Quantile Regression Applications in Climate Change

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INTRODUCTION

The Organization for Economic Co-operation and Development (OECD) Environmental Outlook shows that "greenhouse gas emissions from the transportation sector are projected to double by 2050 due to a strong increase in demand for cars in developing countries, and OECD economies have been responsible for most of the emissions." (OECD, 2011, p.15). In particular, it is extremely important to reduce the emissions of motor vehicles by improving their fuel efficiency (OECD, 2011).

As a result of human actions and the associated energy consumption, especially in the last century, the world has faced serious environmental problems, in particular carbon dioxide (CO_2) emissions (Sterin and Lavrov, 2020). Environmental sustainability is an increasingly important dimension in both business and political decision making. Efficient environmental policy, regulation, and management critically depend on reliable information (Kuosmanen and Zhou, 2021). Research in the field of environmental sustainability has shifted from a country's perspective to a global perspective (Sarkodie, 2021). United Nations, in their sustainable development goals (SDGs), focused on creating human and industrial capacity, improving education, and reducing the impact of climate change and environmental changes (Answer et al., 2021).

There is an urgent need to investigate the issue of climate change from different perspectives as they provide the academic and practice communities with the needed knowledge to understand the issue holistically. Policy makers in various economic and social fields are encouraged to coordinate their policies to balance achieving prosperity for their communities with the environmental implications of those policies (Alotaibi and Alajlan, 2021).

BACKGROUND

Quantile regression is considered an extension to standard linear regression, and its primary purpose is to estimate the median of the outcome variable. Quantile regression can also be used when assumption of linear regression is not satisfied, outliers in data, residuals are not normal, and increase in error variance with increase in outcome variable. Quantile regression techniques are used to ensure or create an understanding of the association amongst variables outside the mean data, which makes it effective to understand the outcomes that are unusually distributed and those having nonlinear relationships with predictor variables. Quantile regressions can be run on various sections of the population based on the unlimited distribution of the dependent variables (Huang et al., 2017; Koenker, 2017).

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Another rationale that justifies quantile regression's significance is that it enables scholars to abandon the presumption that variables have similar working means at the upper tails of the distribution as at the mean, and it also helps in identifying the factors that critically determine the variables. According to Wenz (2019), quantile regression is forecasting, introducing a purposed bias in the outcome. Rather than identifying the mean of the anticipated variable, this type of regression pursues the median and any other quantiles, which are often referred to as percentiles. The main benefit of quantile regression is that its measures are comprehensive against outliers in the outcome measurements. The central position about the quantile regression topic is that they surpass this and are beneficial when there are interests in conditional quantile functions.

Quantile regression is currently a famous approach to offer a broad description of the distribution of an outcome variable on a collection of inputs. A quantile regression number accounts for and measures the level of a particular quantile of the outcome distribution, which is shifted by a one-unit rise in the predictor variable (Huang et al., 2017). Although the goal and aim of regression analysis are to estimate the conditional means of a variable one is interested in, quantile regression is used in estimating any conditional quantile of any level. Many scholars have studied the subject of quantile regression both from frequentist and Bayesian perspectives. Quantile regression is generally essential and shows to be essential when an individual is interested in the relationship amongst sections of the distribution also on limits. Some researchers have also studied the relationship between quantile regression and risk assessment and modeling (Rahman & Vossmeyer, 2019).

Koenker (2017) reported that the quantile classification technique places similar observation numbers into every class. The technique is mainly used for data that is evenly distributed across the range. The primary issue related to this is that quantile regression methodology has features positioned within similar cases, which can have significantly different values, especially when there is no even distribution of data across the range. Wang et al. (2019) conducted a study to ascertain the different issues related to quantiles and quantile regression. When the values having small range differences are positioned into various sets, which suggests a significant difference in the dataset. Therefore, quantile regression can create classification gaps amongst the attribute values, whereby these gaps can cause an over-weighting to the outliers in such a class set. Chen et al. (2021) also provided another issue related to quantiles and quantile regression by saying that when there is incorrect creation of the number of classes having similar values, this can lead to two groups. The primary reason why most analysts and scholars rarely use quantile regression, especially in healthcare research, is that the interpretations appear to be unintuitive.

CURRENT RESEARCH

Socioeconomic Indicators

Alotaibi and Alajlan (2021) investigated the inclusive relationship between socioeconomic indicators and CO_2 emissions in G20 countries using two socioeconomic indicators: LPI for the period 2007 to 2019 and HDI for the period 2000 to 2019, which were chosen based upon the reliability and availability of data. Quantile regression was employed to simultaneously analyze the heterogeneous effects of the explanatory variables, which included four control variables beside the socioeconomic variables. The authors empirically selected the control variables based on their regression quality and introduced them in two empirical models for LPI and HDI. The selected control variables were fossil fuel consumption,