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Abstract

Hardly any literature exists on the relationship between equivalence scales and poverty dynamics for transitional countries. We offer a new study on the impacts of equivalence scale adjustments on poverty dynamics for Russia, using the equivalence scales that we construct from subjective wealth and more than 20 years of household panel survey data from the Russia Longitudinal Monitoring Survey. Our analysis suggests that the elasticity is higher for adding another adult to a two-adult household than a child, and scale adjustments result in lower estimates of poverty lines. We decompose poverty into chronic and transient components and find that chronic poverty as a share of total poverty, defined against an absolute poverty line, is positively related to the adult scale parameter. Chronic poverty, however, is less sensitive to the child scale factor compared to the adult scale factor. Interestingly, income mobility could be classified as either upward or downward depending on the specific scale parameters that are employed. Our results are robust to different measures of poverty, income expectations, reference groups, functional forms, and various other specifications.

Key words: poverty, poverty dynamics, equivalence scale, Russia, panel survey

JEL: I30, J10, O15

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I. Introduction

Obtaining comparable measures of household incomes across households of different sizes and composition—or converting these incomes on a common (equivalence) scale—is a crucial task for welfare measurement. Indeed, a large body of literature has demonstrated that there are substantial effects of scale adjustments on poverty and profiles of the poor for various countries at different income levels (Lanjouw and Ravallion, 1995; Peichl *et al.*, 2012; Bishop *et al.*, 2014). Equivalence scales are often estimated based on expenditure data, one major disadvantage of this method is that it requires strong identifying assumptions (Deaton and Paxson, 1998).

In this paper, we make several contributions to the literature on equivalence scales and poverty measurement. First, we estimate equivalence scales using an alternative source of data, subjective well-being data. While a growing literature has followed this approach using panel data, these studies mostly investigate data on life satisfaction and income satisfaction.[1] We analyze instead a subjective wellbeing question where individuals are asked to evaluate their own level of material welfare on a nine-point scale from "poor" to "rich". This question arguably better captures the multidimensional nature of welfare and is more related to household welfare than satisfaction variables (Ravallion and Lokshin, 2001 and 2002).

Second, we offer new and interesting findings regarding the dynamics of poverty given equivalence scale adjustments (scaling) on long-run household panel data from the Russian Longitudinal Monitoring Surveys (RLMS). It is well-known that policies to address short-term

[1] Two main types of subjective well-being data have been analyzed in the economic literature. The first type asks respondents about a hypothetical minimum income level that is required to reach a specified level of well-being (e.g., Garner and Short, 2004). Since this method assumes that people know what their true minimum income level is, the hypothetical assessment of the situation may lead to interpretation issues of minimum income questions (Steiger *et al.*, 1997). The second type asks respondents to evaluate their level of satisfaction with life or income, and does not have such disadvantage (e.g., Biewen and Juhasz, 2017; Borah *et al.*, 2018). Our paper is more related to the second approach. But we also offer robustness checks using life satisfaction data that are collected in the same household surveys.

static poverty is quite different from those for long-term chronic poverty. Yet, while these dynamics, by definition, requires analysis that must be based on panel data, the data used in the existing literature to investigate the effects of scaling on poverty measurement typically come from cross-sectional surveys (e.g., Newhouse *et al.*, 2017).[2] Such data do not provide a good understanding of how household demographics impact transient or chronic poverty, or put it differently, how employing different scaling parameters affects household poverty dynamic patterns. To our knowledge, we are among the first to investigate the impacts of scale adjustments on poverty dynamics.

Furthermore, the RLMS offers panel data with longer time intervals than most existing studies. 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 the formation of complex extended families.[3]

Finally, the richer countries examined in existing studies, such as Germany, Switzerland or the UK, have a smaller household size on average than that of Russia. This different demographic structure implies that findings on the former countries may not necessarily apply to Russia. Furthermore, our study is especially relevant for Russia for two other reasons. Firstly, the equivalence scale currently embedded in the official poverty lines allows for unequal consumption needs but completely ignores the economies of scale in household size. A direct policy implication of no scale adjustment is that the official poverty lines would oftentimes identify large families with children as those most in need of financial support, regardless of their actual living standards.

[2] But see Dang, Jolliffe, and Carletto (2019) for a review of alternative poverty measurement methods in contexts where no panel data exists.

[3] 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.

Secondly, since recent evidence points to more upward mobility than downward mobility for the population over the past two decades (Dang *et al.*, forthcoming), it would be useful for policymakers to understand whether, and to what extent, this finding can be affected by scale adjustments.

To our knowledge, Ravallion and Lokshin (2002) is the only paper that estimates the relationship between household size and composition and subjective well-being in Russia using panel data. However, this paper uses much shorter panels of three waves.[4] Consequently, their findings are likely biased by insufficient variation in household size and unobserved heterogeneity issues. We better control for unobservable characteristics by using a recently developed econometric technique, the fixed-effect-ordered-logit-type "blow-up and cluster" (BUC) estimator (Baetschmann *et al.*, 2015) that respects the ordinal nature of subjective well-being data. We also tested our results using more flexible econometric models.

Our results suggest that the elasticity is higher for adding another adult to a two-adult household than a child, and scaling results in lower estimates of poverty lines. We decompose poverty into chronic and transient components and find that chronic poverty as a share of total poverty, defined against an absolute poverty line, is positively related to the adult scale parameter. But chronic poverty is less sensitive to the child scale factor than the adult scale factor. Interestingly, income mobility can be classified as either upward or downward depending on the specific scale parameters that are employed. Our results are robust to different measures of poverty, income expectations, reference groups, functional forms, and various other specifications.

This paper consists of seven sections. We briefly review the literature in the next section, before discussing our empirical strategy in Section 3. We subsequently describe the data in section

[4] Another paper by Takeda (2010) used subjective information available in RLMS for calculating equivalence scales with cross-sectional data for 1994 and 2002.

4, and present estimation results in section 5. We offer a wide range of robustness checks and further extensions in Section 6 before finally concluding in Section 7.

2. Brief Literature Review

A number of studies estimate equivalence scales using panel subjective well-being data, but these studies mostly investigate data on life and income satisfaction and focus on richer countries that have panel data such as Germany or the UK (Charlier, 2002; Schwarze, 2003; Falter, 2006; Bollinger *et al.*, 2012; Biewen and Juhasz, 2017; Borah *et al.*, 2018). Our brief overview of these studies, shown in Table A.1, Appendix A, offers several findings. First, although the magnitude of the estimated equivalence parameters differs considerably across studies, all the four studies for Germany find a lower weight for children than that of an additional adult. Only one study by Bollinger *et al.* (2012) finds that children in the UK are associated with diseconomies, but this result mostly applies to the first child. Second, although most studies suggest larger returns to scale than the (old or modified) OECD equivalence scales, non-parametric scales recently estimated for Germany by Biewen and Juhasz (2017) are fairly close to "square-root" equivalence scales.[5] Third, equivalence parameters depend on the types of subjective data/questions used for analysis. For example, analyzing life satisfaction or minimum income data leads to lower estimates of equivalence scales than using income satisfaction data (Charlier, 2002; Falter, 2006).

Yet, these findings may not necessarily apply to Russia, given the latter's different demographic structures. We show four such indicators in Figure 1: the average household size (Panel A), single-person households as a percentage of the total population (Panel B), three-or-more-adults households as a percentage of all households (Panel C), and three-or-more-adults

[5] The old OECD scale assigns a value of 1 to the first household member, 0.7 to each additional adult, and 0.5 to each child. The corresponding figures for the modified OECD scale are 1, 0.5, and 0.3. We discuss the definitions of the square root and other scales in Section 3.

households with children as a percentage of all households (Panel D). Russia has the largest household size, which averages at least 2.6 persons per household for the last ten years, which is followed by the UK (2.3 persons), Switzerland (2.2 persons), and Germany (2 persons) (Panel A). Single-person households are also least common in Russia, accounting for less than 10 percent of the total population on average, while the corresponding figure for Germany is roughly twice higher at 20 percent (Panel B). The corresponding figures for the UK and Switzerland fall somewhere in between, with Switzerland catching up quickly with Germany. Figure 1, Panels C and D also display a clear cross-country difference in the proportion of extended households (i.e., households where multiple adults are present). While less than 10 percent of households in the other three European countries consist of three or more adults (with or without children) on average, the corresponding figure is at least three times higher for Russia.

3. Empirical Strategy

3.1. Measuring Scale Elasticity

We assume the following equation that determines an individual's satisfaction

$$W_{it}^{*} = x_{it}'\theta + \beta ln\left(\frac{Y_{it}}{h_{it}^{e}}\right) + \alpha_i + \varepsilon_{it},\ i = 1..N,\ \mathrm{t} = 1 \ldots \mathrm{T} \tag{1}$$

where W_{it}^{*} is individual i's latent utility and Y_{it} is the total household income. X_{it} is a vector of personal and household characteristics, α_i is an individual-level unobserved component, ε_{it} is the error term. It was expected that satisfaction positively depends on income and negatively depends on household size.[6] Importantly, h_{it}^{e} is the household's equivalence weight that depends on the number of adults (a_{it}) and children (k_{it}), such that $h = a_{it} + k_{it}$; $e[0,1]$ is the scale elasticity parameter to be estimated that also depends on the numbers of adults and children in the household.

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[6] These results are supported by empirical evidence from both richer and developing countries such as Germany and Britain (Van Praag and Ferrer-i-Carbonell, 2004) and Mexico (Rojas, 2007).

In particular, when e equals 1, we have the usual per capita household income variable (without any scale adjustment), and when e equals 0.5, we have the square root scale. Equation (1) was first proposed by Schwarze (2003), which assumes that individuals evaluate their welfare level based on equivalent income rather than total household income when answering the satisfaction question.[7]

Following Schwarze (2003), we also define e_a as the equivalence scale elasticity of a household consisting of adults only, and b as the scale parameter when there are children in the household, such that $e = e_a - bk_{it}$. Both these parameters capture the effects of household size and composition. Parameter e_a is a "baseline elasticity" that will be lowered b times for each child in the household. The smaller e_a is, the greater is the effects of household sizes. If b is positive, children cost less than adults, and the opposite result holds vice versa. High values of b intensify the effect of household composition when the household has many children.

Plugging these values for h_{it}^{e} and e in Equation (1), we can rewrite it as

$$W_{it}^{*} = x_{it}'\theta + \beta lnY_{it} - \beta e_a ln(a_{it} + k_{it}) + \beta bk_{it} ln(a_{it} + k_{it}) + \alpha_i + \varepsilon_{it} \qquad (2)$$

Clearly, the equivalence scale elasticity can be directly derived from the parameters in Equation (2). In particular, dividing the absolute value of the coefficient on $ln(a_{it} + k_{it})$ by that on lnY_{it}, we have $e_a (= \frac{\beta e_a}{\beta})$. Similarly, $b (= \frac{\beta b}{\beta})$ is the scale parameter when there are children in the household.

[7] Compared to other models, the advantages of Equation (1) are that it is easy to implement, it differentiates between adults and children, and it permits estimates of a wide range of possible values of elasticity. This equation assumes a logarithmic relationship between equivalent income and subjective welfare (with decreasing marginal utility from equivalent income). We reexamine this relationship using the non-parametric approach of Biewen and Juhasz (2017) in the sensitivity analysis.

Equation (2) can be stated in the latent continuous utility function when we can observe W_{it} having a limited *J* number of outcomes, which is related to W_{it}^* as follows

$$W_{it} = j \quad if \quad \mu_j < W_{it}^* \leq \mu_{j+1}, \;\; j = 1, \; \ldots, J \tag{3}$$

where the individual-specific thresholds μ_j's are increasing, $\mu_j < \mu_{j+1}$, $\mu_1 = -\infty$, and $\mu_{j+1} = \infty$. The probability of observing outcome *j* for individual *i* at time *t* is then

$$\Pr\left(W_{it} = j | x_{it}, \, ln(.), \alpha_i\right) = \Lambda\left(\mu_{j+1} - x_{it}'\theta - \beta ln\left(\frac{Y_{it}}{h_{it}^e}\right) - \alpha_i\right) - \Lambda\left(\mu_j - x_{it}'\theta - \beta ln\left(\frac{Y_{it}}{h_{it}^e}\right) - \alpha_i\right) \tag{4}$$

If we assume that Λ(.) has a cumulative logistic distribution and unobserved individual heterogeneity does not exist (i.e., α_i= 0), Equation (4) can be estimated as an ordered logit model using pooled cross-sectional data. Indeed, this model is usually employed as the starting point for analysis in most existing studies (Table 1). However, since unobserved individual heterogeneity such as personality traits and preferences likely exist (i.e., $\alpha_i \neq 0$) and it can be correlated with household income or serially correlated over time, it can result in inconsistent estimates (Ravallion and Lokshin, 2002; Ferrer-i-Carbonell and Frijters, 2004; Ravallion, 2012).[8] The individual fixed-effects model is an appropriate model to deal with these issues.

We apply the most recent statistical model, the BUC fixed-effects model that is developed by Baetschmann *et al.* (2015).[9] Consistent estimations of parameters (θ, β) are performed by collapsing ordered variable (*J* levels of W_{it}) into binary outcomes for each choice (*0*, .., *J-1*). The conditional maximum likelihood estimator by Chamberlain (1980) can be subsequently applied to

[8] Van Praag and Ferrer-i-Carbonell (2004) also observe that there will always be omitted variables in satisfaction equations.

[9] Subsequently, Das and Van Soest (1999), Ferrer-i-Carbonell and Frijters (2004) and Baetschmann et al. (2015) introduced new estimators for the fixed effects ordered logit model using the extensions of existing binary choice panel data models. Baetschmann *et al.*'s model is observed to outperform Das and van Soest's estimator if some categories on the ordered scale have small sample size and Ferrer-i-Carbonell and Frijters' estimator if the number of categories on the ordered scale is large (Riedl and Geishecker, 2012).

each of these binary choice models. By copying each observation *J-1* times in the dataset (i.e., "blowing-up" the sample size), so that for every $J-1$ copy of the observation, it is possible to dichotomize the dependent variable at each different threshold. This procedure helps avoid the (severe) loss of information as with the binary (Chamberlain) logit model with fixed effects. We use two-way clustering and cluster the standard errors at both the individual and household-wave levels.

The BUC approach was found to outperform other existing estimators (e.g., Riedl and Geishecker, 2014), but for robustness checks, we also estimate other models such as the pooled ordered logit (POL) model and the linear fixed effects model (FE OLS). While both these models likely yield biased results, they can provide some comparison estimates.[10] For example, empirical evidence for Germany suggests that the equivalence scale parameters in FE models are significantly reduced compared to the pooled regressions (Schwarze, 2003; Borah *et al.*, 2018), but the opposite result holds for Switzerland (Falter, 2006).

3.2. Chronic Poverty and Income Mobility

A common approach to measuring chronic poverty is to identify individuals' permanent incomes, and then defines these individuals as chronically poor if their permanent incomes are below a specified poverty line (Jalan and Ravallion, 2000). In this approach, intertemporal mean of poverty for each individual is defined as

$$p_i = \frac{1}{T}\sum_{t=1}^{T} I(y_{it} < z)\left(1 - \frac{y_{it}}{z}\right)^{\alpha} \quad (5)$$

[10] The POL provides biased estimates if the fixed effects are statistical significant, while the FE OLS does not model well the categorical dependent variable.

where α is a sensitivity of poverty measure to inequality among poor (i.e. poverty aversion indicator), I(.) is the indicator function which is one if the condition is satisfied and zero if not, total poverty is obtained by averaging across all individuals $P = (p_i \dots \dots p_N) = \frac{1}{N}\sum p_i$.

The aggregate chronic poverty index is defined as

$$P_C = \frac{1}{N}\sum_{i=1}^{N} I(\bar{y}_i < z)\left(1 - \frac{\bar{y}_i}{z}\right)^{\alpha} \quad (6)$$

In Equation (6), $\bar{y}_i$ is obtained by averaging all income of over the period for each individual, irrespective of the poverty status of individual at any time. To provide robustness checks on estimation results, we also follow an alternative approach, called the spell approach, which defines individuals as chronically poor if they are poor in a certain number of periods.[11]

Let y_t and z_{tk} respectively represent individuals' income (consumption) and the income threshold k in year t, where t= 1 or 2, and k= 0, *1,…, K*, and a higher number for k indicating a higher income threshold. The minimal and maximal thresholds z_0 and z_K correspond to -∞ and +∞ respectively. Let M^{lo} be the population's relative mobility measure of interest, where l= u (upward mobility) or d (downward mobility), and o= n (unconditional mobility) or c (conditional mobility).

We define the unconditional (probability of) upward mobility for the whole population as follows

$$M^{un} = \sum_{k=0}^{K} P(z_k \le y_1 \le z_{k+1} \; and \; y_2 \ge z_{k+1}) \quad (7)$$

[11] For the spell approach, we employ Foster (2009)'s measure of chronic poverty, which consider an individual to be chronically poor if the percentage of time he spends below the poverty line (z) is at least the duration cutoff (τ) as follows $p_{ci} = \frac{1}{T}\sum_{t=1}^{T} I[\sum_{t=1}^{T}(y_{it} < z) \ge \tau T]\left(1 - \frac{y_{it}}{z}\right)^{\alpha}$, where τ is the minimum percentage of time a person must be in poverty in order to be chronically poor, α is a sensitivity of poverty measure to inequality among poor (i.e. poverty aversion indicator), *I(.)* is the indicator function which is one if the condition is satisfied and zero if not.

Note that this higher income category *k+1* is not just the next higher income category, but can generally include any higher income category. The corresponding probabilities of unconditional downward mobility can be obtained by reversing the inequality signs in Equations (7) for individuals' income level in the second year.

Focusing on the income category k in year *1*, we define the measure of conditional upward mobility for the whole population as follows[12]

$$M^{uc} = \sum_{j=k+1}^{K} P\left(y_2 \geq z_t | z_k \leq y_1 \leq z_{K-1}\right) \qquad (8)$$

4. Data

We analyze the Russian Longitudinal Monitoring Survey (RLMS), which is an annual and nationally representative panel household survey. Our analysis covers 23 years (survey waves) from 1994 to 2017. We restrict the estimation sample to working-age adults, who are 16 years old or older, and exclude households where all members are younger. We also exclude households with an unusually large number of members (e.g., having more than five adults and three children).[13]

Our outcome variable of interest, subjective wealth, captures individual responses to the following question on a scale ranging from one to nine: "Please imagine a nine-step ladder where on the bottom, the first step, stand the poorest people, and on the highest step, the ninth, stand the rich. On which step of the nine steps are you personally standing today?" We plot the distribution of this variable in Figure A.1 in Appendix A, which resembles a somewhat bell-shaped

[12] See Dang *et al.* (forthcoming) for more discussion on these measures of mobility.

[13] Such households represent less than 3% of the data. See Appendix A, Table A.3 for the distribution of household types. But we offer estimates using the whole unrestricted sample in Table 5. The results suggest that the scale parameters for children are lower when using pooled model and even negative (but insignificant) when using fixed effect ordered logit. At the same time, adult scale parameter is robust to using unrestricted sample.

distribution.[14] There is also a reasonable degree of churning over time, with only about 40% of those who score in the range 3 to 5 keeping the same score for the next period. There are in total 44,010 individuals with 254,822 observations. We also offer robustness checks on our estimates by analyzing two other questions in the RLMS asking about satisfaction with life and personal economic conditions.

Our measure of income is the household's total monetary income, which is temporarily deflated and adjusted for regional differences. To reduce the effects of outliers, we trim one-quarter of a percent of the data at both the top and the bottom of the income distribution and only keep individuals with a positive income level. For the other control variables, we include in all models: individual's age (in groups), education level, marital status, employment status, health status, dummy variables indicating whether there are other household members with poor health, and per capita living space.[15] To estimate the pooled regressions, we additionally include individuals' gender, nationality, and an extended set of regional variables. Table A.2 in Appendix A provides the summary statistics for the control variables.

5. Estimation Results

5.1. Scale Parameters

We provide in Table 1 estimates for the equivalence weights of adults and children, using three models: the pooled ordered logit (POL), the linear fixed-effects (FE OLS), and our preferred BUC model. Compared to the FE OLS model, the number of individuals in the BUC model decreases

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[14] Since responses with a score of eight or nine account for less than 1% of the sample, we combine these in one group. But we also estimate scale parameters without this aggregation and obtain similar results (results available upon request).

[15] Frijters and Beatton (2012) show that age effects are better captured with more flexible forms (such as using 5-year age groups) rather than with age and age squared. But we also implement robustness checks with age and age squared and obtain similar results. Since unemployment and health variables may be considered endogenous variables (e.g., Oswald and Powdthavee, 2008; Kassenboehmer and Haisken-De New, 2019), we re-estimate our scale parameters without these variables and obtain similar results.

by almost 13,000 since these individuals were observed only once in the RLMS, or their subjective welfare levels did not changed during the period of study. In all three model specifications, the estimated parameters $\widehat{\beta e_a}$ and $\widehat{\beta b}$ have the expected signs and are both statistically significant, although the statistical significance for $\widehat{\beta b}$ is slightly weaker at the 6 percent level for the BUC model. $\widehat{\beta b}$ is positive, indicating that households with a higher number of children need more resources and bear higher costs.

Using the estimates from Table 1, Table 2 calculates the equivalence scales. Estimates based on the POL model yield 0.6 for the adult parameter e_a and 0.08 for the child parameter b, suggesting that the overall elasticity is higher for adding another adult than a child to a two-adult household. Controlling for unobserved individual heterogeneity in the panel models reduces by about one-third both the estimated equivalence scale parameter for adults (from 0.6 to 0.4) and for children (from 0.08 to 0.05). The scale elasticities estimated from the FE OLS and the BUC models are nearly the same, but we switch to presenting results using the BUC model in the subsequent discussion.[16]

Our estimates suggest a larger scale impact for children on household income in Russia than in Germany and Switzerland (Schwarze, 2003; Falter 2006; Borah *et al.*, 2018), which can be explained by generous transfers to households with children in Russia. At the same time, our results are consistent with those for Germany and Switzerland in terms of the smaller effect of additional children compared to additional adults.

Figure 2 compares our preferred BUC estimated scales with some other common scales, including the simple per capita adjustment, the square-root adjustment, the OECD scales, and the

[16] This result is consistent with that of Ferrer-i-Carbonell and Frijters (2004), who find little difference in estimates for the determinants of happiness in the FE Ordered Logit and FE OLS models, and with that of Riedl and Geishecker (2014) who show that linear and ordered fixed effect models offer similar estimates for the relative size of parameters.

poverty line scale, each normalized to a single adult.[17] For each additional adult (or child), while the per capita and OECD scales display a constant marginal cost, our estimated scales, as well as the square-root scale, have a decreasing marginal cost. Compared to our estimated scales, all the other scales overestimate the weights for either an additional adult or an additional child. Interestingly, our estimated scales also provide lower elasticities than the equivalence scale embedded in the official poverty line for Russia, particularly for large-size households.

5.2. Adjusted Poverty Lines

A natural question arises. What are the implications of these decreasing marginal costs for both adults and children for poverty measurement? We present in Table 3 our proposed population-weighted poverty lines for different family types, based on the estimated parameters of equivalence scales, and compare them with the official poverty thresholds employed by Rosstat. Our absolute poverty lines are derived from Rosstat's official poverty thresholds for different age groups. Our relative poverty lines are computed as two-third of the median income per adult equivalent for each household type, using the parameters that account for differences in economies of scale and composition in the household.

Table 3 suggests that our proposed poverty lines for households, in both absolute and relative terms, are generally much lower than the official poverty thresholds for the country. In particular, for our absolute poverty lines, the official poverty threshold ranges from 50 percent (for a two-adult household) to 160 percent higher (for a five-adult-no-children household) for households without any children. It ranges from 160 percent (for a one-adult-one-child household) to more than 200 percent (for a five-adult-one-child household) higher for households with children. The

[17] We offer a comparison of our results with those in studies for Germany and Switzerland that use similar estimation methods in Appendix A, Table A.4.

corresponding differences for our relative poverty lines are less, but are still considerable. The official poverty thresholds are from about 20 percent to 90 percent higher and 40 percent to 100 percent higher respectively for households without children and households with children.

5.3. Poverty and Income Dynamics

We start first with examining in Figure 3 the extent to which the (headcount) poverty rate for Russia can be affected by the scale parameters. Again, the values of 1 and 0.5 for e_a respectively correspond to the per capita scale and square root scale. The value of 0.1 for e_a indicates an extremely large effect of household sizes. When b increases from 0 to 0.1, it is a situation where for the same household size, households with children have a lower equivalence scale elasticity (i.e., higher economy of size) than households without children. We also examine poverty using either the absolute poverty line (Panel A) or the relative poverty line (Panel B).

Since the relative poverty line is adjusted to scaling by construction, it unsurprisingly provides the opposite scaling effects compared to the absolute poverty line.[18] Yet, Figure 3, Panel A shows that the poverty rate using the absolute poverty line can decrease by 9 to 15 percentage points (from 12 or 18 percent to 3 percent) if e_a decreases from 1 to 0.5, depending on the child parameter values. The poverty rate subsequently remains almost the same, and decreases by one to two percentage point if e_a decreases from 0.5 to 0.1. Figure 3, Panel B displays the opposite results where the poverty rate using the relative poverty line increases slightly by at most four percentage points if e_a decreases from 1 to 0.5, again depending on the child parameter values. It then increases faster by four percentage points if e_a decreases from 0.5 to 0.1.

[18] When we make scale adjustments for income, this results in changes to the population distribution of income and the relative poverty line. For example, most European countries set their relative poverty line at 60% of the national median equivalized disposable income.

On the other hand, poverty is less sensitive to the choice of the child discount factor. It varies by at most 6 percentage points and 2 percentage points respectively for the absolute poverty line and the relative poverty line, when the child scale factor is varied from 0 to 0.1 and keeping e_a fixed.[19]

We turn next to examining poverty duration, which is defined as the average number of consecutive survey years (rounds) an individual spends in poverty. Figure 3, Panels C and D produce qualitatively similar results. Poverty duration is sensitive to changes in e_a, and range from 1.8 to 2.6 years and from 2 to 2.7 years respectively with the absolute poverty line and the relative poverty line. But poverty duration is less sensitive to child scaling and varies by less than 0.2 years for both the absolute and the relative poverty lines.

We provide in Table 4 transient and chronic poverty estimates using Jalan and Ravallion (2000)'s method for three common poverty measures: the headcount poverty rate, the poverty gap index, and the squared poverty gap index. Table 4 shows that the shares of chronic poverty of total poverty are inversely related to the adult scale parameter, regardless of the poverty measures we use. For example, for headcount poverty, the share of chronic poverty decreases by 2 percentage points when e_a increases from 0.3 to 0.6. For the poverty gap and squared poverty gap, the corresponding figure is around a 5-percentage-point decrease. We plot the alternative chronic poverty measures (Foster, 2009) against the scale factors in Appendix A, Figure A.2, which also shows that these measures are more sensitive to scale adjustments for adults than for children.

Figure 4 examines the relationship between scale parameters and unconditional income mobility (Panel A) and conditional income mobility (Panel B) (see Appendix A, Figure A.3 for the

[19] We employ the range of [0, 0.1] for the child scale parameter since it is observed to be less than 0.1 in previous studies. For example, the scale elasticity for each additional child aged between 15 and 17 years was estimated to be 0.086 for Switzerland (Falter, 2006).

corresponding three-dimensional graphs). Three possible scenarios can happen with income mobilty: more upward mobility (as represented by the area in orange), more downward mobility (as represented by the area in purple), and a mixed situation where neither upward mobility or downward mobility dominates (as represented by the gray area in between the two colors above). Interestingly, the selection of specific scale parameters can even change estimation results for mobility. In particular, when income is measured on a per capita basis (e_a=1), there is always more upward unconditional mobility, regardless of the (different values for the) child parameter (Panel A). There is also mostly more upward conditional mobility, except for when the child parameter falls in the interval [0.09, 0.1] (Panel B). Yet when income is measured on a square-root scale, we have more upward unconditional mobility when the child parameter ranges from 0 to 0.03, a mixed situation when the child parameter ranges from 0.03 to 0.08, and even more downward mobility for the rest of the child parameter values. For conditional mobility, the square-root scale results in more downward mobility, for all values of the child parameter (Panel B). These results further emphasize the important role that equivalence scales have in determining estimation results with income dynamics.

6. Robustness Checks and Further Extensions

6.1. Robustness Checks

In addition, we examine a number of other robustness checks and extensions, which include income expectations, different reference groups, other satisfaction variables as dependent variables, measurement error in incomes, and no sample restrictions. We briefly summarize the results below.

Changes in household size or structure are typically expected and may affect subjective wellbeing well before their actual realization. We control for income expectations in the *(t-1)* period and find that this does not affect the estimates of baseline elasticity but slightly increases the child scale parameter up to 0.08 in pooled model (Table 5, row 1).[20]

Relative income rather than total income may affect satisfaction, and if ignored, may result in biased estimates (Borah *et al.*, 2018). We include dummy variables to indicate the relative position of the household in the reference group`s distribution of household incomes in quartile (Appendix A, Table A.8). The reference group is determined for each year and consists of individuals living in households with a similar size in the same primary sampling units. To ensure stability, we only consider the number of households in the reference group as having 10 or more households. We report estimates of the scale parameters for the POL model only, since the variable used to define the reference groups is largely time-invariant, especially at the primary sampling unit level. Controlling for the reference group decreases the child scale parameter to 0.05 in the POL model but does not change the baseline elasticity. More importantly, we still obtain the earlier result that an additional child has a smaller effect compared to an additional adult (Table 5, row 2)[21].

We also analyze the other satisfaction variables in the RLMS as alternative dependent variables for the subjective wealth variables, which is satisfaction with one's life and satisfaction with one's economic conditions. The estimated coefficients on household income and household size are still statistically significant as expected (Appendix A, Table A.7). To save space, we only report the scale parameters derived from the regressions for life satisfaction (Table 5, row 3). Estimation results of the BUC model are robust with the adult scale parameter is about 0.6 and child scale parameter is about 0.04.[22]

[20] We analyze the answer to the following question in the RLMS "*Do you think that in the next 12 months you and your family will live better than today or worse?*" The full regression results are shown in Appendix A, Table A.5.
[21] The full regression results are shown in Appendix A, Table A.6.
[22] The adult scale parameter is still high when using satisfaction with economic conditions (0.8) but child scale parameter is decreasing to 0.02. The POL model also similarly provides a higher elasticity for adults (0.8), as well as for children (0.1) (Table 5, row 3).

As a check on the total household income variable, we generate a new total household income by summing all the net incomes reported by household members (Appendix A, Table A.8). Yet, the estimated scale parameters of 0.3 for adults and 0.06 for children obtained from the BUC models are close to our estimation results (Table 5, row 4). We use the unrestricted sample containing households with more than five adults and three children and estimate our main regressions. Estimation results for children are no longer statistically significant for the BUC model, and are only statistically significant in POL model (Appendix A, Table A.9). At the same time, the estimates for the adult scale parameter remain similar at about 0.6 (Table 5, row 5).

6.2. Role of Pensioners

Our earlier analysis has focused on household sizes and children, but has not discussed the impacts of elderly pensioners on the total household income. Pensioners may have disability or health issues and thus can impose significant costs on the household. On the other side, pensioners often consume less than a working-age adult and can contribute their pension salary to the household income. Our estimates from the RLMS suggest that the share of individuals (in total population) who receive any pension in the past month hovers around 30 percent over the period 1994-2017. The majority of these pensioners (more than 70%) receive retirement or old-age pensions.

We assume that the presence of a pensioner has an effect on subjective well-being through the cost channel only. The inclusion of the number of registered pensioners is additional: pensioner enters the regression twice as a family member in his age group and as a pensioner. We can then modify Equation (1) as follows

$$W_{it}^{*} = x_{it}'\theta + \beta_1 ln\left(\frac{Y_{it}}{(h)^{e_a - bk - cp}}\right) + \beta_2 p_{it} + \alpha_i + \varepsilon_{it}$$

$$= x_{it}'\theta + \beta_1 lnY_{it} - \beta_1 e_a lnh + \beta_1 bk_{it} lnh + \beta_1 cp_{it} lnh + \beta_2 p_{it} + \alpha_i + \varepsilon_{it} \quad (9)$$

where p_{it} is the number of pensioners in the household. In this specification, the total effect of pensioners is then $p_{it}(\beta_1 clnh + \beta_2)$.

Although the interaction term for the household size and the number of pensioners is not statistically significant in both the pooled and BUC regressions (Appendix A, Table A.10), the total effect of pensioners is statistically significant and positive in the BUC model (Appendix A, Table A.11). But the inclusion of pensioners does not change the estimated scale parameters significantly: adult scale parameter still varies between 0.4-0.6 and the child scale parameter is about 0.05-0.06 (Table 5, row 6).

6.3. Alternative Functional Form

As an alternative to Equation (1), we can estimate a non-parametrical function recently proposed by Biewen and Juhasz (2017) as follows

$$f\left(\frac{Y_{it}}{h_{it}^{e}}\right) = ln\ \frac{Y_{it}}{f(a_{it}+k_{it})} \quad (10)$$

where $f(a_{it} + k_{it}) = 1 * a_{it}1k_{it}0 + \beta_{a2ko} * a_{it}2k_{it}0 + \beta_{a2k1} * a_{it}2k_{it}1 + \cdots + \beta_{a5k1} * a_{it}5k_{it}1$, and $a_{it}2k_{it}1$ indicates a household with two adults and one child.

The estimated parameters for this scale are given in Appendix A, Table A.12. The table shows that the “non-parametric” scales for household types are smaller than those estimated using the parametric functional form as in Equation (1). The estimated equivalence weight of a second adult is 24 percent of the first adult, and the estimated equivalence weight of a child is 13 percent, or about half of the second adult. The child scale parameter is similar to our BUC estimates, and also to those obtained by Biewen and Juhasz (2017) for Germany.

7. Conclusion

We estimate equivalence scales using unique subjective wealth data from Russia, and apply these scale adjustments to examine new poverty lines as well as the sensitivity of poverty dynamics. Our findings suggest that the country's official poverty threshold ranges from 50 percent (for a two-adult household) to more than 200 percent (for a five-adult-one-child household) higher than our estimated poverty lines. The poverty rate varies for different adult scale parameters, but less so for children. The shares of chronic poverty of total poverty, defined against an absolute poverty line, are positively related to the adult scale parameter, regardless of the poverty measure. More interestingly, income mobility could be classified as either upward or downward depending on the specific scale parameters that are employed. Our results are robust to different measures of poverty, income expectations, reference groups, functional forms, and various other specifications.

References

Baetschmann, Gregori, Kevin E. Staub, and Rainer Winkelmann. (2015). “Consistent estimation of the fixed effects ordered logit model”. *Journal of the Royal Statistical Society: Series A*, 178(3): 685–703.

Biewen, Martin, and Andos Juhasz. (2017). “Direct estimation of equivalence scales and more evidence on independence of base.” *Oxford Bulletin of Economics and Statistics,* 79(5): 875-905.

Bishop, John A., Andrew Grodner, Haiyong Liu, and Ismael Ahamdanech-Zarco. (2014). “Subjective poverty equivalence scales for Euro Zone countries.” *Journal of Economic Inequality*, 12(2): 265-278.

Bollinger, Christopher R., Cheti Nicoletti, and Stephen Pudney. (2012) “Two can live as cheaply as one... but three's a crowd.” *Institute for Social and Economic Research Working Papers*, No. 2012-10.

Borah, Melanie, Carina Keldenich, and Andreas Knabe. (2018). “Reference income effects in the determination of equivalence scales using income satisfaction data.” *Review of Income and Wealth*, 0(0): 1-35

Charlier, Erwin. (2002). “Equivalence scales in an intertemporal setting with an application to the former West Germany.” *Review of Income and Wealth*, 48(1): 99-126.

Dang, Hai-Anh, Dean Jolliffe, and Calogero Carletto. (2019). “Data Gaps, Data Incomparability, and Data Imputation: A Review of Poverty Measurement Methods for Data-Scarce Environments.” *Journal of Economic Surveys*, 33(3): 757-797.

Dang, Hai-Anh, Michael M. Lokshin, Kseniya Abanokova, and Maurizio Bussolo. (forthcoming). “Welfare Dynamics and Inequality in the Russian Federation during 1994-2015.” *European Journal of Development Research*.

Das, Marcel, and Arthur Van Soest. (1999) “A panel data model for subjective information on household income growth.” *Journal of Economic Behavior & Organization*, 40(4): 409-426.

Deaton, Angus, and Christina Paxson. (1998) “Economies of scale, household size, and the demand for food.” *Journal of Political Economy*, 106(5): 897-930.

Falter, Jean-Marc. (2006). “Equivalence Scales, Poverty Lines and Subjective Data in Switzerland.” *Swiss Journal of Economics and Statistics*, 142(2).

Ferrer-i-Carbonell, Ada, and Bernard MS Van Praag. (2001). “Poverty in Russia.” *Journal of Happiness Studies*, 2(2): 147-172.

Ferrer-i-Carbonell, Ada, and Paul Frijters. (2004). “How important is methodology for the estimates of the determinants of happiness?” *Economic Journal* 114: 641-659.

Foster, James E. (2009). “A class of chronic poverty measures.” *Poverty dynamics: interdisciplinary perspectives*, Part 2, Chapter 3: 59-76

Frijters, Paul, and Tony Beatton. (2012) “The mystery of the U-shaped relationship between happiness and age.” *Journal of Economic Behavior & Organization*, 82(2-3): 525-542.

Garner, Thesia I., and Kathleen S. Short. (2004). “Economic Well-Being Based on Income, Consumer Expenditures and Personal Assessments of Minimum Needs.” In Studies on Economic Well-being: Essays in the Honor of John P. Formby, pp. 319-361. Emerald Group Publishing Limited.

Hulme, David, and Andrew Shepherd. (2003). “Conceptualizing chronic poverty.” *World Development* 31(3): 403-423.

Jalan, Jyotsna, and Martin Ravallion. (2000). “Is transient poverty different? Evidence for rural China.” *Journal of Development Studies*, 36(6): 82-99.

Kassenboehmer, Sonja C., and John P. Haisken-De New. (2009). “You’re fired! The causal negative effect of entry unemployment on life satisfaction.” *Economic Journal*, 119(536): 448-462.

Lanjouw, Jean O., Peter Lanjouw, Branko Milanovic, and Stefano Paternostro. (2004). “Relative price shifts, economies of scale and poverty during economic transition.” *Economics of Transition*, 12(3): 509-536.

Lanjouw, Peter, and Martin Ravallion. (1995). “Poverty and household size.” *The Economic Journal*, 105(433): 1415-1434.

Newhouse, David, Pablo Suárez Becerra, and Martin Evans. (2017). “New global estimates of child poverty and their sensitivity to alternative equivalence scales.” *Economics Letters*, 157: 125-128.

Oswald, Andrew J., and Nattavudh Powdthavee. (2008). “Does happiness adapt? A longitudinal study of disability with implications for economists and judges.” *Journal of Public Economics*, 92(5-6): 1061-1077

Peichl, Andreas, Nico Pestel, and Hilmar Schneider. (2012). “Does size matter? The impact of changes in household structure on income distribution in Germany.” *Review of Income and Wealth*, 58(1): 118-141.

Ravallion, Martin, and Michael Lokshin. (2001). “Identifying welfare effects from subjective questions.” *Economica* 68(271): 335-357.

Ravallion, Martin, and Michael Lokshin. (2002). “Self-rated economic welfare in Russia." *European Economic Review*, 46(8): 1453-1473.

Ravallion, Martin. (2012). “Poor, or just feeling poor? On using subjective data in measuring poverty”. *World Bank Policy Research Working Papers*, No.5968

Riedl, Maximilian and Ingo Geishecker (2014) “Keep it simple: estimation strategies for ordered response models with fixed effects”. *Journal of Applied Statistics*, 41(11): 2358-2374

Riedl, Maximilian and Ingo Geishecker (2010) “Ordered response models and non-random personality traits: Monte Carlo simulations and a practical guide.” *Center for European Governance and Economic Development Research Discussion Paper* 116 (revised edition 2012).

Rojas, Mariano. (2007). “A subjective well-being equivalence scale for Mexico: Estimation and poverty and income-distribution implications.” *Oxford Development Studies* 35(3): 273-293.

Schwarze, Johannes. (2003) “Using panel data on income satisfaction to estimate equivalence scale elasticity.” *Review of Income and Wealth* 49(3): 359-372.

Steiger, Darby Miller, Tina Mainieri, and Linda Stinson. (1997). “Subjective assessments of economic well-being: Understanding the minimum income question.” In *annual American Association for Public Opinion Research Conference, Norfolk, Virginia, in the Proceedings of the Joint Statistical Meetings Section on Survey Research Methods, Alexandria, VA: American Statistical Association*, pp. 899-903.

Takeda, Yuka. (2010) “Equivalence scales for measuring poverty in transitional Russia: Engel's food share method and the subjective economic well-being method.” *Applied Economics Letters* 17(4): 351-355.

Van Praag, Bernard MS, Bernard Van Praag, and Ada Ferrer-i-Carbonell. (2004). "Happiness quantified: A satisfaction calculus approach". Oxford University Press., (revised edition 2008)

Yang, Yang. (2008). "Social inequalities in happiness in the United States, 1972 to 2004: An age-period-cohort analysis." *American Sociological Review* 73(2): 204-226.

Table 1. Detailed regression results, RLMS 1994-2017

Variables	Pooled OL	FE OLS	BUC
Ln household income (β)	0.655***	0.249***	0.412***
	(0.011)	*(0.007)*	*(0.079)*
Ln household size ($-\beta e_a$)	-0.417***	-0.100***	-0.167***
	(0.023)	*(0.016)*	*(0.034)*
Children# Ln household size (βb)	0.051***	0.012**	0.020*
	(0.008)	*(0.005)*	*(0.010)*
Age 16-20	1.027***	0.404***	0.668***
	(0.031)	*(0.029)*	*(0.077)*
Age 21-30	0.386***	0.178***	0.296***
	(0.021)	*(0.021)*	*(0.057)*
Age 31-40	0.188***	0.062***	0.101***
	(0.019)	*(0.014)*	*(0.036)*
Age 51-60	-0.092***	-0.004	-0.006
	(0.019)	*(0.013)*	*(0.039)*
Age 61-70	-0.009	0.057***	0.097
	(0.025)	*(0.019)*	*(0.065)*
Age 71-80	0.103***	0.094***	0.159*
	(0.028)	*(0.023)*	*(0.083)*
Age 80+	0.399***	0.330***	0.542***
	(0.038)	*(0.030)*	*(0.086)*
Female	-0.027*		
	(0.014)		
Russian nationality	-0.262***		
	(0.024)		
Complete secondary	0.193***	-0.010	-0.014
	(0.019)	*(0.012)*	*(0.041)*
Secondary + vocational	0.298***	-0.043***	-0.071
	(0.021)	*(0.016)*	*(0.056)*
University and higher	0.446***	-0.004	0.003
	(0.023)	*(0.022)*	*(0.082)*
Single	-0.260***	-0.029*	-0.048
	(0.023)	*(0.017)*	*(0.037)*
Divorced/widowed/separated	-0.333***	-0.156***	-0.263***
	(0.019)	*(0.013)*	*(0.040)*
Unemployed/out of labor force	-0.275***	-0.162***	-0.269***
	(0.015)	*(0.009)*	*(0.030)*
Bad health	-0.136***	-0.047***	-0.080***
	(0.010)	*(0.006)*	*(0.012)*
Other members with bad health	-0.075***	-0.013*	-0.022*
	(0.011)	*(0.007)*	*(0.012)*
Log of per capita living space	0.000	0.001	0.002
	(0.002)	*(0.001)*	*(0.002)*
Number of observations	237,395	240,640	712,448
Log pseudolikelihood	-403,224	-346,509	-263,848
Number of individuals	42,326	42,894	30,058
Pseudo-R squared	0.043	0.036	0.0285

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the FE OLS and BUC models). All regressions include year fixed effects, pooled model includes regional fixed effects (not reported).

*** p<0.01, ** p<0.05, * p<0.1

Table 2. Scale elasticity parameters, RLMS 1994-2017

Scale parameters	Dependent variable: *subjective wealth*		
	Pooled Ordered Logit	**FE OLS**	**BUC**
Baseline elasticity	0.636***	0.399***	0.407***
$e_a = \beta e_a / \beta$	*(0.03)*	*(0.06)*	*(0.09)*
Additional child	0.078***	0.050**	0.048*
$b = \beta b / \beta$	*(0.01)*	*(0.02)*	*(0.03)*
Overall elasticity e	0.636-0.078*k	0.399-0.050*k	0.407-0.048*k

Note: Standard errors in parentheses are calculated using delta-method. All regressions include age groups, education level, marital status, employment status, respondent`s poor health, dummy whether there are other household members in poor health, dummy indicating whether the person was employed at survey time and per capita living space and time effects as additional variables. Pooled model additionally includes gender, nationality and regional state effects.

Table 3. Alternative poverty thresholds by household size in 2017 (in rubles per month)

Household Type	Estimated with absolute line		Estimated with relative line		Official
	Pooled OL	BUC	Pooled OL	BUC	
Households without children					
One adult, no children	9,607	9,607	10,800	10,800	9,607
Two adults, no children	14,891	12,777	13,913	16,306	19,214
Three adults, no children	19,310	14,987	15,931	20,488	28,821
Four adults, no children	23,153	17,004	17,520	24,066	38,428
Five adults, no children	26,707	18,542	17,397	25,150	48,035
Household with children					
One adult, one child	14,122	12,297	12,226	14,035	19,532
Two adults, one child	17,773	14,218	14,973	18,632	29,139
Two adults, two children	18,734	14,795	15,422	19,493	39,064
Three adults, one child	20,847	15,755	15,225	20,062	38,746
Three adults, two children	20,847	15,852	18,885	24,788	48,671
Four adults, one child	23,537	17,100	20,098	27,685	48,353
Four adults, two children	22,673	16,812	20,311	27,494	58,278
Five adults, one child	26,131	18,253	20,201	28,855	57,960

Note: Absolute poverty line for reference "one adult" is defined as an average minimum subsistence level in 2017 between working-age individual and pensioner. The level of absolute poverty line for working-age individual is 10899 rubles per month, for pensioner is 8315 rubles per months. Absolute poverty line of reference adult is adjusted with weights from Table A.4. Relative poverty line is set on 60% of household size-weighted median equivalized income for each household type using RLMS data in 2017.

Table 4. Chronic and transient poverty by adult scale factors, Jalan-Ravallion decomposition, RLMS 1994-2017

	Equivalent income is computed using				
	e_a=0.3	e_a=0.4	e_a=0.5	e_a =0.6	e_a=0.7
Headcount Poverty					
Total Poverty	0.208	0.200	0.194	0.187	0.182
Transient Poverty	0.049	0.049	0.049	0.049	0.048
Chronic Poverty	0.158	0.151	0.145	0.139	0.134
Share of chronic poverty (%)	*76.3*	*75.5*	*74.8*	*74.1*	*73.7*
Poverty Gap					
Total Poverty	0.068	0.065	0.062	0.059	0.058
Transient Poverty	0.024	0.023	0.023	0.023	0.023
Chronic Poverty	0.045	0.041	0.039	0.036	0.035
Share of chronic poverty (%)	*65.6*	*64.2*	*63.0*	*61.8*	*60.9*
Squared Poverty Gap					
Total Poverty	0.034	0.031	0.030	0.029	0.029
Transient Poverty	0.014	0.014	0.014	0.013	0.013
Chronic Poverty	0.020	0.018	0.017	0.016	0.015
Share of chronic poverty (%)	*58.2*	*56.4*	*55.0*	*53.7*	*52.8*

Note: Relative poverty line is set on 60% of household size-weighted median equivalized income. Both the poverty thresholds and household income are converted to constant 2011 rubles using regional CPI indices provided by the Rosstat. The child scale parameter is set at 0.04.

Table 5. The effect of alternative specifications on scale parameters estimates, RLMS 1994-2017

		Pooled OL		BUC	
Sensitivity scenarios		Baseline elasticity	Additional child	Baseline elasticity	Additional child
1	Expectations	0.649*** *(0.03)*	0.080*** *(0.01)*	0.410*** *(0.09)*	0.050* *(0.03)*
2	Reference group	0.497*** *(0.06)*	0.057* *(0.02)*		
3	Life satisfaction	0.762*** *(0.03)*	0.117*** *(0.01)*	0.659*** *(0.11)*	0.043* *(0.03)*
4	Measurement error	0.571*** *(0.04)*	0.089*** *(0.01)*	0.342*** *(0.10)*	0.056* *(0.03)*
5	Unrestricted sample	0.577*** *(0.03)*	0.020* *(0.01)*	0.306*** *(0.09)*	-0.013 *(0.02)*
6	Pensioners	0.560*** *(0.04)*	0.064*** *(0.01)*	0.352* *(0.15)*	0.046* *(0.03)*

Note: Standard errors in parentheses are calculated using delta-method. All regressions include the same controls as in Table 1.

Figure 1. Distribution of household types in Germany, Russia, Switzerland, and the UK

Source: European Union Statistics on Income and Living Conditions (EU-SILC) and RLMS-HSE

Figure 2. Comparison of different equivalence scales

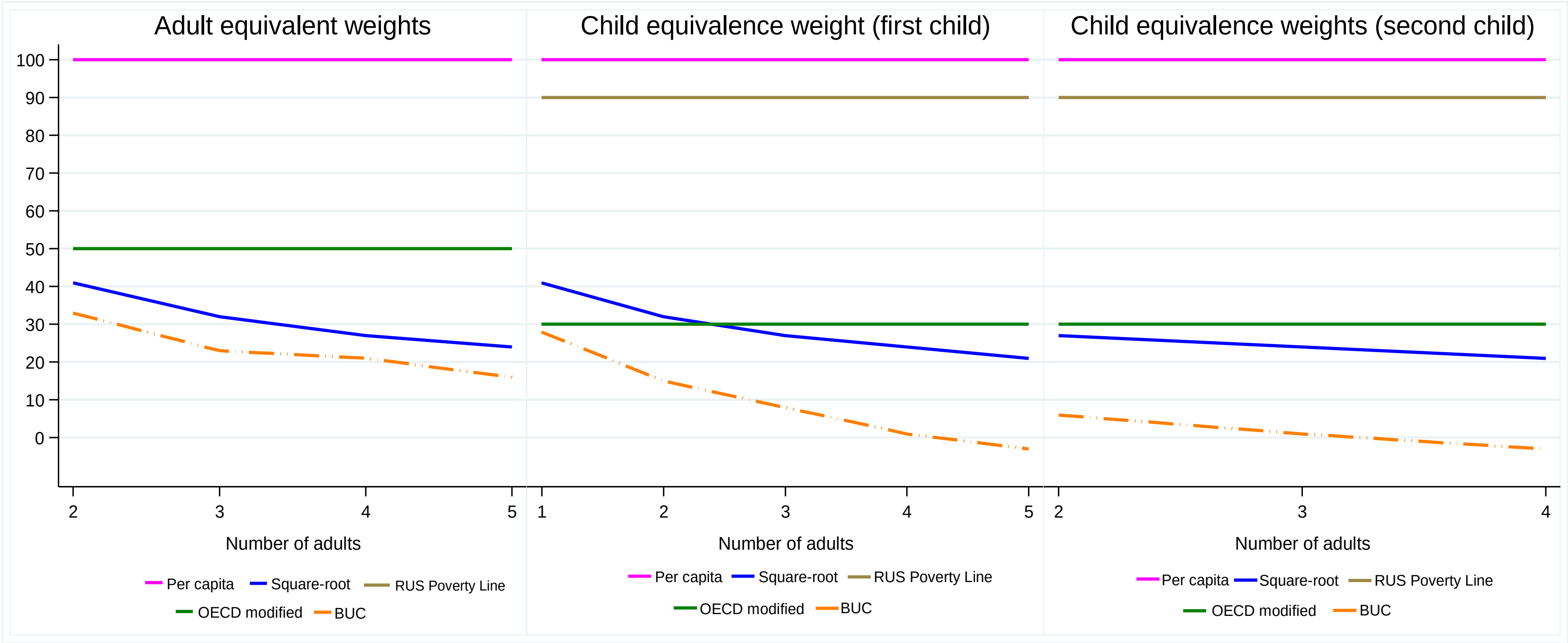
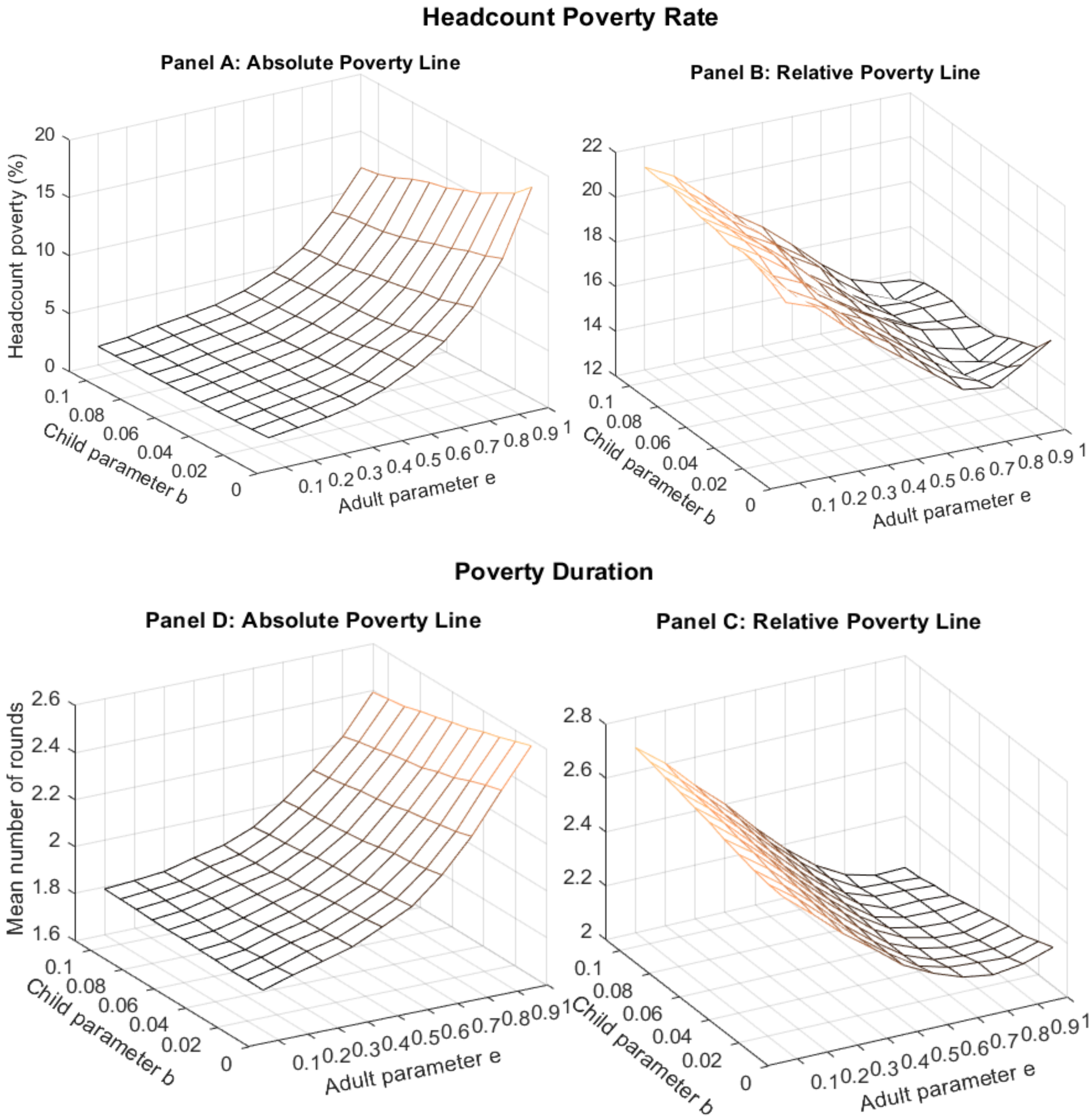
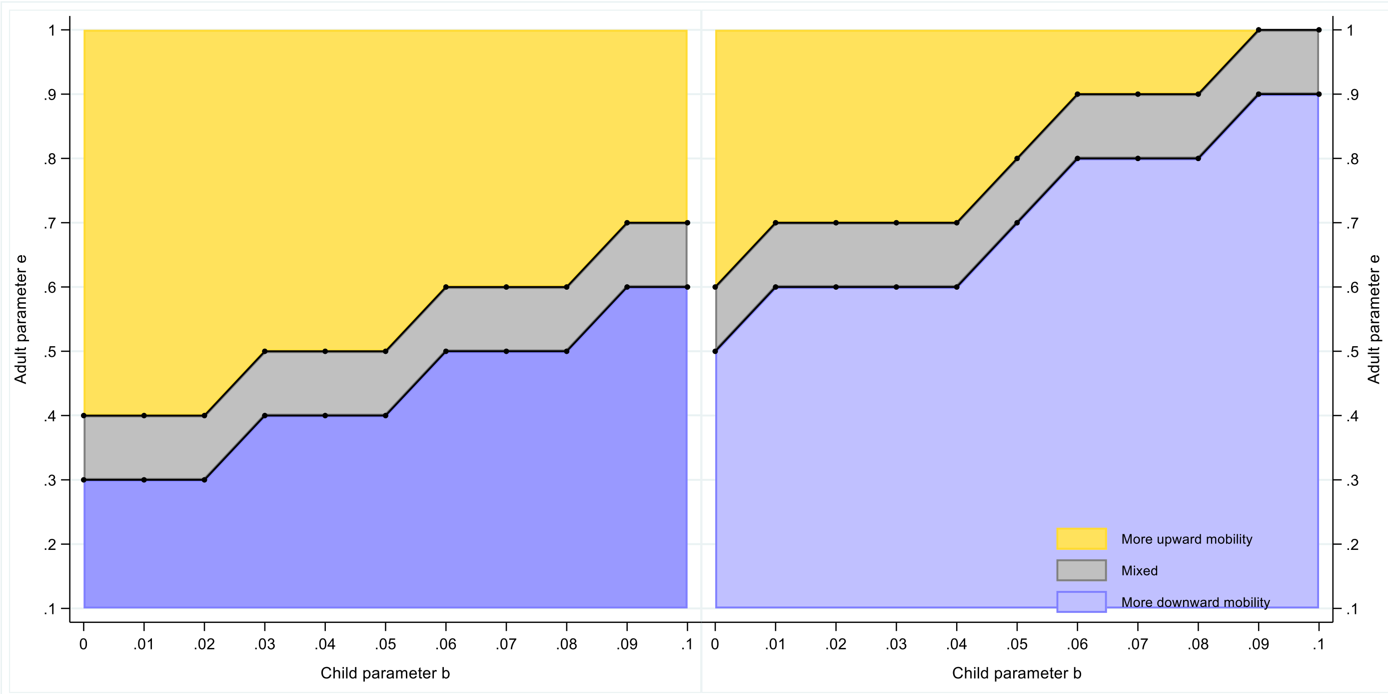


Figure 3. Scale Factors and Headcount Poverty Rate and Poverty Duration, RLMS 1994-2017



Note: Absolute poverty line is defined as a minimum regional subsistence level per person for each year (for cross-sectional poverty in 2017). Relative poverty line is set on 60% of household size-weighted median equivalized income for each year (for cross-sectional poverty in 2017). Both the poverty thresholds and household income are converted to constant 2011 rubles using regional CPI indices provided by the Rosstat.

Figure 4. Scale Factors and Income Mobility, RLMS 1994-2017



Appendix A: Additional Tables and Figures

Table A.1: Overview of subjective scales estimated from panel data

<table>
<tr><th rowspan="2">Author</th><th rowspan="2">Data</th><th rowspan="2">Welfare indicator</th><th rowspan="2">Subsample</th><th rowspan="2">Specification</th><th colspan="3">Weight given to the additional household member</th></tr>
<tr><th>2nd adult (1st adult = 1)</th><th>1st child (in 2/1 adult hh)</th><th>2nd child (in 2/1 adult hh)</th></tr>
<tr><td rowspan="3">Charlier (2002)*</td><td rowspan="3">GSOEP, 1984–91</td><td rowspan="3">Satisfaction with life/ Satisfaction with hh income</td><td rowspan="3">Sample of household heads</td><td>Pooled ordered logit</td><td>0,5</td><td>0.23/0.34</td><td>0.15/0.23</td></tr>
<tr><td>FE ordered logit (Das and van Soest (1999) approach)</td><td>0,43</td><td>0.20/0.28</td><td>0.10/0.16</td></tr>
<tr><td>RE ordered logit</td><td>0,5</td><td>0.26/0.39</td><td>0.19/0.28</td></tr>
<tr><td rowspan="2">Schwarze (2003)</td><td rowspan="2">GSOEP, 1992–99</td><td rowspan="2">Satisfaction with hh income</td><td rowspan="2">Respondents who answered at least twice are included</td><td>Pooled ordered logit</td><td>0,34</td><td>0.17/0.30</td><td>0.08/0.14</td></tr>
<tr><td>FE binary logit</td><td>0,28</td><td>0.13/0.24</td><td>0.06/0.11</td></tr>
<tr><td rowspan="4">Falter (2006)**</td><td rowspan="4">SHP, 1999-2002</td><td rowspan="3">Satisfaction with hh income</td><td rowspan="4">Households who answered at least twice are included</td><td>OLS</td><td>0,43</td><td>0.25/0.39</td><td>0.14/0.22</td></tr>
<tr><td>Orderel probit</td><td>0,43</td><td>0.26/0.4</td><td>0.15/0.23</td></tr>
<tr><td>FE linear model</td><td>0,48</td><td>0.28/0.43</td><td>0.14/0.24</td></tr>
<tr><td>Minimum Income Question</td><td>FE linear model</td><td>0,07</td><td>0.09/0.1</td><td>0.11/0.11</td></tr>
<tr><td rowspan="2">Bollinger et al.(2012)</td><td rowspan="2">BHPS, 1991-2008</td><td rowspan="2">Self-assessed financial situation</td><td rowspan="2">Individuals 18-80 yo who are household heads or the partner of the head with or without minor children</td><td>FE ordered logit (Baetschmann et al. (2015) approach), men</td><td>0,15</td><td>1.12/1.64</td><td>0.68/1.22</td></tr>
<tr><td>FE ordered logit (Baetschmann et al. (2015) approach), women</td><td>0,31</td><td>1.17/1.52</td><td>0.41/0.78</td></tr>
<tr><td>Biewen and Juhasz (2017)***</td><td>GSOEP, 1999–2009</td><td>Satisfaction with hh income</td><td>Individuals≥ 17 yo living in households with less than 6 members</td><td>Nonlinear FE ordered logit (based on Baetschmann et al. (2015))</td><td>0,35</td><td>0,13</td><td>0,13</td></tr>
<tr><td rowspan="3">Borah et al. (2018)****</td><td rowspan="3">GSOEP, 1984-2013</td><td rowspan="3">Satisfaction with hh income</td><td rowspan="3">Individuals≥18 yo, one- or two-adult-households with or without minor children</td><td>Pooled ordered logit</td><td>0.31-0.36</td><td>0.18-0.29/
0.29-0.37</td><td>0.10-0.27/
0.16-0.30</td></tr>
<tr><td>Nonlinear least squares</td><td>0.31-0.25</td><td>0.12-0.31</td><td>0.12-0.31</td></tr>
<tr><td>FE ordered logit (Baetschmann et al. (2015) approach)</td><td>0.26-0.15</td><td>0.16-0.13/
0.24-0.17</td><td>0.10-0.12/
0.15-0.14</td></tr>
</table>

Note: GSOEP - German Socio-Economic Panel; SHP - Swiss Household Panel; BHPS - British Household Panel Survey

*Equivalence weights reflect period-specific equivalence scales based on satisfaction with income in case when the first child is 12 years old and the second child is 6 years old.

**Equivalence weights refer to the model with control variables

***Equivalence weights refer to OECD-type scale

****Equivalence weights reflect the cases without and with reference effect measured with household Mincer equation

Table A.2: Summary statistics, RLMS 1994-2017 (237 395 obs)

	Mean	***SD***
Subjective welfare	3.83	*1.5*
Log of household income	9.93	*0.9*
Household size	3.14	*1.3*
Number of adults	2.59	*1.0*
Number of children	0.56	*0.8*
age16_20	0.07	*0.3*
age21_30	0.19	*0.4*
age31_40	0.19	*0.4*
age41_50	0.17	*0.4*
age51_60	0.16	*0.4*
age61_70	0.12	*0.3*
age71_80	0.08	*0.3*
age80plus	0.03	*0.2*
Female	0.58	*0.5*
Russian nationality	0.87	*0.3*
Incomplete secondary	0.21	*0.4*
Complete secondary	0.32	*0.5*
Secondary + vocational	0.25	*0.4*
University and higher	0.22	*0.4*
Single	0.16	*0.4*
Married	0.63	*0.5*
Divorced/widowed/separated	0.21	*0.4*
Have poor health	0.40	*0.5*
Other household members in poor health	0.53	*0.5*
Employed	0.61	*0.5*
Unemployed/out of labour force	0.39	*0.5*
Log of per capita living space (sqm)	3.10	*3.1*

Note: data are unweighted

Table A.3: Distribution of household types, RLMS 1994-2017

No of adults	No of children	Share of sample (%)
1	*0*	9.36
1	*1*	1.18
1	*2*	0.29
1	*3*	0.03
2	*0*	23.99
2	*1*	12.07
2	*2*	6.01
2	*3*	0.81
3	*0*	15.24
3	*1*	8.54
3	*2*	2.47
3	*3*	0.42
4	*0*	7.60
4	*1*	4.52
4	*2*	1.64
4	*3*	0.34
5	*0*	2.57
5	*1*	1.94
5	*2*	0.75
5	*3*	0.22
Total		***100***
Number of observations		***260,133***

Note: data are unweighted

Table A.4: Comparison of different equivalence scales

Weights		Per capita	Square-root	Modified OECD*	RUS Poverty Line**	Estimated scales			Schwarze (2003)		Falter (2006)		Borah *et al.* (2018)	
						POL	*FE OLS*	*BUC*	*POL*	*FE BL****	*POL*	*FE OLS*	*POL*	*BUC*
Adults	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	2	2.00	1.41	1.50	2.00	1.55	1.32	1.33	1.34	1.28	1.43	1.48	1.31	1.26
	3	3.00	1.73	2.00	3.00	2.01	1.55	1.56	1.59	1.47	1.77	1.86	1.53	1.44
	4	4.00	2.00	2.50	4.00	2.41	1.74	1.77	1.78	1.63	2.06	2.18	1.71	1.58
	5	5.00	2.24	3.00	5.00	2.78	1.90	1.93	1.98	1.76	2.31	2.47	1.87	1.70
1 Adult	1 Child	2.00	1.41	1.30	1.90	1.47	1.27	1.28	1.30	1.24	1.40	1.43	1.29	1.24
2 Adults	1 Child	3.00	1.73	1.80	2.90	1.85	1.47	1.48	1.52	1.41	1.70	1.78	1.49	1.41
	2 Children	4.00	2.00	2.10	3.80	1.95	1.51	1.54	1.59	1.47	1.85	1.90	1.59	1.51
3 Adults	1 Child	4.00	2.00	2.30	3.90	2.17	1.62	1.64	1.69	1.55	1.95	2.04	1.65	1.55
	2 Children	5.00	2.24	2.60	4.80	2.17	1.62	1.65	1.71	1.56	2.04	2.11	1.71	1.62
4 Adults	1 Child	5.00	2.24	2.80	4.90	2.45	1.75	1.78	1.84	1.66	2.17	2.28	1.79	1.66
	2 Children	6.00	2.45	3.10	5.80	2.36	1.71	1.75	1.82	1.65	2.21	2.29	1.82	1.71
5 Adults	1 Child	6.00	2.45	3.30	5.90	2.72	1.87	1.90	1.97	1.76	2.37	2.51	1.91	1.76

Note: Household types whose population share is at least 1%. Children are defined as individuals aged below 16 years (OECD and Rosstat def.)
*First adult has weight 1.0, every further adult 0.5, children 0.3.
**Working-age adult has weight 1.0, pensioner 0.8, children 0.9
*** Fixed Effects Binary Logit

Table A.5: The effect of expectations, RLMS 1994-2017

Main variables	**Pooled Ordered Logit**	**BUC**
Log of household income	0.623***	0.406***
	(0.011)	*(0.079)*
Log of household size	-0.404***	-0.166***
	(0.022)	*(0.034)*
Children*Log of household size	0.050***	0.020**
	(0.008)	*(0.010)*
Expectations in T-1 period (base – "Nothing will change")		
You will live worse	-0.509***	-0.139***
	(0.016)	*(0.017)*
You will live better	0.448***	0.152***
	(0.013)	*(0.014)*
Number of observations	237,395	712,448
Log pseudolikelihood	-400,970	-263,550

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the BUC models). All regressions include the same controls as in Table 1.

Table A.6: The effect of reference group, RLMS 1994-2017

Main variables	**Pooled Ordered Logit**	**BUC**
Log of household income	0.484***	0.282
	(0.021)	*(0.213)*
Log of household size	-0.241***	0.007
	(0.034)	*(0.117)*
Children*Log of household size	0.028**	0.003
	(0.011)	*(0.022)*
Relative income (base – 1st quartile)		
2nd quartile	0.161***	0.071
	(0.021)	*(0.084)*
3rd quartile	0.310***	0.203
	(0.025)	*(0.144)*
4th quartile	0.477***	0.323
	(0.033)	*(0.234)*
Number of observations	140,026	366,511
Log pseudolikelihood	-237,167	-135,630

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the BUC models). All regressions include the same controls as in Table 1.

Table A.7: The effect of welfare definition, RLMS 1994-2017

Dependent variable	*Satisfaction with life*		*Satisfaction with economic conditions*	
Main variables	**Pooled Ordered Logit**	**BUC**	**Pooled Ordered Logit**	**BUC**
Log of household income	0.606***	0.431***	0.863***	0.719***
	(0.010)	*(0.077)*	*(0.013)*	*(0.112)*
Log of household size	-0.462***	-0.284***	-0.790***	-0.569***
	(0.022)	*(0.035)*	*(0.025)*	*(0.046)*
Children*Log of household size	0.071***	0.018*	0.069***	0.015
	(0.007)	*(0.011)*	*(0.008)*	*(0.012)*
Number of observations	240,383	525,832	211,032	446,937
Log pseudolikelihood	-329,968	-196,405	-286,373	-169,660

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the BUC models). All regressions include the same controls as in Table 1.

Table A.8: The effect of measurement error, RLMS 1994-2017

	Pooled Ordered Logit	**BUC**
Log of household income	0.558***	0.372***
	(0.010)	*(0.070)*
Log of household size	-0.318***	-0.127***
	(0.022)	*(0.032)*
Children*Log of household size	0.050***	0.021**
	(0.008)	*(0.010)*
Number of observations	242,768	733,754
Log pseudolikelihood	-413,485	-271,759

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the BUC models). All regressions include the same controls as in Table 1.

Table A.9: The effect of sample restriction, RLMS 1994-2017

Main variables	**Pooled Ordered Logit**	**BUC**
Log of household income	0.640***	0.396***
	(0.011)	*(0.079)*
Log of household size	-0.369***	-0.121***
	(0.022)	*(0.033)*
Children*Log of household size	0.013*	-0.005
	(0.007)	*(0.009)*
Number of observations	245,777	746,710
Log pseudolikelihood	-418,712	-276,200

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the BUC models). All regressions include the same controls as in Table 1.

Table A.10: The effect of pensioners, RLMS 1994-2017

Main variables	**Pooled Ordered Logit**	**BUC**
Log of household income	0.657***	0.409***
	(0.011)	*(0.079)*
Log of household size	-0.368***	-0.144***
	(0.029)	*(0.043)*
Children*Log of household size	0.042***	0.019*
	(0.008)	*(0.011)*
Pensioners*Log of household size	-0.022	-0.044
	(0.023)	*(0.051)*
Number of pensioners	-0.040	0.079
	(0.027)	*(0.060)*
Number of observations	231,972	692,336
Log pseudolikelihood	-394,096	-256,312

Note: Robust standard errors are in parentheses, controlling for two-way clustering (i.e., at the individual for the POL model and at the household-wave level for the BUC models). All regressions include the same controls as in Table 1.

Table A.11: Total effect of pensioners by household composition, RLMS 1994-2017

Total number of hh members	Number of pensioners	Pooled Ordered Logit	BUC
2	*1*	-0.056***	0.049*
		(0.01)	*(0.03)*
3	*1*	-0.065***	0.033*
		(0.01)	*(0.02)*
3	*2*	-0.129***	0.067*
		(0.02)	*(0.03)*
4	*1*	-0.071***	0.022
		(0.01)	*(0.02)*
4	*2*	-0.142***	0.043
		(0.03)	*(0.04)*
5	*1*	-0.076***	0.013
		(0.02)	*(0.03)*
5	*2*	-0.152***	0.026
		(0.03)	*(0.06)*

Note: Standard errors in parentheses are calculated using delta-method

Table A.12: Results for non-parametric scales, RLMS 1994-2017

Parameter	Coefficient
a1k1	1.422***
	(0.233)
a2k0	1.243***
	(0.105)
a2k1	1.374***
	(0.146)
a2k2	1.259***
	(0.161)
a3k0	1.454***
	(0.143)
a3k1	1.704***
	(0.187)
a4k0	1.731***
	(0.198)
a4k1	1.836***
	(0.241)
a5k0	1.968***
	(0.312)
a5k1	1.836***
	(0.326)
Number of observations	74,627
Log pseudolikelihood	-237,360

Note: Robust standard errors are in parentheses, controlling for two-way clustering. All regressions include the same controls as in Table 1.

Table A.13: Estimation results for poverty lines, RLMS 1994-2017

Main variables	**Pooled Ordered Probit**
Log of household income	0.485***
	(0.012)
Log of household size	0.689***
	(0.086)
Ln hh income*Ln hh size	-0.113***
	(0.010)
Log of household size squared	0.118***
	(0.016)
Constant cut1	2.994***
	(0.112)
Constant cut2	3.719***
	(0.112)
Constant cut3	4.486***
	(0.113)
Constant cut4	5.164***
	(0.113)
Constant cut5	6.037***
	(0.113)
Constant cut6	6.652***
	(0.113)
Constant cut7	7.371***
	(0.114)
Number of observations	234,308
Log pseudolikelihood	-397,371

Note: Robust standard errors are in parentheses, controlling for two-way clustering. All regressions include the same controls as in Table 1.

Figure A.1. Estimation sample distribution of subjective welfare variable, RLMS 1994-2017

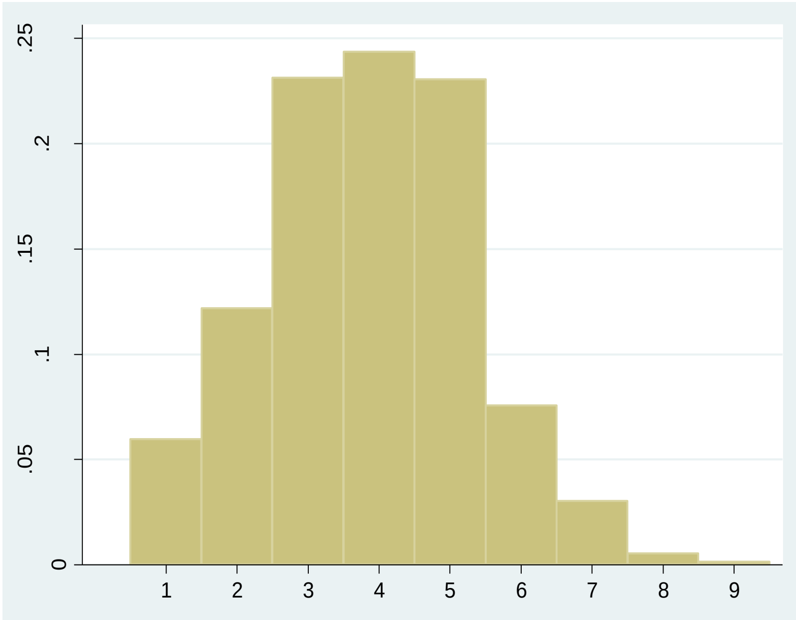
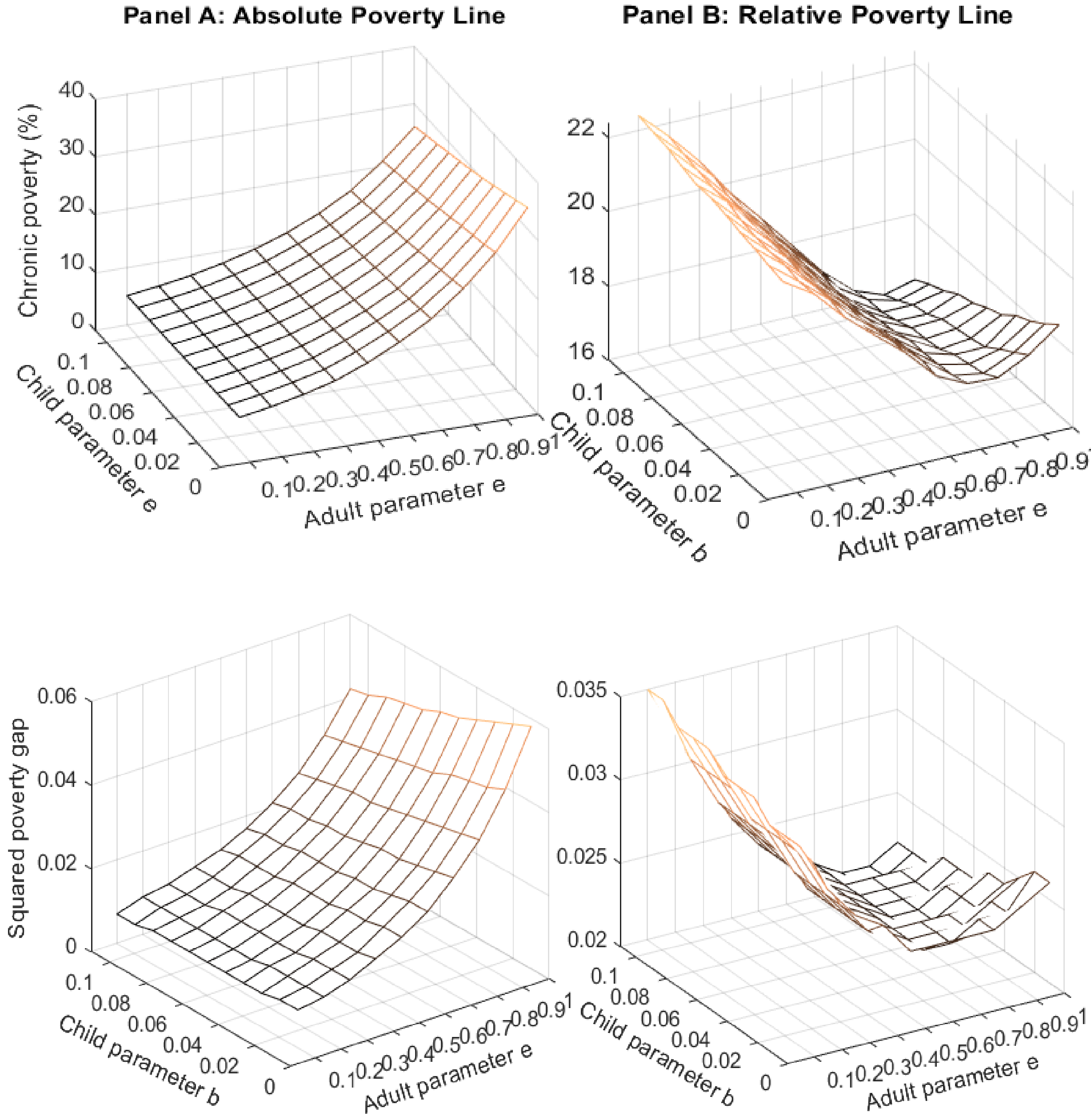


Figure A.2. Sensitivity of chronic poverty to scale factors, Foster`s index, RLMS 1994-2017



Note: Absolute poverty line is defined as a minimum regional subsistence level per person. Relative poverty line is set on 60% of household size-weighted median equivalized income. Both the poverty thresholds and household income are converted to constant 2011 rubles using regional CPI indices provided by the Rosstat.

Figure A.3. Scale Factors and Income Mobility, RLMS 1994-2017