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Research Article

The Potential Relationship Between Income Inequality and Environmental Quality in Iran: The Panel Quantile Regression Approach

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Abstract: This paper addresses the relationship between income inequality and environmental quality in the agriculture sector as the most related sector to the environment. In this context, we used a panel data set for 28 provinces of Iran during 2003-2017 and implemented panel quantile regression. To choose the best econometric specification the *Taylor* diagram is used. To explore whether the effect on income inequality on CO_2 emission is different for rich and poor provinces, we consider the *GINI* × *GDP* interaction term in the model. Results confirmed that *EKC* in the agriculture sector of Iran, and a major and significant effect of energy consumption on CO_2 emission. Findings indicated a threshold per capita income ($ 17.60 thousand) from which the effect of income inequality on carbon emissions changes. Based on these results, Marginal Properties to Emit (*MPE*) is more significant for poor people in low-income provinces than rich ones. Therefore, the government should adopt appropriate policies to increase the income of farmers so that the policy of income distribution, along with social justice, also improves the quality of the environment.

***Keywords*:** agriculture, CO_2 emission, energy consumption, income inequality, marginal properties to emit

JEL Codes: A12, C01, C23, D33, O13, Q53

1. Introduction

The rapid growth of the global economy has created severe socio-economic and environmental problems, including income inequality, climate change, and global warming, which are the most crucial unresolved challenges of human society in the 21st century (Huang & Duan, 2020). Enhancing ocean and air and temperatures, melting of glaciers, increasing the level of the sea, decreasing the products of the agriculture, decimated wildlife, unpredictable rainfall quantity, and decreasing the efficiency of the workforce are some of the results of the climate change issue (Danish et al., 2019). Besides, the income inequality causes many social and economic issues. While, in the international public opinion, for sustainable development, decreasing environmental quality and income inequality are two of the most critical issues, and for future sustainable development in social, economic, and environmental aspects, making accurate policies from now on are needed (Uzar, 2020).

Since 1980, income inequality became a critical issue because of the rapid deterioration of income distribution, and this led to a rising intense scrutiny of income distribution dynamics in most of the countries (Uzar, 2020). However,

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there are extensive researches on the effects of income inequality on unemployment, economic growth, crimes, and poverty; less attention has been paid to the relationship between income inequality and environmental degradation.

The environmental degradation crisis has been a significant issue since 1950. Since the early 1990s, research on the relationship between economic growth and environmental quality was considered. Panayotou (1993), Selden and Song (1995), and Grossman and Kruger (1994) have found an inverse-U relationship between some air and water pollution indices with per capita income, that called Environmental Kuznets Curve (*EKC*) (Chen et al., 2020). Nowadays, the investigation of *EKC* has a critical role in sustainable development and energy policies. There is reliable and extensive literature on the *EKC* hypothesis; some of them confirmed the existence of *EKC* (Holtz-Eakin & Selden, 1995; Panayotou et al., 2000; Bagliani et al., 2008; Tien Pao & Tsai, 2011; Yavuz, 2014; Mladenović et al., 2016; Churchill et al., 2018; Adzawla et al., 2019; Wang & Lee, 2019; Chen et al., 2020); but several of them concluded no evidence of *EKC* (Friedl & Getzner, 2003; He & Richard, 2010; Wang, 2012; Ben Jebli & Youssef, 2015; Ahmed et al., 2017; Adzawla et al., 2019).

Until 1998, to investigate *EKC* researches only focused on the relationship between environmental quality and economic growth, but after 1998, some authors (Unruh & Moomaw, 1998; Suri & Chapman, 1998; Kaufman et al., 1998) suggested that in the *EKC* model the other explanatory variables should be considered, including energy consumption, trade openness, financial development. Few researches emphasize on the income inequality variable and empirically examine the effect of income inequality on environmental quality (Torras & Boyce, 1998; Scruggs, 1998; Magnani, 2000; Marsiliani & Renstorm, 2000; Ravallian et al., 2000). However, this issue has been considered a bit more recently, and it is believed that to avoid the miss specification, a criteria of income inequality should be considered in the *EKC* investigation (Jorgenson et al., 2017; Grunewald et al., 2017; Bae, 2017; Liu et al., 2018; Masud et al., 2018; Liu et al., 2019; Uzar & Eyuboglu, 2019; Ridzuan, 2019; Uddin et al., 2020; Chen et al., 2020; Huang & Duan, 2020).

Due to the significant reason for climate change, Carbon dioxide (CO_2) emission is a global issue, and any country should make its best efforts to reduce its concentration. In the meantime, the agriculture sector, with 13% of the total world's greenhouse emissions, is the second largest greenhouse emitter industry. It is predicted that, by 2030, the agriculture pollutants will be grown to 15% and reached 7 billion tons per year (World resource institute, 2018). Besides, 50% decrease in agricultural pollutants leads to reduce 200,000 deaths each year (Giannakis et al., 2019). In 2018, Iran ranked 7th carbon-emitter country with an emission of 672 million tons. Also, in 2017, $ 34 thousand billion currency was spent on the remediation of air pollution, which was 48.2% of the country's *GDP*. On one side, the agriculture sector of Iran, compared to its *GDP*, annually emitted considerable greenhouse gas, which CO_2 with 12.5 million tons, was the biggest air pollutant in this sector (Energy balance sheet, 2018). On the other side, the agriculture sector is closely linked to the environment in terms of the nature of its production process. The income of many indigenous peoples around forests, pastures, and seas depends mainly on these resources. So, in addition, to solve the econometric problems of not considering income inequality, the effect of income inequality on environmental quality is needed to be investigated in the agriculture sector.

However, there are a few studies on the investigation of *EKC* in the agriculture sector (Li & Zheng, 2011; Liu & Xin, 2014; Xiong et al., 2016; Xu & Lin, 2017; Andreoni & Galmarini, 2012; Liu et al., 2017; Zafeiriou & Azam, 2017; Gokmenoglu & Taspinar, 2018; Zhang et al., 2019); according to our intensive literature survey, there is no study so far that evaluated the effect of the income inequality on environmental quality in the agriculture sector, even for Iran. So, in the present study, we investigate the potential relationship between income inequality and environmental quality in the agriculture sector of Iran. For the first time, we focused on agriculture as it is the most related sector to the environment, and to best evaluate, we used provincial data. Our sample is a panel data set for 28 provinces of Iran during 2003-2017. For the first time, the *Taylor* diagram is used to select the most accurate econometric specification. Due to the skewness of the dependent variable and the power of the quantile regression in such cases, and to explore the heterogeneous effects of the variables on CO_2 emission at different provinces, implemented a Fixed-effect quantile regression. Also, we report the results of pooled quantile regression to declare the importance of choosing the best model for making a correct conclusion. According to economic and social theories, income is a critical and significant factor in the economic and social behavior of a person. Therefore, the use of the *GINI* × *GDP* interaction term helps us to examine whether the type of behavior towards the environment is different in a province with a high income compared to a province with a low income. Besides, we used the *GINI* × *GDP* interaction term to explore the different effects of income inequality in rich and poor provinces.

The paper consists of the following sections: Section 2 describes the theory behind the income inequality-environmental quality relationship. Section 3 presents the existing literature. Section 4 explains the econometric model and data. Section 5 presents empirical results, and Section 6 is the conclusion.

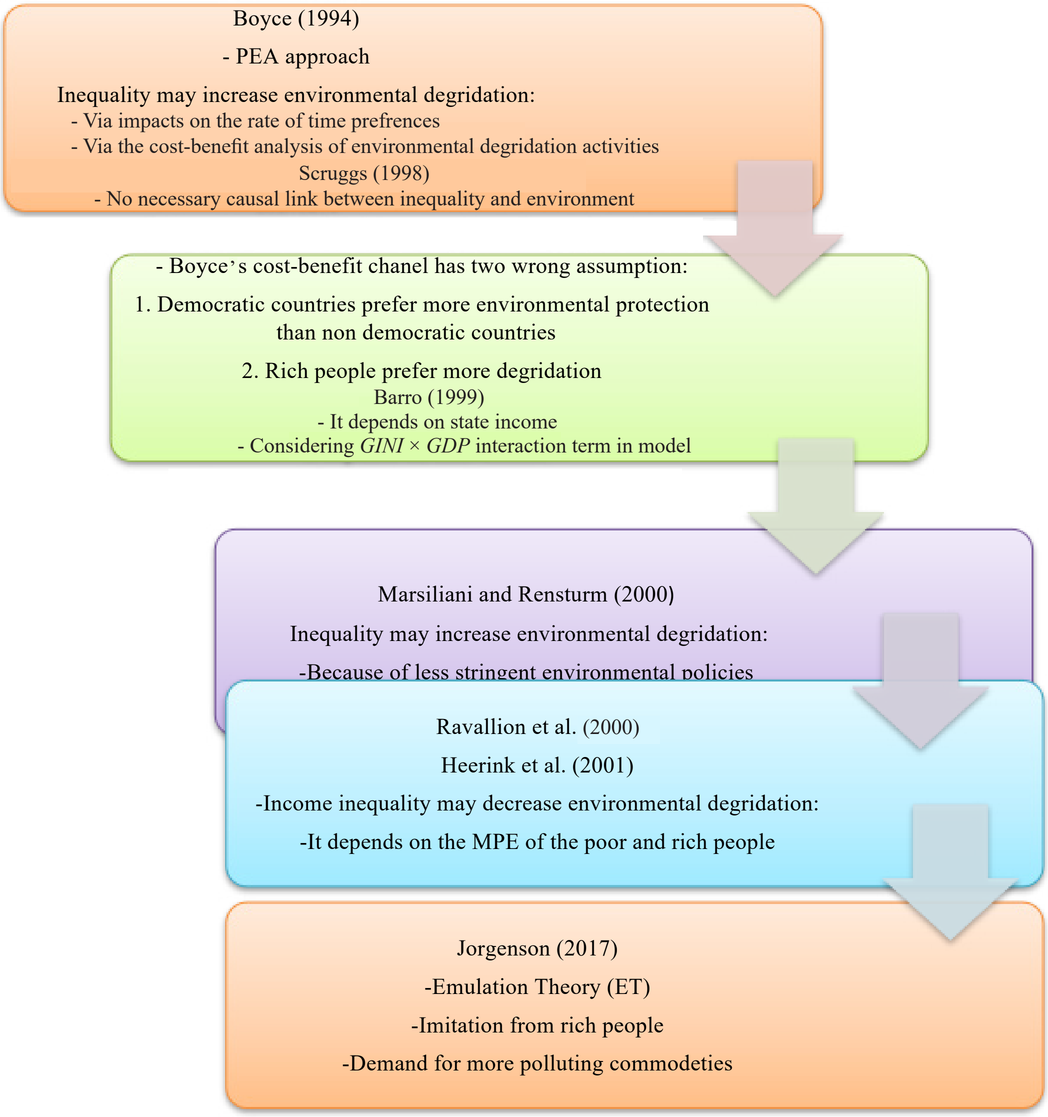

Figure 1. The flowchart of exiting literature on the inequality-degradation relationship

2. Theory

Since 1998, there was growing attention to consider the relationship between income inequality and environmental quality, but there was no unique conclusion for this. There are three different theoretical approaches to explain the relationship between environmental quality and income inequality: (i) Political economy approach or *PEA* (Boyce, 1994; Torras & Boyce, 1998), which is based on the power relations that set the policies of the environment, (ii) Marginal Properties to Emit (*MPE*), which is related to the household's behavior (Ravallion et al., 2000; Heerink et al., 2001; Berthe & Elie, 2015), and (iii) environmental phenomena and inequality or Emulation Theory (*ET*) based on Veblon's (1899) (Jorgenson et al., 2017). We present these approaches graphically in Figure 1. In the other category, Berthe and Elie (2015) have structured this literature in two main groups, *i.e*. (i) household's economic behaviors or *MPE*, and (ii) determination of environmental policy channels (Uzar & Eyuboglu, 2019).

Boyce (1994) was the first person who theoretically investigated the relationship between income inequality and environmental quality. He believed that income inequality would decrease environmental quality in two ways: (i) effect on the rate of time preference: high inequality causes less concern about the future of the earth, and so rises the rate of environmental time preference for both rich and poor people. In simple words, in an unequal country, poor people mostly use the natural capital that cause more degradation in the environment. And the rich people prefer to investigate in high return investment objects rather than environmental projects; (ii) cost-benefit analysis of the activities that degrade the environment: In an unequal country, rich people have more political power, and they often get benefit from environmental degradation projects.

In the other idea, Scruggs (1998) explained that the effects of income inequality on the environment depend on the environmental protection demand-income relationship, which it could be linear (proportional), concave (rich and efficient case), and convex (poor and prudent case) (Uzar & Eyuboglu, 2020). In the linear case, income inequality won't affect the environment (Berthe & Elie, 2015). In the concave case, transferring an extra income unit from rich to poor will improve environmental quality. The convex case is compatible with *EKC* and indicated that by transferring an extra unit of income from poor to rich, the environmental quality would increase (Uddin et al., 2020).

The other reason for how income inequality could decrease environmental degradation is Marginal Properties to Emit (*MPE*), which was first considered by Ravallian et al. (2000). The production and consumption of almost every good create emissions, and there is an implicit demand function for CO_2 emissions for each person. The derivative of this demand function with respect to income is called the *MPE*. Empirical studies have indicated that with different levels of income, *MPE* varies. Also, *MPE* was affected by Marginal Propensity to Consume (*MPC*). According to standard Keynesian consumption theory, the *MPC* for low-income households is bigger than high-income households. So high-income inequality may increase environmental quality (Uddin et al., 2020).

From the *ET* aspect, income inequality can affect consumption status. If low-income people imitate the rich people, then demand for high-polluting commodities such as travel and automobiles increase, which causes more air pollution. On the other side, in unequal countries, because of the long working hours, the energy consumption and CO_2 emission will be increased (Bowles & Park, 2005; Jorgenson, 2017; Uzar & Eyuboglu, 2019).

3. Literature review

In the existing literature, the results on the relationship between income inequality and environmental quality are varied according to the different assumptions made by the authors. These assumptions are as follows: 1) the relationship between individual environmental degradation and individual income, 2) the effects of social norms on environmental degradation due to inequality impacts, 3) the social group's interests in protection or degradation environment, 4) Political demands due to social group's interests, and 5) political decision due to these political demands (Berthe & Elie, 2015).

Some of the studies concluded that there is a positive relationship between income inequality and environmental degradation (Herienk et al., 2001; Mikkelson et al., 2007; Gassebner et al., 2008; Holland et al., 2009; Drabo, 2011; Golley & Meng, 2012; Beak & Gweisah, 2013; Zhang & Zhao, 2014; Hao et al., 2016; Knight et al., 2017; Zhu et al., 2018; Mader, 2018; Uzar & Eyuboglu, 2019; Chen et al., 2020). Some found a negative relationship (Qu & Zhang, 2011; Jun et al., 2011; Guo, 2014; Hubler, 2017; Kusumawardani & Dewi, 2020), and some concluded no significant relationship (Borghesi, 2000; Pandit & Laband, 2009; Clement & Meunle, 2010; Wolde-Rufael & Idowu, 2017). Some studies followed by Barro (1999) have tried to investigate the effects of the interaction between income growth and income inequality on environmental quality (Grunwald et al., 2017; McGee & Greiner, 2018).

The dominant indices for income inequality and environmental quality were the *GINI* index and CO_2 emission, respectively. From the methodological points of view, various studies have used different methods. Some studies implemented time series data (Baek & Gweisah, 2013; Rufael & Idowu, 2017; Jorgenson et al., 2017; Knight et al., 2017; Uzar & Eyuboglu, 2019; Kusumawardani & Dewi, 2020). The most of the studies have used panel data for a group of countries (Qu & Zheng, 2011; Hubler, 2017; Ridzuan, 2019; Hailemariam et al., 2019; Haung & Duan, 2020;

Uddin et al., 2020; Chen et al., 2020); but there is scarce literature for provincial data of a country (Hao et al., 2017). Some studies used cross-section data (Heerink et al., 2001; Golley & Meng, 2012; Knight et al., 2017; Kasuga & Takaya, 2017). We present a summary of the literature review in Table 1.

Table 1. Literature review on the effects of income inequality on environmental degradation

Author (year)	Period (country)	method	Inequality measure	Effects of inequality on environmental degradation
Torras and Boyce (1998)	1977-1999 (58 countries)	pooled	GINI	+
Scruggs (1998)	(OECD)	pooled	GINI	+ (dissolved oxygen) - (SO_2, particulate matter, fecal coliform)
Magnani (2000)	1980-1991 (OECD)	Polled-FE-RE	GINI	+ (only in pooled)
Marsiliani and Restorm (2000)	10 countries	Pooled-FE	GINI	+ (for polled) - and no significant (in FE)
Ravallian et al. (2000)	1975-1992 (42 countries)	Pooled-FE	GINI	-
Heerink et al. (2001)	1985 (64 countries)	Cross-section	GINI	- (for CO_2, SO_2, N, P)
Borghesi (2006)	1988-1995 (37 countries)	Pooled-FE	GINI	- (pooled) + and no significant (FE)
Vernoytsky and Boyce (2010)	1990-2007 (Russia)	Panel	GINI	+
Qu and Zheng (2011)	1980-1999 (36 countries)	RE, GLS	Median income	-
Golley and Meng (2012)	2005 (China)	Cross-section	GINI	+
Beak and Gweisah (2013)	1967-2008 (U.S)	ARDL	GINI	+
Guo (2014)	1978-2010 (China)	VECM	GINI, Theil	-
Jorgenson et al. (2017)	1990-2012 (U.S.A)		GINI	+
Hao et al. (2016)	1995-2012 (China)	GMM	GINI	+
Grunewald et al. (2017)	1980-2008 (world)	Pooled-FE-GFE	GINI	- (for low and median income countries) + (for upper-middle income)
Hubler (2017)	1985-2014 (149 countries)	Pooled (quantile)-FE (quantile)	GINI	- (pooled) - (FE)
Rufael and Idowu (2017)	India, China	ARDL	GINI	No relation
Jorgenson et al. (2017)	1997-2012	Time series	GINI and top 10%	+ (using 10%) None (for GINI)
Ridzuan (2019)	1990-2014 (174 countries)	FE	GINI	+
Hailemariam et al. (2019)	1945-2010 (OECD)	FMOLS, DOLS	GINI and top 10%	- (GINI) + (top 10%)
Uzar and Eyuboglu (2019)	1984-2014 (Turkey)	ARDL	GINI	+
Haung and Duan (2020)	1991-2015 (91 countries)	Panel Threshold Regression	GINI	-

From the literature review, there are three gaps in the investigation of income inequality and environmental quality. First, there are only countable studies that have used provincial data; second, this issue is not debated for the agriculture sector, and third, only a few studies have considered the effects of income growth-income inequality interaction on carbon emission. So, this study effort to cover these gaps.

4. Econometric model and data

4.1 *Econometric model*

In this study, to investigate the effects of income inequality on CO_2 emission in the agriculture sector of Iran, we implemented a panel regression model. Considering cross-sectional and time heterogeneities, reducing the probability of collinearity, reducing the variance-heterogeneity, less estimation bias, high degree of freedom, high estimation efficiency, reflecting more information, suitable for dynamic changes are some of the advantages of using the provincial data. We extended the *EKC* hypothesis in our theoretical framework, which indicates an inverse-*U* relationship between economic growth and environmental quality. According to Grossman and Kruger (1996), the general form of the environmental Kuznets hypothesis is mathematically shown as:

$$Environmental\ degradation\ index = f(GDP, GDP^2, Z) \tag{1}$$

where, for the *Environmental degradation index*, mostly CO_2 emission has been used, which denotes the per capita carbon emission, *GDP* represents the real per capita income, GDP^2 shows the square of the real per capita income. In some studies, the cubic of the per capita income (GDP^3) is also considered, which according to the sign of its coefficient, there will be an *N* or inverse-*N* relationship between economic growth and CO_2 emission, which indicates the rejection of the *EKC* hypothesis. *Z* denotes the control variables, which scholars used indicators such as energy consumption, trade openness, etc. But usually, income inequality was neglected among these indicators. This study, besides energy consumption, which would be a significant factor for carbon emission in the agriculture sector of Iran used income inequality as a crucial indicator for carbon emission. We also consider the $GINI \times GDP$ as an independent variable, which allows us to examine whether the effect of income inequality depends on income and is different in rich and poor provinces (Barro, 1999; Borghesi, 2000; Grunewald et al., 2017).

When the dependent variable has not a normal distribution and is skewed, implementing the Ordinary Least Square (*OLS*) will lead to an incorrect result. Traditional regressions focus on moderate impacts that may over-estimate or even under-estimate the coefficients or even neglect essential relationships. The quantile regression was first introduced by Koenker and Bassett (1978). Unlike the *OLS*, quantile regression examines the final effect of the independent variables on the dependent variable at different points of the distribution. The quantile regression is less sensitive to the perturbation data, and estimates are robust to non-normality. In the presence of variance heterogeneity, quantile regression is more robust than *OLS*. In the present study, the use of the quantile regression allows for examining the factors influencing carbon emissions during the conditional distribution, especially in provinces with high or low emissions. The quantile regression is the generalization of the middle regression to other quantiles (Lin & Xu, 2018; Chen et al., 2020). The conditional quantile $CO2_{it}$ by the condition x_{it} can be expressed as (Zhou et al., 2019):

$$CO2_{it} = (\tau \mid x_{it}) = x_{it}\beta_\tau \tag{2}$$

Where, τ represents the quantiles, x_{it} is the vector of independent variables, and β_τ is the estimated coefficient in each quantile. The conditional quantile function for quantile τ for the present study can be expressed as:

$$Q_{CO2_{it}}(\alpha_{it}, \varphi_{it}, x_{it}) = \alpha_i + \beta_{1\tau}GDP_{it} + \beta_{2\tau}GDP_{it}^2 + \beta_{3\tau}EC_{it} + \beta_{4\tau}GINI_{it} + e_{it}$$

$$(i = 1, 2, ..., 28;\ t = 2003, 2004, ..., 2007) \tag{3}$$

and with the interaction term, can be shown as:

$$Q_{CO2_{it}}(\alpha_{it}, \varphi_{it}, x_{it}) = \alpha_i + \beta_{1\tau}GDP_{it} + \beta_{2\tau}GDP_{it}^2 + \beta_{3\tau}EC_{it} + \beta_{4\tau}GINI_{it} + \beta_{5\tau}GINI_{it} \times GDP_{it} + e_{it}$$

$$(i = 1, 2, ..., 28;\ t = 2003, 2004, ..., 2007) \tag{4}$$

Where, $CO2_{it}$ denotes per capita carbon emission from the agriculture sector in province i at the time t, EC_{it} denotes per capita energy consumption in the agriculture sector of province i at time t, GDP_{it} denotes per capita agricultural gross domestic production of province i at time t, $GINI_{it}$ as an indicator for income inequality, denotes rural *GINI* index in province i at the time t. β_τ represents estimated coefficients for each of the independent variables in quantile τ. α_τ is the country fixed effects, and e_{it} is an error term. *EKC* will be confirmed if $\beta_1 > 0$ and $\beta_2 < 0$. The turning point of the *EKC* will be calculated as: $\frac{\beta_1}{2\beta_2}$.

In equation 3, the *GINI* coefficient (β_4) determines the effects of income inequality on carbon emission. If $\beta_4 < 0$, unlike the justice and welfare aspect, income redistribution is not an acceptable policy in the view of environmental quality. In equation 4, the effect of income inequality on CO_2 emission can be calculated as:

$$\beta_4 + (\beta_5 \times GDP) \tag{5}$$

In this case, the direct effect of inequality can be calculated with β_4, and indirect effects through growth are calculated by β_5. If $\beta_4 < 0$ and $\beta_5 > 0$, then:

$$\frac{\partial yCO2_{it}}{\partial GINI} \underset{<}{\geq} 0 \text{ when } GDP \underset{<}{\geq} -\frac{\beta_4}{\beta_5} \tag{6}$$

And if $\beta_4 > 0$ and $\beta_5 < 0$, then:

$$\frac{\partial yCO2_{it}}{\partial GINI} \underset{<}{\geq} 0 \text{ when } GDP \underset{>}{\leq} -\frac{\beta_4}{\beta_5} \tag{7}$$

Hence, in this case, the effect of income inequality on CO_2 emission depends on the *GDP* level. The overall effect of *GINI* on CO_2 determines with β_4, β_5, and *GDP*. After a threshold value for *GDP*, the effect of income inequality on carbon emission will changed. If after this threshold value, the sign changes from negative to positive, hence, income redistribution helps to increase environmental quality.

4.2 *Data description*

Iran is the 7th biggest CO_2 emitter country, and with the *GINI* index of 0.38, it ranks 68th in the world. Our sample is involved 28 provinces of Iran from 2003-2017. The required data, including CO_2 emission and energy consumption, were collected from the Energy balance sheet of Iran. The rest data, including the *GINI* index, *GDP*, population, and the producer price index for the agriculture sector, were collected from the Statistics Center of Iran. To earn the per capita values, the total values were divided into the agriculture population. To calculate the real income, the income was divided into the producer price index. Table 2 presents the statistical characteristic of the data. In the period of the study, *Zanjan* province had the lowest rural *GINI* index (0.28), and *Yazd* province has the highest one (0.366). *Fars* province has the highest agriculture *GDP*, and the *Bushehr* province has the lowest one. *Zanjan* and *Ghom* provinces were the highest and lowest energy consumer provinces, respectively. The data set analyzed during this study are available in: "https://pep.moe.gov.ir/" and "https://www.amar.org.ir/".

In Figure 2, we plotted the *GINI* index (%) over per capita CO_2 emission to indicate which provinces are positioned in high, median, and low cross-provinces emissions distribution. While *Yazd* and *Ardebil* provinces were among the heightened emitters, *Ardebil* features low inequality. *Lorestan* and *Zanjan* were higher emitters with low-income inequality. *Hormozgan* and *Markazi* provinces were median emitters with high inequality. This figure clearly shows that Iran's provinces are heterogeneous regarding the relationship between inequality and environmental quality. For this reason, and because of the inequalities in carbon emission in the agriculture sector of Iran, the Fixed-Effect quantile regression would be the right choice. However, we will be implemented other tests and graphs to choose the best and most accurate model.

Table 2. Statistical characteristics of the data

Variables	Variable definition	Unit	N.	Mean	S. D	Max
CO_2	Per capita CO_2	Metric ton	420	5.76	1.61	12.13
GDP	Per capita income	million Rial	420	519.01	602.43	1,043.80
Energy consumption	Per capita Gasoline Consumption	10^3 barrels of crude oil equivalent	420	1,017.89	446.73	3,351.71
GINI	Rural GINI index	-	420	34.15	3.87	44.74

Data source: Energy balances worksheet and statistics center of Iran

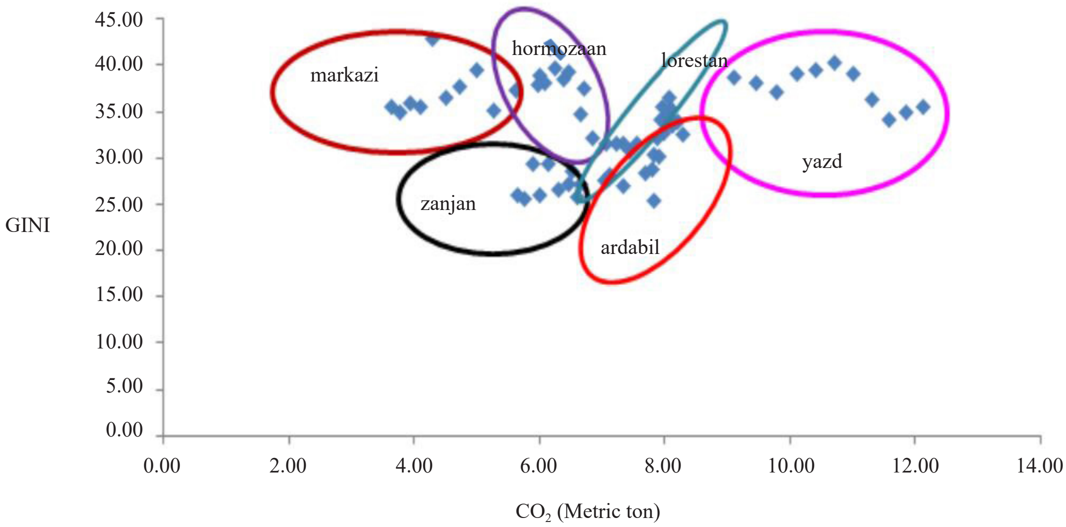

Figure 2. Province's rural GINI indices over per capita CO_2 emission in some provinces of Iran

5. Empirical results

When we estimate the Environmental Kuznets Curve, we should consider four econometric issues in model specification: (i) determining the order of the polynomial, (ii) choosing log-linear or linear specifications, (iii) consideration of integration and co-integration, and (iv) time trends and missing variables (Moosa, 2017). Necessary tests for these items were done, including the *Vuong* test (Vuong, 1989), Unit root test, and the *Wald* test. We consider these issues, and according to the results, selected the best model that was quadratic and logarithmic. The income inequality was considered as an independent variable to avoid missing the variable error. Before choosing the suitable unit root test, a cross-sectional independence test was done.

To be assured in choosing the accurate specification, for the first time, we used the *Taylor* diagram (Taylor, 2001). The *Taylor* diagram by considering *CC* (correlation coefficient or *R*), *RMSE*, and standard deviation simultaneously for the modeled and observed CO_2 emission values, provides a visual display. The model with the closer predicted point to the observed value will be the best model (Shabani et al., 2021). For this goal, first, we estimated the various forms in logarithmic, linear models, and the quadratic with different order polynomials for *GDP*. Then, we draw the *Taylor* diagram using *Mathematica 11*. Software. Figure 3 presents the *Taylor* diagram for examined specifications. It can be seen that the log-quadratic model has the lowest distance and so the best performance. So, both econometric rules and *Taylor* diagram select log-quadratic form.

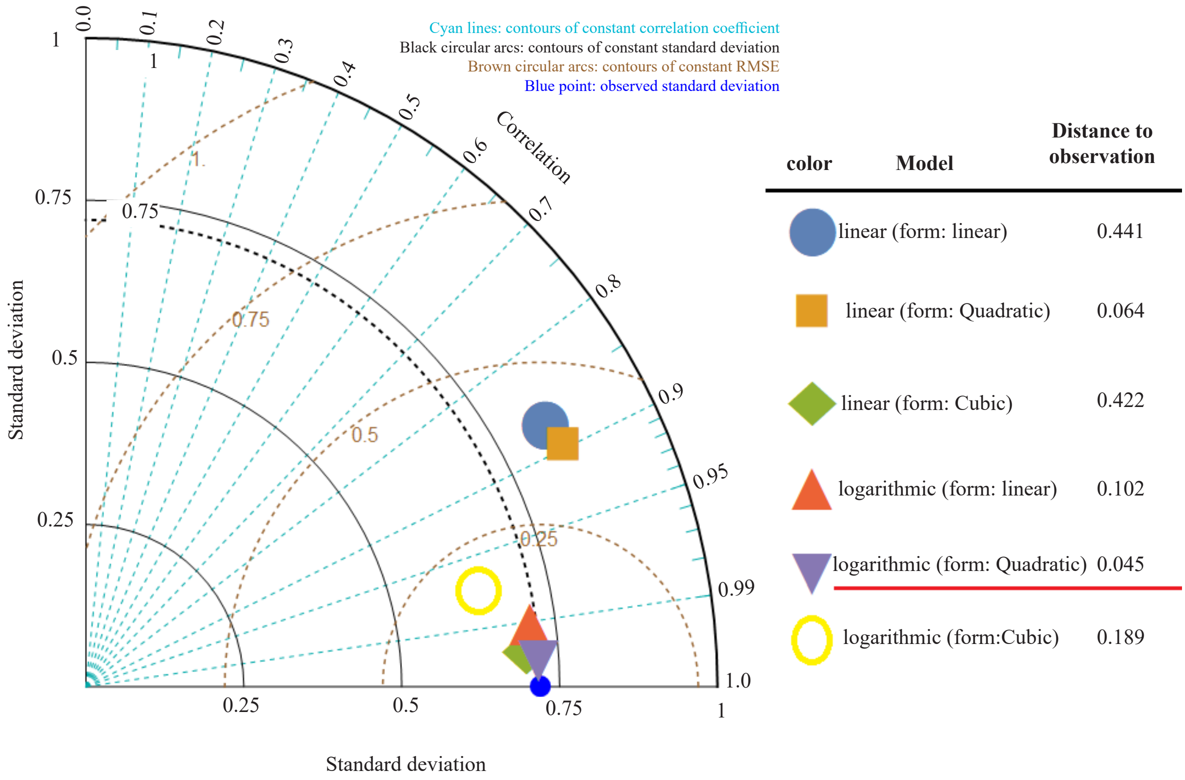

Figure 3. The Taylor diagram of the various specifications

One of the most essential diagnostic tests in the panel data, which should be tested before any analysis to ignore any serious consequences is to evaluate the cross-sectional independence in the panel data. Random and fixed effect modeling in the presence of cross-sectional dependence creates inconsistent estimates. If the regressors and the source of cross-sectional dependence were correlated, common estimators would be inconsistent (Atasoy, 2017). The necessary condition for using unit root tests and adopting any type of econometric model is to examine the independence of sections in panel data. There are three famous cross-sectional independence tests, including *Pesaran's CD* test (2004), *Frees* (1995, 2004), and *Friedman* (1937) tests. *Frees* and *Freidman's* tests are semiparametric, but *Pesaran's CD* test is a parametric test. *CD* test is robustness to structure break and nonnormality of errors and would be used in balanced and unbalanced panel data. The results of cross-sectional independence tests are shown in Table 3. According to all three tests, the null hypothesis is not rejected at 1% significance level. So, cross-sections are independent, and the first generate panel unit root test could be implemented.

Panel data also contains a spurious regression problem like time series, and checking the stationary of the variables is necessary too. Panel unit root tests have better power than time series unit root tests (Martines, 2010). There are two different types of categories for panel data unit root tests. In one category, the unit root test is divided into two groups, including first generating unit root tests for the cross-sectional independence phase, and second generate unit root tests for the cross sectional dependence phase, such as Pesaran's *CIPS* test. In the other category, it is divided into two groups; the first sets of tests consider the existence of a common root for panel data, including *LLC* (Levin et al., 2002), *Breitung* (2000), and *Hadri* (2000). The second set of tests considers the different unit root for each cross-section over time, including *IPS-W* statistics (Im et al., 2003), *ADF-Fisher Chi-square*, and PP-Fisher Chi-square. Also, according to the number of sections or the periods, an appropriate test should be selected. When the number of sections is less than the length of the period (such as our study), the *Fisher-ADF* is an appropriate test, and if the length of the period is greater than the number of sections, the IPS will be the appropriate test.

Table 3. Cross sectional independence test results

Test	Value
Pesaran	1.262 (0.207)
Frees	0.142 (0.954)
Freidman	16.86 (0.933)

The numbers in the parentheses denote p-value

Except for the *Hadri's* test in the other tests, the null hypothesis is the existence of a unit root, and the alternative hypothesis is the stationary of the panel data (Kasman & Duman, 2015; Ben Jebli et al., 2016). We select one test from each group, including *LLC* and *Fisher-ADF*. The optimal lag was chosen by *Schwarz Information Criteria* (*SCI*). Table 4 presents the results of the unit root tests. It can be seen that according to both tests, all of the variables are stationary at the level with intercept. So, our variables are random walk with drift process.

Table 4. Unit root test results (with intercept)

Test	LCO_2	LGDP	$LGDP^2$	LEC	LGINI
LLC	-38.57^{***} (0.000)	-19.55^{***} (0.000)	-24.44^{***} (0.000)	-37.24^{***} (0.000)	-3.73^{***} (0.000)
Fisher-ADF	142.72^{***} (0.000)	8.91^{***} (0.000)	9.07^{***} (0.000)	154.93^{***} (0.000)	3.35^{***} (0.000)

*, **, *** indicates significant level at 10%, 5% and 1% respectively. The numbers in the parentheses denote p-value

Given the cross-sectional independence and stationary of the model's variables, now we should consider a choice between the pooled, Fixed-Effects (FE), and the Random-Effects (RE) models. Model selection results using the *F-Limer* test for deciding between the pooled model and the FE, *Breusch-Pagan LM* test to distinguish between pooled and RE, as well as the *Hausman* test for determining between the FE and RE models, are reported in Table 5. The results show that the appropriate model will be the fixed-effects. However, to compare the results, we also estimated Pooled regression as well.

To choose from *OLS* and quantile regression, we check the distribution of the dependent variable. Figure 4 shows the distribution of the CO_2 emission in the agriculture sector of the Iranian provinces throughout the study. As can be seen, this diagram is skewed to the right. Due to the feature of quantile regression in skew variable modeling, this method is an excellent way to examine all distributions and complete the representation of regression shapes. Therefore, the quantile regression was preferred. Implementing *OLS* regression may lead us to misspecification.

Table 5. Results of Panel model selection tests

Test	statistics	Best model
F-Limer (Pooled or FE)	212.03*** (0.000)	Fixed effect
LM-test (Pooled or RE)	1,882.50*** (0.000)	Random effect
Hausman (FE or RE)	40.93*** (0.000)	Fixed effect

*, **, *** indicates significant level at 10%, 5% and 1% respectively

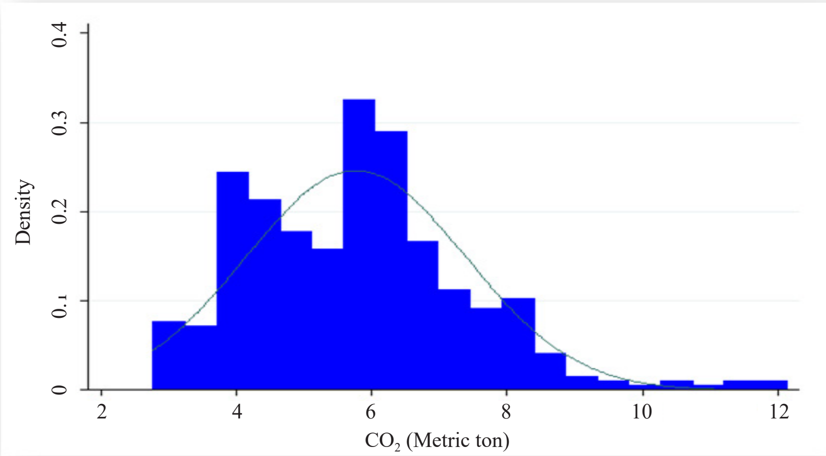

Figure 4. Distribution of the CO_2 emission in the agriculture sector of the provinces of Iran throughout the study (Statistics Center of Iran)

After choosing the best model, we estimated the equation 3 and 4 with *Stata.15* software. The *t* and *F* tests are used to determine if the difference between the coefficients in the various quantiles is statistically zero or not. The results of the quantile regression in fixed effect without interaction term are reported in Table 6. Results show an inverse-U relationship between per capita CO_2 emission and per capita *GDP* at all quantiles. So, the *EKC* hypothesis is confirmed for the agriculture sector of Iran. Energy consumption has a positive and high significant impact on CO_2 emission. There is one negative and significant relationship between per capita CO_2 emission and income inequality. This negative effect increases in the high level of CO_2 concentration quantiles, which indicated the high MPE for poor people compared to rich ones. So, income redistribution would not a comprehensive policy for both social and environmental goals.

Besides, to show the importance of choosing an accurate model to make correct decisions, we reported the results of pooled quantile regression in Figure 5. In this case, however, *EKC* is confirmed, but we can see that, unlike the *FE* regression, the effect of income inequality on CO_2 emission is positive. These different results, also are seen in Marsiliani and Restorm (2000), and Borghesi (2006) studies.

Furthermore, to determine the effect of income inequality on income and its variation in poor and rich provinces, we consider a *GINI* × *GDP* interaction term in the model. Based on the results (Table 7), *EKC* is confirmed for the agriculture sector of Iran. These results are similar to Najafi Alamdarlo (2016), Dogan (2016), Zafeiriou and Azam (2017), Gokmenoglu and Taspinar (2018), and Zhang et al. (2019).

Table 6. Results of the fixed effect quantile regression without interaction term

variable	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.5}$	$Q_{0.75}$	$Q_{0.95}$
LGDP	0.530^{***} (0.002)	0.502^{***} (0.000)	0.488^{***} (0.000)	0.482^{***} (0.000)	0.418^{***} (0.000)
$LGDP^2$	-0.029^{*} (0.014)	-0.026^{***} (0.000)	-0.024^{***} (0.000)	-0.02^{***} (0.001)	-0.021^{***} (0.014)
LEC	0.826^{***} (0.000)	0.857^{***} (0.000)	0.860^{***} (0.000)	0.892^{***} (0.000)	0.950^{***} (0.000)
LGINI	-0.127^{***} (0.006)	-0.160^{***} (0.000)	-0.173^{***} (0.000)	-0.188^{***} (0.000)	-0.205^{***} (0.000)

*, **, *** shows significant level at 10%, 5% and 1% respectively

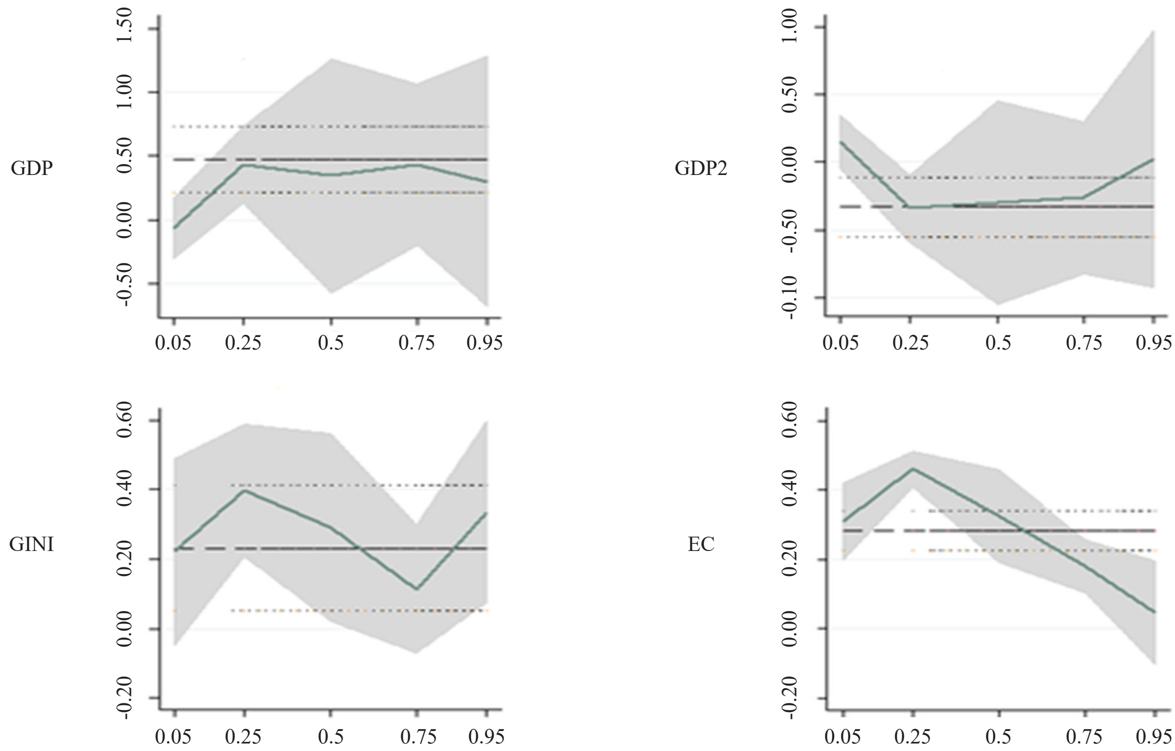

Figure 5. Results of the Pooled quantile regression

In this case, the effect of income inequality on CO_2 emission depends on *GDP*. In each quantile, the per capita income was calculated, which policymakers could utilize to impose an accurate income redistribution policy in each province at a special quantile to receive the best results. For example, for the median quantile ($Q_{0.5}$), until per capita income equals 3,944.19 million Rial ($ 27.36 thousand), an increase in income inequality will decrease carbon emissions. After this income, an increase in income inequality will increase carbon emissions. It shows that poor people in provinces with low-income have higher *MPE* than poor people in high-income provinces. In other words, in rich provinces (i.e., above a threshold level) such as *Fars*, an increase in income inequality will increase CO_2 emission. In poor provinces (i.e., below a threshold level) such as *Bushehr*, income inequality will be led CO_2 emission reduction.

Energy consumption has a positive and high significant impact on CO_2 emission. At the high levels of CO_2

concentration, the effect of energy consumption on CO_2 emission is higher than low levels of CO_2 concentration. The primary energy source in the agriculture sector of Iran is fossil fuels. Due to the high energy subsidies, have such high consumption, which leads to significant amounts of carbon emission. In the provinces with high carbon emissions, there is higher storage pollution, and each additional unit of energy, which results in flow pollution, is added to previous storage pollution and causes such a significant carbon emission.

These results indicated that, in the agriculture sector of Iran, until a specific value, income growth policy is superior to income distribution policy. After a specific amount of income ($ 17.60 thousand/capita), income redistribution would have a positive effect on environmental quality. On the other side, *MPE* for poor people is more significant than rich ones, which indicated that income redistribution would lead to carbon emissions. It does not mean that income redistribution is a desirable policy. According to the theories and results of the study, if the fuel used is low-emission, whether the poor are more likely to pollute or the poor are imitating the rich, the distribution of income will not increase air pollution. Therefore, only in the absence of renewable and clean energy policies the income distribution policy will increase carbon emissions.

Table 7. Results of the fixed effect quantile regression with the interaction term

variable	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.5}$	$Q_{0.75}$	$Q_{0.95}$
LGDP	0.151^{**} (0.052)	0.235^{**} (0.011)	0.312^{***} (0.005)	0.418^{***} (0.000)	0.473^{***} (0.003)
$LGDP^2$	-0.029^{*} (0.014)	-0.026^{***} (0.000)	-0.02^{***} (0.001)	-0.021^{***} (0.014)	-0.018^{**} (0.045)
LEC	0.826^{***} (0.000)	0.857^{***} (0.000)	0.892^{***} (0.000)	0.950^{***} (0.000)	0.983^{***} (0.000)
LGINI	-0.855^{***} (0.002)	-0.738^{***} (0.001)	-0.581^{**} (0.0491)	-0.441^{***} (0.001)	-0.331^{**} (0.004)
LGINI * LGDP	0.096^{*} (0.071)	0.082^{**} (0.035)	0.065^{**} (0.035)	0.050^{**} (0.049)	0.039^{**} (0.027)
$\frac{\partial LnCO2}{\partial LnGINI} > 0$ (Thousands dollar)	GDP > 16.025	GDP > 19.30	GDP > 17.60	GDP > 15.69	GDP > 20.30

*, **, *** shows significant level at 10%, 5% and 1% respectively

6. Conclusion

The present study investigated the potential relationship between income inequality and CO_2 emissions in the agriculture sector of Iran. To this end, provincial data during 2003-2017 and the Fixed-Effect-quantile regression were implemented. To select an accurate modeling, the *Taylor* diagram, various tests and graphical analysis were applied. The fixed-effect-quantile regression lets us explore the heterogeneous effect of income inequality on CO_2 emission by considering cross-sections heterogeneity. We extended the *EKC* hypothesis in our theoretical framework by considering income inequality. Besides, to explore that is the effect of income inequality on CO_2 emission different for poor and rich provinces, we consider a $GINI \times GDP$ interaction term in the model.

The results showed that *GDP* and GDP^2 have positive and negative effect on CO_2 emission, respectively which indicates the validation of the *EKC* hypothesis in the agriculture sector of Iran. The effects of income inequality on CO_2 emission depends on per capita income. In each quantile, there is a threshold per capita income, that the effects of income inequality on CO_2 emission was changed. For the median quantile, until per capita income equals $ 17.60 thousand, income inequality will lead to environmental quality, but after it, income inequality will cause to environmental degradation. Based on the results, *MPE* for poor people in low-income provinces is more than for poor people in high-income provinces. According to the results, it can be suggested that from environmental point of view to a certain extent, income growth has superiority to income distribution. Based on the findings Energy consumption has a positive and high significant impact on CO_2 emission. At the high levels of CO_2 concentration, the effect of energy consumption on CO_2 emission is more elevated than low levels of CO_2 concentration. Furthermore, our finding cleared that income distribution policy from the environmental aspect only would be accepted if the higher energy requires have been made by clean energy sources, especially in low-income provinces. In Iran, the gasoline price is so low ($ 1), and also there is a considerable subsidy for fossil fuel price in the agriculture sector, which this not only has led to profusion in fuels consumption, but also caused high carbon emission. So, realization of gasoline price, targeting energy subsidies via transferring them to research and development to provision low-emitter and clean energy sources, besides an appropriate income growth policy could make the income redistribution policy environmentally friendly policy. Due to the limitation of data, we only used *GINI* index for investigate the effect of income inequality on CO_2 emission. For future researches, the entropy index could be used as income inequality index in estimations.

Declarations

Ethics approval: Not applicable.

Consent to participate: Not applicable.

Consent for publication: Not applicable.

Availability of data and materials: The data set analyzed during this study are available on " https://amar.org.ir/".

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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