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How Does Economic Growth affect the Well-being in Asia?

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Abstract: Investigation is made on the relationship between growth in economic sectors and well-being in Asia, using quantile regression model. Due to the limitation of data set, we thus propose introducing entropy estimation to quantile regression model. The simulation study is also conducted to show the performance and accuracy of the entropy estimation. We compare the entropy estimation with the conventional estimations and find that the entropy estimation outperform the conventional estimation when the data set is overly small. The application results also show that there exists the effect of economic growth on the well-being in some economic sectors.

Keywords: Quantile regression, Generalized Maximum Entropy, Happiness and economic factors

1. INTRODUCTION

The Asian economic region is vital and can affect the growth of global economy for its having more than 30% share of the world nominal GDP. Moreover, Asian nominal GDP and sector composition provided by the World Bank in 2014 showed that all economic sectors: agriculture, industry and manufacturing, and services are the driving force of Asia's economic growth. The share in Asia's GDP by sector is about 47%, 45%, and 8% for industry and manufacturing, services, and agriculture, respectively. Although individual economy has different causality relations but Foreign Direct Investment (FDI) has been a driving force for economic growth through capital accumulation and technological transfers. The significant causality from FDI to exports might imply that the inward FDI has facilitated the Global Value Chains (GVCs) participation in Asian economies (Taguchi and Lar, 2015). On the other hand, the Post-2015 Development Agenda of the World Health Organization (WHO) has a focus on economic growth measured by well-being indicators, such as Gross National Happiness and Index of Social and Economic Welfare beyond GDP (Kumar *et al.,* 2014). Thus, several countries such as Britain, Canada, France, Japan, and Thailand have also added measures of happiness to their official national statistics. Another measure of economic development is National Average Happiness evaluated in terms of six key variables: GDP per capita, social support, healthy life expectancy, freedom to make life choices, generosity, and freedom from corruption. Most Asian countries have the National Average Happiness levels lower than European countries especially the top five rankings of Happiness 2012-2014 by country which are Switzerland, Iceland, Denmark, Norway and Canada (Helliwell, Layard, and Sachs, 2015). According to McGillivray and Clarke (2006), the words "well-being" and "happiness" are often used interchangeably. The economic growth by GDP is taken as a proxy for progress, but it has never been intended for measuring happiness or actual welfare. Furthermore, Ura (2015) advised the limitations of GDP as a measure of progress are that it (i) does not make any distinction between GDP made from good development and GDP made from bad development; (ii) does not adequately value natural, human, and social capital in its measurement; (iii) does not value free time and leisure; (iv) does not value unpaid work; and (v) does not explicitly provide for equity. Besides, the goal of development has shifted from economic growth to improvement of human well-being because the majority of the world's population still suffer from lacking of basic necessities in life (food, shelter, education. and healthcare). Though poverty is one of the causes of low quality of life, improving human well-being does not involve merely monetary value.

Some researchers focused on the merit of sufficiency economy and happiness such as Leerattanakorn and Wiboonpongse (2015) who contended that development with sufficiency economy can contribute income growth together with the happiness to farmers. Also, Kaewmanee,et al. (2014) explored human happiness in five dimensions including physical, economic, social, mental, and spiritual by regressing self-evaluated happiness on the average score of each dimension.

This study, we focus on the effects of economic growth on well-being in Asian countries and quantile regression model will also be applied to analyze the effect of economic growth on the well-being of Asian countries. The intention of this study is to find out whether or not economic growth has a positive effect on the happiness or standard of living. To achieve the conclusive result, the Average National Happiness will be used as a representative of subjective well-being, the dependent variable. However, the limitation of data in macroeconomic study is what should be concerned here. Thus, this study proposes to conduct an entropy estimation of the unknown parameter in the quantile regression. Therefore, a generalized entropy quantile regression is developed in this paper to investigate the relationship between economic growth and well-being in Asia.

The outline of this paper is as follows. Section 2 reviews the quantile regression. Section 3 explains thoroughly about our proposed model and other necessary statistical properties related to our model including the basic idea of entropy. Section 4 involves a Monte Carlo simulation study to assess the finite sample performance of the estimator. The empirical study on economic growth affecting the well-being in Asia is given in Section 5. Finally, conclusion is in the last section.

How to measure happiness and subjective well-being?

The measurement of well-being can be made by two approaches: objective and subjective measures. The first approach measures well-being from the observable facts such as economic, social and environmental statistics. People's well-being is assessed indirectly using cardinal measures. On the other hand, subjective measure of well-being is captured from people's feelings or real experience in a direct way (McGillivray and Clarke 2006; van Hoorn 2007). Easterlin and Angelescu (2007) and Giovannini, Hall and d'Ercole

(2007) proposed to measure the objective well-being from one dimesion variable namely Gross Domestic Product (GDP). For the case of multidimensional well-being, there are three approaches. The first approach is to construct objective measures to complement GDP, offering social and environmental information beyond the economic stance. The second is to adjust GDP by monetizing different aspects that are not counted in the GDP measurement. And, thirdly, to go beyond GDP which is replaced by constructing composite measures that would capture the multidimensional aspects of well-being. These measures are usually constructed using different components, weighted in some way to form a single index.

Another approach to measuring multidimensional well-being is through subjective measures: self reported happiness and life satisfaction. For many centuries the subject of happiness was the realm of theologians and philosophers but recently it transcended into social sciences, first in psychiatry and since 1950 into mainstream social sciences and economics (Easterlin, 2004). Subjective well-being (SWB) refers to how people experience their lives and includes both emotional reactions and cognitive judgments. Psychologists have defined happiness as a combination of life satisfaction and the relative frequency of positive and negative effect. SWB therefore encompasses moods and emotions as well as evaluations of one's satisfaction with general and specific areas of one's life.

Concepts encompassed by SWB include positive and negative effect, happiness, and life satisfaction. Positive psychology is particularly concerned with the study of SWB. Also, SWB tends to be stable over time and is strongly related to personality traits. There is evidence that health and SWB may mutually influence each other, as good health tends to be associated with greater happiness, and a number of studies have found that positive emotions and optimism can have a beneficial influence on health.

2. REVIEW OF QUANTILE REGRESSION MODEL

Quantile regression is a variant of regression technique used in statistics and econometrics. In contrast to the least squares method which results in estimates that approximate the conditional mean of the response variable given certain values of the predictor variables, quantile regression aims at estimating either the conditional median or other quantiles of the response variable. Koenker and Roger (2005) proposed that quantile regression is desired if conditional quantile functions are of interest. One advantage of quantile regression, relative to the ordinary least squares regression, is that the quantile regression estimates are more robust against outliers in the response measurements. However, the main attraction of quantile regression goes beyond that. Different measures of central tendency and statistical dispersion can be useful to obtain a more comprehensive analysis of the relationship between variables.

To explain the principles of quantile regression, consider the following model:

$$y_j = x'_{i,j}\beta_i^{\tau} + \varepsilon_j \qquad ; i = 1,\ldots,k, \text{ and } j = 1,\ldots,\mathrm{n} \tag{1}$$

Where $x'_{i,j}$ is $n \times k$ independent variable, β_i^{τ} is $1 \times k$ vector of coefficients and ε_j is the error which does not assume any distribution. Thus, τ^{th} $(0 < \tau < 1)$ conditional quantile of y_j given $x'_{i,j}$ is simply as

$$Q_y(\tau|x) = x'_{i,j}\beta_i^\tau \tag{2}$$

In the estimation context, the classical estimation of quantile regression model focused on ordinary least squares (OLS) with a general technique for estimating families of conditional quantile functions (see, Koenker and Bassett (1978). The τ specific coefficient vector β^τ can be estimated by minimizing the loss function:

$$\hat{\beta}^\tau = \underset{\beta(\tau)}{\arg\min} \sum_{j=1}^{n} \rho^\tau(y_j - x_{i,j}\beta_i^\tau), \tag{3}$$

The latter **หมายถึงใคร** further extended estimation of this model by introducing a Maximum likelihood estimation. Sánchez.,Lachos, Labra (2013) proposed an alternative estimation for drawing inferences about conditional quantiles regression via maximum-likelihood estimation (MLE). It was proved that the MLE outperforms the competing Barrodale and Roberts (1977) simplex (BR) and Lasso Penalized Quantile Regression (LPQR) of Tibshirani (1996) in their work. The quantile regression estimation for β^τ proceeds by maximizing the likelihood based on the asymmetric Laplace density (ALD):

$$L(\beta^\tau, \sigma|y) = \frac{\tau^n(1-\tau)^n}{\sigma^n}\exp\left(-\sum_{j=1}^{n}\rho^\tau\frac{(y_j - x_{i,j}\beta_i^\tau)}{\sigma}\right), \tag{4}$$

where $\rho^\tau(L) = L(\tau - I(L<0))$ is called the check function by its shape. σ is a nuisance parameter. Note that, the maximization of the likelihood in (4) with respect to the parameter β^τ is equivalent to the minimization of the objective function in (3).

In contrast to the the frequentist view, a number of estimation methods which propose to combine a prior density distribution to frequentist approach have been introduced. These are termed 'Bayesian estimation'. In this direction, recent developments include, Kottas and Gelfand (2001) who considered median regression and suggestednon-parametric modeling for the error distribution based on either Pólya tree or Dirichlet process priors. Yu and Moyeed (2001) proposed the ALD and improper uniform priors to produce a proper joint posterior, and Kozumi and Kobayashi (2011) developed a Gibbs sampling method to estimate the quantile regression model based on a location-scale mixture representation of the ALD. In the Bayesian estimation, Markov Chain Monte Carlo (MCMC) method is employed to extract the posterior distributions of unknown parameters β^τ and provide a convenient way to incorporate a parameter uncertainty into predictive inferences. The posterior distribution of β^τ is given by

$$P(\beta^\tau, \sigma|y) \alpha\, L(\beta^\tau, \sigma|y)\,p(\beta^\tau, \sigma) \tag{5}$$

where $p(\beta^\tau, \sigma)$ is prior distribution of β^τ and σ. In general, we can choose any distribution depending on our belief to produce a proper joint posterior. However, to the best of our knowledge, there are few studies on quantile regression from an entropy based perspective. One of the exceptions is the study carried out by Bera, GalvaoJr, A. F., Montes-Rojas, G. V., and Park (2014). They defined the information entropy of the distribution of probabilities $p = \{p_k\}_{k=1}^{K}$ as an ALD and maximizing entropy measure subject to two moment constraints :

$$f_{ME}(y) = \arg\max_{f} - \int f(y) \ln f(\mathrm{y})\,\mathrm{dy} \tag{6}$$

subject to

$$E\left|y - x\beta^{\tau}\right| = c_1,$$

$$E(y - x\beta^{\tau}) = c_2,$$

where $\int f(y)dy = 1; c_1$ and c_2 are known constants.

Although the entropy estimation has already been proposed, it still adheres to the strong ALD assumption on the entropy measures. Thus, it is greatly desirable to expand the flexibility of entropy estimation by relaxing the ALD in the objective function. Thus, another main contribution of this study is to develop an entropy estimation for quantile regression model without assuming the ALD.

In ecology, quantile regression has been proposed and used as a way to discover more useful predictive relationships between variables in cases where there is no relationship or only a weak relationship between the means of such variables. The need for and success of quantile regression in ecology has been attributable to the complexity of interactions between different factors leading to data with unequal variation of one variable for different ranges of another variable (Cade and Noon, 2003). Also, Wei et al. (2006) proposed another application of quantile regression in the area of growth charts, where percentile curves are commonly used to screen for abnormal growth.

3. METHODOLOGY

3.1. Generalized Maximum Entropy estimation in Quantile regression Model

In this study, it is proposed to use a maximum entropy estimator to estimate the unknown parameters in equation (1). As this estimator for quantile regression and its statistical properties were already discussed, now it is the turn of the concept about the entropy approach. The maximum entropy concept consists of inferring the probability distribution that maximizes information entropy given a set of various constraints. Let p_k be a proper probability mass function on a finite set $\mathcal{A}$ where $\mathrm{A} = \{a_1,..,a_K\}$. Shannon (1948) developed his information criteria and proposed a classical entropy, that is

$$H(p) = -\sum_{k=1}^{K} p_k \log p_k \,, \tag{7}$$

where $\sum_{k=1}^{K} p_k = 1$. The entropy measures the uncertainty of a distribution and reaches a maximum when p_k is uniform distribution Wu (2009).

This entropy concept is applied in the present model by generalizing the maximum entropy as the inverse problem in the quantile regression framework. Rather than searching for the point estimates β_i^{τ}, one can view these unknown parameters as expectations of random variables with M support value for each estimated parameter value (k), $Z = [z_1,..., z_K]$ where $z_k = [\underline{z}_{k1},..., \overline{z}_{km}]$ for all $k = 1,...K$. Note that $\underline{z}$

and $\overline{z}$ denote the lower bound and upper bound, respectively, of each support z_k. Thus parameter β_i^{τ} can be expressed as

$$\beta_i^{\tau} = \rho_{\tau} \begin{bmatrix} \underline{z}_{11} & \cdots & 0 & \cdots & \overline{z}_{1m} \\ \underline{z}_{21} & \ddots & 0 & & \overline{z}_{2m} \\ \vdots & & \vdots & & \vdots \\ \vdots & & 0 & \ddots & \vdots \\ \underline{z}_{k1} & \cdots & 0 & \cdots & \overline{z}_{km} \end{bmatrix} \cdot \begin{bmatrix} p_{11} & \cdots & 0 & \cdots & p_{1m} \\ p_{21} & \ddots & 0 & & p_{2m} \\ \vdots & & \vdots & & \vdots \\ \vdots & & 0 & \ddots & \vdots \\ p_{k1} & \cdots & 0 & \cdots & p_{km} \end{bmatrix}, \tag{8}$$

$$\beta_k = \rho_{\tau} \sum_m p_{km} z_{km} , \tag{9}$$

where p_{km} are the M dimensional estimated probability distribution defined on the set z_{km}. Next, similar to the above expression, ε_j is also constructed as the mean value of some random variable v. each ε_j is assumed to be a random vector with finite and discrete random variable with M support value, $v_j = [v_{j1},...,v_{JM}]$. Let w_j be an M dimension proper probability weights defined on the set v_j such that

$$\varepsilon_i = \rho_{\tau} \begin{bmatrix} \underline{v}_{11} & \cdots & 0 & \cdots & \overline{v}_{1m} \\ \underline{v}_{21} & \ddots & 0 & & \overline{v}_{2m} \\ \vdots & & \vdots & & \vdots \\ \vdots & & 0 & \ddots & \vdots \\ \underline{v}_{J1} & \cdots & 0 & \cdots & \overline{v}_{Jm} \end{bmatrix} \cdot \begin{bmatrix} w_{11} & \cdots & 0 & \cdots & w_{1m} \\ w_{21} & \ddots & 0 & & w_{2m} \\ \vdots & & \vdots & & \vdots \\ \vdots & & 0 & \ddots & \vdots \\ w_{J1} & \cdots & 0 & \cdots & w_{Jm} \end{bmatrix} \tag{10}$$

$$\varepsilon_j = \rho_{\tau} \sum_m w_{jm} v_{jm} . \tag{11}$$

Using the reparameterized unknowns β_k^{τ}, γ_k, and ε_j, one can rewrite equation as

$$Y_j = \rho_{\tau} \sum_m p_{1m} z_{1m} (x'_{1,t}) +,...,+ \rho_{\tau} \sum_m p_{Km} z_{Km} (x'_{K,j}) \; + \rho_{\tau} \sum_m w_{jm} v_{jm} , \tag{12}$$

where the vector support z_{km}^{-} z_{km}^{+} q_{Km} and v_{jm} are convex set that is symmetric around zero with $2 \le M < \infty$. And

$$\rho_{\tau}(\mathrm{L}) = L(\tau - I(L < 0)) \tag{13}$$

is the check function; this gives the τ^{th} sample quantile with its solution.

Then, the Generalized Maximum Entropy (GME) estimator for this model can be constructed as

$$H(p,w)=\underset{p,w}{\arg\max}\{H(p)+H(w)\}\equiv-\sum_{k}\sum_{m}p_{km}\log p_{km}-\sum_{j}\sum_{m}w_{jm}\log w_{jm} \tag{14}$$

subject to

$$Y_j=\rho_\tau\sum_m p_{1m}z_{1m}(x'_{1,j})+....+\rho_\tau\sum_m p_{Km}z_{Km}(x'_{K,j})\ +\rho_\tau\sum_m w_{jm}v_{jm} \tag{15}$$

$$\sum_m p_{km}=1,\sum_m w_{jm}=1, \tag{16}$$

where p, and w are on the interval [0, 1].

Consider regressor $(k=1)$, this optimization problem can be solved using the Lagrangian method which takes the form of

$$L=H(p,w)+\lambda_1'(Y_j-\rho_\tau\sum_m p_{1m}z_{1m}(x'_{1,j})-\rho_\tau\sum_m w_{tm}v_{tm})+a'(1-\sum_m p_{km})+b'(1-\sum_m w_{jm}), \tag{17}$$

where λ_1' , a' and b' are the vectors of Lagrangian multipliers. Thus, the resulting first-order conditions are

$$\frac{\partial L}{p_{1m}}=-\log(p_{1m})-\sum_m \lambda_{1m}\rho_\tau z_{1m}(x'_{1,j})-a_j=0, \tag{18}$$

$$\frac{\partial L}{w_{jm}}=-\log(w_{jm})-\sum_m \lambda_{1m}v_{jm})-b_j=0, \tag{19}$$

$$\frac{\partial L}{\lambda_1}=\left(Y_j-\rho_\tau\sum_m p_{1m}z_{1m}(x'_{1,j})-\rho_\tau\sum_m w_{jm}v_{jm}\right)=0, \tag{20}$$

$$\frac{\partial L}{a_i}=1-\sum_m p_{1m}=0, \tag{21}$$

$$\frac{\partial L}{b_i}=1-\sum_m w_{tm}=0. \tag{22}$$

Thus, we have

$$p_{1m}=\exp(-a_j-\sum_m \rho_\tau\lambda_{1m}z_{1m}(x'_{1,j}))=1, \tag{23}$$

and

$$w_{jm}=\exp(-b_j-\sum_m \rho_\tau\lambda_{1m}v_{jm})=1. \tag{24}$$

Then, by setting $\lambda=0$, solving the first order conditions yields

$$\hat{p}_{1m} = \frac{\exp(-z_{1m}\sum_j \rho_\tau \hat{\lambda}_{1j} x'_{1,j})}{\sum_m \exp(-z_{1m}\sum_j \rho_\tau \hat{\lambda}_{1j}(x'_{1,j}))}, \tag{25}$$

$$\hat{w}_{jm} = \frac{\exp(-\hat{\lambda}_{1j}\rho_\tau v_{1m})}{\sum_m \exp(-\hat{\lambda}_{1j}\rho_\tau v_{1m})}. \tag{26}$$

4. SIMULATION STUDY

Table 1
Bias of quantile regressions with ALD errors

			Bias(%)			
			$\tau = 0.25$			
N	*Parameter*	*True*	*GME*	*Bayesian*	*MLE*	*LS*
20	$\beta_0^{0.25}$	2	-6.9300	-10.9300	-5.0350	-5.0400
	$\beta_1^{0.25}$	3	2.4733	-8.2333	-8.3200	-8.3233
40	$\beta_0^{0.25}$	2	6.6400	9.1050	3.2800	2.6850
	$\beta_1^{0.25}$	3	2.3967	-2.8600	-5.2333	-5.0767
60	$\beta_0^{0.25}$	2	8.0950	5.3800	6.4500	6.9420
	$\beta_1^{0.25}$	3	-6.9300	4.9567	4.2867	-4.3757
			$\tau = 0.50$			
N	*Parameter*	*True*	*GME*	*Bayesian*	*MLE*	*LS*
20	$\beta_0^{0.5}$	2	-2.5795	-8.7950	-13.6350	-16.2550
	$\beta_1^{0.5}$	3	0.2400	-0.3533	-0.8333	-2.8700
40	$\beta_0^{0.5}$	2	2.2729	-0.6100	-0.4500	-0.2750
	$\beta_1^{0.5}$	3	0.2133	-0.4300	-2.0867	-2.0267
60	$\beta_0^{0.5}$	2	2.2809	-0.4950	-0.2200	-0.1750
	$\beta_1^{0.5}$	3	0.2579	0.3060	3.2700	3.3000
			$\tau = 0.75$			
N	*Parameter*	*True*	*GME*	*Bayesian*	*MLE*	*LS*
20	$\beta_0^{0.75}$	2	-4.1050	-33.2400	-30.4100	-29.8250
	$\beta_1^{0.75}$	3	6.2567	-30.3233	-32.1900	-31.5567
40	$\beta_0^{0.25}$	2	7.1200	0.9700	0.5850	-0.5200
	$\beta_1^{0.75}$	3	6.1133	2.4333	2.6567	2.5333
60	$\beta_0^{0.25}$	2	7.3100	-6.6000	-2.285	-2.0650
	$\beta_1^{0.75}$	3	-4.1050	0.5133	0.3001	0.6033

Source: Calculation

In this section, a simulation study was conducted to evaluate performance and accuracy of our proposed Generalized Maximum Entropy (GME) estimation and compare it with the classical estimations, including Least Squares (LS), Bayesian and Maximum Likelihood estimation (MLE). We simulated the data from the quantile regression model where the error term is assumed to be asymmetric Laplace distribution (ALD), $\varepsilon_{i,t}^{\tau} \sim ALD(0,1)$ for three different quantile levels $\tau = (0.25, 0.5, 0.75)$. Hence, the simulation model takes the following form:

$$y_{1,t} = \beta_0^{\tau} + \beta_1^{\tau} x_{1,t} + \varepsilon_{1,t}^{\tau} \tag{27}$$

In the simulation, we set $\beta_0^{\tau} = 2$ and $\beta_1^{\tau} = 3$. We simulated the independent variables $x_{1,t}$ from $N(0,1)$. Our interest is on the bias of the parameters which are obtained from four estimation techniques. We carry out all the experiments with sample size n = 20, 40, and 60; and 100 replications. Computations are performed in the R environment (R Development Core Team, 2012) using the package "quantreg" for LS, written by Koenker (2013), and "bayesQR" written by Benoit, Al-Hamzawi, Yu, and Van den Poel, (2011). For MLE, we follow the estimation technique of Sánchez.,Lachos, Labra (2013) and maximize the likelihood based ALD to obtain the parameters.

Table 1 reports the results of the Monte Carlo simulation. In all cases we compute the percentage relative bias with respect to $\beta_0^{\tau} = 2$ and $\beta_1^{\tau} = 3$. We found that our proposed model can perform well through this simulation study. The overall bias values of parameter at different quantile levels obtained from GME are lower than 10%. Thus, this indicates that GME performs well with accuracy in this simulation study.

Comparing the GME and three other estimations at all quantile levels, we note that when the number of observations is small, $n = 20$, the bias(%) of the GME are mostly smaller than those of Bayesian, MLE and LS. However, the bias(%) of the GME are mostly larger than those of Bayesian, MLE and LS when the number of observations is large, $n \geq 40$. This result suggests that when the number of observations does matter, the GME estimation has a smaller risk and is more precise. Moreover, when we consider the number of observations, we found that its performance seems to be a little better when the number of observations is further increased.

Regarding the performance across quantiles, GME gave better estimates for middle quantile τ =0.50 but poorer ones for lower and upper quantiles. The performance is quite similar between τ =0.25 and τ =0.75. For the case of Bayesian, MLE and LS, these estimations were found to perform similarly between τ =0.25 and τ =0.50.

In summary, entropy approach to quantile regression modeling is effective and it generally outperforms Bayesian, MLE and LS when the number of observations is small. However, GME cannot avoid obtaining considerably biased estimates at the extreme quantile levels.

5. EMPIRICAL RESULTS

To analyze Economic Determinants of Happiness by taking the National Average Happiness (NAH) as a representative of well-being, the study uses the cross-section data on 37 countries in Asia to examine the various links between NAH and Macroeconomic variables, consisting of Output of Agriculture (OA), Output of Services (OS), and Output of Industry and Manufacturing (OM) for the period 2014.These data are collected from the World Bank data and World Happiness Report 2015.

5.1. Model Specification

Here, the cross sectional quantile regression model takes the following form:

$$NAH_j = \beta_0^\tau + \beta_1^\tau OA_j + \beta_2^\tau OS_j + \beta_3^\tau OM_j + \varepsilon_j,$$

where $j = 1,\ldots,n$ countries.

This study considers three quantile levels that are τ = (0.25, 0.5, 0.75) to represent three groups of countries in Asia as classified by the 2008 World Development Report of the World Bank.

5.2. Results and Discussion

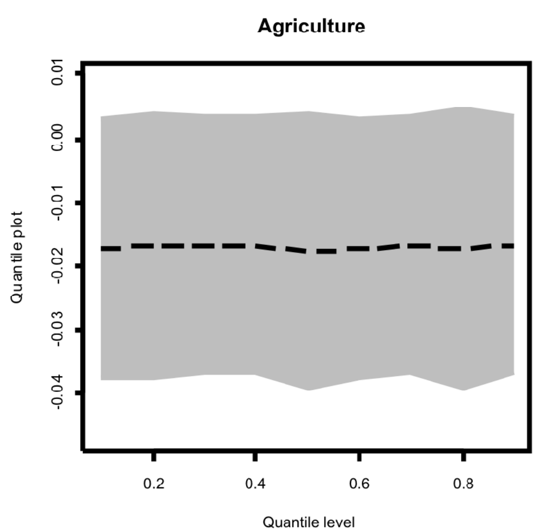
Table 2
Estimates of the parameters and their standard errors (in parentheses) from Quantile regression model

Parameter	τ =0.25	τ =0.5	τ =0.75
β^τ_0	0.8395	0.8558	1.4512***
	(0.5291)	(0.5549)	(0.5201)
β^τ_1	-0.1768***	-0.01771*	-0.0167*
	(0.0103)	(0.0108)	(0.0101)
β^τ_2	0.0703	0.0349	0.0572
	(0.0618)	(0.0647)	(0.0606)
β^τ_3	-0.0239	0.0115*	-0.0026
	(0.0651)	(0.0683)	(0.0640)

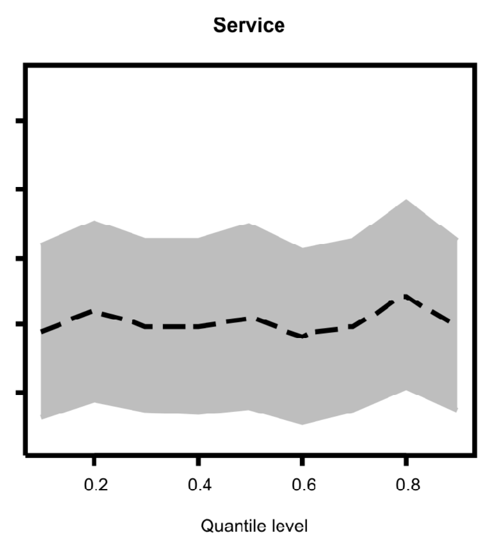
Source: Calculation

Note: "*","**", and "***" are significant at 1%, 5%, and 10% levels.

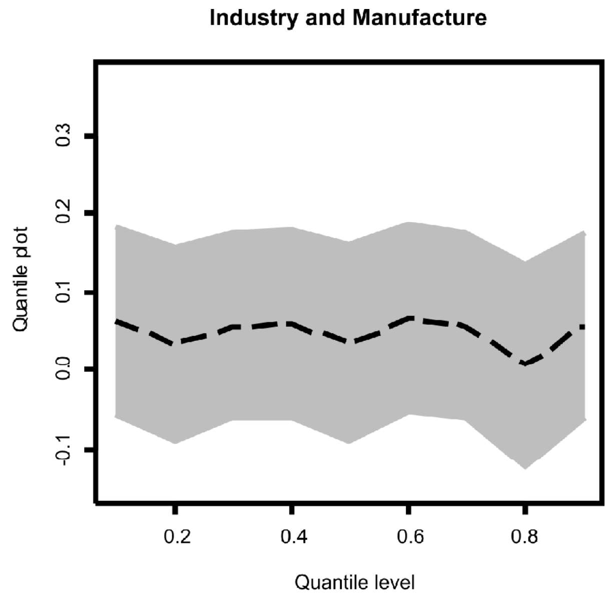
In Table 2, the rows are displaying only the coefficients for our economic output factors, namely Agriculture (β_1^τ), Services (β_2^τ), and Industry and Manufacturing (β_3^τ). These coefficients are provided



(a)



(b)



(c)

Figure 2: GME estimates and 95% confidence intervals for various values of τ

for quantile level at 0.25, 0.50, and 0.75. For the model where NAH is the dependent variable, at τ =0.25, τ =0.5, and τ =0.75, we refer to the least happiness 25%, 50% and 75% of the samples. The results show that the effect of agriculture sector has a negative sign for the 0.25, 0.50, and 0.75 quantiles; thus indicating that agriculture cannot affect the happiness in Asian countries. In other words, the well-being in Asian countries seems not depend on the money income of agricultural sector.

Surprisingly, we found the opposite effect that the more the agricultural output, the lower the happiness level. We expect that the high level of agricultural output corresponds to a large portion of labor employment in the agricultural sector. This implies that the Asian countries as a whole is still at an early stage of development and the degree of urbanization might be not high enough to adversely affect the quality of life of population (Yuen and Chu, 2015). The negative relationship can also be clearly seen in Figure 2(a), where we plot the coefficient β_1^τ and depict the 95% confidence interval for all the parameters in the shaded area.

On the contrary, we find a different result in service; and industry and manufacturing sectors. The effect of these sectors is not significant for the 0.25, 0.50, and 0.75 quantiles, except for industry and manufacturing sector in the middle quantile. In other words, this result indicates that only industry and manufacturing sector has a positive effect on happiness in at least 50% of Asian countries. Consider coefficient parameters β_2^τ and β_3^τ in Figures 2(b) and 2(c), the effect of the two variables (OS and OM) is ether increase or decrease for the higher conditional quantiles, indicating that there exist heterogeneous effects of Service; and Industry and manufacturing sectors on happiness in Asian countries.

Figure 3 plots a fitted line of quantile regression where the dashed red line, black line and green line correspond to the 0.75, 0.50, and 0.25 quantiles, respectively. For the coefficient of agriculture variable, the negative slopes of the quantiles are quite similar for all quantiles. For service sector, Figure 3(b) illustrates the slopes of the quantiles that are extremely different depending on the quantile level. We

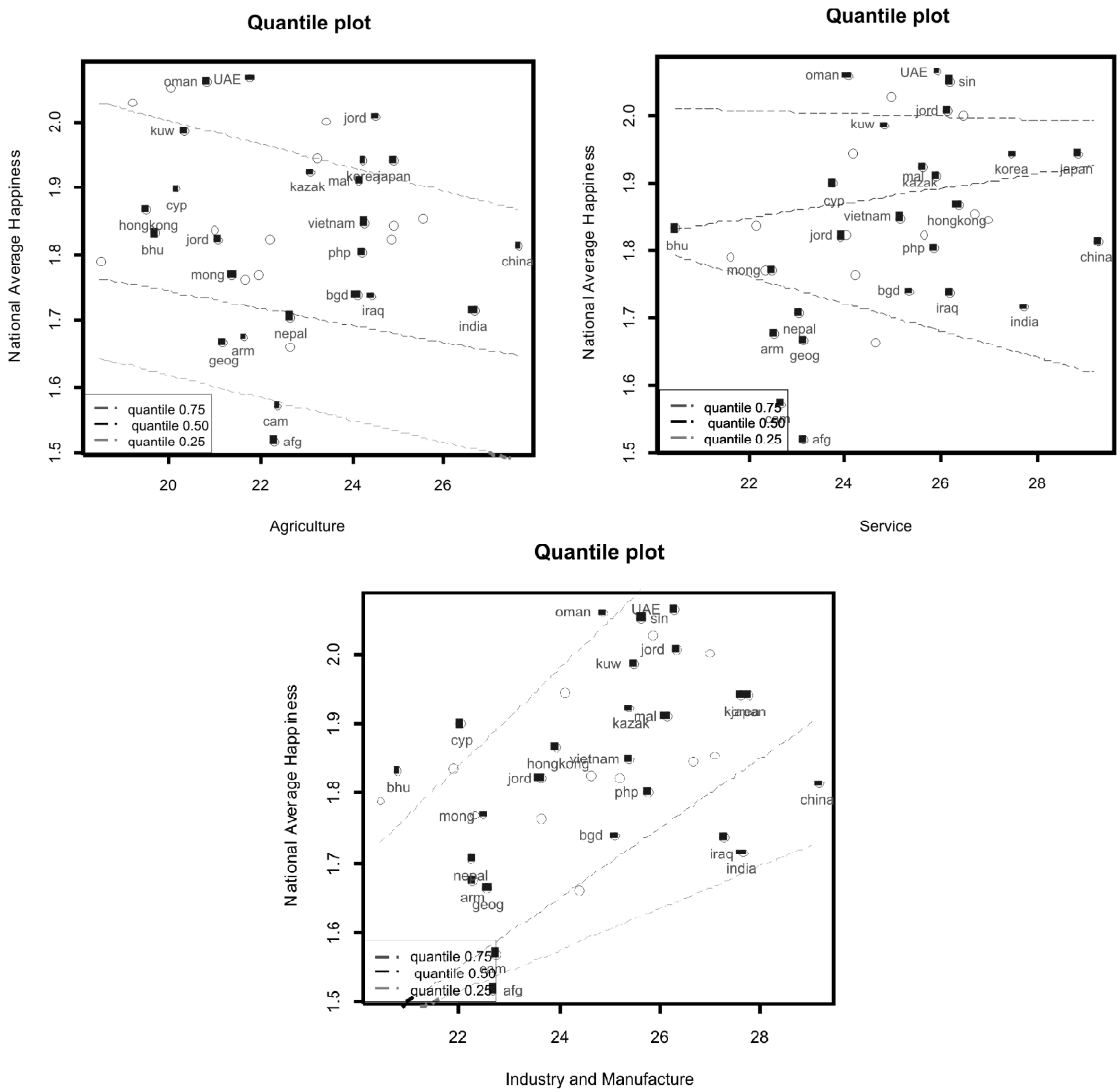


Figure 3: The plot of the data along with the quantile regression lines for values of τ =0.25, τ =0.5, and τ =0.75

observe that the 0.50 quantile (median) shows a positive effect of service on NAH while a negative effect is shown in 0.75 and 0.50 quantiles. In the last sector, industry and manufacturing, Figure 3(c), we find a similar positive slope of the qauntiles. However, the effect of industry and manufacturing sector on happiness is positively stronger at higher quantile. This may indicate that industry and manufacturing sector has a stronger influence on high NAH countries, when compared to the low NAH countries.

6. CONCLUSION

This paper deals with the effect of three main economic sectors on the happiness in Asian countries using a quantile regression model to explain the effects of explanatory variables on different parts of the happiness distribution. However, the inadequacy of data in macroeconomic study is what should be concerned in our study. Thus, this study proposes an entropy estimation of the unknown parameter in the quantile regression. Therefore, a generalized entropy is developed here to estimate the unknown parameters in the quantile regression model when there exist small sample sizes.

Although the entropy estimation haw already been proposed. It still adheres to the strong Asymmetric Laplace Distribution (ALD) assumption on the entropy measures. Thus, it is greatly desirable to expand the flexibility of entropy estimation by relaxing the ALD assumption in the objective function. Thus, another main contribution of this study is to develop an entropy estimation for quantile regression model without assuming the ALD. In this study, both simulation and application studies are employed to measure the performance of our estimation. In the simulation study, the entropy estimation is compared for performance with the conventional estimations, consisting of Bayesian, Ordinary Least Squares, and Maximum likelihood methods. The results show that entropy estimation not only performs well but outperforms those conventional estimations, particularly when the data set is small.

We subsequently apply quantile regression model to investigate the relationship between economic growth and well-being in Asia. In a nutshell, our empirical results suggest the negative effect of agricultural sector on the happiness (measured by NAH) in all Asian countries, while industry and manufacturing having a positive effect on happiness especially in the middle happiness countries. We expect that the higher output of industry and manufacturing may lead to environmental pollution and degradation. On the other hand, the low output of Industry and Manufacturing has not only resulted in the extreme poverty but also caused social tensions and inequality. Lastly, the service sector seems to play a weak role on the happiness of Asian countries.

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