U.S. Multidimensional Poverty by Race and Motherhood: Evidence from Pennsylvania Census Data

Feridoon Koohi-Kamali and Ran Liu

Abstract

The combined influence of gender and race has been a principal defining feature of poverty in the United States, especially for single mothers. While the recent applications of capability-based multidimensional poverty (MP) measurement to the U.S. have examined race and gender, they have done so without taking into account the effects of the intersection of the two. This paper addresses directly that gap in the U.S. literature on multidimensional poverty, employing the U.S. census data for 2006-2010 for Pennsylvania households, a state with key income poverty indicators close to the mid-poverty values for all fifty states. We employ the dual cut-off procedure for our main results to present MP measures by levels of population subgroups. We carry through this approach for four levels of MP measures and finally identify Hispanic and African-American single mothers as the most deprived, though single motherhood remains a key influence on poverty regardless of race. We check robustness of ranking single mother households by race with different dual cut-off values and by two alternative measures based on fuzzy set theory that allow for vagueness in the boundary of poverty. The poverty ranking by single motherhood shows Hispanic as the most deprived, and White as the least deprived, with African-America coming in between. Finally, our probit analysis for chances of being poor based exclusively on the intersection of race and gender/marital status of households indicates that being a non-White single mother household has the largest impact on poverty status defined either multidimensionally or by income. Our findings suggest that effective poverty reduction public policy be targeted especially, though not exclusively, at non-White single mothers.

Preliminary Draft

Please Do Not Quote

U.S. Multidimensional Poverty, Race and Motherhood:

Evidence from Pennsylvania Census Data

Feridoon Koohi-Kamali and Ran Liu* 2014

Department of Economics, Franklin & Marshall College

I. Introduction

A major question in poverty analysis is whether poverty should be examined in terms of inadequacy of income, or directly by looking at welfare indicators such as nutritional status. The measurement of poverty should take into account the differences in poverty between two communities with similar average income levels but notably different levels of achievement, for instance access to health care. The income approach to poverty pays inadequate attention to such questions. Arguing that poverty has many relevant dimensions besides income, Sen (1985) presents a far-reaching theoretical approach to welfare comparison in terms of achievements and capabilities. Multidimensional Poverty (MP) measurement is the applied expression of this approach and is a direct result of addressing the shortcomings of measuring poverty in terms of income. By shifting the emphasis from people's income to their achievement as a more accurate indicator of their welfare, the MP applications have led to many new insights into poverty, especially with regard to developing countries. Although the MP applications to the United States have produced some illuminating results, the *combined* effects of race, gender, and motherhood (children) on poverty have been marginal to these studies. This is an important shortcoming, since the available income poverty literature on the U.S. has consistently highlighted female-headed African-American and Hispanic households as constituting the core

*An earlier version of this paper was submitted for the Theodore Wood prize in Economics at Franklin & Marshall College. Ran Liu wishes to thank the faculty at the F&M Economics Department for their interest in and encouragement of his initial research.

of chronic poverty, yet as far as we are aware, none of the MP applications to the U.S. provide evidence on these crucial features of the poverty profile of the United States.

The issue of gender and race has had a long history in the U.S. poverty literature. Peace (1978) drew attention to the process of the "feminization of poverty" in the United States, and subsequent debate brought into focus the critical impact that race and ethnicity have in that process. There is a good deal of income-based evidence that points to female-headed non-White American families with children as constituting the core of high chronic poverty in the United States. Moore et al. (2009) report for the post-2000 period, indicating that the U.S. children in single-mother households are far more likely to be poor than those living in two-parent households, and although this pattern is evident across all races, the differences are notably higher for African-American and Hispanic female-headed households.[1] Similarly, Gardin (2012) explains that the U.S. official poverty rates in 2007 for African-Americans and Hispanics, which are at least twice as high as those for non-Hispanic Whites, are due to a preponderance of single mothers amongst African-American and a larger number of dependent children for Latinos combined with a lack of high school diploma. Seccome (2000) found that female-headed poverty in the United States increased from 20% in 1980 to 28% in 1998.[2] Rodgers and Rodgers (1993) found that the rise in chronic poverty in the United States during 1970s and 1980s can be accounted for mainly by the chronic poverty of single-mother households without a high school diploma; around 69% of such households were in chronic poverty compared to 36% for the U.S. population as a whole. There is thus a good case for the application of MP to these particular cohorts, which occupy a critical position in the U.S. poverty profile.

The advantages of MP methodology for the analysis of deprivation in the United States have

[1] For 2007, Moore et al. (2009) found that among White households, 32.3 % of children in poverty live in single-mother female-headed households compared to 4.7% living in two-parent households; the comparable figures for African-Americans are 50.2% vs. 11%, and for Hispanics 51.4% vs. 19.3%.

[2] 49% of female single-headed families were in the lowest income quintile compared to 28.5% of male single-headed families, attributable to low female wages particularly for the African-American and Hispanic women, which the study suggests is a main cause of child poverty.

been aptly demonstrated in Alkire and Foster (2010), and there are also other interesting studies of MP for the United States, see Wagle (2007, 2008; 2014. These studies demonstrate many useful properties of the MP approach for the design of public policies; in particular, the approach allows decomposing the aggregate poverty measures into the share of each population group, and it can deconstruct the overall index in order to identify particular dimensions of deprivation that most contribute to the aggregate measure. Finally, one of the least discussed features of capability-based measures of poverty is their potential to provide guidance for designing effective poverty reduction policy tools. A well-known problem in designing policies targeted at alleviating extreme poverty is that the less poor or the non-poor typically claim a greater share of resources allocated to poverty reduction schemes, because the availability of these resources creates new incentives and results in changed behavior by the non-poor. Public policies based on achievement resulting from better or worse capabilities are not subject to such behavior change. It would be hard to change one's health status in order to qualify for public health care. Thus, the MP approach offers a more secure basis for public policies that target effectively those in extreme poverty, Sen (1995).

While these studies take into account the impact of race and gender on MP measures for the U.S.A., none analyzes these effects based on the *intersection* of race and gender, particularly when combined with the presence of children, namely single mothers with a "minority" background. The intersection of race, gender, and motherhood (children) is the focus of this paper's application of MP methodology to the United States. As far as we are aware, this critical dimension of MP measurement has so far not been addressed, or at least not adequately, in the emerging literature on MP poverty in the United States.

In this paper, we provide some evidence that bridges this existing gap by an MP analysis of census data for one U.S. state with average features similar to those of the entire country, namely the Commonwealth of Pennsylvania. We chose Pennsylvania because this state is close to the mid-values of the household poverty rate and household total income across all the fifty states of the U.S., and hence offers preliminary results likely to be similar to those for the entire country. For example, in 2009, the household poverty rate for the United States was 12.6% while it was 11.2%

for Pennsylvania, with a rank of 21st among all the U.S. states; similarly the average U.S. 2009 household income was $50,221, while that for the state of Pennsylvania was $49,520, with a rank of 22nd among all the U.S. states.

We employ data from the American Community Survey (ACS) Public Use Microdata Sample (PUMS) to measure multidimensional poverty for different ethnicities and household types across the state of Pennsylvania. We create a Quadruple Decomposition model for this purpose, and implement it for four different levels of decomposition by ethnicity and by gender of the household-head. We employ MP with a decomposition method to examine the deprivation of U.S. population subgroups in high chronic poverty, with particular attention to the African-American and Hispanic female-headed households with children. Finally, we rely on the property of the MP decomposition of capability in order to obtain the poverty contribution of each dimension to the MP of the different subgroups examined.

Section II examines the literature on MP and our particular approach to it within that literature. Section III spells out the method, the dimensions of deprivation, and their indicators employed in this paper. In Section IV we discuss the data used. Part V presents our results starting from the state level down to the level of the most deprived cohorts within the state, including the results by decomposition. Moreover, we check for the robustness of the results in ranking deprivation by population sub-groups by two alternative methods; by a dual cut-off method of MP, see Akire and Foster (2010), and by an alternative methodology based on fuzzy set theory, see Qizilbash (2006), followed by a discussion of both methods below. A concluding Part VI sums up our main findings and policy implications.

II. Literature

The Multidimensional Poverty approach has its origin in Rawls (1971, 1982), who suggested that in a just society, all citizens should have equal access to what he calls primary goods, including adequate nutrition and education and the right to vote in elections. Welfare comparison by primary goods assumes citizens are all in a “normal range” of health and capability, and this raises two issues. Arrow (1973) first pointed out that the basic shortcoming of this concept as a means of welfare comparison is that equality on the commodity level does not necessarily imply an equal material living standard if there is substantial variation in the health status of the population; a disabled person can achieve less with the same commodity basket than a healthy person. A similar alternative with a more far-reaching theoretical approach to welfare comparison, in terms of achievements and capabilities, is put forward by Sen (1985). A major implication of Sen's approach is that poverty has many relevant dimensions besides income. Therefore, poverty must be assessed in terms of multiple welfare indicators and then suitably aggregated into an overall index.

The second issue is whether the basis of comparison consists of the same set of goods universally, or should be allowed to differ across communities depending on the importance attached to those goods. Nussbaum (2000) argues that a fixed list of universal capabilities should be employed. The boundaries for such a list may be hard to define—emotional security might be considered a capability, for example—and still harder to incorporate properly into an implementable measure of poverty. Similarly, the Wagle (2007) MP framework comes close to this universal approach in including economic well-being, social capability, and three kinds of social inclusion. On the other hand, Sen (1992) avoids a list of the central capabilities and argues in favor of a flexible list, see also Alkire (2008) on taking a pluralistic view of MP poverty measurement.[3]

Multidimensional poverty differs from income-based poverty in that deprivation in one dimension alone without additional information across other dimensions cannot identify the poor. Its methodology overcomes the dilemma posed by two other alternatives based on capability dimensions. One method, the *union* procedure, identifies a poor person if she is deprived in at least *one* of the indicators of capability. The other, the *intersection* method, identifies a person as poor if she is deprived in *all* capability indicators. The union method is excessively broad and leads to MP measures that are too high, while the intersection method is excessively narrow and

[3] For instance, Alkire and Foster's (2010) multidimensional approach for the U.S. has four dimensions (income, health, health insurance, and schooling), whereas for the capability study for Indonesia, they provide three dimensions—expenditure, Body Mass Index (BMI), and years of schooling.

results in poverty measures that are too low, see Atkinson (2003) and Bourguignon and Chakravarty (2003). The multidimensional method examined below is an intermediate method of poverty measurement between the union and intersection approaches.

The methodology of multidimensional poverty as employed in the main part of this paper follows an approach to measurement that is similar to the income poverty approach, by first identifying the poor and then aggregating individual poverty into an overall index. The former is based on an ordinal index that takes the value of 1 if the person (or household) is deprived in a given dimension of capability, and 0 if not deprived in that dimension. The aggregation then obtains a weighted total index for all dimensions of deprivation based on a second criterion of poverty threshold.

Note, however, that the calculation of MP by each welfare indicator is dependent on its overlap with deprivation in other indicators; the greater the overlap, the larger the contribution of that indicator to the overall appears to be. This suggests that indicators that are given greater weight by the researcher will demonstrate a larger contribution to the overall index, see Wagle (2014); also Ravallion (2011). Inherent in this procedure is the assumption of high substitutability among a heterogeneous range of capabilities, for example, that good sanitation can compensate for poor nutrition. However, each dimension of capability may well be valuable independently, regardless of other dimensions. While we acknowledge such drawbacks in the method employed in this paper, we feel that the alternative of defining the index on some universal basis has its own difficulties where the boundaries of deprivation/achievement are concerned; in any case the limitation of our data prevents us from taking such an approach.

An alternative approach to MP is fuzzy set theory. Its application draws strength from the idea that it is futile to attempt exact measurement of poverty since the concept is inherently ambiguous. The fuzzy set approach takes into account the vagueness of the distinction between the poor and non-poor, allowing partial membership in a poverty set based on a membership function, $F*\pi$, where F is the degree of membership in the [0, 1] interval, with $\pi=1$ for those definitely poor and with $\pi=0$ for those definitely non-poor. For those who are poor to *some degree,* $0< \pi <1$; see

Cerioli and Zani (1990).[4] The in-between set then allows for different definitions of poverty groups, see Lelli (2001) or Qizilbash and Clark (2005) for applications. A simplified version of this approach is to focus on just the lower end of the poverty scale and examine changes in the measurement of poverty resulting from degrees of high chronic poverty, see Wagle (2009). This approach is particularly useful for testing the sensitivity of poverty ranking of population groups to the vagueness in the boundaries defining poverty; a simple version of its application will be employed below for robustness in poverty ranking of the groups identified in this study as being in high chronic poverty.

III. Methodology

In order to identify the poor, suppose we record achievement or deprivation of a population of *n* households or individuals in *d* dimensions of deprivation. This results in a matrix of $n*d$, where each row *i* represents individuals and each column *j* the distribution of deprivation/achievement across individuals, typically defined as 1 for deprived and 0 for non-deprived status. The approach allows weighting deprivation in each dimension differently, and one option is to make the dimensional weights add up to the total number of columns, i.e. $\sum_{j=1}^{a} w_j = d$. This results in a matrix of deprivation with elements defined by $z_{ij} = w_j$ that is equal to 1 if *i* is deprived and 0 if not, with the total count equal to $C_i = \sum_{j=1}^{a} z_{ij}$. A second cut-off value *k* is then applied to this total to determine who is multidimensionally poor: the person counts as poor if the weighted count is greater than or equal to *k*. Note that this *dual cut-off* method filters out those who may be deprived in some

[4] A definitely poor household *i* falls below the threshold Φ_j^* on all indicators of a capability dimension *j*, *so* π=1, and $\Phi_{ji} < \Phi_j^*$, while a definitely non-poor household *i* is above the threshold Φ_j^{**} on all indicators, so π=0, and $\Phi_{ji} > \Phi_j^{**}$. Then the degree of membership of *i* to the poor depends on the weighted average of the membership scores on each of the indicators as determined by the weighted average of $(\Phi_j^{**} - \Phi_{ji}) / (\Phi_j^{**} - \Phi_j^*)$. The method requires weighting before aggregation.

dimensions but with an aggregate deprivation count less than *k*. The aggregate multidimensional poverty is then defined as

$$M_0 = \frac{\sum_{i=1}^{n}\sum_{j=1}^{d} z_{ij}}{n.d} \tag{1}$$

This can be expressed as the *product* of two poverty indices, see Alkire and Foster (2010).

The first is a multidimensional head-count index

$$H=q/n \tag{2}$$

where q is the number of multidimensionally poor persons (or households); (2) is the *incidence of multidimensional poverty*. The second index is the average of the weighted indicators for individual i, that is

$$A=\frac{\sum_{i=1}^{n} C_i\,(k)}{d.q} \tag{3}$$

(3) measures the aggregate poverty of an individual i relative to the maximum limit; hence it represents a measure of the *intensity* of poverty. Note that (2) takes into account the number of the poor, but not poverty intensity; while (3) takes poverty intensity into account but not the number of the poor. Thus, their product takes into account both numbers in poverty and the intensity of poverty:

$$M_0 = H*A \tag{4}$$

(4) satisfies most of the desirable properties of a poverty index such as the transfer axiom, see Tsui (2002). However, among its properties the most notably useful, especially for designing poverty-reducing public policies, are its *decomposability* and its *breakdown* into individual dimensions. The decomposability property allows separate poverty measures for each of the population subgroups, e.g. race or region, that make up the aggregate index. This property states that the sum of the population subgroups x and y, weighted by their population share, is equal to the aggregate index (4).

$$M_0 = \frac{n(x)}{n}.M_{0(x)} + \frac{n(y)}{n}.M_{0(y)} \tag{5}$$

The second useful property of (4) is that it can be deconstructed into its constituents to order to obtain the contribution of each indicator in a dimension to the aggregate index (bar over w_j indicates its average value):

$$C_j = \frac{\overline{w}_j}{d / M_0} \tag{6}$$

(a) Dimensions and Their Indicators

We identify four dimensions to set up the capability measurement framework in this study. They are what appear to us to be the most sensible indicators for Pennsylvania. In this paper, we follow the weighting scheme employed in the UNDP Human Development Report (2010, esp. technical note 7) that gives equal weight to each dimension of capability; each dimensional weight is further divided equally among its numbers of indicators, and the total sum of weights is equal to the total number of the ten indicators, see also Alkire and Foster (2010). We feel that despite its shortcomings as discussed above, such a scheme offers a better alternative, particularly given the limitation of the data employed in this paper. For each dimension, the highest possible score is 2.5. Therefore, the maximum score for the capability measurement model is 10 and each dimension contributes up to 25% of the total score. Next, by setting a multidimensional deprivation cut-off point equal to 3, we calculate the proportion of the population that is defined as multidimensionally poor and a poverty intensity index A for that population. Finally, we obtain the Multidimensional Poverty Index M_0 (4) by multiplying (2), the multidimensional poverty headcount ratio H, with (3), the intensity of poverty index A.

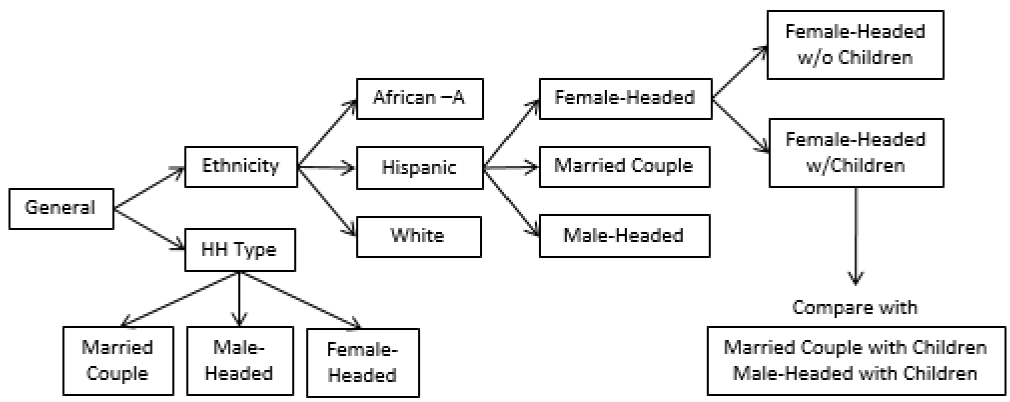
Defining dimensional deprivation by a (1, 0) indicator, our four dimensions are: educational attainment, employment status, supportive income, and living standard. The education attainment dimension reflects the schooling experience of the head of household. We set the cut-off condition for this dimension as the attainment of a high school diploma. Any head of household who does not have a high school diploma will be considered deprived in this dimension. The employment status dimension reflects the working status of the head of household and the spouse. If neither of them is working full time, then the household is deprived in the employment dimension. For example, if both spouses are working less than full time or the householder is working part time while the spouse is not working at all, then they are considered deprived. The third dimension, supportive income, consists of four indicators: receipt of yearly food stamp or Supplemental Nutrition Assistance Program benefits, receipt of public assistance income, receipt of supplementary security income and income headcount deprivation. These indicators act as proxies for the deprivation from which a household is suffering indirectly. A head of household who is receiving any of these supportive incomes will be marked as deprived. The living standard dimension has three indicators: household-size-to-bedroom ratio, vehicle possession, and ownership of real estate. The household-size-to-bedroom ratio is based on the number of people in the household divided by the number of bedrooms. If the result is greater than 2, then this household will be considered a deprived unit. A household will also be considered as suffering from deprivation if there is no possession of a vehicle or a housing unit.

Alkire and Foster (2010) employ personal survey samples, and the research they have conducted reflects individual capability. Thus, they present the poverty allocation among all the groups studied, but do not decompose the general index in terms of the gender of the head of household and the presence of children. In order to examine the deprivation allocation among the ethnicities *and* household types, we must employ household-level data. Therefore, the notable feature of this paper is its focus on the analysis of the key critical features of the poverty profiles in the United States based on that combination, namely, the African-American and the Hispanic female-headed households. As discussed above, the existing evidence by the income-based headcount measurement suggests that these groups constitute a key component of chronically poor U.S. households, and the extent of their deprivation is related critically to the presence of children in the household.

(b) Quadruple Decomposition Model

In order to examine the allocation of deprivation in Pennsylvania, we employ a procedure that decomposes the MP index of the full sample at four different levels. We call this procedure

Quadruple Decomposition. Population subgroups decomposition is a way to break down the overall index to population subgroups from ethnic subgroups and gender of the household head to the basis of the presence/absence of children. For example, the decomposition of the Hispanic subgroup will generate three new subgroups, namely, the Hispanic married couple household, the Hispanic female-headed household, and the Hispanic male-headed household. Diagram 1 explains the procedure employed in this paper for the case of Hispanic households.



(c) Poverty Rank Comparison by Fuzzy Set Theory and M_0.

We examine two alternative methods to check for the robustness of our M_0 results in determining the poor vs. non-poor boundary. One is to adopt a different value for the poverty threshold k in the dual cut-off method. The other is to allow for fussiness or vagueness in the poverty boundary by the fuzzy set methodology discussed above. We employ both approaches for robustness to the ranking of high chronic poverty population groups. However, since the main purpose of our fuzzy set measures is checking for poverty rank robustness rather than obtaining a full set of fuzzy poverty calculations, we rely on simple fuzzy set measures of MP for two different types of boundaries separating the poor from the non-poor; for similar partial fuzzy set measures see also Wagle (2008, 2009). The first is based on counting a household as poor if deprived in at least two of the four capability dimensions. We call this the Fuzzy Set Lower Half (FSLH) measure of standard of living. Given our limited purpose in employment of the FSLH, we set the threshold for the FSLH at 0.375. This threshold value results in an aggregate FSLH population in poverty similar to that obtained by the M_0 index. To check for robustness in vagueness in the poverty boundary, we also calculate and rank another fuzzy poverty measure based on counting a household as poor if deprived in all four dimensions of capability. We call this the Fuzzy Set Extreme Poverty (FSEP). Then we compare poverty by all three measures to find out if ranking by poverty populations changes. Appendix I provides an illustrative example of the application of the FSLH and FSEP measures.

IV. Data Description

The five-year data we use in this project are a modification of the American Community Survey (ACS) Public Use Micro Sample (PUMS) of the state of Pennsylvania from 2006 to 2010 provided by the Census Bureau. The original sample is separated into two parts. One part provides the records of demographic features of housing units, such as the number of people in the household, household family type, household equipment, and household income; the other part provides individual responses from the members in housing units, such as age, sex, educational attainment, and social supportive income. In order to implement our multi-dimensional capability analysis, we match (for the same household) the individual response of the head of household (if available) with the same householder's housing unit from the data set. By adding dummy variables for time, we generate a "super-PUMS" variable and then obtain a matrix containing 280,225 observations (households) with 272 variables. Since there are fewer than 5,000 households of other races, which represent less than 2% of the full sample, we decided to focus on three main ethnicities: African-American, Hispanic, and White, and drop the observations of other races. We finally obtain our modified sample of 269,316 households, which represent a population of 613,611[5].

[5] The U.S. five-year Census has an important shortcoming in lacking health insurance data for the household head, a significant indicator of deprivation in the U.S. The information is available with the three-year PUMS data, but provides only half the number of the five-year PUMS. The three-year PUMS would have been too low for reliable examination of the non-White population. Since these population groups are the main focus of this study, the M_0 indices presented in this paper use the five-year PUMS without health insurance data.

V. Result Analysis

From our modified sample given in Table 1a (bottom row), we obtained an Income Poverty Headcount (*YPH*) of approximately 0.094, while the Multidimensional Poverty Headcount (*MPH*) according to our indicators is *0.168* along with a Poverty Intensity (*A*) of 0.453. Thus, we obtain our Multi-dimensional Poverty Index M_0 as the multiple of *MPH* and *A*, namely, 0.0*76*.

Table 1a – Level 1 Decomposition: Ethnic Subgroups

Subgroup	Population	Contrib.	YP H	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Hispanic	18775	3.06%	0.2625	8.57%	0.436	7.95%	0.5152	0.2246	9.05%
White	553543	90.21%	0.0779	75.00%	0.1441	77.48%	0.4383	0.0631	75.00%
African-A	41293	6.73%	0.2288	16.43%	0.3633	14.57%	0.4958	0.1801	15.96%
Total	613611	100%	0.0937	100%	0.1678	100%	0.4528	0.0760	100%

a. Level 1: Decomposition by Ethnic Subgroups

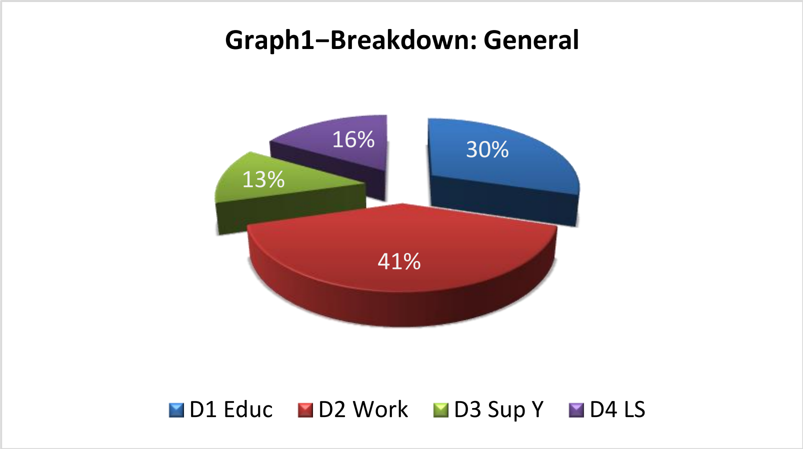
In order to examine the distribution of deprivation among ethnicities, we decompose the index by ethnic subgroups. Table 1a shows that the M_0 has the same poverty ranking as the *YPH*. The Hispanics are the most deprived of the subgroups, the Whites are the least deprived of the subgroups, and the African-American subgroup is in the middle. Similar to the general index, the M_0 index for each subgroup is smaller than its *YPH*. Statistically, we observe that the M_0 indices of African-American and Hispanic subgroups are three and three and one-half times greater than the M_0 index of the White.

b. Breakdown of the Dimensions

We break down the aggregate M_0 by (6). For the full sample (which has the M_0 index as 0.076), the most significant dimension is the dimension of work status, i.e. the employment status of husband and wife, with a non-deprived household defined as having at least one full-time employed member. It has an index of 0.12, which contributes 41% of the total deprivation. The second one is the dimension of education, which captures 30% of the deprivation with an index of 0.09. The other two dimensions, dimension of income deprivation and dimension of living standard, with their indices from 0.04 to 0.05, have less impact than the work and educational dimensions.

Table 1b – General Dimension Breakdown

Dimension	M_0	Contrib.	D1 E	Contrib.	D2 W	Contrib.	D3 Y	Contrib.	D4 LS	Contrib.
Total	0.0760	100%	0.0901	29.65%	0.1242	40.88%	0.0391	12.86%	0.0505	16.61%



In the remainder of this paper, we will discuss the results of applying our Quadruple Decomposition Model to the above sample.

Level 2: Decomposition by Household Type Subgroups

Examining Table 2 for Level 2 decompositions, we obtain an index for the married couple household subgroup and male-headed household subgroup of 0.05 and 0.08 respectively. By contrast, the index for the female-headed household subgroup (0.15) is three times greater than the M_0 index of the married couple household subgroup and twice as large as the index of the male-headed household subgroup. Female-headed households are 22% of the sample; they contribute 42% to the deprived population, whereas the married couple households are 64% of the population, yet their contribution to the deprived population is just under 43%; the male-headed households' percentage contribution remains unchanged. Therefore, the female-headed household subgroup is the most deprived subgroup in the Level 2 decomposition.

Table 2 – Level 2 Decomposition: The African-American Subgroup

Subgroup	Population	Contrib.	MP H	A	M_0	Contrib.
Married Couple	396572	64.63 %	0.1148	0.4389	0.0504	42.86%
Male-Headed	81000	13.20 %	0.1930	0.4389	0.0847	14.72%
Female-Headed	136039	22.17 %	0.3072	0.4731	0.1453	42.42%
Total	613611	100 %	0.1678	0.4528	0.0760	100%

Summary: Level 1 and Level 2 Decompositions

From the two decompositions above, we observe that the most deprived are the following subgroups: the Hispanic, the African-American, and the female-headed household subgroups. We will next proceed to Level 3 decomposition to generate a more detailed matrix of capability of these three subgroups.

c. Level 3: Decomposition by Household Type Subgroups within Ethnic Subgroups

(a) The African-American Subgroup

Table 3 shows that the more deprived households belong to the female-headed household category (47%), rather than to the married couple subgroup (31%). The African-America married couple households' M_0 is 0.09, whereas the African-American female-headed households' M_0 is 0.25. The 0.15 difference between the indices is due to the fact that African-American female-headed households account for the greatest portion (64%) of the deprived African-American population.

Table 3 – Level 3 Decomposition: The African-American Subgroup

Subgroup	Population	Contrib.	MP H	A	M_0	Contrib.
Married Couple	12843	31.10%	0.1995	0.4626	0.0923	15.93%
Male-Headed	9098	22.03%	0.3483	0.4616	0.1608	19.67%
Female-Headed	19352	46.87%	0.4790	0.5167	0.2475	64.40%
Total	41293	100%	0.3633	0.4958	0.1801	100%

(b) The Hispanic Subgroup

The Hispanic female-headed household subgroup constitutes 33% of the total Hispanic population and accounts for nearly 50% of the deprived Hispanic population (Table 4). The reason is that the Hispanic female-headed household has a M_0 index of 0.332 (33%). Compared to the indices of the married couple household subgroup (0.15) and the male-headed household subgroup (0.22), the Hispanic female-headed household subgroup is more severely deprived. From part (a), we also note that the female-headed households in the Hispanic subgroup are even more deprived than the female-headed households in the African-American subgroup (0.33 as opposed to 0.25, see Table 3 above).

Table 4 – Level 3 Decomposition: The Hispanic Subgroup

Subgroup	Population	Contrib.	MP H	A	M_0	Contrib.
Married Couple	8935	47.59 %	0.3116	0.4854	0.1512	32.05%
Male-Headed	3600	19.17 %	0.4628	0.476	0.2203	18.81%
Female-Headed	6240	33.24 %	0.5986	0.5549	0.3321	49.15%
Total	18775	100 %	0.4360	0.5152	0.2246	100%

(c) The White Subgroup

The White female-headed subgroup is the most deprived household type within the White population, with M_0=0.12 (Table 5). The M_0 indices for the White married couple household subgroup and White male-headed household subgroup are fairly low, 0.05 and 0.07 respectively. Thus, the M_0 index for White female-headed households is still notably higher than those for the other White subgroups. That is why this type of household occupies 20% of the population but contributes 37% of the deprived population. However, the index of the White female-headed household subgroup is just 0.12, even lower than the index of the Hispanic married couple household subgroup at 0.15 (see Table 4 above).

Table 5 – Level 3 Decomposition: The White Subgroup

Subgroup	Population	Contrib.	MP H	A	M_0	Contrib.
Married Couple	374794	67.71 %	0.1072	0.4342	0.0465	49.90%
Male-Headed	68302	12.34 %	0.1581	0.4265	0.0674	13.17%
Female-Headed	110447	19.95 %	0.2607	0.4484	0.1169	36.93%
Total	553543	100 %	0.1441	0.4383	0.0631	100%

d. Level 4: Further Decomposition by Presence of Children inside Level 3 Decomposition

(a) The African-American Subgroup

As shown in Table 6, when the female-headed household subgroup is further decomposed, we notice that the index for the subgroup of female-headed households with children increases to 0.31 compared with the index of the female-headed household subgroup as a whole (0.25, see Table 3 above). By contrast, the M_0 index for the female-headed household subgroup without child declines to 0.17. This suggests that the presence of children in a female-headed household is a significant factor in explaining chronic poverty in the U.S.

Table 6 – Level 4 Decomposition: The African-American Subgroup

Subgroup	Population	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Fe-H w/ Child	10899	56.32%	0.5676	66.73%	0.5394	0.3061	69.67%
Fe-H w/o Child	8453	43.68%	0.3648	33.27%	0.471	0.1718	30.33%
Total	19352	100%	0.4790	100%	0.5167	0.2475	100%

When we re-organize a new sample, combining only the three types of African-American households with children by marital status (Table 7), we find that 53% of the population among the households with children are the female-headed households, and they account for 76% of the deprived population. The 0.31 M_0 index demonstrates their severe deprivation compared to the subgroup of married couples with children (0.08) and the subgroup of male-headed households with children (0.24).

Table 7 – Level 4 Decomposition: the African-American Subgroup—With Children Only

Subgroup	Population	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Mar-C w/ Child	7736	37.73%	0.1788	16.40%	0.4599	0.0822	14.41%
Ma-H w/ Child	1870	9.12%	0.4610	10.22%	0.5120	0.2360	10.00%
Fe-H w/ Child	10899	53.15%	0.5676	73.37%	0.5394	0.3061	75.59%
Total	20505	100%	0.4112	100%	0.5236	0.2153	100%

(b) The Hispanic Subgroup

In order to examine further the extreme deprivation of the Hispanic female-headed household subgroup, we decompose this subgroup, in Table 8, according to the presence of children in the household. We note that the M_0 index for the subgroup of female-headed households with children reaches nearly 0.4, twice the size of M_0 for the female-headed households without children. Hence, the most deprived subgroup in this sample is the subgroup of Hispanic female-headed households with children. Once again, the presence of children in the Hispanic female-headed households proves to be a significant factor for the chronic poverty of this particular subgroup.

Table 8 – Level 4 Decomposition: The Hispanic Subgroup

Subgroup	Population	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Fe-H w/ Child	4326	69.33%	0.6826	79.06%	0.5701	0.3892	81.23%
Fe-H w/o Child	1914	30.67%	0.4086	20.94%	0.4974	0.2032	18.77%
Total	6240	100.00%	0.5986	100.00%	0.5549	0.3321	100.00%

We note that the female-headed households with children constitute 35% of the population, and contribute 55% of *all* deprived households with children, as shown in Table 9.

Table 9 – Level 4 Decomposition: The Hispanic Subgroup—With Children Only

Subgroup	Population	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Mar-C w/ Child	6819	55.41%	0.3201	37.93%	0.4828	0.1546	34.39%
Ma-H w/ Child	1161	9.43%	0.5332	10.76%	0.5290	0.2820	10.68%
Fe-H w/ Child	4326	35.15%	0.6826	51.31%	0.5701	0.3892	54.93%
Total	12306	100%	0.4677	100%	0.5326	0.2491	100.00%

(c) The White Subgroup

For this subgroup, we see that the female-headed households with children are substantially more multidimensionally deprived than the childless female-headed households (Table 10). The former subgroup has an M_0 index that is 0.12 higher than the M_0 for the latter (0.20 – 0.08).

Table 10 – Level 4 Decomposition: The White Subgroup

Subgroup	Population	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Fe-H w/ Child	34883	31.58%	0.4296	52.05%	0.4663	0.2003	54.12%
Fe-H w/o Child	75564	68.42%	0.1827	47.95%	0.4291	0.0784	45.88%
Total	110447	100%	0.2607	100%	0.4484	0.1169	100%

By putting all the with-children categories of the White subgroup together in Table 11, we observe that the subgroup of the female-headed households is the still the most deprived, with M_0=0.20, nearly twice the M_0 for the male-headed households.

Table 11 – Level 4 Decomposition: the White Subgroup—sWith Children Only

Subgroup	Population	Contrib.	MP H	Contrib.	A	M_0	Contrib.
Mar-C w/ Child	194206	79.56%	0.0877	47.49%	0.4201	0.0368	45.27%
Ma-H w/ Child	15018	6.15%	0.2561	10.72%	0.4327	0.1108	10.53%
Fe-H w/ Child	34883	14.29%	0.4296	41.78%	0.4663	0.2003	44.20%
Total	244107	100%	0.1469	100%	0.4407	0.0647	100%

(d) Comparison between the African-American and Hispanic Female-Headed Households with Children

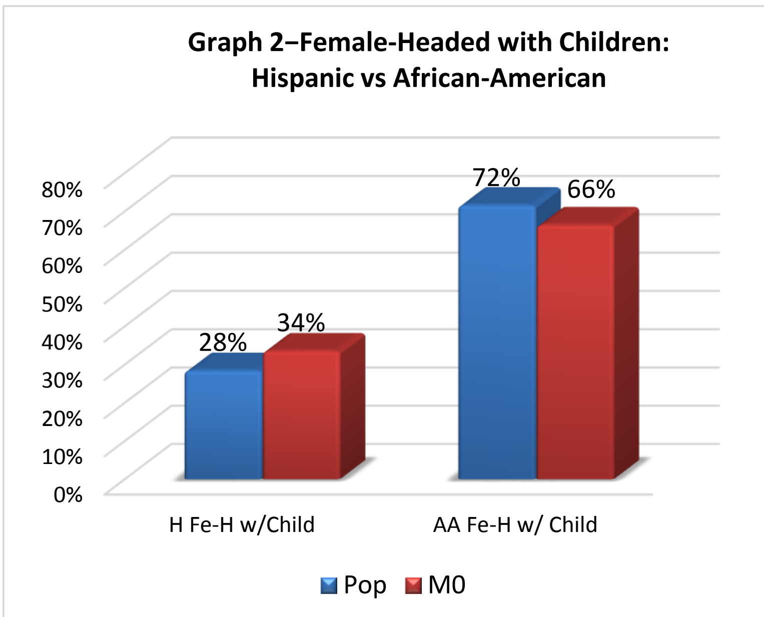
Since the non-White population of Pennsylvania in this study is about 10% of the total (Table 1.a), the above analysis suggests the subgroup of non-White mothers in female-headed households is clearly the most significant subgroup experiencing chronically high poverty in the state. In order to obtain a clearer picture of the chronic poverty of female-headed households, we focus in the following discussion on the M_0 indices of the two most deprived subgroups, namely African-American and Hispanic. In the new sample given in Table 12, the Hispanic female-headed household has a higher rate of deprivation than the African-American subgroup. This follows the M_0 poverty ranking that we mentioned at the beginning of this section, namely, that the Hispanic subgroup is worse off than the other two subgroups (Table 1.a). This subgroup has an M_0 index that is 0.08 greater than the M_0 for the subgroup of the African-American female-headed households with children (0.39 - 0.31, Table 12). The population of the Hispanic female-headed households with children accounts for 28% of the female-headed ethnic (Hispanic and African-American combined) population, but contributes 34% of the total population in poverty of that subgroup compared to the African-American subgroup, which contributes 66.5 % to the M_0 but has a population share of 72%. Note that the Hispanics have an income poverty rate that is 0.12 higher than the M_0 for the African-Americans (0.55 – 0.43, Table 12). Thus, relative to their population share, the Hispanic female-headed households with children are more deprived than the African-American female-headed households with children *both* in terms of the Income Poverty Headcount measure (MP H column) and the Multidimensional Poverty Index (M_0 column). This is in contrast with Akire and Foster's (2010) finding for the U.S., which suggests that

Hispanics are better off in the employment dimension.

*Table 12 – Female-Headed Households with Children: Hispanic vs. African-American**

Subgroup	Population	Contrib.	MP H	A	M_0	Contrib.
H Fe-H w/ Child	4326	28.41%	0.6826	0.5701	0.3892	33.54%
AA Fe-H w/ Child	10899	71.59%	0.5676	0.5394	0.3061	66.46%
Total	15225*	100%*	0.6003	0.5492	0.3297	100%

**Sample consists exclusively of a combination of the two non-White ethnic subpopulation households with children*



To discover the reasons for the difference in deprivation for these two subgroups, we need to break down the aggregate index into the contribution of each dimension to see where the capability deprivation is most acute. For a better understanding of dimensional breakdown, we place our examination in the context of a broader comparison of the statistics for Hispanic and African-American households before further disaggregation by gender status of the household head. This is given in Table 13 without disaggregation by household type. We note that for the Hispanic subgroup, educational deprivation—notably lack of a high school diploma—is the most important contributor to their M_0, while for the African-American subgroup the key influence is attributable to deprivation in work status. In addition, the Hispanic subgroup has a somewhat lower level of deprivation in both the dimension of income and the dimension of living standard, compared to the African-American subgroup.

Table 13 – Dimension Breakdown: Ethnic Subgroups

Subgroup	M_0	Contrib.	D1 E	Contrib.	D2 W	Contrib.	D3 Y	Contrib.	D4 LS	Contrib.
Hispanic	0.2246	9.05%	0.2894	32.09%	0.2832	31.41%	0.1439	15.96%	0.1852	20.54%
White	0.0631	75.00%	0.0771	30.52%	0.1084	42.93%	0.0295	11.70%	0.0375	14.85%
African-A	0.1801	15.96%	0.1735	24.08%	0.2633	36.55%	0.1207	16.75%	0.1630	22.62%
Total	0.0760	100%	0.0901	29.65%	t.1242	40.88%	0.0391	12.86%	0.0505	16.61%

Further disaggregated breakdown by ethnicity is employed for the two types of female-headed household subgroups in Table 14 (African-Americans) and Table 15 (Hispanics). We note that the African-American female-headed households with children suffer from a very high deprivation level score (0.54) in the dimension of employment status, as does the subgroup of the African-American population in general. However, the index for the educational dimension is 0.17, nearly identical for this population group as a whole given in Table 13; this is lower than the index for the dimension of welfare income support (0.26) and the dimension of living standard (0.26).

Table 14 – Dimension Breakdown: The Hispanic Subgroup—Female-Headed Only

Subgroup	M_0	Contrib.	D1 E	Contrib.	D2 W	Contrib.	D3 Y	Contrib.	D4 LS	Contrib.
Fe-H w/ Child	0.3892	81.23%	0.3465	22.26%	0.5982	38.43%	0.3219	20.68%	0.2900	18.63%
Fe-H w/o Child	0.2032	18.77%	0.2962	36.45%	0.1923	23.65%	0.1519	18.69%	0.1724	21.21%
Total	0.3321	100%	0.3311	24.92%	0.4737	35.66%	0.2698	20.31%	0.2540	19.12%

Table 15 for the subgroup of Hispanic female-headed households with children has a pattern of deprivation different from that for the total Hispanic subgroup given in Table 13. With a 0.6 index in the dimension of work status, the Hispanic female-headed household subgroup has more extreme deprivation in employment than in education (0.35). On the other hand, the subgroup of

Hispanic female-headed households without children follows the same pattern of allocation of deprivation across dimensions as the total Hispanic subgroup. In particular, educational deprivation remains the second most important contributor to the aggregate M_0 of this subgroup, and it has a far greater impact on the Hispanic single mothers than on the African-American single mothers (0.35 compared to 0.17).

Table 15 – Dimension Breakdown: The African-American Subgroup—Female-Headed Only

Subgroup	M_0	Contrib.	D1 E	Contrib.	D2 W	Contrib.	D3 Y	Contrib.	D4 LS	Contrib.
Fe-H w/ Child	0.3061	69.67%	0.1666	13.61%	0.5372	43.87%	0.2596	21.20%	0.2612	21.33%
Fe-H w/o Child	0.1718	30.33%	0.2174	31.63%	0.1983	28.84%	0.1064	15.48%	0.1653	24.04%
Total	0.2475	100%	0.1888	19.07%	0.3892	39.31%	0.1927	19.46%	0.2193	22.15%

We interpret this as suggesting that the presence of children in the African-American and Hispanic female-headed household subgroups forces the mothers to spend more time in the household rather than in the labor market. Without the presence of a spouse, this becomes a serious disadvantage that decreases the competitiveness of the single mothers in the labor market. In addition, lack of education plays a critical role for the Hispanic single mothers, as it does in general for the Hispanic group as a whole.

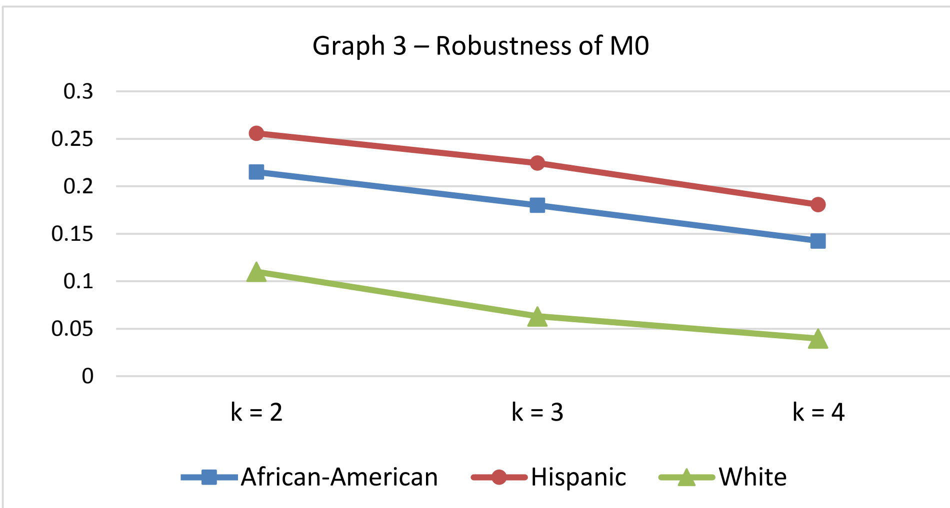
e. Robustness of the Multidimensional Poverty Approach

In this section we check for the robustness of our results using the two alternative methods discussed above. First, we use the dual cut-off method by changing the threshold k=3 to values lower and higher than 3 so now k equals 2, or 3, or 4. We apply this procedure to ranking poverty status by the race of the household head. Second, we employ fuzzy set measures of MP based on the FSLH and FSEP. The results by the dual cut-off M_0 method are displayed in Graph 3, and reported in Table 16. Graph 3 shows that for each value of k, for instance k=2, M_0 for Hispanics are the highest and for Whites the lowest, with African-Americans in between. Note however that Table 16 also shows that the gap between White poverty and non-White poverty becomes more pronounced as we adopt k values closer to extreme poverty (third column).

Graph 4 and Table 17 focus on the main household populations by gender, race, and presence of children identified above as high chronic poverty groups in Pennsylvania; comparing M_0 with FSLH and FSEP values. Once again, allowing for vagueness in separating the poor and non-poor

Table 16 – M_0 According to Different ***k***

M_0	k = 2	k = 3	k = 4
African-American	0.2152	0.1801	0.1427
Hispanic	0.2560	0.2246	0.1809
White	0.1101	0.0631	0.0398

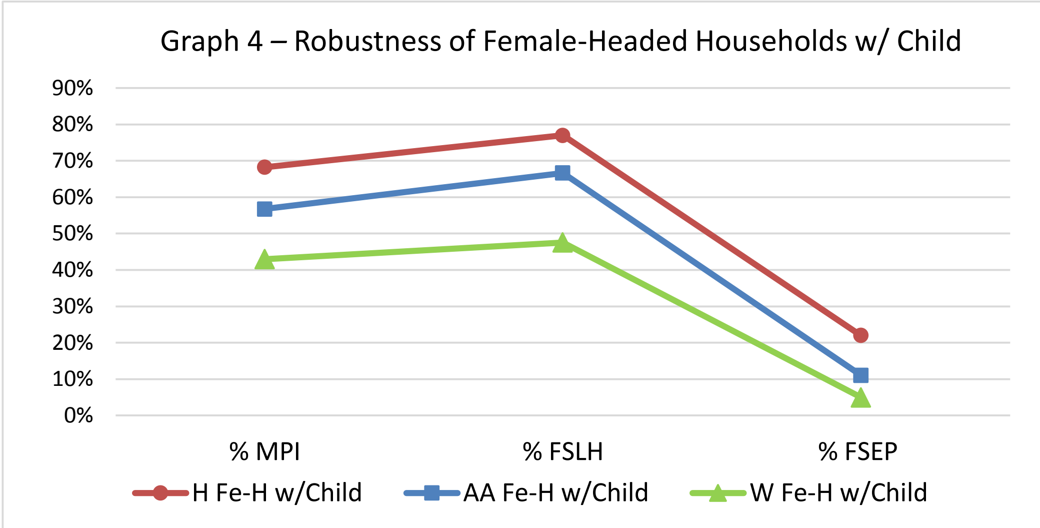


by FSLH and FSEP produces the same ranking as M_0, that is, Hispanics have the highest poverty ranking and Whites the lowest and African-American are in between; and once again the FSEP gap between the White and non-White poor is more pronounced compared to the FSLH.

Table 17 – Robustness of Fe-H w/ Child Using Fuzzy Set Theory

Subgroups	% MPI	% FSLH	% FSEP
Hispanic Fe-H w/Child	68.26%	76.98%	22.05%
African-A Fe-H w/Child	56.76%	66.65%	11.05%
White Fe-H w/Child	42.96%	47.56%	5.00%

** % MPI: Percentage of population deprived by MPI standard.*
** % FSLH: Percentage of population deprived using Fuzzy Set Lower Half standard.*
** % FSEP: Percentage of population deprived using Fuzzy Set Extreme Poverty standard.*



We conclude that our capability-based measures of poverty appear to be robust to the cut-off point employed for M_0 calculations, and robust if we allow for a substantial degree of fuzziness in the boundary between the poor and the non-poor.

f. Poverty Profiles: Income-based and Multidimensional

In this section, we estimate Probit models for predicting the probability of being in poverty, conditional on the variables revealed in the previous section to be the important determinants of the MP index, identifying and comparing the poverty profile for Pennsylvania by the M_0 index and Head-Count Income poverty. The dependent variable indicator is zero for non-poverty status and 1 for poverty status[6] (if $k > 3$ in column 3 and if income is below the poverty line in column 2). The results appear in Table 18.

The main aim in this section is to examine the effects of the demographic categories, as

[6] The poverty status dummy in the binomial Probit technique is based on the cumulative normal function, and estimated non-linearly by applying maximum likelihood techniques to $Z_i = \Phi^{-1}(P_i) = \beta_0 + \beta_1 x_{1i} + \beta_{2i} x_{2i}$; where Φ^{-1} is the inverse of that function, and P_i = probability that the poverty status dummy=1. Moreover, the coefficient significance levels are based on the standard normal distribution, since in large samples the *t*-distribution converges on the standard normal distribution. This makes the *z*-distribution appropriate in the context of the asymptotic properties of Probit.

identified in our M_0 analysis, on the probability of being poor. For this reason, all other variables defining deprivation are excluded; the analysis is exclusively in terms of the combined household categories defined by race, gender, and presence of children. With three racial groups in this study, there are nine demographic categories depending on gender and marital status of the households with and without children, with White non-married male-headed households acting as the excluded base category. The results appear in Table 18, the second column for income-based poverty and the third for M_0 poverty.

The poverty profiles suggested by the two approaches have a great deal in common, and both are highly consistent with the M_0 analysis and results reported above. First, all categories in both models, with the exception of White male-headed with children and White female-headed without in the third column, affect poverty profile in the expected positive direction. Second, note that within each racial category, the coefficient estimates for female-headed households with children are the largest in size and the most significant. This suggests single motherhood is the most important feature that increases the chances of being poor in terms of income or M_0. Still, there are equally significant racial differences within the female-headed households with children in terms of the increased chance of being poor. This brings us to the third aspect: the estimated coefficient size for the female-headed households with children can be ranked as the largest for Hispanic, the next largest for African-Americans, and the smallest for Whites, with their statistical significance levels following the same ranking. Being a female-headed Hispanic household with children increases the chances of being poor by two times for income-based poverty, and over one and one-half times for M_0; the corresponding values for African-American female-headed households with children are 1.79% and 1.24%, and those for a White female-headed household with children are 1.50% and 0.90%. Fourth, note that being a White male-headed household with children reduces significantly the chances of being poor by M_0, but increases significantly by income poverty; the same applies to the married couple without children, though for the latter a two-earner family would seem to act as a preventive force in the capability space. In general, however, there is a considerable degree of agreement between the earlier M_0 analysis and the probit results here; the latter confirm and reinforce the main results of the above M_0 calculations.

We note that the overall fit by pseudo R^2 for both equations is rather low, a common feature given the limited variation in the dependent variable of the Probit model. A better measure of the overall fit is the frequency of "success" accurately predicted by the Probit model, that is, the frequency of correctly predicting the actual values 1 or 0, relative to the total frequency of success and failure combined. The correctly predicted poverty outcomes, at around 89.9% for the income-based model and 83.7% for the capability-based model, are very high in both models. It is also interesting to note that the main determinants of M_0 can explain the income poverty profile even better than the multidimensional poverty profile, given the somewhat higher fit by both measures in column 2.

V. Conclusion

The MP is a complement to the income-based poverty measures, not an alternative to them. The MP has its own weaknesses, but its method can also be illuminating. In this paper, we have not only analyzed the overall index and ethnic subgroups' MP indices, as do Alkire and Foster (2010 and others, but have done so based on the key features of the U.S. poverty profile suggested by the Income Poverty Headcount in the United States, namely, the chronic poverty of the African-American and the Hispanic female-headed households with children.

We also obtain the same deprivation ranking as Alkire and Foster (2010) did. The Hispanic subgroup is the most deprived while the African-American subgroup is the second. Moreover, we also find that the Hispanic subgroup is more deprived in the educational dimension, while the African-American subgroup is more deprived in employment status. This follows the same pattern as Alkire and Foster's (2010) result. However, our model has developed a different framework centered on decomposition according to the gender of the head of the household. This allowed us to provide direct evidence that the African-American and Hispanic female-headed households with children are the most deprived subgroups. Our analysis suggests that targeting these segments of) the Pennsylvanian population would be an effective method of poverty reduction, especially

Table 18 – Probit estimates by income-based poverty and by multidimensional poverty for probability of falling into poverty conditional on key features of the household (abs. *z*-values in brackets)		
Race/Gender/Child Presence∅	Income-Based Poverty	Multidimensional Poverty
Hispmalehwchild	0.9262 (22.62)	0.5679 (16.41)
Hispmalehwochild	0.6303 (10.50)	0.5545 (12.39)
Hispmarriedwchild	1.3464 (16.40)	1.1335 (14.93)
Hispmarriedwochild	0.9696 (27.14)	0.9416 (32.33)
Hispfemalehwchild	2.0996 (54.99)	1.5547 (40.30)
Hispfemalhwochild	1.5401 (41.77)	0.8075 (10.51)
Aframalehwchild	0.6825 (16.27)	0.1474 (4.12)
Aframalehwochild	0.3559 (7.77)	0.4000 (13.29)
Aframarriedwchild	1.4497 (24.96)	0.9803 (17.87)
Aframarriedwochild	0.8995 (41.49)	0.6331 (36.77)
Afrafemalehwchild	1.7880 (73.11)	1.2424 (53.83)
Afrafemalhwochild	1.3206 (67.11)	0.6591 (37.93)
Whitmalehwchild	0.2288 (16.01)	-0.3171 (-30.92)
Whitmarriedwchild	0.9029 (35.66)	0.4184 (19.60)
Whitmarriedwochild	0.7822 (62.32)	-0.0336 (-3.48)
Whitfemalehwchild	1.4960 (94.10)	0.8946 (66.56)
Whitfemalhwochild	0.9277 (80.28)	0.1600 (19.26)
Intercept	-1.9812 (-205.32)	-1.1152 (-198.60)
Log-Likelihood	-77796.36	-112958.74
N	269316	269316
pseudo R^2⊕	0.1166	0.0654
% Success Predicted ⊗	0.899	0.837

∅ *Reference missing group: White single male-headed households without children.*
⊕ *McFadden pseudo* $R^2 = \{1 - (\text{log-likelihood}_R/\text{log-likelihood}_{UR})\}$; *$_R$= restricted model exclusive of all explanatory variables, and $_{UR}$= unrestricted model.*
⊗ *Calculated as the actual frequencies of the poverty indicators successfully predicted by the model (the cases where the actual and the predicted values are either both 1, or both 0), out of the total counts of predicted successes and failures (cases of [0, 1] or [1, 0]) combined.*

with regard to work status, for instance improved wage rates for part-time work likely to benefit single mothers, in addition to better educational and linguistic services for Hispanics. Moreover, our probit analysis reveals that the main factors that determine our M_0 measures also provide sensible explanatory variables for the profile of the poor in Pennsylvania in terms of multidimensional deprivation *and* income deprivation.

Bearing in mind the broad similarity of income poverty rates and average household income between Pennsylvania and the averages for the United States, we believe that the preliminary multidimensional capability measurement results for the state of Pennsylvania reported in this paper are likely to reflect the broad poverty pattern of M_0 for the United States as a whole. However, given the changes in the population ethnicity composition across the U.S. and the data limitation of this study, notably with regard to access to health insurance, important differences in gender and ethnic patterns of multidimensional poverty are likely to emerge from a fuller investigation that covers the entire country. Table A below explains the procedure with a simple example with one indicator for each dimension.

APPENDIXA: Fuzzy Set Demonstration

Table A Illustration of FSLH & FSEP						
Indicators	Household					
	1		**2**		**3**	
Household Size	3		4		3	
Dimension	Score	≥ .375	Score	≥ .375	Score	≥ .375
D1 Educ	0	N	2.5	Y	0	N
D2 Work	2.5	Y	2.5	Y	0	N
D3 Sup Y	0	N	1.25	Y	0	N
D4 LS	0.83	Y	0.83	Y	0.83	Y
# Deprived Dim.	2		4		1	
Category	FSLH		FSLH/FSEP		Non-deprived	
% Deprived	$\% \, FSLH = \frac{FSLH \; Pop}{Tot \; Pop} = \frac{(3+4)}{(3+4+3)} = 70\%$ $\% \, FSEP = \frac{FSEP \; Pop}{Tot \; Pop} = \frac{4}{(3+4+3)} = 40\%$					

* *FSLH: Deprived using Fuzzy Set Lower Half standard.*
* *FSEP: Deprived using Fuzzy Set Extreme Poverty standard.*

Suppose we have three households in a sample. Upon obtaining the deprivation score for each dimension for each household based on the same weighting scheme outlined for M_0 (each indicator=1, weighted and aggregated across all dimensions), we compare the dimensional deprivation score obtained with the fuzzy set threshold set equal to 0.375 and applied uniformly to every dimension. If the deprivation score for a given dimension is greater than 0.375, the household is counted as deprived in that dimension. After going through every dimension for each household, we count the number of deprived dimensions for each household. We categorize the households by the following two standards: a household that has less than two deprived dimensions is counted as non-deprived; a household that has two or more deprived dimensions is categorized as deprived based on the Fuzzy Set Lower Half standard (FSLH). As an alternative fuzzy measure, a household that is deprived in all four dimensions is also counted as deprived based on the Fuzzy Set Extreme Poverty standard (FSEP). Then we work out the headcount of the deprived population by both the FSLH and FSEP, and dividing them by the total population, obtain the percentage of the deprived population by both standards. Table A illustrates the difference between the FSLH and FSEP with a simple example, assuming one indicator in each of our four dimensions.

References

Alkire, S. (2008), “Choosing Dimensions: The Capability Approach and Multi-dimensional Poverty,” in N. Kakwani and J. Silber (eds.), *The Many Dimensions of Poverty*, New York: Palgrave Macmillan, 89–119.

Alkire, S., and J. Foster (2010), “Counting and Multi-dimensional Poverty Measurement,” *Journal of Public Economics*, **95**: 476–487.

Arrow, K. (1973), “Some Ordinalist-Utilitarian Notes on Rawls’ Theory of Justice,” *Journal of Philosophy*, **70 (9)**: 245–263.

Asselin, L. (2009), *Analysis of Multi-dimensional Poverty: Theory and Case Studies*, Ottawa: Springer/IDRC.

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

Atkinson, A.B., and F. Bourguignon (1982), “The Comparison of Multi-dimensional Distribution of Economic Status,” *The Review of Economic Studies*, **49**: 183–201.

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

Burnham, L. (1985), “Has Poverty Been Feminized in Black America?” *Black Scholar* **16(2)**: 14–24.

Cerioli, A., and S. Zani (1990), “A Fuzzy Approach to the Measurement of Poverty,” in C. Dagum and M. Zenga (eds.), *Income and Wealth Distribution, Inequality and Poverty*, Berlin: Springer Verlag.

Chakravarty, S.R., D. Mukherjee, and R.R. Renade (1998), “On the Family of Subgroup and Factor Decomposable Measures of Multi-dimensional Poverty,” *Research on Economic Inequality*, **8**: 175–194.

Chakravarty, S.R., and J. Silber (2008), “Measuring Multi-dimensional Poverty: The Axiomatic Approach,” in N. Kakwani and J. Silber (eds.), *Quantitative Approaches to Multi-dimensional Poverty Measurement*. New York: Palgrave Macmillan, 192–209.

Chiappero-Martinetti, E. (2000), "A Multi-dimensional Assessment of Well-being Based on Sen's Functioning Approach," *Rivista Internazionale di Scienze Sociali*, **108**: 207–239.

Deutsch, J., and J. Silber (2005), "Measuring Multi-dimensional Poverty: An Empirical Comparison of Various Approaches," *The Review of Income and Wealth*, **51**: 145–174.

Duclos, J.Y., D.E. Sahn, and S.D. Younger (2006), "Robust Multi-dimensional Poverty Comparisons," *The Economic Journal*, **116**: 943–968.

Duclos, J.Y., D.E. Sahn, and S.D. Younger (2007), "Robust Multi-dimensional Poverty Comparisons with Discrete Indicators of Well-being," in S.P. Jenkins and J. Micklewright (eds.), *Poverty and Inequality Re-examined*, Oxford: Oxford University Press, 185–208.

Foster, J., M. McGillivray, and S. Seth (2009), "Rank Robustness of Composite Indices," *Oxford Poverty & Human Development Initiative, OPHI Working Paper* 26.

Gardin, C. (2012), "Poverty among Minorities in the United States: Explaining the Racial Poverty Gap for Blacks and Latinos," *Applied Economics*, **44**: 3793–3804.

Harsanyi, J. (1953), "Cardinal Utility in Welfare Economics and in the Theory of Risk-Taking," *Journal of Political Economy*, **61(5)**: 434–435.

Lelli, S. (2001), "Factor Analysis vs. Fuzzy Sets Theory: Assessing the Influence of Different Techniques on Sen's Functioning Approach," Paper presented at the Conference on Justice and Poverty, Von Hugel Institute, St. Edmond's College, Cambridge.

Moore, K.A., Z. Redd, M. Bukhauser, K. Mbwana, and A. Collin (2009), "Children in Poverty: Trends, Consequences, and Policy Options," *Child Trend Research Brief* , Publication #2009-11.

Nussbaum, M. (2000), *Women and Human Development*. New York: Cambridge University Press.

Pearce, D. (1978), "The Feminization of Poverty: Women, Work and Welfare," *Urban and Social Change Review*, **11(1, 2)**: 28–36.

Qizilbash, M., and D. Clark (2005), "The Capability Approach and Fuzzy Poverty Measures: An

Application to the South African Context," *Social Indicators Research*, **74**: 103–139.

Qizilbash, M. (2006), Philosophical Accounts of Vagueness, Fuzzy Poverty Measures and Multidimesionality", in A. Lemmi and G. Betti (eds.) Fuzzy Set Approach to Multidimensional Poverty Measuremently, New York: Springer: 9-28

Ravallion, M. (1996), *Poverty Comparison: A Guide to Concepts and Methods*, Cambridge: Belknap.

Ravallion, M. (2011), "On Multi-dimensional Indices of Poverty," *World Bank Policy Research Working Paper*, Number 5580.

Rawls, J. (1971), *A Theory of Justice*. Cambridge: Belknap.

Rawls, J. (1982), "Social Unity and Primary Goods," in A.K. Sen and B. Williams (eds.), *Utilitarianism and Beyond*, Cambridge: Cambridge University Press.

Rodgers, J.R., and J.L. Rodgers (1993), "Chronic Poverty in the United States," *Journal of Human Resources*, **28.1**: 25–54.

Seccombe, K. (2000), "Families in Poverty in the 1990's: Trends, Causes, Consequences, and Lessons Learned," *Journal of Marriage and the Family*, **62**: 1094–1113.

Sen, A. (1976), "Poverty: An Ordinal Approach to Measurement," *EconometricaI,* **44**: 219–231.

Sen, A. (1985), *Commodities and Capabilities*, New York: Elsevier.

Sen, A., (1987), *The Standard of Living*, in G. Hawthorn (ed.), *The Standard of Living*, Cambridge: Cambridge University Press, 1–38.

Sen, A. (1992), *Inequality Reexamined*. Cambridge , MA: Harvard University Press.

Sen, A. (1995), "The Political Economy of Targeting", in D. van de Walle and K. Nead (eds.), *Public Spending on the Poor: Theory and Evidence,* Baltimore: The Johns Hopkins University Press, 11–24.

Sen, A. (1996). *On the Foundations of Welfare Economics: Utility, Capability and Practical Reason*, in F. Farina, F. Hahn, and S. Vannucci (eds.), *Ethics, Rationality and Economic Behaviour,* Oxford: Clarendon Press, 50–65.

Sen, A. (2004), "Capabilities, Lists, and Public Reason: Continuing the Conversation," *Feminist*

Economics, **10**: 77–80.

Thorbecke, E. (2008), “Multi-dimensional Poverty: Conceptual and Measurement Issues,” in N. Kakwani and J. Silber (eds.), *The Many Dimensions of Poverty*, New York: Palgrave Macmillan, 3–20.

Tsui, K. (2002) “Multi-dimensional Poverty Indices,” *Social Choice & Welfare*, **19**: 69–93.

Wagle, U. (2007), “Multi-dimensional Poverty: An Alternative Measurement Approach for the United States?” *Social Science Research*, **37(2)**: 559–580.

Wagle, U. (2008), *Multi-dimensional Poverty Measurement: Concepts and Applications*, New York: Springer Science.

Wagle, U. (2009), “Capability Deprivation and Income Poverty in the United States, 1994 and 2004: Measurement Outcomes and Demographic Profile,.” *Social Indicators Research*, **94 (3)**: 509–533.

Wagle, U. (2014), “The Counting-based Measurement of Multi-dimensional Poverty: The Focus on Economic Resources, Inner Capabilities, and Relational Resources,” *Social Indicators Research*, **94 (3)**: 223–240.