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# The Important Role of Equivalence Scales: Household Size, Composition, and Poverty Dynamics in Russia

Equivalence scales take an important role in household welfare analysis since we often have to analyze incomes (or consumption) from households of different sizes and composition to obtain comparable measures of household living standards. Indeed, a large body of literature has demonstrated that there are substantial effects of scale adjustments on poverty, inequality, as well as profiles of the poor for various countries at different income levels (Lanjouw and Ravallion, 1995; Lanjouw et al., 2004; Rojas, 2007; Peichl et al., 2012; Bishop et al., 2014).

In this paper, we attempt to make several new contributions to the literature on equivalence scales and poverty measurement. First, we estimate equivalence scales using subjective well-being data. While a number of studies have measured equivalence scales using this approach (Charlier, 2002; Schwarze, 2003; Biewen and Juhasz, 2017; Borah et al. 2018), these studies mostly investigate data on life/income satisfaction. We analyze instead a self-rated subjective wellbeing question in the Russian Longitudinal Monitoring Surveys (RLMS) where individuals are asked to evaluate their own level of material well-being on a nine-point scale from "poor" to "rich". This indicator has been observed to better capture the multidimensional nature of welfare and may be more directly related to household welfare than satisfaction data (Ravallion and Lokshin, 2001 and 2002). But we also offer robustness checks using life satisfaction data that are collected in the same household surveys.

Our second contribution is that we offer new and interesting findings regarding dynamics of poverty given equivalence scale adjustments (scaling). It is well-known that policies to address transient poverty is quite different from those for chronic poverty. Yet, while these dynamics by definition requires analysis based on panel data,[1] the data typically used in the existing literature to investigate the effects of scaling on poverty measurement are cross-sectional surveys (see, e.g., Newhouse et al. 2017). Such data do not allow us to understand how household demographics impact chronic poverty, or more precisely speaking, how employing different alternative equivalence scales affects household poverty dynamic patterns.

Finally, the existing studies focus on richer countries, such as Germany or the UK. We focus our analysis on Russia over the past two decades, which offers an interesting case study of a middle-income country in transition. Despite an increasing share of single persons living alone, the average Russian household size is still larger than that in Germany or UK due to its significant proportion of extended families. Our proposed analysis is especially relevant for

[1] But see Dang, Jolliffe, and Carletto (forthcoming) for a review of alternation poverty measurement methods in contexts where no panel data exists.

Russia where the equivalence scale embedded in the official poverty lines is adjusted for the unequal needs in consumption but completely ignores economies of scale in household size. This official adjustment typically identifies large families with children as those most in need of financial support, regardless of their actual living standards. Furthermore, we analyze the RLMS, which offer panel data with longer time intervals than other related studies cited above.[2] Longer-run panel data allow us to extend our analysis to broader definitions of households—including multigenerational households—and to better capture demographic changes caused by births as well as the formation of complex extended families.

To our knowledge, Ravallion and Lokshin (2002) is the only paper that estimated the relationship between household size/composition and subjective well-being in Russia; however, this paper uses shorter panels of three waves.[3] As such, their findings are likely biased by insufficient variation in household size and unobserved heterogeneity issues. We controlled for unobservable characteristics by using the fixed-effect ordered logit model, or the composite likelihood "Blow-up and Cluster" estimator (Baetschmann et al., 2015), which respects the ordinal nature of subjective well-being data. We also tested our results using a more flexible nonlinear specification with fixed effects recently proposed by Biewen and Juhasz (2017).

## II. Preliminary Results

We offer preliminary, but new, findings suggesting that Russian pensioners impose a lower economic burden than working-age adults (i.e., the elasticity is higher for a household with four working-age adults than for a household with two working-age adults and two pensioners). Our findings are robust to inclusion of reference income and are not likely biased due to the "status effect" that plays important role in calculating equivalence scales (Borah et al, 2018) (Table 1).

**Table 1. "Blow-up and Cluster" regression results (linear specification with fixed effects), RLMS 1994-2017**

[2] Only Borah et al. (2018) used longer panel data to analyze equivalence scales but their analysis was restricted to "classical households", which consist of either a single adult or two partnered adults, with or without children for Germany.

[3] Another paper by Takeda (2010) use or cross-sectional data only.

| Variables | Dependent variable: Subjective wealth | |
|---|---|---|
| | *No reference effect* | *Reference effect* |
| Log of household income | 0.400*** | 0.301*** |
| | *(0.02)* | *(0.04)* |
| Log of household size | -0.174*** | -0.185*** |
| | *(0.04)* | *(0.04)* |
| Pensioners#Log of household size | 0.034* | 0.030* |
| | *(0.02)* | *(0.02)* |
| Children#Log of household size | 0.017 | 0.031** |
| | *(0.01)* | *(0.01)* |
| Quntile of relative income | | |
| Q2 | | 0.047 |
| | | *(0.03)* |
| Q3 | | 0.124*** |
| | | *(0.04)* |
| Q4 | | 0.240*** |
| | | *(0.06)* |
| *Number of BUC observations* | 549 499 | 549 499 |
| *Number of individuals* | 25 843 | 25 843 |
| ***Scale elasticity parameters*** | | |
| Baseline elasticity | 0.435*** | 0.615*** |
| | *(0.11)* | *(0.17)* |
| Additional child | 0.042 | 0.104* |
| | *(0.03)* | *(0.05)* |
| Additional pensioner | 0.085 | 0.098 |
| | *(0.04)* | *(0.06)* |

**Note:** Robust standard errors in parentheses. All regressions include demographic controls and year fixed effects. Relative income was calculated using "cell averages" approach proposed by Borah et al (2018).

These results are also consistent with those obtained by Schwarze (2003) and Biewen and Juhasz (2017) for Germany in terms of smaller equivalence weights for adults and children. There is also a lower elasticity for households with children (Table 2).

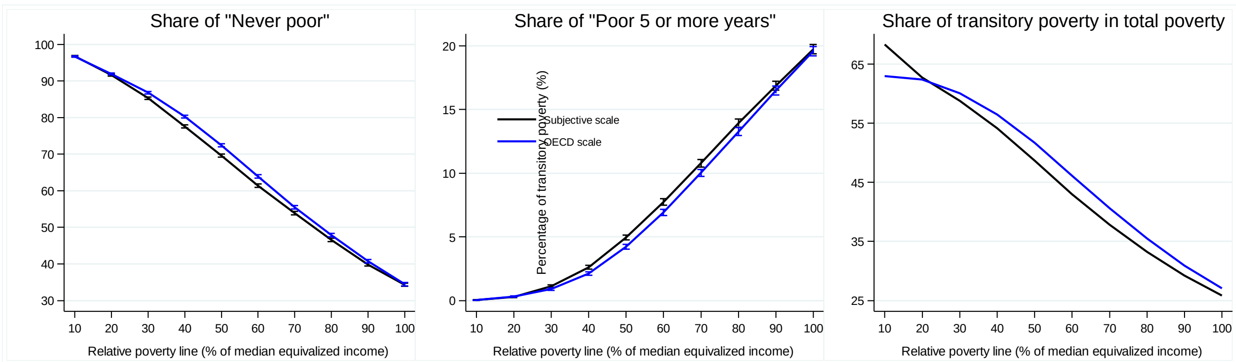
**Table 2. Comparison of different equivalence scales**

| Weights | | Square-root | Modified OECD | Schwarze (2003) | Biewen and Juhasz (2017) | Subjective wealth scale |
|---|---|---|---|---|---|---|
| **Adults** | **1** | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | **2** | 1.41 | 1.50 | 1.28 | 1.37 | 1.34 |
| | **3** | 1.73 | 2.00 | 1.47 | 1.69 | 1.60 |
| | **4** | 2.00 | 2.50 | 1.63 | 2.04 | 1.80 |
| **2 Adults** | **1 Child** | 1.73 | 1.80 | 1.41 | 1.48 | 1.52 |
| | **2 Children** | 2.00 | 2.10 | 1.47 | 1.61 | 1.62 |
| | **3 Children** | 2.24 | 2.40 | 1.48 | 1.74 | 1.64 |

**Note:** Schwarze (2003) main results were based on binary logit model with fixed effects, Biewen and Juhasz (2017) results were based on "Blow- up-and-Cluster" method suggested by Baetschmann et al. (2015)

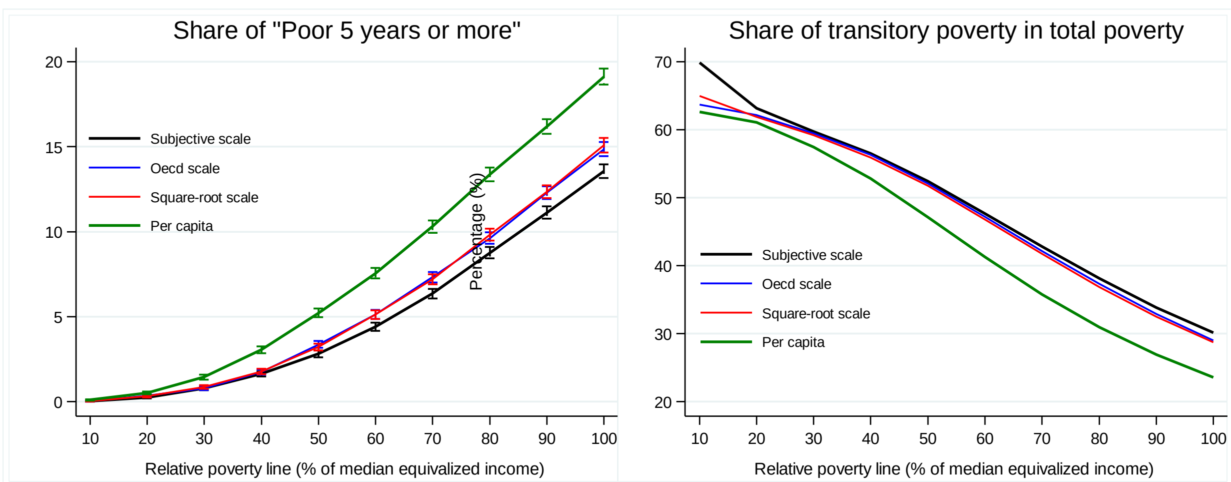
We also provide new evidence that scaling is not only important for measuring cross-sectional or “transient” poverty, but also has strong effects on chronic poverty (Figure 1).

**Figure 1. Chronic versus transitory poverty, all individuals, RLMS 1994-2017**




In particular, the share of the chronically poor (poor in 5 survey rounds and more) individuals living in households with children grows a half to two times larger without scale adjustments (Figure 2).

**Figure 2. Chronic versus transitory poverty, individuals living in households with children, RLMS 1994-2017**




Our results showed that proper accounting for economies of size leads to the sharp reduction of poverty gap between children and pensioners. Furthermore, one-person households—rather than large households—are most susceptible to the risks of poverty (Table 3).

**Table 3. Difference in poverty rates between children and pensioners (in percentage points, by number of children)**

| Years | All households with children | Households with | | | |
|---|---|---|---|---|---|
| | | 1 child | 2 children | 3 children | >3 children |
| 2010 | 3.02 | 2.46 | 2.65 | 6.19 | 8.50 |
| 2011 | 0.11 | 0.51 | -0.59 | 2.04 | -2.97 |
| 2012 | 0.86 | 0.60 | 1.57 | -0.16 | 0.33 |
| 2013 | -0.18 | -0.47 | -0.52 | 4.17 | -3.00 |
| 2014 | -0.50 | -0.91 | -0.13 | 0.53 | -1.05 |
| 2015 | -1.21 | -1.00 | -0.68 | -4.32 | -1.02 |
| 2016 | -0.67 | -1.26 | -0.09 | 1.04 | -4.00 |
| 2017 | -1.01 | -1.08 | -0.99 | 0.57 | -3.35 |

1. **Spillover Effects Engendered By Spatial Dependence: Case Of Russian Regional Inflation**

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The main objective of doing spatial econometrics is to make some inferences on spillover effects caused by spatial dependence. The term *spatial dependence* (SD) is broad and used particularly to address that distributed in geographical space units have economic interactions. SD appears in various forms, e.g. *spatial autocorrelation*, *non-linear tail dependence*, etc. In vast amount of studies (where researchers apply spatial econometrics) spatial autocorrelation (SA) is in the focus of examination.

In context of regional inflation, given that regions (spatially distributed units) are not closed economies (i.e. they interact and trade – exporting/importing good and services), an inflation level in a particular region depends not only on its internal economic, social, geographical and other features, but also on the same features of other regions of the country. It is highly likely that higher level of inflation in a particular region may induce acceleration in the price growth in other regions and vice versa (spillover effects). The detection of this phenomenon suggests the presence of *spatial autocorrelation* in the levels of regional inflation. One may expect the highest spatial autocorrelation among the levels of inflation of regions that are considered as 'neighbors' (usually determined as territories that share common borders), because of the highest expected (usually) similarity of their socio-economic features.

At first, in this research we examine whether regional inflation in Russia exhibits spatial autocorrelation and to what extend it is determined by spatial pattern of the country (in other words, whether spatial autocorrelation depends on the distance between regions). Secondly, we measure spillover effects for the inflation's determinants and test for their statistical significance.

In our research, regional CPIs serve as the quantitative measure of inflation. There are 79 Russian regions in the data set. The time span includes fifteen years, namely from 2002 to 2016. Several statistics (metrics) based on different spatial weights matrixes (matrixes of inverse distances with and without thresholds and binary matrix) are applied to test for spatial autocorrelation. These metrics are Moran's I, APLE (approximate profile likelihood estimator) and ML estimator of SAR model.

In this study, inferences on statistical significance for Moran's I and APLE statistics are based on both permutation and Monte-Carlo tests, while LR test is used to test for significance of ML estimates of SAR model. In addition, we discuss the power of the applied tests based on our simulation-permutation study in line with Anselin and Rey's (1991) contribution.

Results suggest that, at first, statistically significant spatial autocorrelation is detected for almost all examined years (there is no statistically significant SA for 2002 and 2012 years, as our analysis shows). Second, enhancement in distance threshold in spatial weight matrix leads to concurrent increase in values of SA in all metrics, except Moran's, (in other words, spatial autocorrelation grows as additional variation, coming from the regions, is taken into the analysis). Based on this, we conclude that spatial autocorrelation among Russian regional levels of inflations exhibits heterogeneity pattern.

For further analysis of heterogeneity of SA and spillover effects that it induces, a spatial panel econometric model with two matrixes is applied:

$$\mathcal{A}\pi \;\; = \mathbb{X}\beta + \varepsilon$$
$$\varepsilon \sim \varepsilon|\mathbb{X} \sim \mathrm{Normal}(0,\ \sigma^2 \mathrm{I}_{\mathrm{TN}})$$
$$\pi|\mathbb{X} \sim \mathrm{Normal}(\mathcal{A}^{-1}\mathbb{X}\beta,\ \sigma^2(\mathcal{A}^{-1})'\mathcal{A}^{-1})$$

$\mathrm{I}_{\mathrm{TN}} = (\mathrm{I}_{\mathrm{T}} \otimes \mathrm{I}_{\mathrm{N}})$ is $\mathrm{TN} \times \mathrm{TN}$ identity matrix;

$\mathcal{A} = (\mathrm{I}_{\mathrm{T}} \otimes \mathrm{A})$ is $\mathrm{TN} \times \mathrm{TN}$ matrix of spatial filters for panel;

$\mathrm{A} = (\mathrm{I}_{\mathrm{N}} - \rho_1 \mathrm{W}_1) * (\mathrm{I}_{\mathrm{N}} - \rho_2 \mathrm{W}_2)$ - sequential spatial filter;

$\rho_1$ – 1-st scalar, $\rho_2$ – 2-d scalar;

$\mathrm{W}_1 = \left\{ \frac{1}{\mathrm{d}_{\mathrm{ij}}} \;\middle|\; \mathrm{d}_{\mathrm{ij}} \le \mathrm{X\,km.} \right\}$;

$\mathrm{W}_2 = \left\{ \frac{1}{\mathrm{d}_{\mathrm{ij}}} \;\middle|\; \mathrm{d}_{\mathrm{ij}} > X\,km. \right\}$;

$\mathbb{X}$ – matrix of explanatory variables.

The results of estimation are presented in Table 1. In this research, we are mostly interested in estimates of $\rho_1$, $\rho_2$ and $\rho$ ($\rho$ is the SA coefficient for the model with one spatial weight matrix), that is why the estimates of other parameters are not reported. The reported coefficients ($\rho_1$, $\rho_2$ and $\rho$) represent coefficients of spatial autocorrelation when spatial interaction is absorbed and formed with the certain spatial weight matrix. Because the data set has the panel structure, the estimates of $\rho_1$, $\rho_2$ and $\rho$ represent resulted average SA for the whole time span of fifteen years.

*Table 1. Results of estimation.*

| **Parameters of spatial autocorrelation** | **Estimates** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Model 1 (one matrix)** | | | | **Model 2 (two matrixes)** | | | |
| | **W500** | **W1000** | **W2000** | **WID** | **W500** | **W1000** | **W2000** | **WID** |
| $\rho$ | 0.48 | 0.57 | 0.65 | 0.72 | - | - | - | - |
| $\rho_1$ | - | - | - | - | 0.38 | 0.68 | 0.77 | - |
| $\rho_2$ | - | - | - | - | 0.76 | 0.65 | 0.43 | - |
| CORR($\hat{\pi}; \pi$)^2 | 30.4 | 29.6 | 30.1 | 30.8 | 32.3 | 33.7 | 33.1 | - |
| RMSE | 312.9 | 294.3 | 270.7 | 250.9 | 234.0 | 212.6 | 221.5 | - |
| LR for H0: $\rho = 0$ | 287.7 | 435.4 | 630.2 | 805.2 | 1065 | 1178 | 1087 | - |

Results of estimation, at first, strongly demonstrate that there is the heterogeneity of statistically significant spatial autocorrelation of levels of inflation of Russian regions (i.e. that spatial autocorrelation is highly depended on the distance between the regions) during examined period of time. Second, the magnitude of detected spatial autocorrelation is almost equal for regions that are within 1000 km. and outside this distance. Third, we quantify the spillover (indirect) effects, then test their estimates for statistical significance (we fail to accept their insignificance). The calculations show that indirect effects for the models without distance threshold is almost equal to the spillover effect for the models with threshold of 1000 km (the distance for which SA's heterogeneity is eliminated).

Obtained results are useful for forecasting, namely for predictions of proliferation of inflationary shocks among Russian regions (that is, how an accelerated price growth in a source-region transfers to other regions)