Journal of Research and Rural Planning
Volume 8, No. 3, Summer 2019, Serial No. 26
eISSN: 2383-2495 ISSN: 2322-2514
http://jrrp.um.ac.ir

Dynamic Poverty Analysis in Rural Areas of Iran

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Received: 22 May 2018 ***Accepted: 10 January 2019***

Abstract

Purpose- With increasing governmental revenue and budgets, their responsibility for community development and growth has increased. The first step to policy-making in order to attain the desired welfare levels is identify and measure the related indicators such as poverty in the best possible way. In Iran, most of conducted poverty surveys due to the lack of panel data cannot decompose households to transient and chronic poverty group. In this situation, the Synthetic panel data is a useful and new approach to estimates of poverty mobility in countries with only cross-sectional statistics. Therefore, based on this method we calculated the poverty dynamic of rural areas in Iran.

Design/methodology/approach- The present study, initially calculates the absolute poverty line of rural areas in Iran in 2012, 2015 and 2016, and then calculates the status of mobility of poverty during those years based on Synthetic panel data approach.

Finding- The results of the estimation of probability functions for studying poverty dynamics indicated that in rural areas of Iran there was a kind of state dependence in poverty. According to the results, there is a dependency state in the rural poverty situation, where more than 86% of the households who were poor in 2016 were also poor (non-poor) during the first period (2012 or 2015) and only with the probability of less than 14% of the poor (non-poor) households during the past years was in the non-poor (poor) state.

Key word- Poverty measurement, Dynamic poverty, Synthetic panel data, Rural areas, Iran.
Paper type- Scientific & Research.

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How to cite this article:
Garivani, F., Ahmadi Shadmehri, M. T., Fallahi, M.A., & Raghfar, H. (2019). Dynamic poverty analysis in rural areas of Iran. *Journal of Research & Rural Planning,* 8(3), 13-25.

http://dx.doi.org/10.22067/jrrp.v5i4.72911

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1. Introduction

According to the concept of “welfare state”, the state plays a key role in the protection and promotion of the economic and social well-being of its citizens based on policies and their implementations. In this regard, the control of poverty in society and its Reduction Strategies, as well as the protection of vulnerable groups (those at the highest risk of poverty) can be in the area of governments' responsibilities. Hence, measuring and identifying poverty is one of the essential parts of knowledge for developing community-based programs and policies for poverty eradication, because, as Ravallion (1998) states, a credible measure of poverty can be a powerful tool for focusing policymakers' attention on the living conditions of the poor people. The purpose of presenting a poverty profile is to determine the main facts of poverty (such as inequality) and its sustainability, and then examine the pattern of poverty based on geography and household characteristics. Other reasons for measuring poverty are (a) to be able to predict and evaluate the effects of policies and programs designed to help the poor, and (b) to assess the effectiveness of institutions aimed at helping the poor (Haughton & Khandker, 2009).

After Adam Smith's and Amartya Sen's definitions of poverty, extensive studies have been conducted on the identification and measurement of poverty. Most of them have used a static method for measurement. In these studies, the poverty line and aggregate poverty measures are assessed for different communities in a given year and the characteristics of people are identified, but sustainability and dynamics of poverty cannot be found in these studies. There are fewer studies on dynamics of poverty, for example: Whelan et al (2002), Jenkins and Rigg (2001), Jenkins (2000), Jarvis and Jenkins (1997). These studies are based on panel data and show that poverty is more widespread than suggested by cross-sectional studies, since the underlying process is the result of the accumulation and attrition of household resources (Shen et al, 2006). Salehi-Isfahani and Majbouri (2010) examined poverty and inequality in Iran in a dynamic context using a 4-year panel data, collected during 1992–1995. They showed short-term income mobility was relatively high, which helped reduce high inequality. They found that chronic poverty was a more serious problem in urban than rural areas, while transient poverty was geographically more uniformly distributed. Goshu (2013) investigated the dynamics and determinants of poverty and vulnerability in rural areas of Ethiopia using panel data of households between 2004 and 2009. They showed that depth and severity of poverty were reduced, but had increasing incidence. While many households were escaping from poverty, others were descending into the poverty trap, indicating reduction of relative poverty among the poor and the non-poor. Determinants of poverty status were household size, livestock holding, farming occupation, life status, social network, regional dummies, and other exogenous shocks. Unlike static poverty studies, dynamic poverty studies do not have a long history especially in developing countries. One reason is the lack of actual panel data in these countries. To overcome this limitation, methods such as pseudo-panel data or synthetic panel data have been presented to measure the poverty dynamics in countries with no cost/income panel data for households. (For more studying, see: Banks, Richard and Ager., 2001; Mckenzie, 2004; Pencavel, 2007). Since cross-section samples are typically refreshed each time that the surveys are conducted, synthetic panels are possibly less exposed to the concerns about measurement errors that are often found at actual panel data. Hence, pseudo-panel data is an interesting field of research. Dang and Lanjouw (2013) proposed a method to construct synthetic panel data from cross sections which can provide point estimates of poverty mobility. In contrast to traditional pseudo-panel methods that require multiple rounds of cross-sectional data to study poverty at the cohort level, the proposed method can be applied to settings with as few as two survey rounds and also permits investigation at the more disaggregated household level. Dang et al. (2014a) used synthetic panel data from two rounds of cross-section household surveys in 2005 and 2011 to investigate poverty dynamics in Senegal. More than half the population experienced changes in its poverty status and more than two-thirds of the extreme (food) poor move up one or two welfare categories. According to them, factors such as rural residence, disability, exposure to some kind of natural disaster, and informality in the labor market are associated with a heightened risk of falling into poverty. In another study, Dang et al. (2014b) proposed both parametric and non-parametric approaches to construct synthetic panels at the household level from two rounds of cross sections with rather parsimonious assumptions, and tested data sets for Vietnam and Indonesia.

In Iran, until 2012 there was also no actual panel data that could track individuals' characteristics over time and form the basis of income and poverty dynamics studies. Since 2013 onwards, there have been actual panel data sets for household income and expenditure for two consecutive years of 2013 and 2014, but this short interval cannot show the actual dynamics of poverty. According to Walker and Ryan (1990), at least a 7 or 8-year interval is necessary for proper measurement. The studies that conducted to construct pseudo-panel data in Iran are based on pseudo panels developed by Deaton (1985) from multiple rounds of cross-sectional data. However, pseudo-panel data requires a large number of repeated cross-sectional data (Bourguignon, Guo and ki 2004). The existing pseudo-panel methods may be of limited appeal to policy makers interested in the mobility of certain population groups, or to economists concerned with mobility due to idiosyncratic shocks to income or consumption (Dang et al. 2014b). Thus, in the absence of actual panel data, synthetic panel data derived from cross-sectional household data can be used to study poverty dynamics in Iran. Considering the importance of being informed of poverty dynamics in Iran, and its application in planning and policy making on improving community welfare, the aim of this study is to measure poverty dynamics of rural areas of Iran using Dang and Lanjouw (2013)'s presented synthetic panel data.

2. Research Theoretical Literature

In order to effectively reduce poverty, it is necessary to identify the factors leading to transitions into and out of poverty line. To do so, we require panel data, especially at the household or individual level. On the other hand, for various reasons such as the high cost of collecting panel data, it is not possible to provide panel data for many developing countries, and instead it is common to collect cross-sectional data. To overcome this limitation, Dang and Lanjouw (2013) developed a method using panel data based on repeated cross-sectional data. They generalized the method of Dang et al. (2014b) by (a) introducing a method to approximate the appropriate correlation term and its theoretical upper bound using each country's own cross sectional surveys, and (b) developing construction of the synthetic panels to settings where more than two rounds of data are available, and (c) extending the investigation of household transitions into and out of poverty to a much more general setup of household movements among different consumption groups (Dang & Lanjouw, 2013). In this section, first we present a brief review of the method described by Dang et al. (2014b) and then a brief review of the modified method developed by Dang and Lanjouw (2013).

2.1. Theoretical bound estimation on poverty mobility

Dang et al. (2014b) considered two cross-sectional survey periods *j* (j=1 or 2). Both are random samples of households *i* (i=1, …, N). If *x* shows household characteristics observed in period j, and y presents household consumption or income in period *j*, for prediction of household consumption (or income) on household characteristics for periods 1 and 2, we can write:

$$y_{i1} = \beta_1' x_{i1} + \varepsilon_{i1}$$
$$y_{i2} = \beta_2' x_{i2} + \varepsilon_{i2} \quad (1)$$

x_{ij} is the vector of household characteristics which can include time-invariant variables such as sex, ethnicity, religion, language, place of birth, and parental education as well as deterministic characteristics such as age. The percentage of households that are poor in the first period but non-poor in the second period can be defined as below:

$$P(y_{i1} < z_1,\ y_{i2} > z_2) \quad (2)$$

Furthermore, the percentage of poor households in the first period that escape poverty in the second period can be defined as:

$$P(y_{i2} > z_2 | y_{i1} < z_1) \quad (3)$$

In the above equations, Z_1 and Z_2 represent the poverty line in periods 1 and 2, respectively. In case of availability of panel data, we can estimate the quantities in equations 2 and 3; otherwise, we have to use synthetic panels. By assuming that the underlying population being sampled in periods 1 and 2 are the same (Assumption 1), we can rely on the time-invariant variables x_{ij} that are collected in both survey periods to predict the consumptions in period 1 for households interviewed in period 2, and vice versa. Also, we can assume that error terms ε_{i1} and ε_{i2} are completely independent of each other (have bivariate normal distribution) with correlation coefficient (ρ) and standard deviations σi_1 and σi_2 (Assumption 2). The lower bound and upper bound estimates of poverty mobility can be determined by obtaining appropriate values for ρ. If (is known, we can estimate quantities in Equation 2 as:

$$P(y_{i1} < z_1 and\ y_{i2} > z_2) = \Phi_2\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, -\frac{z_2 - \beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, -\rho\right) \quad (4)$$

Where, $\Phi_2(.)$ represents the standard bivariate normal cumulative distribution function. Parameters β_j and σ_{ε_j} can be estimated using Equation 1, and (can be estimated based on Cohort-aggregated household consumption data. Equation 4 indicates that a lower (higher) value of (means a higher (lower) probability of being poor in the first period but non-poor in the second period (Dang & Lanjouw, 2013). Since (is mostly unknown, Dang et al. (2014b) suggested that one can start by assuming that (is either 0 or 1.

2.2. Theoretical (estimation)

Dang and Lanjouw (2013) indicated some drawbacks in the method presented by Dang et al. (2014b) for identifying bound estimates on poverty dynamics. For example, some countries with actual panel data may need a more reasonable empirical range of (values. Also, (may be different for different household welfare outcomes. In this regard, they offered following propositions to estimate (based on a country's own cross-sectional data:

Proposition 1- Approximate estimation: Assume household consumption follows a simple linear dynamic data-generating process given by $y_{i2} = \alpha + \delta' y_{i1} + \eta_{i2}$ **(*)** where η_{i2} is the random error term. Also assume that the sample size of each household survey round is large enough, the number of cohorts (C) constructed from the survey data is fixed, and the cohort dummy variables satisfy the relevance and exogeneity criteria for instrumental variables for y_{i1} in **(*)**. The simple correlation coefficient $\rho_{y_{i1}y_{i2}}$ can then be approximated with the synthetic panel cohort-level simple correlation coefficient $\rho_{y_{c1}y_{c2}}$ where c indexes the cohorts constructed from the household survey data." (Dang & Lanjouw, 2013, p.9)

In the absence of true panel data, we do not observe y_{i1} for the same household with household consumption in period 2, but we can predict it by projecting household consumption in period 1 on the cohort dummy variables. Cohorts can be constructed from age or combination of age and other time-invariant characteristics as long as the cell size for each cohort is large enough (Dang & Lanjouw, 2013, p.11).

Proposition 2- Point estimation: If R_j^2 (j=1 and 2) represents the coefficients of determination obtained from estimating Equation 1, and x_i shows the vector of household time-invariant characteristics, the partial correlation coefficient (can be estimated by:

$$\rho = \frac{\rho_{y_{i1}y_{i2}}\sqrt{var(y_{i1})\,var(y_{i2})} - \beta_1'\,var(x_i)\beta_2}{\sigma_{\varepsilon_1}\sigma_{\varepsilon_2}} \quad (5)$$

Or

$$\rho = \frac{\rho_{y_{i1}y_{i2}} - \sqrt{R_1^2 R_2^2}}{\sqrt{1-R_1^2}\sqrt{1-R_2^2}} \quad (\text{if } \beta_1 \approx \beta_2) \quad (6)$$

If the estimated parameters in Equation 1 for two periods be close to each other, the partial correlation coefficient for household consumption can be interpreted as the simple correlation coefficient purged of its multiple correlation with household (time-invariant) characteristics in the two survey rounds, and then reweighted by the shares of the unexplained predicted errors. (Dang & Lanjouw, 2013)

2.3. Poverty mobility for three or more survey periods

Dang and Lanjouw (2013) generalized the general setting where there are three or even more rounds of survey data. We assume there are *k* periods. Household consumption levels can be explained by household characteristics for survey round by following equations (j=1,…, k):

$$y_{ij} = \beta_j' x_{ij} + \varepsilon_{ij} \quad (7)$$

$$P(y_{i1} \sim z_1 and y_{i2} \sim z_2, \dots, y_{ik} \sim z_k) = \Phi_k\left(d_1 \frac{z_1 - \beta_1' x_{ij}}{\sigma_{\varepsilon_{i1}}}, d_2 \frac{z_2 - \beta_2' x_{ij}}{\sigma_{\varepsilon_{i2}}}, \dots, d_k \frac{z_k - \beta_k' x_{ij}}{\sigma_{\varepsilon_{ik}}}, \Sigma\rho\right) \quad (8)$$

Where, Zj is the poverty line in period j, and $\Phi_k(.)$ shows k-variate normal cumulative distribution function. For more discussion, see Dang and Lanjouw (2013).

3. Research Methodology

In order to analyze the poverty dynamics of rural areas in Iran using Synthetic panel data, the expenditure/income cross-sectional survey data for the years 2012, 2015, and 2016 were used. These data includes expenditure/income characteristics of households as well as other socio-economic characteristics such as age, gender, number of students, number of household employees, etc. collected each year by the Iranian Statistics Center for about 19,300 households in rural areas. The base year of this study (i.e. second period or X_{i2}) was 2016 and the age of selected households in this year was between 30 and 60 years (according to the age of the household head). For other years, the age was adjusted relative to the base year.

Poverty line defines the level of consumption (or income) needed for a household to escape poverty. The cost of basic needs (CBN) approach was applied to measure absolute poverty line during the studied years. In this approach, the basket of goods consists of food and non-food items; thus, the cost to meet basic needs is generally measured in two steps. At first, the minimum food expenditure required to live in a healthy situation, known as the food poverty line, is calculated. Then, the minimum nonfood expenditure for measuring nonfood poverty line is calculated. The consumption aggregate is finally obtained adding up these expenditures on food and non food items.

The food poverty line can be calculated based on the food energy intake method which shows expenditure (or income) per capita against food consumption (in calories per person per day) to determine the expenditure (or income) level at which a household acquires enough food. According to the Iranian Ministry of Health Department for Improving Nutrition, the average of energy consumption in 2012 was 2573 kcal per day. We used the Orshansky method to add the minimum nonfood expenditure to the food poverty line which is based on Engel's Law. In this method, the average ratio of household food expenditure to total household expenditures is calculated and then, multiplicative inverse of fraction is multiplied by the food poverty line to determine the total poverty line. The calculation of poverty line and the correlation term (was done in STATA software.

In analyzing household characteristics, there were different sizes of households that made it difficult to compare the welfare of households. Considering the saving aspect of collective consumption, household expenditure does not always increase as the household size increases. In order to solve this problem, using the equivalent scales, we can relate the expenditure of households with different sizes to each other. In this study, we used the equivalents proposed by Iranian Ministry of Health Department for Improving Nutrition to assign an appropriate equivalent scale related to the gender and age of household members. Equivalents in Table 1 are similar to those presented by Dercon and Krishnan (1998).

Table 1. Adult equivalence scales

(Source: Iranian Ministry of Health Department for Improving Nutrition, 2018)

Years of age	Men	Women
0-1	0.24	0.22
1-2	0.33	0.30
2-3	0.39	0.36
4-5	0.47	0.43
6-11	0.66	0.61
12-17	1.05	0.84
18-29	1.04	0.79
30-60	1.00	0.76
60 plus	0.81	0.69

After calculating the poverty line, Dang and Lanjouw (2013)'s proposed technique mentioned in Section 2 was used to assess the poverty mobility in rural areas of Iran. Gender, age, education level of household head, and residential area were considered as explanatory variables (household characteristics) for the estimation of Equation 1. The monthly poverty line and poverty indicators of the rural households per adult equivalence for the years 2012, 2015, and 2016 are presented in Table 2. As can be seen from this table, the absolute poverty line in rural areas has risen from 1,725,800 Rials in 2012 to 29,776,575 Rials in 2016. Moreover, poverty indices show that the poor population of rural areas in Iran has increased from 42.7% to 48.1% from 2012 to 2016. Also, the poverty gap and severity of poverty have increased among surveyed households.

Table 2. Absolute poverty line (Rials) per adult equivalence and poverty indices (percentages) of the rural households

Index	2012	2015	2016
Absolut poverty line	1725800	2726181	2976757
Headcount Ratio	42.7	45.8	48.1
Poverty Gap	13.2	15.0	15.9
Poverty Severity	5.6	6.7	7.1

For examining the poverty mobility, since expenditure /income of about 49% of households was the same for two consecutive years of 2015 and 2016, first, the poverty mobility was estimated using a synthetic panel data only for this group of households. This was done to compare the actual panels and synthetic panels obtained in this with those presented by Dang and Lanjouw (2013) in estimating poverty mobility.

4. Research Findings

Table 3 presents the values of obtained correlation coefficient ($\rho_{yi\,2015yi\,2016}$). Partial correlation coefficient (ρ) of residues of household consumption regression on explanatory variables (gender, age, education level of household head, and region) was estimated by:

$$y_{ij} = \beta_0 + \beta_1 gen_{ij} + \beta_2 age_{ij} + \beta_3 edu_{ij} + \beta_4 reg_{ij} + \varepsilon_{i1} \quad (9)$$

For households living in Tehran, *reg* (region) was considered to be 1 and for other cities as 0. From Table 3, we can say that the difference in correlation coefficient of household consumption in two 2015 and 2016 using actual panels and synthetic panels is 0.7%. This difference for the partial correlation coefficient (ρ) of regression residues is 0.07%. In the study of Dang and Lanjouw (2013), the estimated cohort-level simple correlation coefficient for Bosnia-Herzegovina, Lao PDR, Peru, Vietnam, and United States was between 0.01 and 0.18 with a relative difference of 2-18%. This indicates that the synthetic panel data has no considerable difference with actual panel data in Iran, and this approach can be used to analyze poverty mobility based on cross-sectional data in the absence of actual panel data.

Table 3. Estimated values of (using actual panel data and synthetic panel data for years 2015 and 2016

Coefficient	Actual panels	Synthetic panels	Relative difference (%)
$\rho_{yi\,15yi\,16}$	0.9862	0.9931	% 0.70
ρ	0.9714	0.9721	% 0.07

Values of estimated correlation coefficient for the years 2012 and 2016 are presented in Table 4. By comparing these results with those shown in Table 3, it can be said that the (values are less than ρ_{yijyij} values. This confirms the compatibility of the estimate with theoretical foundations. In order to study the household transitions into and out of poverty line in 2015 and 2016, both actual panels and synthetic panels were used, but for estimating poverty mobility in 2012 and 2016, only the synthetic panel method was employed.

Table 4. Estimated values of (based on synthetic panel data for years 2012 and 2016

Coefficient	$\rho_{yi\,12 yi\,16}$	ρ
Actual panels	0.939	0.9195

Table 5. Poverty dynamics (Joint probabilities) based on actual and synthetic panel data for three years

First Period and Second Period	2015-2016		2012-2016
	Actual panels	Synthetic Panels	Synthetic Panels
Poor, Poor	46.2 (0.110)*	43.7 (0.110)	43.6 (0.105)
Poor, Nonpoor	3.79 (0.012)	6.21 (0.009)	6.39 (0.02)
Nonpoor, Poor	3.78 (0.011)	6.20 (0.008)	6.35 (0.018)
Nonpoor, Nonpoor	42.26 (0.109)	43.8 (0.108)	43.6 (0.105)

*Numbers in parentheses are standard errors

By using actual panel data, 46.2%, 3.79%, 3.78% and 46.26% and by using synthetic panel data, 43.7%, 6.21%, 6.20%, and 43.8% of rural households were poor in the two periods of 2015 and 2016, poor in 2015 but non-poor in 2016, non-poor in 2015 but poor in 2016, and non-poor in both periods, respectively. In 2012 and 2016, 43.6% of rural households were poor in two periods, 6.39% poor in 2012 but non-poor in 2016, 6.35% non-poor in 2012 but poor in 2016, and 43.6% poor in both years (Table 5).

As the educational level of the household head increases, the rural households' probability of being poor decreases in the two periods of 2012-2016, and 2015-2016, while their probability of being non-poor increases (Fig. 1b,c). Moreover, the probability of a transition from being non-poor to being poor in two periods due to the increase in educational level of household head did not show a regular trend (Fig.1a). The only important thing was the low probability of exiting poverty (<0.1). In 2012-2016, with increased educational level, the chance of entering poverty regularly reduced in the households with both male and female heads (Fig.1d).

Table 6 presents conditional probabilities of poverty status by two methods in three years. The probability of being poor in 2016, given that they were poor in 2015, is 92.39% using actual panels and 87.12% using synthetic panels. For the period 2012-2016, this probability is 86.83% using synthetic panels. The proportion of the households that were poor in 2016 given that they were non-poor in 2015 is 7.60% using actual panels and 12.88% using synthetic panels.This proportion for the period 2012-2016 is 13.16% using synthetic panels. Moreover, the proportion of the households who were non-poor in 2016 given that they were poor in 2015 is 7.58% using actual panels and 12.87% using synthetic panels. This proportion for the period 2012-2016 was 13.18% using synthetic panels. Also, by using these two methods respectively, there are probabilities of 92.41 and 87.13% that the households were non-poor in 2016, given that they were poor in 2015. This probability for the period 2012-2016 using synthetic panels is 86.82%.

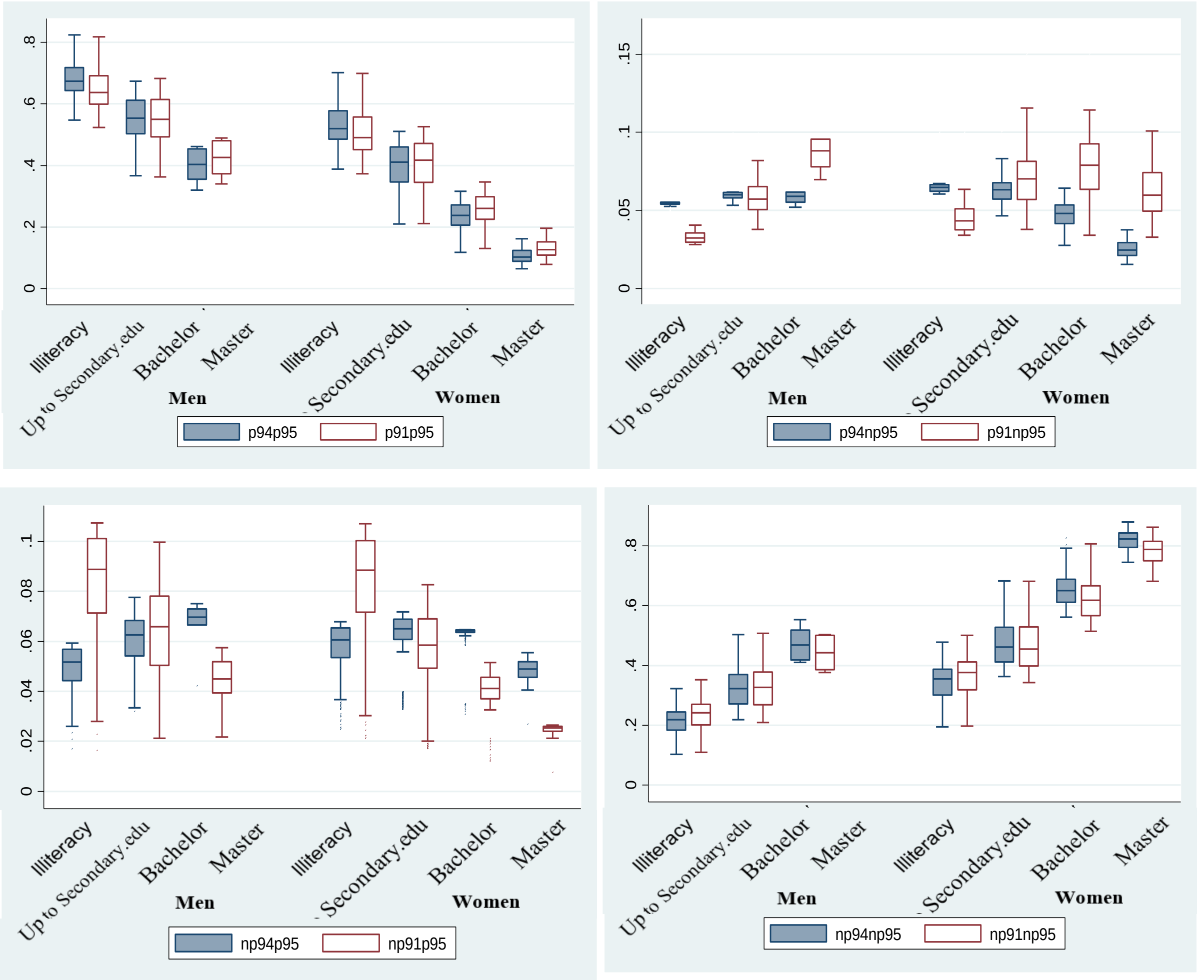

Figure 1. Joint probability (%) of poverty in households categorized by gender and education of household head (p=poor, np=non-poor)

Table 6. Poverty dynamics (conditional probabilities) based on actual and synthetic panels for years 2012, 2015, and 2016

First Period--> Second Period	2015-2016		2012-2016
	Actual panels	Synthetic Panels	Synthetic Panels
Poor--> Poor	92.39 (0.02)*	87.12 (0.025)	86.83 (0.041)
Poor--> Nonpoor	7.60 (0.02)	12.88 (0.025)	13.16 (0.041)
Nonpoor--> Poor	7.58 (0.016)	12.87 (0.024)	13.18 (0.046)
Nonpoor--> Nonpoor	92.41 (0.016)	(87.13) (0.024)	86.82 (0.046)

*Numbers in parentheses are standard errors

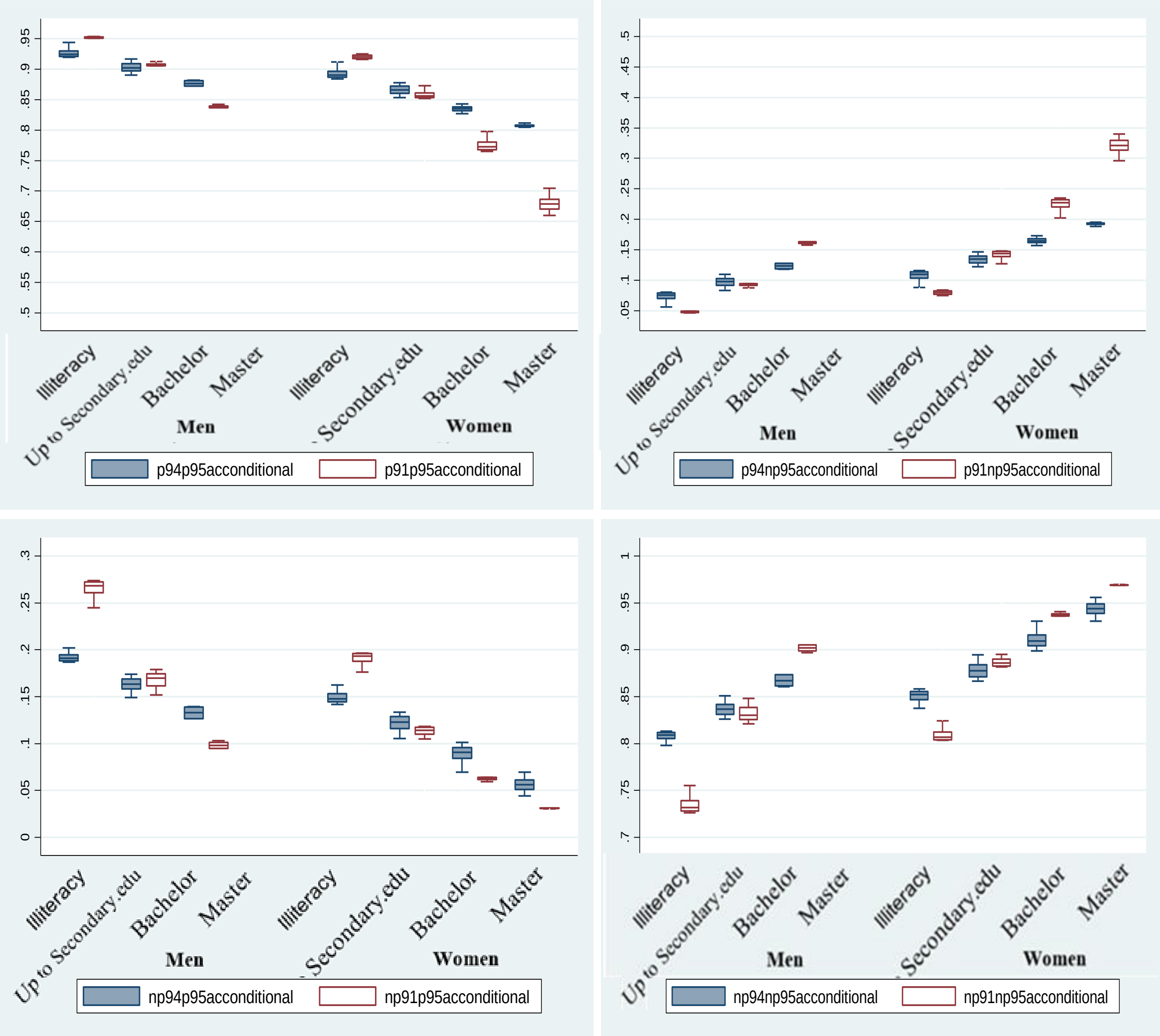

Figure 2. Comparing conditional probabilities in households categorized by gender and education of household head (p=poor, np=non-poor)

Figure 2 plots conditional probabilities of poverty for the households with different genders and educational levels of household heads. As can be seen, the probability of change in poverty status provided that the status remains unchanged in the base year, had almost the same trends in female-headed and male-headed households. With an increase in the educational level of the household head, the probability of being poor in 2016 provided that the households were poor in 2012 and 2015, decreased. However, the probability of being non-poor in 2016 provided that the households were poor in 2012 and 2015, increased. Furthermore, the probability of being poor in 2016 provided that they were non-poor in 2012 and 2015, increased as the educational level of the household head increased. The results in Figure 2 also show the increasing likelihood of remaining non-poor in rural areas in 2016 if households were non-poor in 2012 and 2015.

5. Discussion and Conclusion

In this study, poverty dynamics of rural areas of Iran was investigated for the years 2012, 2015, and 2016. The findings revealed that the absolute poverty line in rural areas has risen from 2012 to 2016. Since the survey of household income in Iran is conducted using cross-sectional data, actual panel data cannot be used for dynamic analysis of the welfare and poverty status of households. For such studies, we need to use other methods that make estimates close to reality. In this study we used the method presented by Dang and Lanjouw (2013). To check the accuracy of the method, first poverty dynamics for the years 2015 and 2016 were estimated by using both actual panels and synthetic panels. In the first method (actual panels), only joint households whose heads had age range of 30- 60 years in 2016, and 29-59 years in 2015 were selected for the study. In the second method (synthetic panels), analysis was with respect to the age range of household head and according to the techniques provided by Dang and Lanjouw (2013). In this regard, based on Deaton (1985)'s method, households were divided into 31 age groups and the partial correlation coefficient of the residuals was calculated. Comparing estimates using the actual panels and the synthetic panels, the relative difference in 2015 and 2016 was only 0.7%. Also, the maximum values that the partial correlation of the residuals can have were equal to the simple correlation for household consumption. Hence, we concluded that our results are consistent with Dang and Lanjouw's theory.

The results of the estimation of probability functions for studying poverty dynamics indicated that in rural areas of Iran there was a kind of state dependence in poverty. During the studied years, more than 86% of the households that were poor (non-poor) in 2016, were also poor (non-poor) during the first period (2012 or 2015). Only less than 14% of the poor (non-poor) households in 2016 were likely to be non-poor (poor) in the first period. One of the reasons for the state dependence in poverty is that the mood of those who are in the poverty line can be negatively affected. Experienced poverty can lead to a negative state, loss of motivation and even devaluation resulting in less chance of finding jobs for the unemployed, or finding low-quality jobs or unstable businesses which increase the risk of poverty. Another reason is that being poor can be related to negative motivations which can make the unemployed people feel that it is worthless to find a job, or even make them keep their low-wage job. Considering the heterogeneity of welfare and income levels of households in the provinces of Iran, it is expected that the sustainability of poverty be different and requires more studies in this area.

Acknowledgments: The current paper is extracted from the doctoral dissertation of the first author (Fatemeh Garivani) in the Department of Economics, Faculty of Economics & Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran.

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مجلّهٔ پژوهش و برنامه‌ریزی روستایی
سال ۸، شمارهٔ ۳، تابستان ۱۳۹۸، شمارهٔ پیاپی ۲۶
شاپای چاپی: ۲۵۱۴-۲۳۲۲ شاپای الکترونیکی: ۲۴۹۵-۲۳۸۳
http://jrrp.um.ac.ir

تحلیل پویایی فقر در مناطق روستایی ایران

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تاریخ دریافت: ۲ خرداد ۱۳۹۷ تاریخ پذیرش: ۲۰ دی ۱۳۹۷

چکیده مبسوط

۱- مقدمه

اندازه‌گیری و شناسایی فقر از ملزومات و جزو لاینفک دانش جهت تدوین برنامه‌ها و سیاست‌های فقرزدایی جامعه است. بعد از ارائه تعاریف آدام اسمیت و آمارتیا سن از فقر مطالعات گسترده‌ای در حوزه شناسایی و اندازه‌گیری فقر ایستا صورت گرفت؛ در مقابل آن بررسی پویایی فقر بویژه در کشورهای در حال توسعه از قدمت طولانی برخوردار نیست. یکی از دلایل این امر نبود داده‌های تابلویی قابل اتکا در این جوامع است. برای غلبه بر این نقصان، دنگ و همکاران در سال ۲۰۱۳ رویکرد داده‌های تابلویی ترکیبی را برای مطالعات فقر با استفاده از داده‌های مقطعی ارائه دادند. با توجه به اهمیت شناخت و آگاهی از پویایی‌های فقر کشور و به‌کارگیری آن در برنامه‌ریزی‌ها و سیاست‌گذاری‌های بهبود رفاه جامعه، بررسی پویایی‌های فقر مناطق روستایی کشور به روش داده‌های تابلویی ترکیبی دنگ و همکاران (۲۰۱۳) محور پژوهش حاضر خواهد بود.

۲- مبانی نظری تحقیق

پویایی فقر به فرآیندهای تغییرات اجتماعی اطلاق می‌شود که منجر به افزایش، کاهش یا تداوم فقر می‌شوند. پویایی فقر دو بعد اصلی دارد: فرآیندهای بلندمدت که به فقر مزمن مربوط می‌شوند و فرآیندهای کوتاه‌مدت که باعث ایجاد فقر گذرا می‌گردند. به‌طورکلی پویایی فقر جریان ورود و خروج خانوارها از فقر را بررسی می‌کند و با ذخیره فقر متفاوت است. لذا هدف اصلی آن نشان دادن تغییر و تحول وضعیت افرادی است که فقر را تجربه کرده‌اند.

نتیجه کاربردی بررسی پویایی فقر رسیدن به گروه‌های اجتماعی هدف برای سیاست‌گذاری‌های اجتماعی و اقتصادی و بررسی و اصلاح در سیاست‌های کلان است. از این حیث هنگامی که در جامعه فقر گذرا وجود دارد باید سیاست‌های محافظت از گروه غیر فقیر و نیز اقشار آسیب‌پذیر از ورود به دایره فقر اولویت باشد در حالیکه در شرایط فقر مزمن باید مداخلات ساختاری بلندمدت مانند سرمایه‌گذاری در سرمایه انسانی و بهبود زیرساخت‌ها مورد توجه قرار گیرد (دنگ و همکاران، ۲۰۱۴).

۳- روش تحقیق

به منظور تحلیل پویایی‌های فقر مناطق روستایی کشور از داده‌های پیمایش هزینه – درآمد خانوار برای سال‌های ۱۳۹۱، ۱۳۹۴ و ۱۳۹۵ استفاده شده است. سال پایه در این پژوهش سال ۱۳۹۵ بوده و خانوارهای انتخاب شده بر اساس سن سرپرست خانوار در این سال بین ۳۰ تا ۶۰ سال است و برای دیگر سال‌ها نسبت به سال پایه تعدیل شد. با استفاده از رویکرد اورشانسکی محاسبه خط فقر مطلق محاسبه و به منظور بررسی میزان تحرک فقر در مناطق روستایی کشور از رویکرد دنگ و همکاران (۲۰۱۳) بهره گرفته شده است. جنسیت، سن، میزان تحصیلات سرپرست خانوار و منطقه محل سکونت به عنوان متغیرهای توضیحی در نظر گرفته شده است.

۴- یافته‌های تحقیق

خط فقر ماهانه و شاخص‌های فقر برای خانوارهای روستایی کشور بر حسب فرد معادل بالغ در سال‌های ۱۳۹۱، ۱۳۹۴ و ۱۳۹۵ که به روش خط فقر مطلق (با رویکرد اورشانسکی) محاسبه شد به ترتیب

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۱۷۲۵۸۰۰، ۲۷۲۶۱۸۱ و ۲۹۷۶۷۵۷ ریال است. برای بررسی میـزان تحرک فقر با استفاده از معادله (۱) استفاده شد.

$$y_{ij} = \beta_0 + \beta_1 gen_{ij} + \beta_2 age_{ij} + \beta_3 adu_{ij} + \beta_4 reg_{ij} + \varepsilon_{i1}$$

که در آن i نماد خانوار، j نمایانگر سال مورد مطالعه، gen جنسیت سرپرست خانوار، age سن سرپرست خانوار، adu میـزان تحصـیلات سرپرست خانوار و reg نشان‌دهنده محل سـکونت خـانوار اسـت کـه برای خانوارهای ساکن تهران عدد ۱ و برای دیگر مناطق کشور عـدد ۰ لحاظ شده است. نتایج نشان می‌دهد بر اسـاس رویکـرد داده‌هـای تابلویی واقعی بـیش از ۴۶ درصـدخانوارهای روسـتایی در سـال‌های ۱۳۹۴ و ۱۳۹۵ در وضعیت فقر ثابتی هستند. همچنین، در سـال‌های ۱۳۹۱ و ۱۳۹۵، ۴۳/۶ درصد خانوارهـا در هـر دو سـال فقیـر، ۶/۳۹ درصد در سال ۱۳۹۱ فقیر و در سال ۱۳۹۵ غیر فقیـر، ۶/۳۵ درصـد خانوارها در سـال ۱۳۹۱ غیـر فقیـر و در سـال ۱۳۹۵ فقیـر و ۴۳/۶ درصد خانوارهـا در هـر دو سـال فقیـر بوده‌انـد.احتمال فقیـر بـودن خانوارهای روستایی در سال ۱۳۹۵ به شرط فقیر بودن آن‌ها در سال ۱۳۹۴ بر اساس دو رویکرد داده‌های تابلویی واقعی به ترتیب برابـر بـا ۹۲/۳۹ و ۸۷/۱۲ درصد است. این شاخص برای سال ۱۳۹۱ و ۱۳۹۵ بر اساس رویکرد داده‌های تابلویی ترکیبی برابر با ۸۶/۸۳ درصد است. نسبت خانوارهایی که در سال ۱۳۹۵ فقیر هستند به شـرط آنکـه در سال ۱۳۹۴ غیر فقیر باشند به ترتیب ۷/۶۰ و ۱۲/۸۸ درصد بر اساس دو رویکرد مذکور بوده درحالی‌که درصـد ایـن جمعیـت بـرای سـال ۱۳۹۱ و ۱۳۹۵ برابر با ۱۳/۱۶ درصد می‌باشد.

۵- بحث و نتیجه‌گیری

در این پژوهش از روش دنگ و همکاران سال ۲۰۱۳ کـه بـر مبنـای تابع احتمالات حاصل از رگرسیون مصرف بـر روی متغیرهـای ثابـت زمانی است، برای تحلیل پویایی فقر مناطق روسـتایی اسـتفاده شـد. برای بررسی میـزان دقیـق بـودن روش در ابتـدا پویـایی فقـر بـرای سـال‌های ۱۳۹۴ و ۱۳۹۵ دو رویکـرد داده‌هـای تـابلویی واقعـی و داده‌های تابلویی ترکیبی مورد بررسـی قـرار گرفـت. در رویکـرد اول، فقط خانوارهایی مشترک با سرپرست بین ۳۰ تا ۶۰ سال برای سـال ۱۳۹۵ و ۲۹ تا ۵۹ سال برای ۱۳۹۴ انتخاب و تحرک فقر آن تحلیـل شد. در رویکرد دوم، تحلیل با رعایت بـازه سـنی سرپرسـت خـانوار و روش تحلیل پویایی فقر برمبنای شیوه دنگ و همکاران انجام شد. رویکرد داده‌های تابلویی ترکیبی برای اندازه‌گیری میـزان همبسـتگی جزئی باقیمانده‌های رگرسیون از روش گروه‌بندی بر پایه روش دیتون (۱۹۸۵) بهره گرفته است که در این راستا در مقاله حاضر خانوارها به ۳۱ گروه سنی تقسیم و ضریب همبستگی جزئی باقیمانده‌ها محاسبه شد. ایـن شـاخص در سـال‌های ۱۳۹۴ و ۱۳۹۵ بـر اسـاس رویکـرد داده‌های تابلویی واقعـی و ترکیبـی فقـط ۰/۷ درصـد تفـاوت نسـبی داشته‌اند.

بررسی پویـایی فقـر بـر اسـاس تـابع احتمـالات مشـترک و شـرطی نامعادلات مصرف و خط فقر در دوره‌های مختلـف صـورت مـی‌گیـرد. نتایج حاصل از برآورد این تابع احتمالات نشان می‌دهد که در مناطق روستایی کشور نوعی وابسـتگی حالـت در وضـعیت فقـر وجـود دارد. جهت تشریح این مطلب طی سال‌های مورد مطالعـه اعـم از رویکـرد داده‌های تابلویی و ترکیبی بیش از ۸۶ درصد خانوارهایی که در سـال ۱۳۹۵ فقیر (غیـر فقیـر) بودنـد در دوره اول (سـال ۱۳۹۱ یـا سـال ۱۳۹۴) نیز فقیر (غیر فقیر) بوده و تنها با احتمال کمتر از ۱۴ درصـد خانوارهای فقیر (غیر فقیر) سال ۱۳۹۵ در دوره قبل غیر فقیر (فقیر) بوده‌اند.

کلمات کلیدی: اندازه‌گیری فقر، فقر پویا، داده‌های تابلویی ترکیبی، مناطق روستایی، ایران.

تشکر و قدردانی

پژوهش حاضر برگرفته از رساله دکتری نویسنده اول (فاطمه گریوانی)، گروه اقتصاد، دانشـکده علـوم اداری و اقتصـادی، دانشگاه فردوسـی مشـهد، مشهد، ایران. است.

ارجاع: گریوانی، ف.، احمدی شادمهری، م. ط. فلاحی، م. ع. و راغفر، ح. (۱۳۹۸). تحلیل پویایی فقر در مناطق روستایی ایران. *مجلـه پـژوهش و برنامه‌ریزی روستایی*، ۸(۳)، ۱۳-۲۵.

http://dx.doi.org/10.22067/jrrp.v5i4.72911