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Poverty dynamics in Palestine using repeated cross-sectional data analysis

تحليل ديناميكية الفقر في فلسطين بإستخدام بيانات المقاطع العرضية المتكررة

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Dedication

To whom I carry my name with all pride ……. My dear father,

To whom was the secret of my success, to the spring of tenderness ……. My dear mother,

To those who supported me and the source of my strength …. My older brother" Hilmi",

To my Brothers and Sisters,

To my Friends,

To my colleagues.

To everyone who helped me to finish this research

With all my love and respect

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Abstract

Dynamic relations and transitions over time are important aspects in different fields. Dynamic models require panel data for at least two periods. However, panel data collection requires high costs. So, in many countries there is a lack of panel data. When only cross-sectional data are available, we will not be able to analyze dynamic relations which will lead to lack of knowledge and capability of prediction of important indicators for the development of people's life. In this thesis, we will apply Dang and Lanjouw (2013), in addition to other traditional approaches, to estimate the transition probabilities of getting into and out of poverty. This thesis can initiate this kind of analysis by highlighting methods of repeated cross-sectional data analysis, which is widely available in different Palestinian surveys. The results show that the rate of mobility of refugees in the poverty is greater than that of the non-refugees, but there is no evidence that there is a difference between refugees and non-refugees to get out of poverty. ***Thus, the migration caused by the Israeli occupation affected the refugees by increase the probability of entering the trap of poverty.***

ملخص

تعتبر العلاقات الديناميكية والتحولات على مر الزمن من الجوانب الهامة في مختلف المجالات. تتطلب النماذج الديناميكية بيانات طولية لفترتين على الاقل. ومع ذلك،فإن جمع البيانات الطولية يتطلب تكاليف عالية .لذلك، في كثير من البلدان هناك نقص في البيانات الطولية. وعندما تكون البيانات العرضية فقط هي المتاحة، فلن نكون قادرين على تحليل العلاقات الديناميكية ،الامر الذي يؤدي إلى نقص في المعرفة والقدرة على التنبؤ بمؤشرات هامة لتطوير حياة الناس .في هذه الأطروحة، سوف نطبق منهجية Dang and Lanjouw (2013)، بالإضافة إلى الأساليب التقليدية الأخرى، لتقدير احتمالات الدخول والخروج من دائرة الفقر .هذه الأطروحة يمكن أن تبدأ هذا النوع من التحليل من خلال تسليط الضوء على أساليب تحليل البيانات العرضية المتكررة، والتي هي متاحة على نطاق واسع في مختلف الدراسات الفلسطينية. وقد أظهرت النتائج أن معدل دخول اللاجئين في الفقر أكبر من معدل دخول غير اللاجئين، ولكن لا يوجد دليل احصائي على وجود فرق بين اللاجئين وغير اللاجئين للخروج من دائرة الفقر.وبهذا، فإن عملية تهجير الاحتلال الإسرائيلي للمواطنين الفلسطينيين أثرت على اللاجئين من خلال زيادة احتمالية الدخول في فخ الفقر.

Chapter 1

Introduction

Dynamic relations and transitions over time are important aspects in different fields. In economics, transitions are smooth over time implying dependence of economic relations on previous period values. Thus, dynamic models need to be analyzed. For instance, wages of employees, employment status transition, and poverty status transition are all dependent on previous status.

Dynamic models require panel data for at least two periods. However, panel data collection requires high costs. So, in many countries there is a lack of panel data (longitudinal data) where multiple cases (people, firms, countries etc.) were observed at two or more-time periods, Thus, statistical centers usually tend to repeat different samples of cross-sectional surveys (repeated cross-sections). When only cross-sectional data are available, we will not be able to analyze dynamic relations which will lead to lack of knowledge and capability of prediction of important indicators for the development of people's life.

Recent researches show that we can obtain synthesized panels from repeated cross-sectional data under appropriate conditions. Although there is a loss of individual information at the survey level, researches show that the estimations are accurate to those obtained by true panel values. On the other hand, one of the advantages of repeated cross sections suffer from much lower than the panel data problems like nonresponse and attrition.

In the absence of panel data from the Palestinian Central Bureau of Statistics (PCBS), literature related to the Palestinian economic relations does not analyze the dynamics of these relations. The classes of Palestinian may have difference level of mobility in poverty. This study focuses on comparing the refugees and non-refugees in mobility in and out of poverty.

This study contains five chapters, we start in the next chapter with discusses the reasons of Poverty and the relationships between alternative estimators that are proposed in the literature to estimate dynamic models from RCS data. chapter three shows the methodology of the research. Chapter four discusses the results. Finally, chapter five for Conclusions and recommendations.

Chapter 2

Literature Review

Poverty is a global problem and social phenomenon with economic extensions and political implications of multiple forms and dimensions. Its size, intensity, causes and implications are characterized by large disparities across countries. While main stream economists mostly explain poverty by low marginal productivity or by households' choice of low labor levels, heterodox economists explain poverty and income distribution by institutional factors determining the historical path of the division of income (Eichner and Kregel, 1975).

The length of a poverty trap reflects the persistence of poverty in the historical path of a household. One of the starting researches on poverty dynamics, Bane and Ellwood (1986) found that 60% of the poor were in a poverty spell since 8 years or more. Poverty spell exits were mostly due to an increase in earnings but with a shorter spell duration.

Hence, many studies tried to explain the causes of poverty, including demographic and social factors such as gender, age, location and education. The study of Sara McLanahan (1985) uses a panel data taken from Michigan Panel Study of Income Dynamics to answer the question that whether and why offspring in female-headed households are more likely to experience poverty. The results indicate that growing up in a female-headed family increases the risk of poverty.

Julius and Bawane (2011) outlines the issues of education and poverty that are related to the issues of chicken-egg relations. The study linked the number of poor with educational indicators. Data showed that provinces with lower levels of poverty had higher literacy rates, higher school enrollment rates and lower drop-out rates, while areas with higher levels of poverty experienced lower rates of literacy and weak academic performance. The study concluded that the poor are deprived of education. Moreover, the study of Kızılgöl and Demir (2010) which aimed to analyze parameters determining poverty in terms of income and expenders from TUIK's Household Budget Questionnaire of 2002-2006 using the pooled data of 2002-2006 showed that the poverty risk decreases as the educations and age of household head increases. There is also a correlation between the prevalence of chronic poverty and the location. In Egypt, 66% of the chronic poor lived in rural household (Haddad & Ahmed, 2002). According to Estudillo et al (2013) the strong dependence on agriculture as a major source of household income will not lead to improved living standards, and has contributed to increased non-farm income to improve living standards and reduce poverty in rural areas in Asia. The study found that not only the quantity of non-farm jobs but also the quality of non-agricultural formal employment plays an important role in providing decent income and preventing rural families from falling into poverty.

Moreover, increasing farm income tends to invest in education for children who will then be excluded from non-agricultural jobs (Otsuka et al., 2009).

There is evidence that conflicts, oppression and displacement lead to significant losses in the assets of displaced victims. Whether migration is forced or preventive, displaced families leave a base of assets that appear insufficient to escape poverty (Ibanez and Moya, 2010). Moreover, Conflicts left many people unable without the ability to participate actively in society, factors that contributed to the aggravation of poverty (Muthomi et al., 2015), There is also a relationship between development and conflict. In a study of (Panday, 2011) conducted in Nepal, the results showed that the areas with the largest conflict intensity were the poorest and suffered from the lowest level of development.

The process of forced mass displacement leads to significant losses in the physical and human capital of displaced families (Branković & Oruč, 2016), a study by the World Bank Group and the United Nations High Commissioner for Refugees (UNHCR) (Paolo et al, 2016) revealed that Syrian refugees in Jordan and Lebanon suffer from extreme levels of poverty and expect the situation to worsen in the near future. The same is true for Palestinian refugees; according to the Main Findings Report of Palestinian Central Bureau of Statistics (PCBS) (2011) that poverty is still significantly more prevalent among refugees than among non-refugees.

In order to analyze poverty dynamics, we need household panel data sets. Since it is difficult to follow individual households over time, Deaton (1985) introduced a grouping method from retrieving dynamic information from repeated cross section data sets. He suggested to regroup individuals sharing some common characteristics into cells and to use the average within these cells as observations in a pseudo panel. Common characteristics can be date of birth, gender or geographical location if there is no migration of the households. As underlined in Verbeek (2008), the variables involved in the definition of the groups play the same role as instrumental variables. Consequently, the grouping variables have first to be exogenous (on other word being uncorrelated to the unobservable in the equation) and second, they have to define observation groups where the explanatory variables are correlated with these pseudo instruments (i.e. The instrument must be relevant). Of course, the grouping variables cannot be time varying variables and have to be observed for all individuals in the sample.

Moffitt (1993), extends several ways for estimation of dynamic models – linear with fixed effects- using Repeated cross-sectional (RCS) data, firstly, identification conditions for the linear fixed model. secondly, the estimation methods for the linear fixed effects model are demonstrated which make use of the individual micro data and economize on parameters. Third, considering autoregressive linear models .and finally, the methods are extended to models with discrete dependent variables, both with and without fixed effects.

Let us start from a simple linear panel data model with fixed effects:

$$y_{it} = x_{it}^{'}\beta + \alpha_i + \varepsilon_{it}$$

Where x_{it} denotes a k-dimensional vector of explanatory variables, i = 1 ... n is the individual index and t = 1 ... T is the time index. If the data set is a repeated cross-section, we cannot use a within estimator as we have no common observation between the waves to compute $\bar{x}_i$, Instead, Deaton (1985) assumes that there exist time invariant characteristics which serve to aggregate observations on a cohort basis (individuals sharing some common characteristics). For example, Deaton and Irish (1985) following cohorts of household selected individuals born in a 5-year interval, subdivided the head of the household into manual or non-manual worker. While Blundell, Duncan and Meghir (1998) employ interval of 10 years, interacted with two groups of education.

If we aggregate all observations to cohort basis, so as to define mean groups:

$$\bar{y}_{ct} = \bar{x}_{ct}^{'}\beta + \alpha_c + \varepsilon_{ct}$$

with c = 1 ... C, C being the maximum possible number of cohorts. The fixed effect parameter α_c is assumed to be constant over time. Then we can compute cell means in the following way $\bar{x}_{ct} = \sum_t x_{ct} / T$ and then apply the within estimator.

we take no longer into account an individual effect α_i constant over time, but a cohort effect α_c still constant over time. Deaton (1985) proves the consistency of this estimator when the number of cohort's C tends to infinity while Moffitt (1993) assumes that C is constant when n, the number of individuals, tends to infinity.

The previous approaches ignore individual observations and can lead to a great loss of information. An alternative approach was taken in a series of papers, mainly Dang and Lanjouw (2013) and Dang et al. (2014), following an initial idea of Elbers et al. (2003). In most developing countries, censuses do not collect information on income or expenditure, so estimates of poverty are not available even in the census years, and to fill this gap, The World Bank recently invested in a methodology to generate statistics on poverty and inequality in small areas, household survey is used to calculate estimates of poverty in census small areas, the methodology developed by Elbers et al (2003); this approach is based on out-of-sample imputation methodology to estimate the poverty in small areas (development of poverty maps.) using a specification that includes only variables that depend only on time, then apply the parameter estimates of this model on the same fixed time invariant regression in the second round of the survey to provide an estimate for the consumption of the first period (unobserved) or income of individuals who surveyed in the second round. And then the mobility analysis can be based on the actual consumption observed in the second round along with this estimate of the first round.

Despite the widespread application and increasing popularity of poverty mapping, little formal investigation has been achieved of its property. The original paper of Elbers et al (2003) describes the procedure, but does not provide a description of the general characteristics on which the estimate is based or consider the likelihood or consequences of assumptions failure. Moreover, Elbers et al (2003) requires the validity of two assumption. The first one is Measurement of Predictors (MP):$X_h = \hat{X}_h \ for \ all \ h$ where $X_h$is the value of the correlates for household h as observed if h is included in the survey sample and $\hat{X}_h$ is the corresponding measurement in the census. The second assumption is Area Homogeneity (AH). The necessity and importance of the first assumption (MP) is if the correlates have to be used to link census and household data. The area homogeneity assumption AH required, for instance, that the probability of being poor given X in the small area A is the same as in the larger region R. (Tarozzi & Deaton, 2009)

Dang et al. (2014) suggests both parametric and non-parametric approach using two rounds of cross- sections at the household level to build synthetic panels, and then used to estimate the upper and lower bounds of household's mobility into and out of poverty. The paper of Dang and lanjouw (2013) generalized the method of Dang et al. in many important aspects. The first one, by introducing a method to find a point estimate of the appropriate correlation term the cross-sectional surveys for each country's. The point estimation of the correlation term allows us to use point and interval estimates of poverty dynamics instead of bound estimates as suggested by Dang et al. (2014). Moreover, Dang and Lanjouw (2013) provide standard error formula for point estimates, which is not found with the bound estimates of Dang et al. (2014). Second, Dang and Lanjouw (2013) generalize the construction of the synthetic panels to be available for more than two rounds. Third, the framework of Dang and Lanjouw (2013) extends Dang et al (2014) to analyze poverty mobility of household to much more general set up of household mobility among different consumption groups.

In the absence of panel data from the Palestinian Central Bureau of Statistics (PCBS), literature related to the Palestinian economic relations does not analyze the dynamics of these relations. This thesis can initiate this kind of analysis by highlighting methods of repeated cross-sectional analysis, which is widely available in different Palestinian surveys.

Chapter 3

The Methodology

3.1 Estimation Method

We consider the case of two rounds of cross-sectional surveys, denoted round 1 and round 2. We assume that survey rounds are random samples of the interest population, each have sample N_1 and N_2 households respectively.

Then for the population as a whole, the linear projection of the log of income using round 1 survey, y_{i1}, is given by:

$$y_{i1} = \beta_1' x_{i1} + \varepsilon_{i1} \qquad (3.1)$$

Where x_{i1} the vector of characteristics of household *i* in survey round 1.

And similarly, the linear projection of the log of income using round 2 survey, y_{i2}, is given by:

$$y_{i2} = \beta_2' x_{i2} + \varepsilon_{i2} \qquad (3.2)$$

Where x_{i2} the vector of characteristics of household *i* in survey round 2 with the same set of explanatory variables in both regression models. The choice of the explanatory variables is based on selection of time-invariant variables.

The idea of Dang and Lanjouw (2013) is to simulate the unobserved individuals in one of the two periods. Because both y_i and y_j are drawn from the same population and are function of the same time invariant exogenous variables, we can project consumption in round 1 for households in round 2 after separate estimations of the above two regression equations (3.1 and 3.2).

Let Z_1 and Z_2 denote the log of the poverty lines in round 1 and round 2 respectively. Then, we can head to estimate the degree of mobility in and out of poverty which is our aim. So, if we are interested in knowing what ratio of households in the population is above the poverty line in round 2 after being under the poverty line in round 1, which is represented by the degree of movement out of poverty for households over the two periods, we have to estimate:

$$P(y_{i2} > Z_2 | \, y_{i1} < Z_1) \qquad (3.3)$$

We can easily estimate the previous probability (3.3), if we have panel data. Otherwise, we can use synthetic panels for this purpose, where we have to make assumptions on the explanatory variables. Dang et al. (2014) assume two standard assumptions, the first one that the underlying population being sampled in survey rounds 1 and 2 are the same, Specifically, $x_{i1} = x_{i2}$,and $y_{i1}|x_{i1}$ and $y_{i2}|x_{i2}$ have identical distributions.

The second assumption is that $\varepsilon_{i1}$and ε_{i2}have a bivariate normal distribution with correlation coefficient ρ and standard deviations $\delta_{\varepsilon 1}$and $\delta_{\varepsilon 2}$ respectively.

Dang et al. (2014) make a first loose assumption on ρ assumed that its bounded by the interval [0,1] ,since for any $x,y\ and\ \rho$,$\frac{\partial \Phi_2(x,y,\rho)}{\partial \rho} = \phi_2(x,y,\rho) > 0$,and in the absence of information about ρ , Dang et al. (2014) suggest one can start by assuming that ρ either 0 or 1. If $\rho = 0$, then mobility reaches its upper bound. If $\rho = 1$, then mobility reaches its lower bound. Dang et al. (2014) propose a distribution free procedure based partly on simulation to compute these bounds. In this model, ρ is not identified, this is the reason why Dang et al. (2014) can give only bounds for poverty transition probabilities. If we assume that the two error terms are Gaussian, the probability of entering poverty becomes:

$$P(y_{i2} < Z_2 and\ y_{i1} > Z_1) = \Phi_2\left(\frac{Z_1-\beta_1' x_{i2}}{\delta_{\varepsilon 1}}, -\frac{Z_2-\beta_2' x_{i2}}{\delta_{\varepsilon 2}}, -\rho\right) \qquad (3.4)$$

Where $\Phi_2(.)$ stands for the standard bivariate normal cumulative distribution function (cdf), (and $\phi_2(.)$ for the pdf)

Since ρ is usually unknown in most fields, the approach of Dang and Lanjouw (2013) is that they give a point estimate of ρ, thus a point estimate of the transition probabilities and more precise interval estimation of ρ. Dang and Lanjouw (2013) propose that we can first approximate the simple correlation coefficient $\rho_{y_{i1}y_{i2}}$ between birth cohort-aggregated household consumption between the two surveys, and then estimate ρ using the following formula:

$$\hat{\rho} = \frac{\rho_{y_{i1}y_{i2}}\sqrt{var(y_{i1})var(y_{i2})} - \beta_1' var(x_i)\beta_2}{\delta_{\varepsilon_1}\delta_{\varepsilon_2}} \quad (3.5)$$

Then, in order to estimate quantity (3.3), divide quantity (3.4) by $\Phi\left(\frac{Z_1-\beta_1' x_{i2}}{\delta_{\varepsilon 1}}\right)$

And by the definition, we have to note that:

$$P(y_{i2} < Z_2 |\, y_{i1} < Z_1) + P(y_{i2} > Z_2 |\, y_{i1} < Z_1) = 1 \quad (3.6)$$

Which means, for the poor families in the first period, they can fall into either one of two categories in the second period (poor or non-poor)

Corollary 3.1: Another estimate for ρ

If $\beta_1 \approx \beta_2$, ρ can be also estimated by

$$\hat{\rho} = \frac{\rho_{y_{i1}y_{i2}} - \sqrt{R_1^2 R_2^2}}{\sqrt{1-R_1^2}\,\sqrt{1-R_2^2}} \quad (3.7)$$

Where R_j^2, for j = 1,2, represent the coefficients of determination obtained from estimating equations (3.1) and (3.2) respectively.

Corollary 3.2: Upper bound (UB) for ρ

Assume that the error terms $\varepsilon_{i1}$and ε_{i2} in equation (3.1) and (3.2) respectively follows the traditional household random effects model and can be broken down as $\varepsilon_{\mathrm{ij}} = u_i + v_{ij}$ where the unobserved household effects $u_i \sim N(0, \sigma_u^2)$, the idiosyncratic error terms $v_{ij} \sim N(0, \sigma_v^2)$ for j=1,2, and cov$(v_{i1}, v_{i2}) = 0$. An upper value for ρ is given by the cohort aggregated correlation coefficient $\rho_{y_{i1}y_{i2}}$

Corollary 3.3: Lower bound (LB) of $\rho_{y_{i1}y_{i2}}$

The sample correlation coefficient $\rho_{y_{i1}y_{i2}}$ for household consumption from the two rounds is greater than or equal (the equality when all error terms are zero) its lower value:

$$\frac{\beta_1' var(x_i)\beta_2}{\sqrt{var(y_{i1})var(y_{i2})}} \ or \tag{3.8}$$

$$\sqrt{R_1^2 R_2^2}\ when\ \beta_1 \approx \beta_2 \tag{3.9}$$

3.2 Conditions for consistency

Dang et al. (2014) method described above needs two key conditions to give us consistent estimates of the degree of movement into and out of poverty.

First condition: The underlying population sampled is the same in the both rounds. This ensures that as N $\to\infty$, $\hat{\beta} \to \beta$.

This condition will not be satisfied if the sampling methodology or measurement of income or consumption is changed between the two rounds, or if the populations changes through birth, death, or migration out of the population. For repeated cross-sectional analysis, its best to satisfy this assumption to restrict attention to household headed by age, say from 25 to 55. Analysis of mobility for the younger household whose less than 25 and the older than 55 is very difficult, since these ages are often when households are beginning to form, or starting dissolve

Second condition: The independence, $\varepsilon_{i1}$is independent of y_{i2}, since we defined through a linear projection its orthogonal to x_{i1} (3.1) and thus for x_{i2}, which implies the independence between ε_{i1} and ε_{i2}. If this assumption is satisfied, then the conditional distribution of ε_{i1} $(\varepsilon_{i1}|y_{i1} > Z)$ is the same for the unconditional distribution ε_{i1}.This allows us to use the unconditional distribution instead of conditional of the estimated residuals in the second step.

3.3 The marginal and conditional Transitions

Let us put our model for the first period as a matrix form, we first define the vectors:

$$ys_1 = \binom{\tilde{y}_1}{y_1} \quad , \quad X = \binom{X_2}{X_1},$$

Where $\tilde{y}_1, y_1$ respectively two vectors with n_1 and n_2 dimensions and X_1, X_2 are two matrices with corresponding number of rows. Our first period model can be written as:

$$ys_1 = X\beta_1 + v_1 \tag{3.10}$$

And the model for period 2 written:

$$ys_2 = X\beta_2 + v_2 \tag{3.11}$$

We can easily define two dummy variables indicate for the two periods if a household is in a state of poverty or not, resulting from the simulation of $\tilde{y}_{i1}$and $\tilde{y}_{i2}$:

$$d_1 = \mathbb{I}(\mathrm{ys}_1 < z_1) \qquad d_2 = \mathbb{I}(\mathrm{ys}_2 < z_2)$$

Where $d_j$is an indicator function that equal 1 if the household is poor and 0 if the household non-poor for period j, j=1,2.

We can form a matrix of marginal poverty transition which doesn't include any effect of refugee status.

$$\mathcal{P}_{11} = \sum(d_1 \times d_2)/\sum d_1 \ , \qquad \mathcal{P}_{12} = \sum(d_1 \times (1 - d_2))/\sum d_1$$

$$\mathcal{P}_{21} = \sum((1 - d_1) \times d_2)/\sum(1 - d_1) \qquad \mathcal{P}_{22} = \sum((1 - d_1) \times (1 - d_2))/\sum(1 - d_1)$$

We shall then compare the marginal probabilities to the conditional probabilities including the effect of refugee status.

3.4 Summarized framework to obtain poverty mobility for two periods:

Step 1: Using the data in survey round 1, estimate equation (3.1) and obtain the predicted coefficient $\hat{\beta}_1{}'$, and predicted standard error $\hat{\delta}_{\varepsilon 1}$ for the error term $\varepsilon 1$. And similarly, using the data in survey round 2 we estimate equation (3.2) and predicted $\hat{\beta}_2{}'$ and $\hat{\delta}_{\varepsilon 2}$.

Step 2: Aggregate data in both survey rounds 1 and 2 by cohorts and obtain the estimated cohort-level simple correlation coefficient $\rho_{y_{i1}y_{i2}}$. Calculate $\hat{\rho}$ using equation (3.5) , and check that $\rho_{y_{i1}y_{i2}} \geq \hat{\rho}$ (since $\rho_{y_{i1}y_{i2}}$ is the upper bound of $\hat{\rho}$, Corollary 3.2) and $\rho_{y_{i1}y_{i2}} \geq \frac{\beta_1' var(x_i)\beta_2}{\sqrt{var(y_{i1})var(y_{i2})}}$ (Corollary 3.3).

Step 3: For each household in survey round j for j=1,2, calculate absolute quantities of poverty mobility as $\Phi_2\left(d_1\frac{z_1-\beta_1' x_{ij}}{\delta_{\varepsilon 1}}, d_2\frac{z_2-\beta_2' x_{ij}}{\delta_{\varepsilon 2}}, \hat{\rho}_d\right)$ where $\hat{\rho}_d = d_1 d_2 \hat{\rho}$. Calculate the statured error using equation (3.3)

3.5 Data and variables

3.5.1 The study data

In Palestine, poverty is defined in terms of household consumption rather than income. The poverty status is defined as a variable that indicates whether household consumption is below the poverty line. Poverty lines have been prepared according to the real household consumption patterns. The first poverty line (extreme poverty line) was calculated to reflect the basic needs of the food, clothing and housing budget. The second poverty line (poverty line) has been prepared in a way that reflects the basic needs budget as well as other needs such as health care, education, transport, communications, personal and household care, furnishings and other household items. The poverty lines have been modified to reflect the various household consumption needs based on family composition (size of household and number of children). The household consumption and the poverty line must be compatible in term of household composition. In 2004 the average household composition was 2 adults and 4 children. In 2011 the average household composition was 2 adults and 3 children. The poverty line is defined by the Palestinian Central Bureau of Statistics (PCBS) for a representative (average) household, which was 1934 NIS in 2004 and 2293 NIS in 2011. (NIS= New Israeli Shekel)

We need to make the level of household consumption compatible with those of the official poverty lines. And to do that, we adopted Oxford (old OECD) equivalence scale. Oxford equivalence scale is $N_i = 1 + 0.7N_a + 0.5N_c$, where N_i is the equivalized size for the household i and N_a is the number of adults without the household head and N_c is the number of children under 15 years in the household i .

To obtain a number compatible with the official poverty line, the household consumption for household i is divided by N_i and then multiplied by $(1 + 0.7 \times 1 + 0.5 \times 4)$ for 2004 and by $(1 + 0.7 \times 1 + 0.5 \times 3)$ for 2011.

In other words, $\text{adjcons}_i = \frac{cons_i}{N_i} \times 3.7$ for (2004), and $\text{adjcons}_i = \frac{cons_i}{N_i} \times 3.2$ for (2011). Where adjcons_i is the adjusted consumption and $cons_i$ is the consumption for the household i .

3.5.2 The study variables

Dependent variable: The consumption

Independent variables: The independent variables include:

1- Age of household head.
2- Area (West Bank, Gaza strip, Jerusalem)
3- Connection to Public Water Networks (connect, not connect)
4- Gender of household head (male, female)
5- Household size (HH_size)
6- Locality type (Urban, Rural, Camp).
7- Refugee status (refugee, Not refugee).
8- Type of housing unit (apartment, not apartment)

Chapter 4

The Results

4.1 Descriptive Statistics

This section explores the sample characteristics in terms of sex and age of the household head, place of residence, refugee status and poverty status. This will help us to identify the time invariant explanatory variables.

Table (4.1): Comparison between Descriptive statistics for 2004 and 2011

	2004		2011	
	Frequency	Percent	Frequency	Percent
Male	2828	91.3%	3812	88.3%
Poor	796	25.7%	1110	25.7%
Refugee	1570	50.7%	2095	48.5%

From the Table (4.1), the percentage of male-headed households decreased by 3% from 2004 to 2011, and the percentages of refugees in the both samples are approximately equal, while the percentage of poor in the both years is the same.

Table (4.2) The locality type of the sample for 2004 and 2011

Locality Type	2004		2011	
	Frequency	Percent	Frequency	Percent
Urban	1412	45.6%	2262	52.4%
Rural	952	30.7%	1151	26.7%
Camp	734	23.7%	904	20.9%
Total	3098	100%	4317	100%

Table (4.2) shows that type of locality distribution is different between 2004 and 2011. We can notice migration from rural localities and refugee camps to urban areas. Thus, type of locality cannot be used as an explanatory variable.

Table (4.3) The age of the household head and the size of the household (HH_size) for 2004 and 2011

	2004		2011	
	Mean	S.D	Mean	S.D
Age	45.03	14.075	46.90	13.843
HH_Size	6.6446	3.28497	6.0104	2.74269

From the table (4.3) the household size decreased from 6.64 to 6.01 for 2004 and 2011 respectively, so we didn't take the household size as an explanatory variable, because the variables' distribution must be time independent.

Finally, the variables that we consider as time invariant are: sex of household head, year of birth for household head (age), refugee status, region, house type and connection to the public water network. These variables explore less variation across time and are considered in previous studies.

Table (4.4) The cross table between the refugee status and poverty status for 2004 and 2011

Refugee status / Poverty status	2004		2011	
	Refugee	Not Refugee	Refugee	Not Refugee
Poor	29.5%	21.8%	31.9%	19.9%
Not Poor	70.5%	78.2%	68.1%	80.1%
Total	100%	100%	100%	100%

From the table (4.4) we can observe different dynamics in the poverty rates between refugees and non-refugees. The poverty rate increased between 2004 and 2011 for refugees from 29.5% to 31.9%, but decreased for non-refugees from 21.8% to 19.9%. Anyway, the table shows that the percentage of poor among refugees is higher than among non- refugees in both years.

4.2 Comprehensive Analysis

Table (4.5): The Estimated regression model using OLS for 2004 and 2011
The dependent variable is log (adjcon)

	2004			2011		
Coefficients:	Estimate1	S. D1	Sig.	Estimate2	S. D2	Sig.
(Intercept)	8.614	0.1416	***	8.868	0.0897	***
Gaza strip (GS)	-0.2558	0.0222	***	-0.4010	0.0197	***
Jerusalem(Jrs)	0.6384	0.0361	***	0.7375	0.0422	***
Refugee Status (ref)	-0.0940	0.0209	***	-0.0861	0.0181	***
Age	-0.0301	0.0061	***	-0.0333	0.0041	***
Age^2	0.0004	0.0000	***	0.0004	0.0000	***
Sex (male)	- 0.1772	0.0381	***	-0.1745	0.0282	***
Apartment House	0.2255	0.0217	***	0.1683	0.0174	***
Public water network	0.1324	0.0314	***	0.0889	0.0286	**
R^2	0.2355			0.2483		

Sig. codes "***" 0 , "**" 0.001 , "*" 0.01 , "." 0.05 , " " not sig.
The bases: for Area (West bank), for sex (Female), Refugee status (refugee)

The table (4.5) shows the results for the independent linear regression model of the log of the consumption in 2004 and 2011. It shows that all variables are significant for both years at least at the level 0.1%. In Gaza strip, the average consumption is

25.58% less than the West Bank in 2004 and the gap increased to 40.1% in 2011, while the average consumption in Jerusalem 63.84% (in 2004) and 73.75% (in 2011) higher than the rest of the West Bank. Refugee households consume on average 9.4% than non-refugees in 2004 and 8.61% in 2011. In contrast to previous studies, household consumption has a convex relation to the age of the household's head. In

other words, the increase in the age of the head of the household decreases the probability of his entry into poverty. Moreover, male-headed households consume around 17% less than female-headed households

Table (4.6): The marginal transition matrix

2004 \ 2011	Poor	Non-poor
Poor (LB , UB)	0.4761 (0.4301 , 0.5323)	0.5256 (0.4677 , 0.5699)
Non-poor (LB , UB)	0.3110 (0.3010 , 0.3204)	0.6890 (0.6796 , 0.6990)

From table (4.6), the marginal probability of chronic poverty is 0.4761, while the mobility out of poverty is 0.5256, and the mobility in the poverty status is 0.311

Since our interest is to study the difference in poverty dynamics between refugees and non-refugees, we need to split the transition matrix by the refugee status of households.

Table (4.7) The conditional transition matrix for non-refugees

2011 / 2004	Poor	Non-poor
Poor (LB , UB)	0.4179 (0.3658 , 0.4450)	0.5821 (0.5550 , 0.6342)
Non-poor (LB , UB)	0.1494 (0.1422 , 0.1610)	0.8506 (0.8390 , 0.8578)

Table (4.7) shows the conditional mobility of poverty for non-refugees. The mobility out of poverty for non-refugees is 0.5821 with confidence interval (C.I) (0.5550, 0.6342), and the mobility in the poverty is 0.1494 with C.I (0.1422, 0.1610)

Table (4.8) The conditional transition matrix for refugees

2011 / 2004	Poor	Non-poor
Poor (LB , UB)	0.3535 (0.3287 , 0.3759)	0.6465 (0.6241 , 0.6713)
Non-poor (LB , UB)	0.3110 (0.3010 , 0.3204)	0.6890 (0.6796 , 0.6990)

The table (4.8) shows the conditional mobility of poverty for refugees. The mobility out of poverty for refugees is 0.6465 with (C.I) (0.6465 , 0.6713), and the mobility in the poverty is 0.311 with C.I (0.3010 , 0.3204)

Chapter 5

Conclusions and Recommendations

5.1 conclusions

This paper gave a first estimation of poverty transition probabilities using the Palestinian Expenditure and Consumption Survey (PECS) repeated cross sections. In the marginal estimation, although the probability of transition out of poverty is higher than the probability of moving into poverty, the probability of chronic poverty (staying in a poverty trap) is considerably high of 0.4761.

From tables (4.7) and (4.8) we conclude that the rate of mobility of refugees in the poverty is greater than the entry of the non-refugees, but there is no statistically significant evidence that there is a difference between refugees and non-refugees to get out of poverty. Thus, even if there is no statistically significant evidence for higher chronic poverty among refugees, they are more vulnerable to economic difficulties and they are more likely to get into a poverty trap.

5.2 Recommendations

Increase the focus of Palestinian researchers and research centers on the use of repeated cross-sectional data to study many other dynamic fields. As well as the study of poverty dynamic between the West Bank and the Gaza Strip

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