution of each parameter to be generated by the MCMC simulations. Our study also compared the estimates from the Bayesian quantile regression with the OLS (mean) and the frequentist quantile regression. We also considered three different consumption measures, namely, total expenditure (TE), work-related expenditure (WRE), and nonwork-related expenditure (NWRE).

The consumption drops in TE, WRE, and NWRE are 14%, 39%, and 5%, respectively, under the OLS (mean model), which agree with studies from Fisher and Marchand [18] and Fisher et al. [15] who found that the WRE has the highest drop, and the NWRE has the lowest drop. The results also prove that a broader measure of consumption may diminish the retirement consumption puzzle, as indicated by the smaller drop in the NWRE.

As expected, the drops in TE, WRE, and NWRE under the Bayesian median regression model ($\theta = 0.50$) are quite comparable to the OLS, indicating that the median model may be used as a substitute for the mean model.

The consumption drops upon retirement are statistically significant at all quantiles under the Bayesian quantile regression, where larger drops at lower percentiles and smaller drops at higher percentiles indicate a regressive distributional effect (regressive trend). The WRE shows a relatively uniform drop, while the drops in NWRE have more variations at lower percentiles (from 0.10 to 0.50), indicating that the NWRE drops are the source behind the variations of drops. Our study agrees with Aguila et al. [17] who found larger consumption drops at lower percentiles (regressive trend) but disagrees with Fisher and Marchand [18] who found larger consumption drops at higher percentiles (progressive trend).

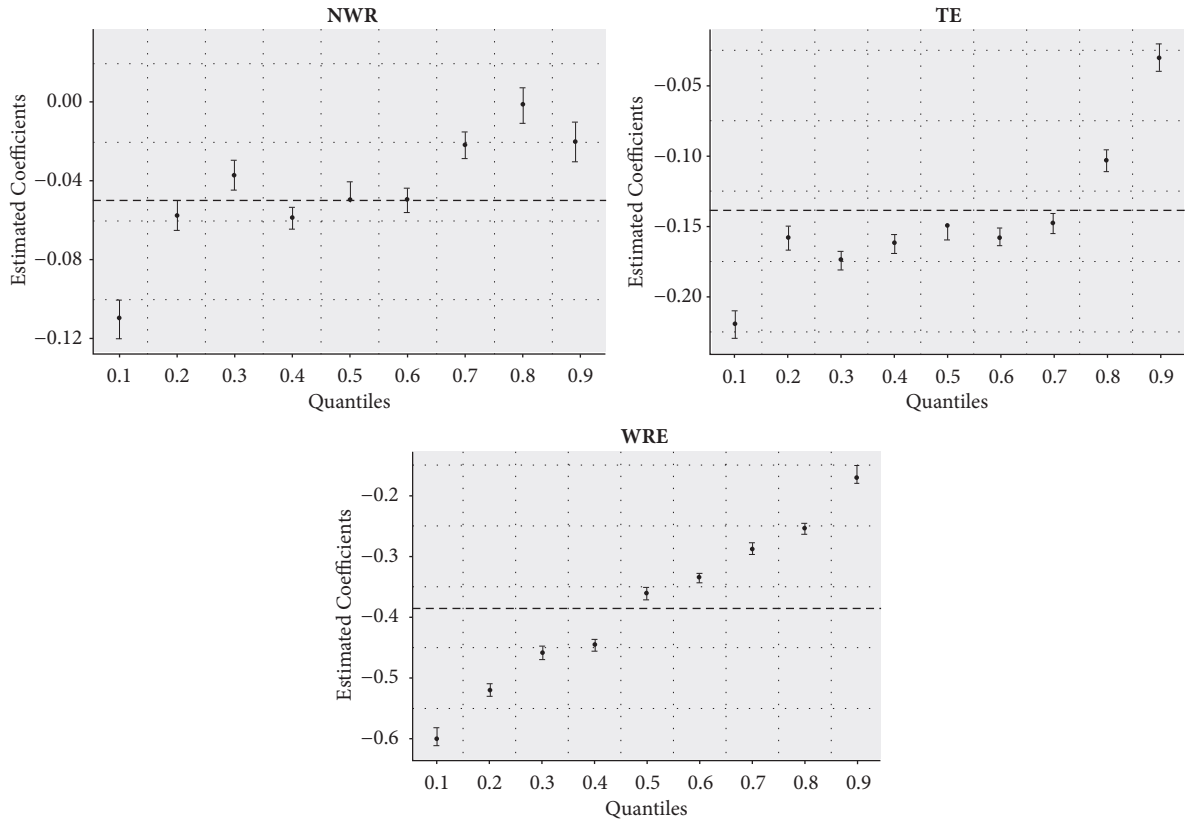

Figure 2: Regression estimates and 95% credible intervals for Bayesian quantile regression.

It should be noted that different data may provide different results.

The smaller drop among higher consumption retirees (or retirees with higher income) under the Bayesian quantile regression imply that the retirees with higher consumption have more savings and/or retirement benefits. The results are consistent with the expectations of life cycle theory which states that higher income households save more than lower income households. The larger drop at lower percentiles under the Bayesian quantile regression implies that the smaller consumption responses (or retirees with lower income) are exposed to larger consumption shocks.

Comparison between the Bayesian and the frequentist quantile regressions shows that the estimates are similar at all quantiles. The main difference between both models is that the standard deviations under the Bayesian model are different than the standard errors under the frequentist model. The differences are expected since the estimates under both approaches are obtained under different estimation methods.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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