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An Application for Mexico Using Panel Data Information

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Abstract*

This paper compares the dynamic consistency of targeting methodologies that use multidimensional welfare indicators with those based on means and proxy means tests using panel data from Mexico. To make these comparisons, an extension of the Alkire and Foster (2008) dual cutoff multidimensional poverty methodology is proposed. This extension provides a relative approach to multidimensional deprivation that ranks individuals according to an aggregate of their relative position in the distribution of a set of welfare attributes or outcomes. The extension gives particular importance to deprivations that affect smaller portions of the population, as these deprivations are especially critical in defining relative multidimensional welfare. The findings, disaggregated by geographical area (urban and rural), suggest that taking into account deprivation in multiple dimensions may lead to more dynamically consistent measures of well-being and thus more dynamically consistent targeting algorithms.

JEL Classifications: I32, I38

Keywords: Targeting, Multidimensional welfare indicators, Poverty, Deprivation

* The opinions and conclusions expressed in this paper are those of the authors and do not necessarily reflect the official position of the Inter-American Development Bank. Please address correspondence to César P. Bouillon (cesarb@iadb.org).

1. Introduction

Targeting methods are essential components of social safety net programs, such as conditional cash transfers. Conceptually, targeting is intended to answer the question of who should benefit from a given development initiative. Targeting mechanisms are justified by budgetary reasons, equity considerations, limiting the unintended consequences of transfer programs (especially disincentives to labor force participation), and improving the effectiveness of interventions when benefits are likely to have higher impacts on specific population groups. Equity considerations imply that certain populations, in a given country or region, are more likely to be underdeveloped according to certain ascribed characteristics such as their age, gender, and membership of a marginalized group, among others. Targeting mechanisms are also necessary to compensate for geographical welfare disparities, particularly for certain isolated regions or rural localities.

In order to improve social safety net effectiveness, and given the high levels of poverty and social exclusion still remaining in many developing countries, looking for ways to improve targeting mechanisms for social government expenditure is needed. Several studies have analyzed the efficiency of different targeting methodologies (see, for example, Coady and Parker, 2004, and Grosh, 1994). Most of these studies, however, have used cross-section data to determine if the admission of a household into a program was adequately performed or not. To the best of our knowledge, none of these studies has considered the dynamic nature of poverty and deprivation and how this can influence the consistency of targeting methods across time.

We consider a targeting measure to be dynamically consistent when a household that was poor in an initial period, and was consequently admitted into a welfare program, will remain poor in following periods. Note that for some programs targeting may not need to be dynamically consistent, either because they aim to protect beneficiaries from short poverty spells or they are expected to rapidly increase household capabilities or opportunities. Analyzing the dynamic consistency of targeting measures is relevant for programs that are aimed at the "structurally poor" and support beneficiaries for long periods of time, such as Conditional Cash Transfer Programs. Moreover, in most cases these programs target beneficiaries based on cross sectional data and do not have the flexibility of re-targeting and updating beneficiaries' rosters frequently. This is usually due to data limitations (e.g., it is too costly to recertify beneficiaries constantly) or to political reasons, as social conflicts could emerge from frequently including and excluding some households.

In recent years it has been common to assert that poverty is a multi-dimensional phenomenon, and thus poverty reduction programs are increasingly adopting a multidimensional approach (including Social Investment Funds and Conditional Cash Transfer Programs). Yet, many of these programs still use one-dimension targeting methods. Methods that target populations based on highly volatile or unpredictable variables, such as income, are not likely to be consistent over time. The movement of households in and out of poverty over time leads to problems of leakage and under-coverage. In addition, programs in developing countries usually rely on proxy means tests as income is very difficult to verify. Proxy means testing involves predictions of income based on fairly easily observed characteristics. The correlation of these characteristics with income evolves over time, introducing further errors into the targeting process.

In this paper a multidimensional welfare measure is constructed in which both income and other well-being indicators are included. Using panel data information from Mexico, our objective is to compare the dynamic consistency of targeting methodologies that use multidimensional welfare indicators with that of techniques based on means and proxy means tests. The multidimensional indicator constructed is based on an extension of the Alkire and Foster (2008) dual cutoff multidimensional poverty methodology. Our method replaces the arbitrary judgment of threshold values by adopting a relative approach to deprivation. For this, we rank individuals according to their relative position in the distribution of a set of welfare attributes or outcomes among the population at large.

Our findings, which are disaggregated by geographical area (urban and rural), suggest that taking into account deprivation in multiple dimensions may lead to more dynamically consistent rankings of people's well-being and thus more dynamically robust targeting. Our results also show that adopting a multidimensional approach in targeting processes can be even more dynamically consistent when programs are looking to target the poorest or most deprived population.

A study of this type can shed light on how to improve the targeting mechanisms used by development programs and contribute to improve the social public expenditure allocation. It is important to highlight that we do not intend to provide conclusions in terms of which measure is most appropriate for analyzing poverty. Instead, we will be looking only at the dynamic consistency of each measure. Multidimensional well-being indicators can incorporate dimensions not highly correlated with income, which can lead to identifying populations groups other than those traditionally identified as poor. The issue of choosing which dimensions and variables are relevant will finally depend on society's consensus on which variables are related with poverty, the objectives of each program and the availability of information.

The paper is structured as follows. The next section discusses the related literature. Section 3 presents an example using information from the Oportunidades program in Mexico to motivate our discussion of the dynamic consistency of targeting. Section 4 explains the methodology used for the construction of our relative multidimensional welfare indicator and the estimation of proxy means test targeting, and Section 5 describes the data used in our empirical application presenting some descriptive statistics of the sample. Section 6 presents the main results, and Section 7 concludes.

2. Literature Review

Even though most empirical work on poverty still uses a one-dimension measure to judge a person's well-being, usually per capita income, many authors have recognized that income itself may not be an appropriate variable on which to measure human deprivation. A person with a higher income level may not be able to improve some of his monetary and non-monetary attributes. Moreover, markets for some non-monetary attributes may not exist or could be highly imperfect (Tsui, 2002; Duclos et al., 2006; Bourguignon and Chakravarty, 2003; Atkinson, 2003). Therefore, as a person's well-being has dimensions that cannot be purchased, income as the sole indicator of well-being is inappropriate and should be supplemented by other attributes or variables.

The idea that there are many facets to poverty and deprivation has been the source of many studies in the recent years. The need to go beyond income has been highlighted, especially by Sen (1992), who supported the idea that poverty should be seen as a capability deprivation, where living is seen as a set of interrelated functionings (or outcomes) consisting of being and doing. Rawls' *A Theory of Justice* (1971) has also been very influential in this line of thinking. Rawls proposed that ensuring the well-being of a person required certain basic needs to be met. These needs are regarded as the means that are necessary for people to take part in the life of their society and include economic means as well as institutional rights and freedoms (Freeman, 2007).

Despite the extensive size of the literature on multidimensional poverty and deprivation, no single multidimensional welfare index has received unanimous approval. Constructing a multidimensional welfare indicator is ethically and empirically problematic, as it requires the definition of the welfare dimensions to consider, the weight of each dimension, deprivation cutoffs for each dimension, aggregation across individuals of individual deprivation statuses and the estimation of multidimensional poverty lines. There are still differences among analysts, especially regarding the relevant dimensions and their relative importance. This has lead to an increasing supply of multidimensional well-being indicators, sometimes yielding different results (Battiston et al., 2009).

Tsui (2002) makes one of the first attempts to tackle the problem of multidimensional poverty. He clarifies the axiomatic basis for the design of multidimensional poverty measures and generalizes the class of subgroup consistent poverty indices introduced by Foster and Shorrocks (1991) to a multidimensional framework. Later, Bourguignon and Chakravarty (2003) also propose a multidimensional framework, which is formalized in terms of shortfalls from threshold levels of attributes themselves, and is determined independently of attribute distributions. Their paper examines various aggregation rules using different postulates for a measure of poverty, making a distinction between additive and non-additive poverty measures.

Atkinson (2003) adopts a social welfare function approach, based on the Bourguignon and Chakravarty methodology, and brings out the role played by the cardinalization assumptions (the degree of concavity of the social welfare function) and the weighting of different attributes. He distinguishes two different forms of aggregation. The first combines different elements of deprivation at the individual level, which are then summed over individuals first to form an aggregate index for the country. The second sums across individuals first, to form a total indicator for all individuals in one dimension, and then combines the total indicators for different attributes.

More recently, Alkire and Foster (2008) have proposed a new methodology for multidimensional poverty measurement consisting of an identification method that extends the traditional union and intersection approaches, and the Foster, Greer and Thorbecke (FTG) class of poverty measures, which satisfies several desirable properties including decomposability.

Their identification procedure employs two cutoff levels: one for each individual dimension to determine whether a person is deprived in that dimension and a second for the weighted aggregation of dimensions that identifies whether a person is multidimensionally poor. The identification method is particularly well suited for use with ordinal data. Individual deprivation levels are estimated using FGT poverty measures.

Several empirical applications of the multidimensional welfare measures summarized above exist. Alkire and Foster (2008) apply their methodology to data from Indonesia and the U.S. Bourguignon and Chakravarty (2003) apply their measures to evaluate the evolution of poverty in rural Brazil in the 1980s. Paes de Barros et al. (2006) introduce a scalar indicator to estimate the degree of multidimensional poverty of families using Brazilian household surveys. Krishnakumar and Ballon (2008) operationalize the capability approach using the latent variable methodology. They specify a structural equation model for Bolivia to account for the unobservable and multidimensional aspects that characterize human development.

López and Ortiz (2008) compare a monetary measurement of poverty with a multidimensional measurement that quantifies the probability of falling into poverty on the basis of several well-being indicators or variables using Mexican data. They include dimensions weakly correlated to household income to highlight the relevance of multidimensional poverty measures. Their dimensions include socio-demographic variables, exposure to violence and shocks, access to health and basic insurance, among others. Based on these comparisons they quantify the magnitude of the exclusion error of income-based measures (assuming that their multidimensional measure is the "true" poverty measure), finding large errors when considering higher income poverty lines.

In terms of relative multidimensional poverty, Poggi (2007) analyses the causes leading to social exclusion dynamics in Europe. He defines social exclusion as a person's deprivation in one or more functionings that include both economic and social features. Given that a functioning can be achieved at different levels at a point in time, and any choice about the threshold (below which an individual is counted as deprived) has some degree of arbitrariness, he fixes the threshold in each dimension as 50 percent of the functioning's mean distribution. Following Poggi's work, Conconi and Ham (2007) propose a method for the measurement of relative multidimensional poverty, extending the Foster Greer Thorbecke (FGT) measurements. They apply this measure to Argentinean cross-section surveys from 1998 to 2002.

Battiston et al. (2009) calculate multidimensional poverty measures for six Latin American countries (Argentina, Brazil, Chile, El Salvador, Mexico, and Uruguay). Their estimates are based on the extensions developed by Alkire and Foster (2008) and Bourguignon and Chakravarty (2003).[1] Their study incorporates the weighting of different dimensions derived from a participatory study on the voices of the poor performed in Mexico.[2] They observe large differences among countries and also within countries between urban and rural areas and conclude that increasing access to proper sanitation and improving education should be policy priorities, as they are the largest contributors to multidimensional poverty.

In terms of targeting, there are many studies evaluating different targeting techniques. The existing literature, however, largely focuses on the description of individual programs (Coady and Parker, 2004) and comparative analysis tends to cover a single region (Grosh, 1994; Braithwaite et al., 2000), method or intervention (Kakwani and Son, 2006). In addition, most studies presented use cross-section information to compare different targeting mechanism and there is no literature to the best of our knowledge that compares the dynamic consistency of different targeting mechanisms.

One of the most complete works in term of targeting methods is that of Coady, Grosh and Hoddinott (2002). Their paper assesses the efficacy of targeting interventions in developing countries using a comprehensive database of 111 interventions in 47 countries. Their findings indicate that programs using means testing, geographic targeting and self-selection based on work requirements are associated with an increased shared of benefits going to the bottom two quintiles. On the contrary, proxy means testing, community-based selection of individuals and demographic targeting show good results on average but with considerable variation. Their conclusions point out that methods that rely on static indicators of living standards (such as proxy means tests) are likely to perform less well than those that rely on self-selection when there is a considerable movement of households in and out of poverty.

Pérez, Issamu and Veras (2008) analyze alternative targeting methods for Paraguay's CCT program Tekoporã. They are particularly interested in comparing a multidimensional

[1] Battiston et al. (2009) incorporate six dimensions into their multidimensional poverty measure. The dimensions are: i) income; ii) children attending school; iii) education of the household head; iv) sanitation; v) water; and vi) shelter.
[2] The study was carried out by the Mexican Secretaría de Desarrollo Social (Székely, 2006). In this study, poor individuals were asked about their valuation of different dimensions. These results were used to produce a ranking of the six indicators used by Battiston et al. (2009).

quality-of-life index with a proxy means test for income. They focus on the efficiency and efficacy of these approaches by examining primarily the trade-off between leakage and coverage. They conclude that a multidimensional measure is better able to identify the extremely poor. This might be due to the fact that the parameters of the proxy means test are usually estimated using the entire income distribution of a population and may not accurately fit the lower tail of the distribution.

Recently, Coady and Parker (2009) have analyzed the targeting performance of the Oportunidades program in urban areas. Considering the different targeting stages implemented by the program, they evaluate the performance of two complementary methods: an initial self-selection process by households who acquire knowledge of the program, and an administrative targeting process based on a means test approach. They evaluate the performance in terms of the effectiveness of the program at channeling a high proportion of benefits to lower welfare households. Their findings highlight the importance of proxy means targeting in the context of universal knowledge, and call for further improvements in the proxy means algorithm to decrease under-coverage and leakage. Their analysis uses only cross-section data, however, and therefore does not discuss the increase in leakage and under-coverage that emerges as a result of the low dynamic consistency of some targeting measures.

3. Dynamic Targeting Performance of the Oportunidades Conditional Cash Transfer Program in Mexico

To motivate our discussion on the need for looking for alternative measures of welfare to improve the dynamic consistency of targeting methods, we present a brief example using data from the Oportunidades program, which is the one of the oldest and largest Conditional Cash Transfer (CCT) programs implemented in Latin American.[3] We show that, even though the program is relatively well targeted to the poorest population, there seems to be some problems in terms of the dynamic consistency of its targeting method.

Oportunidades (previously known as Progresa) was first implemented in rural areas in 1997 and was expanded in 2002 to urban areas of Mexico. The program aims at breaking the vicious cycle of poverty by investing in children’s human capital, particularly through

[3] Other programs similar to, and inspired by, the Oportunidades program have been implemented in Brazil (Bolsa Escola), Colombia (Familias en Acción), Honduras (Programa de Asignación Familiar), Jamaica (Program of Advancement through Health and Education), and Nicaragua (Red de Protección Social)

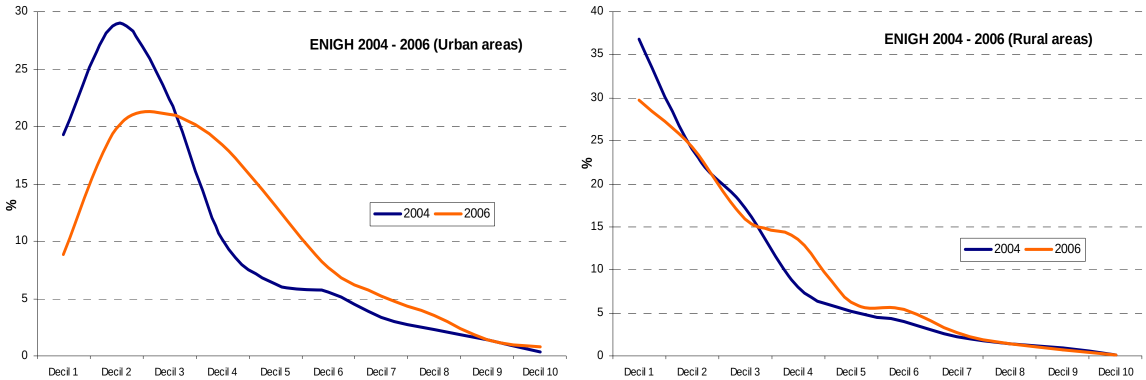
investment in health, education and nutrition. The program transfers cash to poor households under the condition that they engage in behaviors that are consistent with the accumulation of human capital. A vast amount of studies have demonstrated that Oportunidades has had important impacts in children's schooling, health and nutrition. In addition, some studies concluded that the current targeting performance of Oportunidades compares very favorably to that of other similar social safety-net programs in developing countries (Coady, Grosh and Hoddinott, 2004).

Oportunidades uses a combination of targeting methods to identify eligible households. Geographic targeting methods are used to identify the poorest localities for participation in the program. Once localities have been identified, a proxy means test is used to identify poor households within each locality.[4] In rural areas a census of socio-economic characteristics was performed in each locality to identify poor households by a proxy means test. In urban areas, given the high costs of performing a census of this kind, a strong element of self-selection is introduced. This implies that individuals must to some extent select themselves to be beneficiaries (Coady and Parker, 2004 and 2009).

Using data from the Mexican Household Survey (ENIGH) of 2004 and 2006 we calculate the percentage of households receiving the benefits of Oportunidades in each income decile. As was mentioned before, the program proves to be relatively well targeted to the poorest population in the country as, on average, 70 percent of households receiving Oportunidades benefits belong to the bottom three deciles of the income distribution. The self-selection component in urban areas seems relevant, as the participation of households in the first income decile is lower than that in the next three deciles. This could be due to financial and opportunity costs of participation, and lack of information, among other factors.

Even though the program has been relatively well targeted, there seems to be room for improvement in the dynamic consistency of the targeting method. Despite the fact that the ENIGH information presented in the following graphs does not trace the same households over time, it serves to show that there is a shift in the distribution of beneficiaries from lower income deciles to higher income deciles between 2004 and 2006. This is particularly important in urban areas, where income is more volatile and living conditions have notably improved in recent years. While 50 percent of households receiving benefits belonged to the bottom two income deciles of the distribution in 2004, this percentage decreases to 30 percent in 2006 in urban areas of Mexico.[5]

Figure 1. Distribution of Households Receiving Oportunidades Benefits by Income Deciles, Urban and Rural Areas



Source: Authors calculations based on ENIGH 2004 and ENIGH 2006

4. Methodology

4.1 Dynamic Targeting Efficiency

We are interested in the dynamic efficiency of targeting algorithms. If all households in a country (or the geographical area in which a targeted social program operates) can be ranked by a welfare measure or indicator y_i (this indicator can be income, another indicator of social well-being, such as years of schooling or an index of welfare derived from a set of social indicators) and we defined a cutoff z, households will be eligible for program intervention if $y_i < z$.

To assess the dynamic targeting efficiency of our two methodologies (multidimensional relative targeting and income-based targeting, both means and proxy means) we will assume that households are targeted at time t and then we will assess the dynamic consistency of the targeting decision both at time t and $t+1$, given by $y_{i,t} < z$ and $y_{i,t+1} < z$.

[4] Given that income easily verifiable, eligibility for "proxy means" programs is based on easy to collect household or individual level indicators, which are thought to be correlated with household income and, in this sense, are a "proxy" for income.

[5] In rural areas this rate was 60 percent in 2004 and 55 percent in 2006.

This exercise is relevant for programs that target beneficiaries based on cross-sectional data and do not have the flexibility to re-target and update beneficiary rosters frequently, either due to the nature of the program (e.g., programs that are aimed at the “structurally poor” and accompany beneficiaries for long periods of time, such as Conditional Cash Transfer Programs) or due to data limitations (e.g., it is too costly to recertify beneficiaries). In the next subsections we explain each targeting methodology.

4.2 Multidimensional Poverty Measurement and Targeting

The multidimensional targeting methodology that we use is an extension of Alkire and Foster (2008) dual cutoff multidimensional poverty measurement. The methodology requires first a definition of the dimensions or indicators of interest to target households or individual beneficiaries (y_d); second, a definition of cutoff points to identify households or individuals with development deprivation in each dimension (z_d); third, a definition of weights (w_d), a weighted measure of deprivation in each dimension (g_d^{α}) and an algorithm to aggregate across dimensions (G^{α}); and finally, a definition of the aggregate cutoff to identify eligible households and individuals using the multidimensional criteria (z).

This paper extends the Alkire and Foster methodology through a relative poverty approach that facilitates comparisons with other targeting methods. To derive the multidimensional relative targeting algorithm we first define a relative poverty line, η, $0 \leq \eta \leq 1$. A poverty line η implies that $\eta \times 100$ percentage of the population is defined as poor and is going to be the share of population targeted by the program. Once the set of relevant dimensions for the multidimensional algorithm is defined ($d = 1,..., D$), the vector of deprivation cutoffs and the dimensional weights will be derived from the relative poverty line and the relative position of the household in the distribution of the dimension. Each of these functions needs to be defined specifically for continuous dimensions, discrete dimensions and dichotomous dimensions.

4.2.1 Continuous Dimensions

In the case of continuous dimensions $y_{i,d}$ such as income or consumption the cutoff point for the continuous dimension and the relative poverty line ($z_d(\eta)$) is defined solving the identity:

$\eta = \Pr[y_d < z_d(\eta)] = \int_0^{z_d(\eta)} f(y_d)dy_d$, where $f(y_d)$ is the p.d.f. of the continuous variable y_d, which can be estimated non-parametrically through a kernel procedure. For continuous variables we also set $w_{i,d} = \frac{1}{F(y_{i,d})}$, where $F(\bullet)$ is the c.d.f. y_d, i.e., the weight of the deprivation for household i decreases if it is better ranked in the distribution of that dimension. In this case $g_{i,d}^{\alpha} = w_{i,d}\left(\frac{z_d - y_{i,d}}{z_d(\eta)}\right)^{\alpha}$ for $y_{i,d} < z_d(\eta)$, and $g_{i,d}^{\alpha} = 0$ otherwise. For comparability with the other targeting schemes, we will also estimate $g_{i,d}^{\alpha}$ using expected income from a log linear income regression model $y = e^{X\hat{\beta}}$, where $\hat{\beta}$ is estimated by OLS from the model $\ln y = X\beta + \varepsilon$.

4.2.2 Discrete Dimensions

In the case of discrete dimensions such as years of schooling, the cutoff is also defined by solving the inequality: $\Pr(y_d < z_d(\eta)) \leq \eta$.[6] In this case: $w_{i,d} = \frac{1}{\Pr(y_d \leq y_{i,d})}$ and $g_{i,d}^{\alpha} = w_{i,d}\left(\frac{z_d(\eta) - y_{i,d}}{z_d(\eta)}\right)^{\alpha}$ for $y_{i,d} < z_d(\eta)$, and $g_{i,d}^{\alpha} = 0$ otherwise.

4.2.3 Dichotomous Dimensions

In the case of discrete dichotomous dimensions such as access to basic social services, the cutoff point is always $z(\eta) = 1$, i.e. being deprived in the dichotomous dimension ($y_{i,d} = 0$). In this case we set $w_{i,d} = \frac{1}{1-\bar{y}_d}$ and $g_{i,d}^{\alpha} = w_{i,d}$ for $y_{i,d} = 0$, and $g_{i,d}^{\alpha} = 0$ otherwise.

4.2.4 Identification of the Relative Poor (Target Population)

Finally, to identify the relative poor (or in our case the population eligible for the program) we focus on the case in which $\alpha = 0$, and we calculate the weighted relative multidimensional deprivation score of each household $G_i^{\alpha} = \sum_d g_{i,d}^{\alpha}$ we estimate the relative multidimensional cutoff $z(\eta)$ to solve $\eta = 1 - \int_0^{z(\eta)} f(G^0)dG^o$ where $f(G^0)$ is the p.d.f. of G^0, that, as with

[6] For $\Pr(\min(y_d)) > \eta$, $z_d(\eta) = \min(y_d)$

continuous dimension, can be estimated through a kernel procedure. A household will be considered eligible for program benefits in this case if $G_i^0 > z(\eta)$. In dynamic terms targeting is dynamically consistent for household *i* if $G_{i,t}^0 > z_t(\eta)$ and $G_{i,t+1}^0 > z_{t+1}(\eta)$.

We estimate dynamic targeting consistency for the multidimensional algorithm using both observed income and predicted income.

4.3 Means Test Targeting

For means test targeting we first derive a relative poverty line based on the percentage of population that we want to target in the program. This line $z(\eta)$ can be found by solving: $\eta = \int_0^{z(\eta)} f(y)dy$. In this case dynamic targeting efficiency for household i is given by: $y_{i,t} < z_{y,t}(\eta)$ and $y_{i,t+1} < z_{y,t+1}(\eta)$.

4.4 Proxy Means Test Targeting

We estimate a Log Linear Income Algorithm taking into account that only certain household characteristics are observed and they are use to predict household income. Existing data sources such as household surveys or census are used to create targeting algorithms that predict income based on observable and easily verifiable household characteristics. Income is predicted using standard OLS regression techniques:

$$\ln y = X\beta + \varepsilon$$

Cutoff points are then derived as a function of the percentage of households (η) that the program wants to target. Thus the cutoff point $z(\eta)$ is derived to solve $\eta = \int_0^{z(\eta)} f(X\hat{\beta})d(X\hat{\beta})$. A household will be considered eligible for program benefits in this case if $X_i\hat{\beta} < z(\eta)$. Dynamic targeting consistency for household i is given by: $X_{i,t}\hat{\beta} < z_t(\eta)$, $y_{i,t} < z_{y,t}(\eta)$ and $y_{i,t+1} < z_{y,t+1}(\eta)$.

5. Data and Descriptive Statistics of the Sample

We use the Mexican Family Life Survey (MxFLS),[7] a multi-thematic and longitudinal database that collects a wide range of information on socioeconomic indicators, demographics and health indicators on the Mexican population. The MxFLS is the first longitudinal Mexican survey with national representation. The survey follows household members who were surveyed in the original baseline, regardless of their decision to reside in Mexico or in the United States. The multidimensional and dynamic characteristics of the MxFLS facilitate the study of different demographic and socioeconomic phenomena present in welfare dynamics.

The baseline sampling was undertaken in 2002 and was designed by the National Institute of Geography Statistics and Information (INEGI). The baseline is a probabilistic, stratified, multi-staged, and independent sample composed of private households in Mexico. Primary sampling units were selected under criterions of national, urban-rural and regional representations. The second wave was conducted during 2005-2006 with a 90 percent re-contacting rate at household levels.

Given that we present our results disaggregating them by geographical area (urban and rural), we exclude from our sample all migrant households. In this way we are excluding the possibility that changes observed in the deprivation status from one period to the other might be related to migration decisions. We also exclude observations with missing values in any of the variables we use to construct our multidimensional welfare measure. Our final sample is composed of 4,207 households (approximately 19,180 individuals), 45 percent living in urban areas and 55 percent in rural areas.

Table 1 presents some descriptive statistics for the sample. As is expected, poverty levels (measured by income) are higher in rural areas. Rural areas are worse off in other several household characteristics as well. The education of the head of the household in rural areas is, on average, two years less than in urban areas. Access to basic services, such as having a toilet or running water in the house, is also more restricted in rural areas. In addition, more children in rural areas are malnourished and work to support their household economies. On the other hand, exposure to violence seems to be higher in urban areas. On average, more than 60 percent of the urban population lives in areas where there are robberies, street gangs, armed groups, or alcoholic and drug-addicted persons, among other concerns. In terms of the exposure to shocks, such as unemployment, the death of a member of the household, sickness, and natural disasters, people are more vulnerable to suffer these shocks in urban areas.

Looking at changes in the variables between the two periods of study, there has been a decrease in food-based poverty levels, particularly in rural areas, and also an increase in poverty levels considering the asset-based poverty line,[8] mainly in urban areas. This finding could be indicating that households in the lower part of the distribution are improving their welfare status more than households in the upper part of the income distribution. Also noteworthy is the decrease in the labor market participation rates of head of households between 2002 and 2005. This is particularly important in urban areas, and it could lead to an increase in transient poverty levels. Finally, it is important to highlight the decrease in exposure to violence from one period to the other in both urban and rural areas.

Table 1. Descriptive Statistics of the Sample

Variables	2002			2005		
	National	Urban	Rural	National	Urban	Rural
Sample size	4320	1974	2346	4320	1974	2346
%	100	46	54	100	46	54
Food-based poverty	41.85	31.41	50.64	40.93	31.91	48.51
Human capacity poor	49.54	39.82	57.72	48.43	40.93	54.73
Asset-based poverty	69.19	63.02	74.38	70.74	66.51	74.3
Age head of the household	46.23	44.72	47.5	49.06	47.67	50.23
Number of members in the household	4.55	4.3	4.75	4.55	4.3	4.75
Dependency rate	0.17	0.16	0.18	0.13	0.1	0.14
Per capita income	1130.89	1599.71	736.41	1281.33	1750.94	886.18
Years of education head of the household	5.48	6.79	4.37	5.93	7.28	4.79
Maximum schooling gap in the household	0.67	0.56	0.76	0.7	0.59	0.79
Head of household works	73.63	73.3	73.91	69.63	68.79	70.33
Children under 15 years old working	2.22	1.77	2.6	1.9	1.42	2.3
Undernutrition children under 10 years old	1.64	1.47	1.79	0.74	0.81	0.68
Undernutrition members above 15 years old	11.97	10.08	13.55	9.51	7.6	11.13
Has a kitchen in the household	91.2	91.24	91.17	92.87	94.33	91.65
Has a bathroom in the household	69.54	92.6	50.13	75.9	94.88	59.93
Has water in the household	78.27	87.23	70.76	74.84	86.07	65.39
Experiences violence in the neighborhood	57.55	65.2	51.11	50.62	57.55	44.8
Experienced a shock in the last 5 years	25.86	27.51	24.47	22.85	25.13	20.93

Source: Authors' calculations based on MxFLS 2002 and 2005.

[7] In Spanish ENNVIH (Encuesta Nacional sobre los Niveles de Vida de los Hogares Mexicanos).

[8] Mexico has three poverty lines: (a) The food-based poverty line, which is defined as the cut-off that reflects the minimum level of income deemed necessary to buy a basic basket of food; (b) the human capacity poverty line, which represents the minimum level of income deemed necessary to be able to afford a basket of food and basic health and education needs; and (c) the asset-based poverty line, which adds clothing needs, house infrastructure needs and transport needs to the previously defined poverty lines.

6. Results

6.1 Summary of Results

Based on the existing literature on multidimensional poverty measures and considering the rich amount of information provided by the MxFLS, we identify eight dimensions for constructing our multidimensional welfare indicator. Dimensions included in our analysis (presented in Table 2) try to reflect several important aspects that determine a person's well-being. They include income, education, household structure, health, labor status, access to basic services, and exposure to violence and shocks. Within each dimension we select a series of indicators to determine if a household can be considered deprived in each dimension. We include a total of 13 variables or indicators for our eight dimensions.

The selection of dimensions and variables in the construction of a multidimensional welfare measure is a controversial one. Although scholars and practitioners in the field agree that poverty is best understood as a multidimensional phenomenon, there are still differences regarding the relevant dimensions and their relative importance (López and Ortiz, 2009; Battiston et al., 2009). In the case of multidimensional targeting the choice of dimensions and variables should depend on the objectives of each program, the availability of information and its verifiability. Therefore, the multidimensional welfare measure constructed in this paper can be considered only a particular empirical application to show how targeting based on multidimensional indicators may be dynamically more consistent than targeting based on one-dimension measurements.

Even though our dimensions try to reflect achievements rather than means (following the capability approach proposed by Sen, 1992), we include income as our first dimension. We believe household per capita income can provide relevant information about the evolution of household welfare. In addition, it has been long argued that income dimensions as well as basic needs indicators are relevant when assessing well-being and that there can be significant targeting errors when only one of them is used (Battiston et al., 2009). In this paper we construct a measure in which both income and other indicators are included. Throughout our results, we will include and exclude the income variable from our multidimensional welfare indicator as a way of performing a sensitivity analysis.

Table 2. Dimensions and Variables Used to Construct the Multidimensional Welfare Measure

Dimensions	Variables
Income	Monthly per capita income
Education	Head of the household with less than primary complete
	Schooling gap greater than 2 years in any of the children between 6-18 years old attending school
Household structure	Dependency rate (Members older than 65 and below 5 years old / Total number of members in the household)
Health	Z_score of children below 10 years old
	A member above 15 years old in the household considers he/she has a bad nutritional status
Work	Head of the household is not working
	Having children below 15 years old in the household that work
Services	Not having running water inside the household
	Not having a flush toilet in the household
	Not having a kitchen as a separate room in the house
Violence	Street violence in the area where the household lives
Shocks	Household has experienced a shock in the last 5 years (death, illness, unemployment, natural disasters)

Source: MxFLS.

Table 3 and Table 4 present correlation matrices for different poverty and welfare measures. We show our multidimensional welfare indicator, both including and excluding the income dimension. We also calculate different relative welfare measures considering two cutoff points. In urban areas we consider the bottom 10 percent and 20 percent of the population, and in rural areas the bottom 20 percent and 40 percent. As expected, one-dimension poverty measures, based solely on income, are highly correlated. As we decrease the cut-off point of our relative measures, the correlation with the traditional poverty measurements (food-based, human capacity and asset-based) decreases. When we exclude the income dimension from our multidimensional measure there is an important decrease in its correlation with other poverty measures. This suggests that we are including dimensions that are not highly correlated with income and, in some cases, this could justify the need for a multidimensional approach.

The Matrices presented in Table 3 and Table 4 show correlation coefficients not only within a given year but also between two years; this allows extracting some conclusions about the persistence of poverty and deprivation within each measure. From looking at the correlation coefficients, we can see that multidimensional welfare measures, particularly those that exclude income, tend to be more persistent in time, and persistency is higher in rural areas. The higher persistency of multidimensional measures is strongly related to the variables included in the construction of such indicators. As is well known, income can be a very unpredictable variable, which leads to important movements of households into and out of poverty from one period to another.

Table 5 and Table 6 present the correlation coefficients of variables included in our multidimensional welfare measure. The correlation coefficients highlight the importance of education as one of the main determinants of household income. In rural areas access to basic services, such as toilets, is also highly correlated with income as well as the education of the head of the household. The education of the head also seems important in determining his or her working status, both in rural and urban areas. More educated heads of household display higher rates of participation in the labor market. As expected, higher dependency rates are associated with lower levels of income, lower levels education among members in the household and higher under-nutrition levels among children.

It is noteworthy to look at the interaction between the violence and income variables. In urban areas, exposure to violence increases as household income decreases. In rural areas, violence is positively correlated with income. An important debate concerns the extent to which crime and violence are causally rooted in poverty. While poverty has long been considered the major determinant of violence, more recently it has been demonstrated that inequality is more influential than poverty, with income inequalities being generally more marked in urban than in rural areas (Moser, 2004). The positive correlation observed in rural areas could be related to the fact that households with higher income levels generally live in urban locales with more population, where street violence tends to be greater.

One important aspect to look at is the correlation between variables included in our multidimensional welfare measure and household income. As López and Ortiz (2009) mention, the relevance of a multidimensional poverty measure comes from the fact that, although many dimensions and variables are highly correlated with income, there are many others that go beyond the economic capacity of a household and, therefore, are capturing other important aspects of deprivation. As our results show, some of the variables included are not correlated with income, such as exposure to shocks and violence.

If we observe the correlation coefficients of each variable between the two periods of study, we can obtain some insights in terms of their persistency or volatility. As expected, variables related to education, house infrastructure and demographic characteristics remain more stable across time. In contrast, variables such as violence, labor market participation and exposure to shocks are less correlated between the years of study. Changes in labor market participation can be strongly related to the economic conditions of the areas where the household is living. Particularly noteworthy is that, even though labor among children is generally low, it seems to be a very volatile variable. This suggests that children may be considered a reserve labor force able to enter the labor markets when the household experiences a shock.

Table 3. Correlation Coefficients among Different Poverty and Welfare Measures 2002–2005 (Urban Areas)

	Poverty measures	Year 2002									Year 2005								
		Food-based poverty	Human capacity poverty	Asset-based poverty	Relative income poverty (10%)	Relative income poverty (20%)	Multidim. welfare (10%)	Multidim. welfare (20%)	Multidim. welfare no income (10%)	Multidim. welfare no income (20%)	Food-based poverty	Human capacity poverty	Asset-based poverty	Relative income poverty (10%)	Relative income poverty (20%)	Multidim. welfare (10%)	Multidim. welfare (20%)	Multidim. welfare no income (10%)	Multidim. welfare no income (20%)
Year 2002	Food-based poverty	1.00																	
	Human capacity poverty	0.83	1.00																
	Asset-based poverty	0.52	0.63	1.00															
	Relative income poverty (10%)	0.50	0.42	0.26	1.00														
	Relative income poverty (20%)	0.74	0.62	0.39	0.67	1.00													
	Multidim. welfare (10%)	0.26	0.21	0.14	0.52	0.34	1.00												
	Multidim. welfare (20%)	0.41	0.34	0.22	0.66	0.52	0.66	1.00											
	Multidim. welfare no income (10%)	0.05	0.05	0.04	0.04	0.03	0.50	0.65	1.00										
	Multidim. welfare no income (20%)	0.06	0.06	0.07	0.04	0.05	0.37	0.52	0.66	1.00									
Year 2005	Food-based poverty	0.22	0.24	0.22	0.11	0.20	0.07	0.13	0.05	0.08	1.00								
	Human capacity poverty	0.24	0.26	0.26	0.13	0.22	0.08	0.15	0.07	0.08	0.82	1.00							
	Asset-based poverty	0.25	0.29	0.35	0.12	0.18	0.05	0.13	0.05	0.08	0.48	0.59	1.00						
	Relative income poverty (10%)	0.06	0.08	0.10	0.07	0.09	0.06	0.07	0.03	0.07	0.49	0.40	0.24	1.00					
	Relative income poverty (20%)	0.13	0.15	0.15	0.09	0.15	0.04	0.07	0.03	0.05	0.73	0.60	0.35	0.67	1.00				
	Multidim. welfare (10%)	0.01	0.02	0.04	0.00	0.03	0.28	0.23	0.33	0.29	0.27	0.22	0.10	0.54	0.34	1.00			
	Multidim. welfare (20%)	0.06	0.06	0.07	0.04	0.09	0.25	0.30	0.38	0.36	0.41	0.33	0.17	0.68	0.53	0.66	1.00		
	Multidim. welfare no income (10%)	0.01	0.00	-0.01	0.00	0.03	0.36	0.38	0.54	0.47	0.06	0.04	0.00	0.04	0.04	0.50	0.59	1.00	
	Multidim. welfare no income (20%)	0.01	0.00	0.00	0.00	0.03	0.26	0.34	0.48	0.48	0.08	0.06	0.02	0.08	0.05	0.38	0.51	0.65	1.00

Source: Authors' calculations based on MxFSL.

Table 4. Correlation Coefficients among Different Poverty and Welfare Measures 2002–2005 (Rural Areas)

	Poverty measures	Year 2002									Year 2005								
		Food-based poverty	Human capacity poverty	Asset-based poverty	Relative income poverty (20%)	Relative income poverty (40%)	Multidim. welfare (20%)	Multidim. welfare (40%)	Multidim. welfare no income (20%)	Multidim. welfare no income (40%)	Food-based poverty	Human capacity poverty	Asset-based poverty	Relative income poverty (20%)	Relative income poverty (40%)	Multidim. welfare (20%)	Multidim. welfare (40%)	Multidim. welfare no income (20%)	Multidim. welfare no income (40%)
Year 2002	Food-based poverty	1.00																	
	Human capacity poverty	0.87	1.00																
	Asset-based poverty	0.60	0.69	1.00															
	Relative income poverty (20%)	0.49	0.42	0.29	1.00														
	Relative income poverty (40%)	0.81	0.70	0.48	0.61	1.00													
	Multidim. welfare (20%)	0.26	0.23	0.15	0.55	0.33	1.00												
	Multidim. welfare (40%)	0.42	0.37	0.25	0.60	0.53	0.61	1.00											
	Multidim. welfare no income (20%)	0.02	0.02	0.02	0.07	0.04	0.52	0.56	1.00										
	Multidim. welfare no income (40%)	0.05	0.06	0.07	0.07	0.05	0.34	0.52	0.61	1.00									
Year 2005	Food-based poverty	0.33	0.34	0.31	0.21	0.30	0.13	0.20	0.06	0.09	1.00								
	Human capacity poverty	0.33	0.35	0.33	0.20	0.29	0.13	0.20	0.07	0.09	0.88	1.00							
	Asset-based poverty	0.31	0.33	0.38	0.16	0.26	0.11	0.18	0.07	0.11	0.57	0.65	1.00						
	Relative income poverty (20%)	0.20	0.20	0.17	0.21	0.23	0.15	0.19	0.07	0.07	0.51	0.45	0.29	1.00					
	Relative income poverty (40%)	0.30	0.30	0.26	0.21	0.29	0.13	0.19	0.05	0.07	0.84	0.74	0.48	0.61	1.00				
	Multidim. welfare (20%)	0.10	0.09	0.06	0.14	0.12	0.34	0.31	0.37	0.27	0.28	0.24	0.16	0.55	0.33	1.00			
	Multidim. welfare (40%)	0.20	0.20	0.15	0.19	0.21	0.30	0.35	0.33	0.32	0.52	0.46	0.30	0.62	0.60	0.61	1.00		
	Multidim. welfare no income (20%)	-0.02	0.00	-0.03	0.04	0.01	0.35	0.34	0.51	0.45	0.06	0.05	0.05	0.11	0.06	0.55	0.54	1.00	
	Multidim. welfare no income (40%)	0.09	0.10	0.09	0.09	0.09	0.29	0.39	0.46	0.52	0.14	0.14	0.14	0.13	0.13	0.40	0.51	0.61	1.00

Source: Authors' calculations based on MxFSL.

Table 5. Correlation Coefficients among Variables of the Multidimensional Welfare Measure (Urban Areas)

Variables		Year 2002													Year 2005												
		Income	Head education	Max. Edu. Gap	Dependency rate	Children work	Head works	Children undernut.	Adults undernut.	Water	Toilet	Kitchen	Violence	Shocks	Income	Head education	Max. Edu. Gap	Dependency rate	Children work	Head works	Children undernut.	Adults undernut.	Water	Toilet	Kitchen	Violence	Shocks
Year 2002	Income	1.00																									
Year 2002	Head education	0.25	1.00																								
Year 2002	Max. Edu. Gap	-0.16	-0.07	1.00																							
Year 2002	Dependency rate	-0.11	-0.10	-0.17	1.00																						
Year 2002	Children work	-0.04	-0.04	0.12	-0.06	1.00																					
Year 2002	Head works	0.03	0.12	0.05	-0.09	0.02	1.00																				
Year 2002	Children undernut.	-0.03	0.00	0.00	0.00	0.02	0.04	1.00																			
Year 2002	Adults undernut.	-0.05	-0.11	0.08	-0.02	0.05	-0.05	0.00	1.00																		
Year 2002	Water	0.07	0.06	0.02	-0.02	-0.01	-0.02	-0.03	0.04	1.00																	
Year 2002	Toilet	0.08	0.10	-0.02	-0.08	-0.01	-0.05	-0.05	0.00	0.23	1.00																
Year 2002	Kitchen	0.09	0.08	0.02	-0.10	0.00	-0.04	0.01	-0.04	0.12	0.12	1.00															
Year 2002	Violence	-0.02	-0.03	0.04	-0.04	0.01	0.04	0.04	0.03	0.00	-0.02	-0.02	1.00														
Year 2002	Shocks	-0.02	-0.04	0.03	-0.01	0.03	-0.07	0.05	0.02	-0.03	-0.03	0.03	0.10	1.00													
Year 2005	Income	0.48	0.27	-0.14	-0.11	-0.04	0.04	-0.03	-0.07	0.08	0.09	0.06	-0.05	-0.05	1.00												
Year 2005	Head education	0.23	0.95	-0.06	-0.10	-0.04	0.13	0.00	-0.11	0.06	0.11	0.08	-0.03	-0.04	0.27	1.00											
Year 2005	Max. Edu. Gap	-0.15	-0.07	0.69	-0.11	0.12	0.04	0.04	0.07	-0.03	-0.05	0.01	0.04	0.03	-0.14	-0.07	1.00										
Year 2005	Dependency rate	-0.02	-0.20	-0.16	0.71	-0.04	-0.15	-0.03	0.01	0.01	-0.02	-0.04	-0.06	0.00	-0.03	-0.21	-0.14	1.00									
Year 2005	Children work	-0.05	-0.04	0.08	-0.04	0.02	0.01	-0.02	-0.01	-0.02	-0.05	-0.01	0.00	0.00	-0.05	-0.04	0.09	-0.05	1.00								
Year 2005	Head works	0.05	0.16	0.00	-0.08	0.00	0.34	0.04	-0.05	0.00	-0.02	-0.03	0.04	-0.01	0.08	0.14	0.01	-0.16	0.00	1.00							
Year 2005	Children undernut.	-0.04	-0.02	-0.03	0.04	-0.01	0.02	0.46	0.01	-0.02	-0.04	0.01	0.03	0.05	-0.02	-0.02	0.01	0.00	-0.01	0.00	1.00						
Year 2005	Adults undernut.	-0.07	-0.11	0.05	0.00	0.05	-0.01	0.01	0.11	-0.02	-0.01	-0.03	0.04	0.05	-0.04	-0.11	0.08	0.04	0.01	0.01	0.00	1.00					
Year 2005	Water	0.04	0.07	-0.01	0.01	0.01	-0.04	-0.01	0.00	0.18	0.14	0.12	0.03	-0.01	0.07	0.07	0.01	0.02	-0.03	-0.01	0.00	0.01	1.00				
Year 2005	Toilet	0.06	0.10	-0.03	-0.05	-0.02	-0.02	-0.03	0.00	0.20	0.51	0.14	0.03	0.00	0.08	0.12	-0.04	0.00	0.01	0.00	0.00	-0.02	0.18	1.00			
Year 2005	Kitchen	0.09	0.08	-0.05	-0.03	0.02	-0.06	0.01	0.02	0.09	0.10	0.34	-0.02	0.04	0.08	0.09	-0.08	-0.02	-0.08	-0.04	0.02	-0.04	0.16	0.12	1.00		
Year 2005	Violence	-0.07	-0.04	0.06	-0.04	0.01	0.02	0.01	0.05	-0.01	-0.04	0.00	0.22	0.05	-0.07	-0.04	0.06	-0.07	0.02	0.04	0.01	0.02	0.04	-0.04	-0.01	1.00	
Year 2005	Shocks	-0.01	-0.02	0.01	-0.02	0.03	-0.03	0.00	0.08	0.01	0.04	0.00	0.02	0.09	-0.03	-0.02	0.03	0.01	0.05	-0.06	-0.01	0.09	0.00	0.03	-0.05	0.10	1.00

Source: Authors' calculations based on MxFSL.

Table 6. Correlation Coefficients among Variables of the Multidimensional Welfare Measure (Rural Areas)

Variables		Year 2002													Year 2005												
		Income	Head education	Max. Edu. Gap	Dependency rate	Children work	Head works	Children undernut.	Adults undernut.	Water	Toilet	Kitchen	Violence	Shocks	Income	Head education	Max. Edu. Gap	Dependency rate	Children work	Head works	Children undernut.	Adults undernut.	Water	Toilet	Kitchen	Violence	Shocks
Year 2002	Income	1																									
Year 2002	Head education	0.2243	1																								
Year 2002	Max. Edu. Gap	-0.1711	-0.0786	1																							
Year 2002	Dependency rate	-0.044	-0.0987	-0.1977	1																						
Year 2002	Children work	-0.0134	-0.0305	0.1007	-0.059	1																					
Year 2002	Head works	0.1142	0.1187	0.0176	-0.1126	0.0206	1																				
Year 2002	Children undernut.	-0.0528	0.0059	0.0215	0.004	0.0186	0.0097	1																			
Year 2002	Adults undernut.	-0.059	-0.1236	-0.0051	0.0422	0.0059	-0.0302	0.0332	1																		
Year 2002	Water	0.0869	0.0891	-0.0719	0.0164	-0.0062	-0.0575	-0.0356	-0.0748	1																	
Year 2002	Toilet	0.2235	0.2209	-0.1235	-0.0632	-0.0193	-0.0008	-0.0234	-0.0877	0.2295	1																
Year 2002	Kitchen	0.0404	0.0439	0.0089	-0.0269	-0.0064	-0.0113	-0.0049	0.0094	0.0547	0.0935	1															
Year 2002	Violence	0.0124	0.0525	-0.0204	-0.0166	0.0477	0.0174	0.0463	0.0547	0.0245	0.0598	-0.0114	1														
Year 2002	Shocks	0.0144	0.0224	0.0434	-0.0448	0.0391	-0.046	0.0157	0.0348	-0.0342	0.011	-0.0159	0.1377	1													
Year 2005	Income	0.421	0.2549	-0.1323	-0.1185	-0.0331	0.0692	-0.0345	-0.0701	0.0717	0.1848	0.0156	0.0046	0.0038	1												
Year 2005	Head education	0.217	0.9514	-0.0844	-0.0865	-0.031	0.1228	0.0102	-0.1219	0.0958	0.2322	0.0402	0.0617	0.0178	0.2629	1											
Year 2005	Max. Edu. Gap	-0.1555	-0.086	0.7575	-0.1645	0.1141	0.0215	0.0244	0.0115	-0.0701	-0.0887	0.0168	-0.0152	0.0246	-0.135	-0.0893	1										
Year 2005	Dependency rate	0.0232	-0.2242	-0.2316	0.7173	-0.0548	-0.1344	-0.0329	0.0833	0.0182	-0.0441	0.0199	-0.0456	-0.0257	-0.0744	-0.2172	-0.2152	1									
Year 2005	Children work	-0.0545	-0.0429	0.1137	-0.0426	0.0294	0.0138	0.0015	0.0253	0.002	-0.0062	0.016	0.0082	-0.0043	-0.0467	-0.0422	0.0817	-0.0423	1								
Year 2005	Head works	0.0318	0.1594	0.0216	-0.1467	0.0166	0.3432	-0.0004	-0.0272	-0.024	-0.0188	-0.0248	-0.0015	-0.0493	0.0674	0.1588	0.0011	-0.1777	0.0139	1							
Year 2005	Children undernut.	-0.0245	0.0073	0.0044	0.0249	0.0187	0.0243	0.4631	0.0434	-0.0148	-0.0107	-0.0297	-0.0019	0.0503	-0.0239	0.0083	0.0064	-0.0166	0.0224	0.0076	1						
Year 2005	Adults undernut.	-0.0546	-0.1092	0.0321	0.0566	0.0096	-0.0169	0.0144	0.1052	0.009	0.0047	0.0222	0.0415	0.0172	-0.0304	-0.1004	0.0447	0.0622	0.0106	-0.0268	0.0033	1					
Year 2005	Water	0.1006	0.075	-0.0603	0.0086	0	-0.0564	-0.0269	-0.0679	0.3025	0.2039	0.0754	-0.0071	0.0159	0.1069	0.0833	-0.0476	0.0333	0.0426	-0.0195	0.0056	-0.0005	1				
Year 2005	Toilet	0.2023	0.1782	-0.1156	-0.0249	-0.0194	-0.0359	-0.0171	-0.0665	0.1983	0.5285	0.0843	0.052	-0.0099	0.2018	0.1837	-0.1009	0.0035	0.0112	-0.0074	0.0045	-0.0068	0.2375	1			
Year 2005	Kitchen	0.0673	0.0734	-0.0418	-0.0608	-0.0092	-0.0243	-0.0071	0.0034	0.0731	0.0862	0.2265	0.0133	-0.0105	0.0674	0.0603	-0.0211	-0.0075	-0.0179	-0.0048	-0.0318	0.0171	0.0986	0.1218	1		
Year 2005	Violence	0.0286	0.0497	-0.0087	-0.0071	0.0201	-0.0202	0.0506	0.0005	0.0343	0.085	0.0048	0.1294	0.0042	0.0422	0.0457	0.0168	-0.0228	0.0337	-0.02	0.0404	0.0346	0.0108	0.0762	0.0194	1	
Year 2005	Shocks	0.0232	0.0242	-0.0031	0.0049	0.0084	0.0072	0.0341	0.0263	0.0246	0.0587	0.0338	0.0175	0.0687	-0.0065	0.0163	0.0271	0.0227	-0.03	0.0044	-0.0012	0.0006	-0.0229	0.062	0.0349	0.1293	1

Source: Authors' calculations based on MxFSL.

Another way of looking at the persistency of different welfare and poverty measures is to calculate transitions matrices and compare the percentage of households that go in and out of poverty from one period to the other. Table 7 reinforces what was mentioned before, showing higher mobility rates for one-dimension poverty measures. In rural areas, the percentage of households changing their poverty status from one year to the other is 33 percent with the food-based poverty measure. This percentage decreases to 24 percent when using the asset-based poverty line. When we use relative poverty lines and compare one dimension with multi-dimension poverty algorithms we see that, with a relative line of 20 percent of the population, 25 percent change their poverty status with the income poverty measurement and this percentage decreases to around 20 percent for the welfare multidimensional indicator and 15 percent for the multidimensional indicator that excludes income. Poverty dynamics seems to be slightly higher in urban areas when compared to rural areas, particularly when considering one-dimension welfare measures.

Table 7. Poverty and Welfare Dynamics Considering Different Measures

Poverty/Welfare dynamics 2002-2005		Food-based poverty	Human capacity poverty	Asset-based poverty	Relative income poverty (20%)	Multidim. w/income	Multidim. no income
Urban areas	Poor - Poor	14.54	22.46	49.64	6.31	8.39	11.18
	Non poor - Non poor	51.92	42.18	20.7	66.56	69.77	72.41
	Poor - Non poor	16.87	17.39	13.25	13.82	11.13	8.33
	Non poor - poor	16.67	17.96	16.41	13.3	10.71	8.07
	Total	100	100	100	100	100	100
Rural areas	Poor - Poor	32.77	40.1	62.34	7.3	9.17	11.84
	Non poor - Non poor	33.77	27.79	13.81	67.67	69.9	72.78
	Poor - Non poor	17.96	17.74	12.01	12.54	10.48	7.78
	Non poor - poor	15.51	14.37	11.84	12.49	10.44	7.6
	Total	100	100	100	100	100	100

Source: Authors' calculations based on MxFSL.

6.2 Dynamic Consistency of Targeting Methods

Table 8 presents the results of the dynamic consistency of different targeting methods. We compare measures in two groups. In the first group, we compare a means test approach with a multidimensional welfare indicator that uses observed income for its construction. The second group compares a proxy means test approach with a multidimensional welfare indicator that includes estimated income levels.[9] When presenting the results for the second group, we clearly distinguish estimation errors that lead to classifying a household incorrectly (as poor or non-poor) in the first year of the survey. For targeting purposes, this would imply that some households would be incorporated in the program when they are actually not deprived, or else that they would be excluded from the program when they are actually poor.

When using a means test approach we assume that complete information is obtained on household income and/or wealth. This approach requires the existence of verifiable records, such as pay stubs, or income and property tax records. It also requires the administrative capacity to process this information and continually update it in a timely manner (Coady, Grosh and Hoddinott, 2002). When this capacity is missing, other targeting mechanisms need to be used. The most commonly applied, is the proxy means test, which involves generating a score for applicants based on easy to observe characteristics of the household (education of its members, access to basic services, demographics, etc.). Usually the indicators used to calculate this score and their weights are derived from statistical analysis of household survey data.

Higher persistency levels, excluding estimation errors, will imply that a given method can perform more dynamically consistently, as there are higher probabilities that a household that was targeted in the first period will remain deprived in the second period. Looking at the results in both comparison groups, we can see that multidimensional targeting methods can perform dynamically better than one-dimension or income-based targeting methods. For example, in the case of a program that aims to target the poorest 20 percent of households in rural areas, when using the means test approach 7 percent of the population remains poor in both periods, this percentage increases to 10 percent when using a multidimensional measure. When comparing the proxy means test with the multidimensional welfare approach (considering the estimated income) the targeting efficiency gap between methods is slightly bigger (4 percent vs. 8 percent).

It is important to highlight that estimating income, as done by the proxy means test approach, introduces further errors to the dynamic consistency of one-dimension methods of targeting. When we compare the estimation errors that arise for not classifying a household in the right group in the first year of the survey, we can see that the proxy means test presents higher estimation errors than estimated multidimensional welfare measures. Estimation errors are also higher in rural areas, where the percentage of households incorrectly classified in the first period is 24 percent with the proxy means approach and 15 percent with the multidimensional measure.

[9] Regression results from the proxy means test can be found in the Appendix.

In urban areas, the percentages of households with estimation errors are 15 percent and 9 percent, respectively.

Given that we are dealing with relative deprivation measures, the results presented in Table 8 have been disaggregated considering two bottom or cut-off lines. In rural areas we calculate our results considering the bottom 20 percent and 40 percent. In urban areas we consider the bottom 10 percent and 20 percent of the population. As the table shows, as we move to lower deciles of the deprivation distribution targeting errors increase and the dynamic consistency of targeting is reduced. To further explain this point, we perform a sensitivity analysis to show how well one-dimension and multidimensional measures perform when considering different cut-off points in our relative context.

Table 8. Dynamic Consistency of Income and Multidimensional Targeting Methods, 2002-2005

	Poverty dynamics	Means Test	Multdim. (observed income)	Proxy means test	Multidim. (estimated income)	Means Test	Multdim. (observed income)	Proxy means test	Multidim. (estimated income)
		Bottom 10%				*Bottom 20%*			
Urban areas	Poor - Poor	1.62	3.65	0.76	3.34	6.38	8.92	3.14	7.5
	Non poor - Non poor	81.21	83.69	75.08	79.94	66.16	69	58.05	63.73
	Poor (error) - Poor			1.27	0.46			3.85	1.82
	Non poor (error) - Non poor			6.94	3.9			9.02	5.67
	Poor - Non poor	8.76	6.33	1.82	2.43	13.88	11.04	4.86	5.37
	Non poor - Poor	8.41	6.33	7.14	5.88	13.58	11.04	9.73	9.22
	Poor (error) - Non poor			6.13	3.75			8.11	5.27
	Non poor (error) - Poor			0.86	0.3			3.24	1.42
	Total	100	100	100	100	100	100	100	100
		Bottom 20%				*Bottom 40%*			
Rural areas	Poor - Poor	7.37	9.51	3.92	7.84	22.89	24.38	16.33	20.38
	Non poor - Non poor	67.39	69.52	58.53	63.77	42.67	44.42	33.25	38.49
	Poor (error) - Poor			3.71	1.71			6.69	5.03
	Non poor (error) - Non poor			9.12	5.8			9.68	6.95
	Poor - Non poor	12.62	10.49	3.5	4.69	17.22	15.6	7.54	8.65
	Non poor - Poor	12.62	10.49	8.91	8.78	17.22	15.6	10.53	10.57
	Poor (error) - Non poor			8.87	5.75			9.42	5.92
	Non poor (error) - Poor			3.45	1.66			6.56	4.01
	Total	100	100	100	100	100	100	100	100

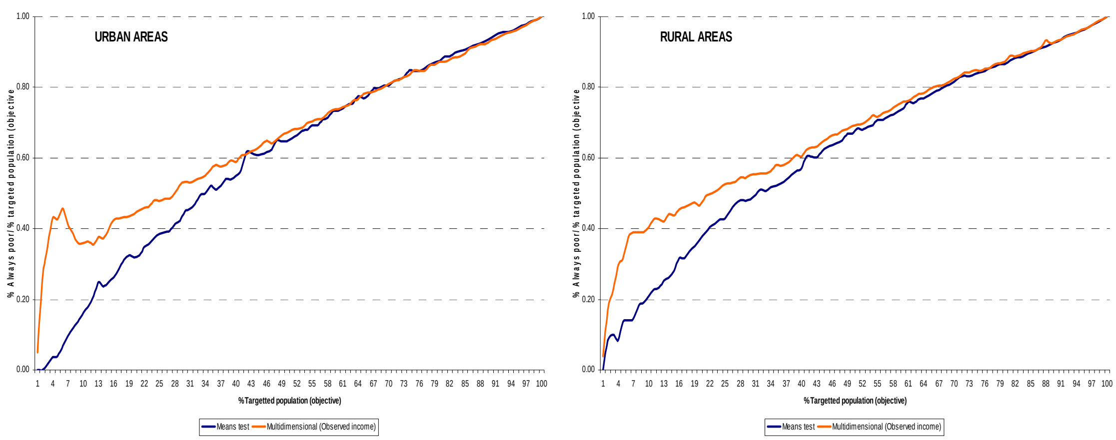
Source: Authors' calculations based on MxFLS.

Figure 2 presents a sensitivity analysis for our results in terms of the dynamic consistency of targeting measures. We graph the persistency of deprivation when considering different cut-off points (or centiles) to construct our multidimensional and one-dimensional measures. As is well known, it is always more difficult to target the lowest centiles of the population. In general, the multidimensional measure performs better than one-dimensional measures, and the advantages of this measure are more notable in urban areas. There is a clear difference between methodologies that employ observed income and those that estimate income from easily observed characteristics. In the first case, when the percentage of population targeted increases, the means test approach performs quite similarly to the multidimensional approach. In the second case, the advantage decreases at a slower pace as the dynamic targeting errors arising from the estimation of income needed from the proxy means test are more important for the one-dimensional case.

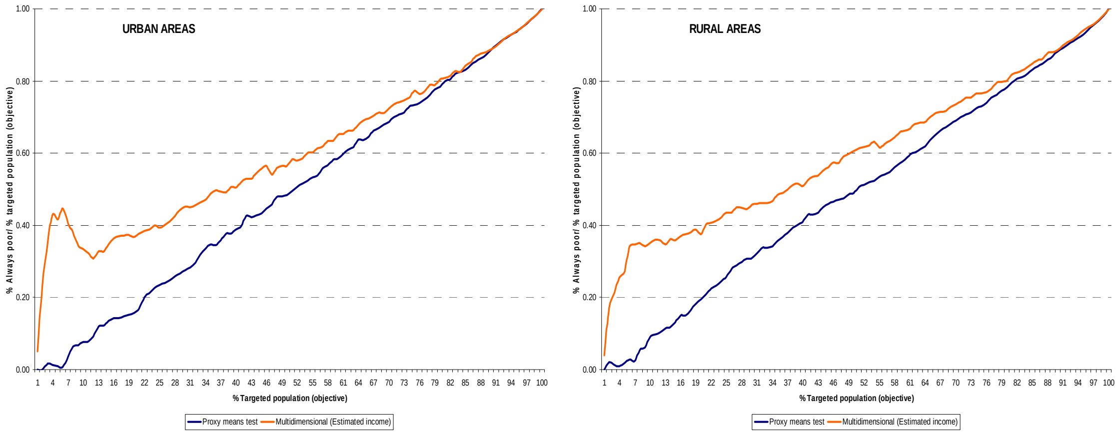
On average, the percentage of poor population correctly targeted by the multidimensional measure is three times higher than that of the one-dimensional algorithm in urban areas and two times higher in rural areas when using the estimated income or proxy means test. If we look at each individual centile, the highest gaps are in the first centiles and in urban areas. In all cases, gaps are greater when considering measures that estimate income. In the fifth centile, for example, there is a maximum level of 43, which represents the number of times greater that is the number of adequately poor population targeted by the multidimensional measure when compared to the one-dimensional measure. This difference is 16 times greater in rural areas. When using observed income, the differences are seven and three times greater, respectively, when comparing multidimensional and one-dimensional measures.

Figure 2. Persistence of Poverty and Deprivation Considering Different Cut-Off by Centiles

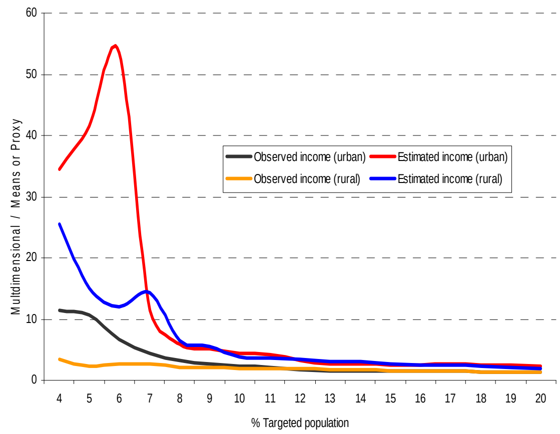
a. Means Test vs. Multidimensional Measure (with Observed Income)



b. Proxy Means test vs. Multidimensional Measure (with Estimated Income)



c. Percentage of Adequately Targeted Poor with Multidimensional Measure over the Percentage of Adequately Targeted Poor with One-Dimension Measure



Source: Authors calculations based on MxFLS.

7. Conclusions

This paper compares two types of targeting algorithms (a multidimensional welfare indicator and a means and proxy means test) using panel data from Mexico and discusses its dynamic consistency. This exercise is relevant for programs that target beneficiaries based on cross-sectional data and do not have the flexibility to re-target and updating beneficiary rosters frequently, whether due to the nature of the program, data limitations or political reasons.

The results presented suggest that multidimensional welfare measures may be dynamically more consistent when compared to one-dimensional targeting methodologies. This means that a household that was considered deprived on multiple dimensions in a first period, and was consequently admitted into a program, will be more likely to remain deprived in the following period when compared to a household that was considered deprived only on the basis of its income level. Particularly notable is that relative multidimensional targeting methods perform relatively better in targeting deprived households at the bottom of the distribution of welfare attributes and outcomes.

The choice of multidimensional welfare index to be computed is a relevant issue, as there is an increasing supply of multidimensional poverty and well-being indicators, sometimes yielding different results. In this paper, we have extended the Alkire and Foster (2008) methodology. Our selection of dimensions and indicators is the result of the literature review undertaken for this study and also of the availability of information. At the end, relevant dimensions and weights should be defined by each program or project according to its specific objectives, the availability of information and its verifiability

For policymakers, it will be important to evaluate each targeting mechanism in the context of each particular program. Moving from one-dimensional to multidimensional targeting methods should not be too difficult, as most information required to construct these types of measures is readily available. Throughout this process, it will be good to clearly understand the costs (economic, social, and political) involved as well as the benefits a program can get from it.

To replace the arbitrary judgment of threshold values generally involved in these measures, we adopted a relative approach to deprivation. For this, we rank individuals according the each attribute or dimension and look at the relative availability of that attribute in the population at large. We also give a larger weight to deprivations that affect a small portion of the population, as we believe these are more critical in defining deprivation. Further studies are needed to determine the best way of constructing these measures.

Finally, it is important to mention that the availability of panel data may allow exploring other potential targeting techniques that can more explicitly take into account income and welfare dynamics by modeling the dynamic income-generating process into targeting algorithms.

References

Atkinson, A.B. 2003. “Multidimensional Deprivation: Contrasting Social Welfare and Counting Approaches.” *Journal of Economic Inequality* 1: 51-65.

Alkire, S. and J. Foster. 2008. “Recuento y Medición Multidimensional de la Pobreza.” Documento de Trabajo OPHI 7. Oxford, United Kingdom: University of Oxford, Oxford Poverty & Human Development Initiative.

Battiston, D. et al. 2009. “Income and Beyond: Multidimensional Poverty in Six Latin American Countries.” OPHI Working Paper 17. Oxford, United Kingdom: University of Oxford, Oxford Poverty & Human Development Initiative.

Besley, T., and R. Kanbur. 1993. “The Principles of Targeting.” Working Papers. Policy, Research and External Affairs. Washington, DC, United States: World Bank.

Bourguignon, F., and S. Chakravarty. 2003. “The Measurement of Multidimensional Poverty.” *Journal of Economic Inequality* 1(1): 25-49.

Braithwaite, J., C. Grootaert and B. Milanovic, editors. 2000. *Poverty and Social Assistance in Transition Countries*. New York, United States: St. Martin’s Press.

Coady, D., M. Grosh, and J. Hoddinott. 2002. “Targeting Outcomes Redux.” Discussion Paper 144. Washington, DC, United States: International Food Policy Research Institute, Food Consumption and Nutrition Division.

Coady, D., and S. Parker. 2004. “An Evaluation of Targeting of the Oportunidades Program in Urban Areas.” Mexico City, Mexico. Instituto Nacional de Salud Pública. Mimeographed document.

Coady, D., and S. Parker. 2009. “Targeting Social Transfers to the Poor in Mexico.” IMF Working Paper WP/09/60. Washington, DC, United States: International Monetary Fund.

Conconi, A., and A. Ham. 2007. “Pobreza Multidimensional Relativa: Una Aplicación a la Argentina.” CEDLAS Documento de Trabajo 57. La Plata, Argentina: Centro de Estudios Distributivos, Laborales y Sociales.

Duclos, J..-Y., D.E. Sahn and S.D. Younger. 2006. “Robust Multidimensional Poverty Comparison.” *Economic Journal* 113, 943–968.

Foster, J., and A. Shorrocks. 1991. “Subgroup Consistent Poverty Indices.” *Econometrica* 59: 687-709.

Freeman, S.R. 2007. *Rawls*. London, United Kingdom and New York, United States: Routledge Taylor & Francis Group.

Grosh, M. 1994. “Administering Targeted Social Programs in Latin America: From Platitudes to Practice.” Washington, DC, United States: World Bank.

Kakwani, N., and H. Son. 2006. “Evaluating Targeting Efficiency of Government Programmes: International Comparisons.” DESA Working Paper 13. New York, United States: United Nations, Department of Economic and Social Affairs.

Krishnakumar, J., and P. Ballon. 2008. “Estimating Basic Capabilities: A Structural Equation Model Applied to Bolivia.” *World Development* 36: 992-1010.

López Calva, L.F., and E. Ortiz Juárez. 2009. “Medición Multidimensional de la Pobreza en México: Significancia Estadística en la Inclusión de Dimensiones No Monetarias.” *Estudios Económicos* (número extraordinario): 3-33.

Moser, C. 2004. “Urban Violence and Insecurity: An Introductory Roadmap.” *Environment and Urbanization* 16(2): 3-16.

Paes de Barros, R., M. Carvalho and S. Franco. 2006. Pobreza Multidimensional No Brasil. Texto Para Discussão No 1227. Rio de Janeiro, Brazil: Instituto de Pesquisa Econômica Aplicada (IPEA).

Pérez, R., G. Issamu and F. Veras. 2008. “Debating Targeting Methods for Cash Transfers: A Multidimensional index vs. an Income-Proxy for Paraguay Tekoporã Programme.” IPC Evaluation Note 2. Brasilia, Brazil: United Nations Development Programme, International Poverty Centre.

Poggi, A. 2007. “Does Persistence of Social Exclusion Exist in Spain?” *Journal of Economic Inequality* 5: 53-72

Rawls, J. 1971. *A Theory of Justice*. Cambridge, United States: Harvard University Press.

Sen, A. 1983. “Poor, Relatively Speaking.” *Oxford Economics Papers* 35: 153-169.

Sen, A. 1992. “Inequality Reexamined.” Cambridge, United States: Harvard University Press.

Székely. M. 2006. *Desmitificación y Nuevos Mitos sobre la Pobreza: Escuchando “Lo que dicen los pobres.*” Mexico City, Mexico: Editorial Porrúa.

Tsui, K. 2002. “Multidimensional Poverty Indices.” *Social Choice and Welfare* 19: 69-93.

Appendix

Table A1. Regression Results for the Proxy-Means Test in Urban Areas

Variables	2002	2005
Year of education head of the household	-0.0014	0.0255**
	(0.0116)	(0.0118)
Number of members in the household	-0.1189***	-0.1567***
	(0.0128)	(0.0135)
Head of household works	0.1541***	0.2379***
	(0.0522)	(0.0527)
Age of the head of the household	0.0100***	0.0079***
	(0.0021)	(0.0022)
Dependency rate	-0.3443***	-0.4136***
	(0.1259)	(0.1487)
House has a phone line	0.2830***	0.1167**
	(0.0493)	(0.0503)
House has a kitchen	0.1199	0.1492
	(0.0738)	(0.1050)
House has a toilet	-0.0152	0.0295
	(0.0888)	(0.1018)
Running water in the house	0.0479	0.0642
	(0.0669)	(0.0730)
Electronic equipment in the house	0.5088**	0.1945
	(0.2107)	(0.1270)
Home appliances	-0.3645**	-0.0005
	(0.1723)	(0.1391)
Household is the owner of the house	-0.1010*	0.0951*
	(0.0526)	(0.0554)
Education of adult members in the household	0.0975***	0.0777***
	(0.0151)	(0.0155)
Localities with more than 100.000 inhabitants	0.0982*	0.1022*
	(0.0591)	(0.0572)
Constant	5.7874***	5.7005***
	(0.1875)	(0.2275)
Observations	1974	1974
R-squared	0.1775	0.1942

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2. Regression results for the Proxy-Means Test in Rural Areas

Variables	2002	2005
Year of education head of the household	-0.0027	0.0146
	(0.0116)	(0.0114)
Number of members in the household	-0.1243***	-0.1259***
	(0.0110)	(0.0111)
Head of household works	0.2868***	0.1555***
	(0.0554)	(0.0511)
Age of the head of the household	0.0061***	0.0005
	(0.0020)	(0.0020)
Dependency rate	-0.2627**	-0.4564***
	(0.1122)	(0.1228)
House has a phone line	0.3958***	0.1691***
	(0.0587)	(0.0471)
House has a kitchen	-0.0924	0.0440
	(0.0818)	(0.0798)
House has a toilet	0.1244**	0.1213***
	(0.0524)	(0.0467)
Running water in the house	-0.0189	0.0644
	(0.0524)	(0.0456)
Electronic equipment in the house	0.2949***	0.1741**
	(0.0877)	(0.0844)
Home appliances	0.2422***	0.3224***
	(0.0720)	(0.0707)
Household is the owner of the house	0.0471	0.0583
	(0.0494)	(0.0487)
Education of adult members in the household	0.0834***	0.0545***
	(0.0138)	(0.0150)
Localities with 2.500 to 14.999 inhabitants	0.3268***	0.1537***
	(0.0570)	(0.0514)
Constant	5.1564***	5.7069***
	(0.1642)	(0.1586)
Observations	2346	2346
R-squared	0.1928	0.1884

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1