Regional Disparities in Subjective Well-Being: A Spatial Econometric Approach

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Abstract

This study aims to explore spatial externalities in subjective well-being as a source of regional disparities. Using a household panel dataset collected in South Africa, this study estimates spatial econometric models to show micro-level spatial dependence by considering individual heterogeneities. The estimation results show strong spatial dependence in SWB, confirming that spatial externality within a geographical cluster is an essential factor to explain the regional disparities.

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1. Introduction

After the pioneering work by Easterlin (1974), the analysis of happiness or subjective well-being (SWB) has become popular in social sciences in the last four decades. Its use does not limit to academia, and it is also becoming a popular index for policymakers (Stiglitz et al., 2009). The underlying presumption is that these subjective indices can measure people's welfare, albeit imperfectly. As supportive evidence, previous studies have shown some consistent patterns in the relationship between individual characteristics and SWB across region or countries (e.g., Frey and Stutzer, 2002).

In contrast to these consistent patterns in SWB, it is also known that there is a considerable difference in the level of SWB across region or countries (e.g., Pittau et al., 2010; Oswald and Wu, 2011; Aslam and Corrado 2012). Interestingly, the regional disparities remain even after controlling for individual characteristics. One way to explain these disparities is to attribute them to the regional level heterogeneities in institutions and amenities. Previous studies have shown that political institutions and city environments are important determinants of SWB (e.g., Brereton et al., 2008; Frey and Stutzer, 2000).

In addition to these economic analyses, there is a literature in psychology that argues SWB is “contagious”: people tend to feel happy when the surrounding people are happy (e.g., Fowler and Christakis, 2008; Ballas and Tranmer, 2012). Such spillover effect can also explain regional heterogeneities in SWB. However, the estimated spillover effect is often confounded with the regional heterogeneities, and the identification of such spillover requires rigorous econometric approach.

This study aims to test spatial externalities in SWB using spatial econometric approach. We analyze micro-level panel data from South Africa, where inequalities across municipalities are a very salient issue. The previous studies using spatial econometric approach for SWB analysis use country or region level data, and they do not focus on individual-level spillover within a region (Stanca, 2010; Lin et al., 2014; 2017). A more relevant study is Tumen and Zeydanli (2015), who shows that there is no significant spatial spillover in SWB in the UK by estimating multi-level linear-in-means model. The current study is different from theirs in that we test the spillover effect by explicitly controlling for individual and region level heterogeneities.

To preview the result, this study shows a significant spatial spillover in SWB within a geographical cluster, which is robust to the inclusion of individual or regional level heterogeneities. To the best of my knowledge, this is the first study that finds significant micro-level spillover of SWB in a developing country.

2. Data and Empirical Strategy

We analyze the data collected by the National Income Dynamics Study (NIDS), which is the first nationally representative household panel data in South Africa. They have been conducting the survey every two years since 2008. Currently, total of five rounds of survey data (in 2008, 2010, 2012, 2014, and 2017) are available for the analysis. In the dataset, the question regarding SWB is: "Using a scale of 1 to 10 where 1 means "Very dissatisfied" and 10 means "Very satisfied," how do you feel about your life as a whole right now?" We restrict the sample to each household head to save the computational burden.

In order to test spatial externalities in SWB, we employ a spatial econometric approach, which has been developed to incorporate spatial dependence and heterogeneities (e.g., Anselin, 1988). Specifically, we estimate the following combined spatial lag and error (SAC) model with fixed effects:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \delta_i + \zeta_t + u_{it} \tag{1}$$

$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \epsilon_{it}$$

where y_{it} is the level of SWB of individual *i* at round *t*, x_{it} is the set of control variables, and δ_i and ζ_t are individual and round fixed effects, respectively. w_{ij} is the (*i*, *j*) element of the time-invariant *n* x *n* weight matrix *W*, which is defined as:

$$w_{ij} = \begin{cases} 1/n_d & if\ (i,j) \in d \\ 0 & otherwise \end{cases}$$

where n_d denotes the number of the sample living in district d. This means that the spatial lag term, $\sum_{j=1}^{N} w_{ij} y_{jt}$, is the average level of SWB at the district level. Thus, our main parameter of interest is ρ, which captures the spillover effect within the same district. Note that this model allows the error term to be spatially correlated as well, which is captured the parameter λ.

The advantage of this specification is that we can incorporate individual fixed effects, which nest the district fixed effects. Since that institutional differences that generate regional disparities in SWB are expected to be stable over time (Frey and Stutzer, 2000), the estimated ρ captures a pure spillover effect.

An important issue in the estimation of the spatial econometric models is that they are structural equations due to spatial dependence and the OLS estimators are known to be inconsistent (e.g., Anselin, 1988). For this reason, we employ the maximum likelihood (ML) estimation and the transformation approach proposed by Lee and Yu (2010) for handling the incidental parameter problem resulting from individual fixed effects.

However, the ML approach involves two strict restrictions in the estimation. Firstly, the estimation of the model requires a balanced panel data. For this reason, we restrict the sample to the balanced panels of (1) round 1 and 2, (2) round 1 to 3, (3) round 1 to 4, (4) round 1 to 5, in order to fully utilize both cross-sectional and time-series variations. Note that longer panel data can suffer more serious sample selection problem due to attrition. Secondly, the weight matrix is assumed to be time-invariant. Therefore, we need to restrict the sample to those who did not move across the districts during the sample period. For these reasons, we have to lose huge samples.

In order to complement these caveats, we also estimate the following spatial autoregressive (SAR) model with several types of fixed effects:

$$y_{it} = \rho \sum_{j=1}^{N} w_{tij} y_{jt} + x_{it}\beta + \delta_i + \zeta_t + \phi_d + \eta_{pt} + \epsilon_{it}. \tag{2}$$

A noticeable difference from the model (1) is that the weight matrix is time-variant, allowing the respondent to move across districts. For this reason, we can include district fixed effects ϕ_d separately from individual fixed effects. Besides, we include province-round fixed effect η_{pt} to control for the potential time-variant geographical heterogeneities. However, because of the data structure, including the spatial error term is virtually impossible. Therefore, the models (1) and (2) have their own advantages and disadvantages.

Due to the above-mentioned issues, the same ML approach cannot be applied to the estimation of the model (2). Instead, we employ the instrumental variable (IV) approach, by using the first-order spatial lag terms of the dependent variables as instruments for the endogenous variable $\sum_{j=1}^{N} w_{ij} S_{jt}$.

3. Estimation Results

Table 1: Estimation Results (Summary)

	(1)	(2)	(3)	(4)	(5)
Sample	Round 1-2	Round 1-3	Round 1-4	Round 1-5	All
Estimation	ML	ML	ML	ML	IV
Spatial lag	0.844***	0.773***	0.552***	-0.383*	0.815***
	(0.058)	(0.067)	(0.068)	(0.219)	(0.159)
Spatial error	-1.689*	-1.291**	-0.487**	0.455***	NA
	(0.977)	(0.635)	(0.196)	(0.100)	NA
Other control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Round FE	YES	YES	YES	YES	YES
District FE	NO	NO	NO	NO	YES
Province-round FE	NO	NO	NO	NO	YES
Observations	2,952	3,816	2,589	2,236	33,817

Columns (1) – (4) of Table 1 shows the estimation results of the model (1) with a different set of the samples. The spatial lag term, which is our main parameter of interest, is significantly positive in most cases, indicating that there are spatial spillovers in SWB within districts even after controlling for individual or district level heterogeneities. However, it is negative and marginally significant in column (4). This contradicting result might come from severe attrition in the sample: the number of respondents reduces from 2,952 in the panel of round 1 and 2 to 559 in the panel of five rounds. This sample selection problem might lead to a biased estimate in the spatial lag term. Interestingly, the spatial error term is significant in all specifications, suggesting there are unobserved heterogeneities that are spatially correlated.

As mentioned above, the standard spatial econometric approach can suffer from sample selection due to the construction of the balanced panel data and the time-invariant weight matrix. For this reason, we also estimate the model (2), and the result is shown in column (5). Most importantly, the spatial lag term is significantly positive in all specifications, supporting the spatial externalities in SWB after controlling for the individual and region level heterogeneities. Although not shown in the table, we also confirm the U-shape effect of age, the negative effect of being unemployed or economically inactive, and the positive effect of better health and higher income. Intriguingly, the coefficient on the average income within a district is significantly negative across specifications, supporting the comparison income hypothesis. This result contrasts Kingdon and Knight (2007), who finds a positive effect of the comparison income on SWB.

4. Conclusion

This study finds significantly positive spatial spillover effects in SWB, implying the existence of non-institutional factors in regional disparities in SWB. To the best of my knowledge, this is the first spatial econometric analysis of SWB using micro-level panel data in a developing country.

Our results indicate that spatial econometrics is an effective approach to test the spillover effect of SWB within a geographical cluster. However, one thing to be mentioned is that the estimated impact does not necessarily indicate the causal effect of neighbors' SWB on his/her own SWB. Rather, our main interest lies in the existence of spillover in SWB, which is an equilibrium of the reflection effect between these two variables. Therefore, testing the strict causal relationship remains an important issue to be explored in future research.

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