Subjective Well-Being and Objective Poverty Indices:
Evidence from Panel Data in South Africa

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Abstract

This study investigates the relationship between subjective well-being and two objective poverty indices: income poverty and multidimensional poverty. Though these indices are popular both in academics and policy-making, their relationship has been largely unexplored. By applying the Blow-up and Cluster estimation of fixed effects ordered logit model to a panel data collected in South Africa, this study finds that income poverty significantly aggravates subjective well-being, though the effect of multidimensional poverty is not clear. Moreover, a large part of the variation in subjective well-being cannot be explained by these objective poverty indices, suggesting strong disparity between subjective and objective welfare measures.

Keywords: subjective well-being; poverty line; multidimensional poverty index; panel data
JEL classification: I32, D60, O12

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1. Introduction

One of the fundamental issues in economics is how to measure welfare. The measurement is especially important in order to discuss the effect of development projects on poverty alleviation, which is one of the most popular topics in recent development economics. A natural and straightforward way to measure welfare is to use income or consumption compared to the poverty line. In fact, it is the most common target variable in both academics and policymaking.

However, poverty involves many non-monetary aspects as well as monetary aspect. Thus, relying solely on income or consumption is insufficient to measure poverty. As candidates of these non-monetary welfare measures, this study focuses on two other indices which are becoming popular in both academics and policymaking. One is multidimensional poverty index (MPI) (e.g., Alkire and Foster, 2011), which is based on capability approach by Sen (1985). The other is subjective well-being (SWB), which is a measure of people's subjective assessment of their life.

Given the recent trend of measuring welfare by these indices, investigating the relationship among them is especially important to discuss their complementarity. As for the relationship between SWB and income poverty, though numerous studies have shown the positive relationship between SWB and income (e.g., Easterlin, 2001; Frey and Stutzer, 2002; MacKerron, 2012), very few studies have focused on the poverty index directly. As for SWB and MPI, virtually no rigorous qualitative analysis has been conducted on their relationship in spite of the conceptual similarity between SWB and capability approach (MacKerron, 2012). Although there are several exceptional studies (e.g., Ravallion and Lokshin, 2002; Kingdon and Knight, 2006), the issue of across-individual comparison, which is one of the fundamental issues in SWB analysis, remains to be unexplored. Furthermore, in order to avoid spurious correlation resulting from unobserved heterogeneities, extending these studies into panel data setting remains to be an important issue.

The aim of this study is to fill this gap by investigating qualitative relationship among these welfare indices. For this purpose, we estimate fixed effect ordered logit model by employing the Blow-up and Cluster method developed by Baetschmann et al. (2015). By doing so, we can analyze the issue by taking into account for individual-specific heterogeneities as well as the ordinal nature of the dependent variable.

2. Data and Poverty Lines

Although South Africa is regarded as one of the emerging economies, its monetary and non-monetary aspects of poverty still remain important social issues. This study uses the dataset from the National Income Dynamics Study (NIDS), which is the first national household panel study in South Africa. It is led by the Southern Africa Labour and Development Research Unit (SALDRU) based at the University of Cape Town's School of Economics. NIDS started in 2008 and currently, 4 rounds of panel data are available. Its original sample is nationally representative over 28,000 individuals in 7,300 households across the country. It is a multi-purpose survey covering a wide variety of socio-economic situation.

Statistics of South Africa published three national poverty lines in 2012: the food poverty line (R305), the lower-bound poverty line (R416), and the upper-bound poverty line (R577) as of 2008 (Statistics South Africa, 2014). Since the World Bank's conventional $1.25 poverty line captures acute poverty, this study uses the upper bound national poverty line as a complement. Note that these poverty lines are adjusted for the price level.

MPI consists three dimensions: education, health, and living standard. In order to construct this index, we need to set the indicators, the weight, and the cutoffs. Theoretically, there are many ways to choose these criteria. We follow Rogan (2016), who analyzes MPI using NIDS dataset by modifying Alkire and Santos (2014) approach, and calculate MPI score for each individual. Those who with MPI score lower than the threshold (1/3) are classified as MPI poor. Note that MPI is defined at the household level, and there is no variation within a household. Thus, we restrict the sample only to household heads.

3. Empirical Strategy

The main purpose of this study is to investigate the relationship among SWB, income poverty, and MPI. For this purpose, we estimate the following regression model:

$$SWB_{it} = \beta_1 I(y_{it} < z_y) + \beta_2 I(MPI_{it} < z_{MPI}) + X_{it}\gamma + \tau_t + \eta_i + \epsilon_{it} \quad (1)$$

where SWB_{it} is *i*'s SWB at time *t*, $I(y_{it} < z_y)$ and $I(MPI_{it} < z_{MPI})$ are indicator functions that take one if their income or MPI score is less than its poverty line, X_{it} is a vector of other controlling variables, τ_t is survey-round dummies, η_i is individual fixed effects. Note that our main parameters of interest are β_1 and β_2, which represent the effect of objective poverty indices on SWB.

In order to capture the impact of the "intensity" of these indices, we also estimate the following model based Ravallion and Lokshin (2002):

$$SWB_{it} = \beta_1 \ln\left(\frac{y_{it}}{z_y}\right) + \beta_2 \left(\frac{MPI_{it}}{z_{MPI}}\right) + X_{it}\gamma + \tau_t + \eta_i + \epsilon_{it} \quad (2)$$

Note that β_1 is expected to be positive because higher income is associated with higher SWB, while β_2 is expected to be negative because higher intensity of MPI is associated with lower SWB.

The problems associated with SWB analysis are (i) the ordinal nature of the dependent variable, and (ii) individual comparison. (i) can be addressed by using ordered response model (e.g., ordered logit/probit model). (ii) can be addressed, albeit partially, by including individual fixed effect to control for the individual-specific mean. However, once we try to incorporate these two issues at the same time (e.g., fixed effect ordered logit/probit model), it is difficult to obtain consistent estimates from the standard maximum likelihood (ML) approach because of the incidental parameter problem (e.g., Neyman and Scott 1948; Lancaster 2000). Recently, however, Baetschmann et al. (2015) develop the Blow-up and Cluster (BUC) estimator of fixed effects ordered logit model by extending the conditional ML approach. The advantages of the BUC estimator are that it is consistent and that it has good finite sample properties. Thus, we estimate fixed effect ordered logit models for models (1) and (2) by employing BUC approach.

Another important statistic for this study is the coefficient of determination. Since we are interested in the overlap of the three indices, it is informative to see how much of the variation in SWB can be explained by income poverty and MPI. Since the conventional pseudo-R^2 is known to be downward-biased in our case (Veall and Zimmerman, 1996), this study uses (normalized) Aldrich and Nelson pseudo- R^2 by following Ravallion and Lokshin (2002).

Since MPI comprises nine variables in this study, it cannot be calculated for observations with missing values in at least one of them. For this nature, MPI tends to suffer from missing observations and the resulting sample size becomes smaller. In order to deal with this issue, we employ the multiple imputation method. For imputation, we use logit model for each indicator with the same control variables in the main specifications as well as other time-invariant characteristics. The number of the simulated data (D) is 50. We use Rubin's rule (Rubin, 1987) to obtain the coefficient estimates and their variances.

4. Results[1]

Being income poor significantly aggravates SWB and it is robust to the inclusion of other controlling variables. However, once we control for household income, it becomes insignificant while income itself has a significantly positive effect on SWB. Note that this result does not mean being in poverty does not affect SWB. Rather, it means that lower income does lead to lower SWB, but that having the income lower than the poverty line has no additional effect after controlling for income.

In contrast to these significant impacts of income poverty, the effect of being MPI poor is not significant in all specifications, though the point estimates are all negative. However, the coefficient on MPI is significantly negative if we do not control for individual fixed effect. This implies that MPI is affected by unobserved heterogeneities, which can result in spurious correlation, and casts doubt on cross-sectional analysis.

[1] Estimation results are available on request.

In terms of Aldrich and Nelson pseudo-R^2, the objective poverty indices themselves explain only 7.5% of the variation in SWB and it increases only to 11.9% even after controlling for other independent variables. In other words, 88 - 92% of the variation remains to be unexplained. Therefore, the overlap between subjective and objective welfare index is extremely low.

As for the model (2), the effect of income measured by the poverty line is significantly positive, which is consistent with Ravallion and Lokshin (2002). The effect of MPI is significantly negative without controls, but its significance is gone with controls. Thus, MPI is not necessarily a good predictor of SWB. A large part of the variation (88 – 92%) remains to be unexplained, confirming the limited overlap between subjective and objective welfare measures.

Using the coefficient estimates in the model (2), we can calculate the substitution rate between income and multidimensional poverty indices (e.g., van Praag et al., 2005; Powdthavee, 2008). The calculated substitution rates imply that around 1.8 – 3.0 times more poverty line income is necessary to compensate for the decrease in SWB from one unit change in MPI index. In this sense, MPI is more acute poverty measure than income poverty in terms of SWB.

5. Concluding Remarks

This study investigated the relationship between subjective well-being and objective poverty indices (i.e., income poverty and MPI). Although these indices are popular in both academics and policymakers, rigorous econometric analysis on their relationship has not been conducted very much. In order to fill this existing gap in the literature, we applied the Blow-up and Cluster estimation for fixed effect ordered logit model, which enables us to handle the potential problems associated with SWB analysis. Using a panel data collected in South Africa, we found that income poverty significantly affects subjective well-being, though the effect of multidimensional poverty is not clear. This result suggests that SWB is affected especially by the monetary factor, rather than the deprivation of capabilities. Moreover, a large part of the variation in subjective well-being cannot be explained by these objective poverty indices, suggesting strong complementarity between subjective and objective welfare measures. In terms of the substitutability between income and multidimensional poverty, we found that being multidimensional poor is 1.8 – 3.0 times more severe than being income poverty in terms of SWB. Thus, MPI can be regarded as an acute poverty measure than income poverty, which is intended by Alkire and Santos (2014).

Reference

Alkire, S. and J. Foster (2011) “Counting and multidimensional poverty measurement,” *Journal of Public Economics* 95, 476–487

Alkire, S. and M. E. Santos (2014) “Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index,” *World Development* Vol. 59, pp. 251–274.

Baetschmann, G, K. E. Staub and R. Winkelmann (2015) "Consistent estimation of the fixed effects ordered logit model," *Journal of the Royal Statistical Society, Statistics in Society, Series A*, Vol. 178, No. 3, pp. 685–703.

Easterlin, R. (2001), 'Income and happiness: towards a unified theory', *Economic Journal*, 111, 465–84.

Frey, B. S. and A. Stutzer (2002) "What Can Economists Learn from Happiness Research?" *Journal of Economic Literature*, Vol. 40, No. 2, pp. 402-435.

Kingdon, G. G. and J. Knight (2006) "Subjective well-being poverty vs. Income poverty and capabilities poverty?" *Journal of Development Studies*, 42:7, 1199-1224.

Lancaster, T. (2000) "The incidental parameter problem since 1948." *Journal of Econometrics* 95, 391–413.

MacKerron, G. (2012) "Happiness Economics From 35 000 Feet," *Journal of Economic Surveys* Volume 26, Issue 4, 705–735.

Neyman, J. and Scott, E. (1948) "Consistent estimation based on partially consistent observations." *Econometrica* 16, 1–32.

Powdthavee, N. (2008) "Putting a price tag on friends, relatives, and neighbours: Using surveys of life satisfaction to value social relationships," *Journal of Socio-Economics* 37, 1459–1480

Ravallion, M. and M. Lokshin (2002) "Self-rated economic welfare in Russia," *European Economic Review* 46, 1453–1473

Rogan, M. (2016) "Gender and Multidimensional Poverty in South Africa: Applying the Global Multidimensional Poverty Index (MPI)," *Social Indicators Research* 126: 987–1006.

Rubin, D. (1987) *Multiple Imputation for Nonresponse in Surveys*. New York: John Wiley.

Sen, A.K. (1985) *Commodities and Capabilities*. Elsevier, Amsterdam; New York. North- Holland.

Statistics South Africa (2014) "Poverty Trends in South Africa: An examination of absolute poverty between 2006 and 2011" available at: https://beta2.statssa.gov.za/publications/Report-03-10-06/Report-03-10-06March2014.pdf

van Praag, Bernard M. S. and B. E. Baarsma (2005) "Using Happiness Surveys To Value Intangibles: The Case Of Airport Noise," *Economic Journal*, 115, 224–246.

Veall, M., K. Zimmerman (1996) "Pseudo-R2 measures for some common limited dependent variable models." *Journal of Economic Surveys* 10 (3), 241–259.