the review of income and wealth

Review of Income and Wealth
Series 68, Number S1, April 2022
DOI: 10.1111/roiw.12559

DO ADJUSTMENTS FOR EQUIVALENCE SCALES AFFECT POVERTY DYNAMICS? EVIDENCE FROM THE RUSSIAN FEDERATION DURING 1994–2017

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Hardly any literature exists on the relationship between equivalence scales (ESs) and poverty dynamics for transitional countries. We analyze ESs constructed from subjective wealth and more than 20 waves of household panel survey data from the Russia Longitudinal Monitoring Survey between 1994 and 2017. We find that the ES elasticity is sensitive to household demographic composition and ES adjustments result in lower estimates of poverty lines. We decompose poverty into chronic and transient components and find that chronic poverty is positively related to the adult scale parameter. However, chronic poverty is less sensitive to the child scale factor compared with the adult scale factor. Interestingly, the direction of income mobility might change depending on the specific scale parameters that are employed. The results are robust to different measures of chronic poverty, income expectations, reference groups, functional forms, and various other specifications.

JEL codes: I30, J10, O15

Keywords: poverty, poverty dynamics, equivalence scale, Russia, panel survey

1. Introduction

Obtaining comparable measures of household incomes across households of different sizes and composition—or converting these incomes on a common

Note: We would like to thank the editor Ilya Voskoboynikov, two anonymous reviewers, Conchita D'Ambrosio, Sam Freije-Rodriguez, Rostislav Kapeliushnikov, Ambar Narayan, Sergey Roshchin, Jacques Silber, Ruslan Yemtsov, and seminar participants at IARIW conferences, Centre for Labour Market Studies, and World Bank for useful feedback on earlier versions. We are grateful to Martin Biewen for sharing his Stata code. We would also like to thank the UK Foreign Commonwealth and Development Office (FCDO) and NRU-HSE Basic Research Program for additional funding assistance.
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[Corrections made on 14th April 2022, after first online publication: Author order has been revised in this version.]

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(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 and Pestel, 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 (ESs) and poverty measurement. First, we estimate ESs using an alternative source of data, subjective well-being data. While a growing literature has followed this approach using panel data, these studies mostly rely on life satisfaction and income satisfaction questions.[1] We analyze a subjective well-being 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 closely related to household welfare than satisfaction variables (Ravallion and Lokshin, 2001, 2002).

Second, we offer new and interesting findings regarding the dynamics of poverty given ES 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 static poverty are quite different from those for long-term chronic poverty.[2] Yet, while these dynamics, by definition, require an 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).[3] Such data do not provide a good understanding of how household demographics impact transient or chronic poverty, or to put it differently, how employing different scaling parameters affects household poverty dynamic patterns. To our knowledge, we offer the first study to investigate the impacts of scale adjustments on poverty dynamics. As discussed later, we employ several different definitions of poverty dynamics for a more robust analysis.

Furthermore, the RLMS offers a longer panel compared to most existing studies. Such data allow us to extend our analysis to broader definitions of households—including multigenerational households—and to better capture demographic changes related to the formation of extended families.[4]

Finally, the more affluent countries examined in existing studies, such as Germany, Switzerland, or the United Kingdom, have, on average, a smaller

[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), and the second type asks respondents to evaluate their level of satisfaction with life or income (*e.g*. Biewen and Juhasz, 2017; Borah *et al*., 2019). Our paper is more related to the second approach and we also offer robustness checks using life satisfaction outcomes.

[2]We employ two popular approaches in the literature to decompose poverty into chronic and transient components. Jalan and Ravallion (2000) define individuals as chronically poor if their permanent incomes are below a specified poverty line, while Foster (2009) considers individuals to be chronically poor if they spend some specified time below the poverty line.

[3]But see Dang *et al*. (2019) for a review of alternative poverty measurement methods in contexts where no panel data exist.

[4]Only Borah *et al*. (2019) 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.

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household size than that of the Russian Federation. This different demographic structure implies that findings on the former countries may not necessarily apply to the latter, or middle-income transition economies in general. Furthermore, our study is especially relevant for Russia for two other reasons. First, the ES, currently embedded in the Russian official poverty lines, allows for unequal consumption needs but ignores the economies of scale in household size. A direct policy implication of no scale adjustment is that the official poverty lines would often identify large families with children as those most in need of financial support, regardless of their actual living standards. Second, in his address to the Federal Assembly in 2020, the Russian president discussed the falling incomes of the country and the need to create favorable conditions to raise real incomes.[5] However, recent evidence points to more upward mobility than downward mobility for the population over the past two decades (Dang *et al*., 2020). Consequently, it would be important for policymakers to understand to what extent the income trends can be affected by scale adjustments.

To our knowledge, Ravallion and Lokshin (2002) and Takeda (2010) are the only two other papers that estimate the relationship between household size and composition and subjective well-being in Russia using panel data. However, besides analyzing older data, these two papers use shorter panels and cross-sectional data, respectively. 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 and Staub, 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 ES 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. Nevertheless, 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, and present estimation results in Section 5. We offer a wide range of robustness checks and further extensions in Section 6 before concluding in Section 7.

2. Brief Literature Review

The sensitivity of poverty (and inequality) estimates to choices of ESs has been widely recognized in studies on both richer countries, such as Germany (Peichl *et*

[5]See http://en.kremlin.ru/events/president/news/62582.

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al., 2012) and European countries (Bonke and Schroder, 2008), and poorer countries, such as China (Bishop and Luo, 2006), Ghana (Regier *et al.*, 2019), India (Meenakshi and Ray, 2002), or sub-Saharan Africa (Newhouse *et al.*, 2017).

A separate branch of the literature focuses on subjective ESs and their effects on cross-national measures of poverty and inequality. In particular, Bishop *et al.* (2014) analyze data for 15 European countries and find that applying subjective ESs significantly decreases the poverty rates and changes the demographic composition of the poor but does not alter the countries' poverty rankings. Employing a similar approach, Kalbarczyk-Stecliket *et al.* (2017) find lower subjective poverty rates for 23 European countries, including Central and Eastern Europe. Both studies find larger economies of scale compared to expert scales (the OECD scale and the square root scale) and lower economies of scale in Eastern and Southern European countries compared to Western European countries. Most recently, Mysíková *et al.* (2020) derive implicit subjective ESs based on subjective income poverty lines for 26 EU countries and find apparent differences between the Eastern and Western European regions. These studies, however, analyze cross-sectional data.

A number of studies estimate ESs using panel subjective well-being data, but these studies mostly investigate data on life and income satisfaction and focus on richer countries such as Germany or the United Kingdom (Charlier, 2002; Schwarze, 2003; Falter, 2006; Bollinger *et al.*, 2012; Biewen and Juhasz, 2017; Borah and Keldenich, 2019). An 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 four studies for Germany find a lower weight for children than that of an additional adult. Only Bollinger *et al.* (2012) demonstrate that children in the United Kingdom are associated with diseconomies, but this result mostly applies to the first child. Second, while most studies suggest larger returns to scale than the (old or modified) OECD ESs, non-parametric scales recently estimated for Germany by Biewen and Juhasz (2017) are reasonably close to "square-root" ESs.[6] 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 ESs 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 households with children as a percentage of all households (Panel D).

Russia has the largest household size, which averaged at least 2.6 persons per household for the last ten years, which is followed by the United Kingdom (2.3 persons), Switzerland (2.2 persons), and Germany (2 persons) (Panel A).

[6]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.

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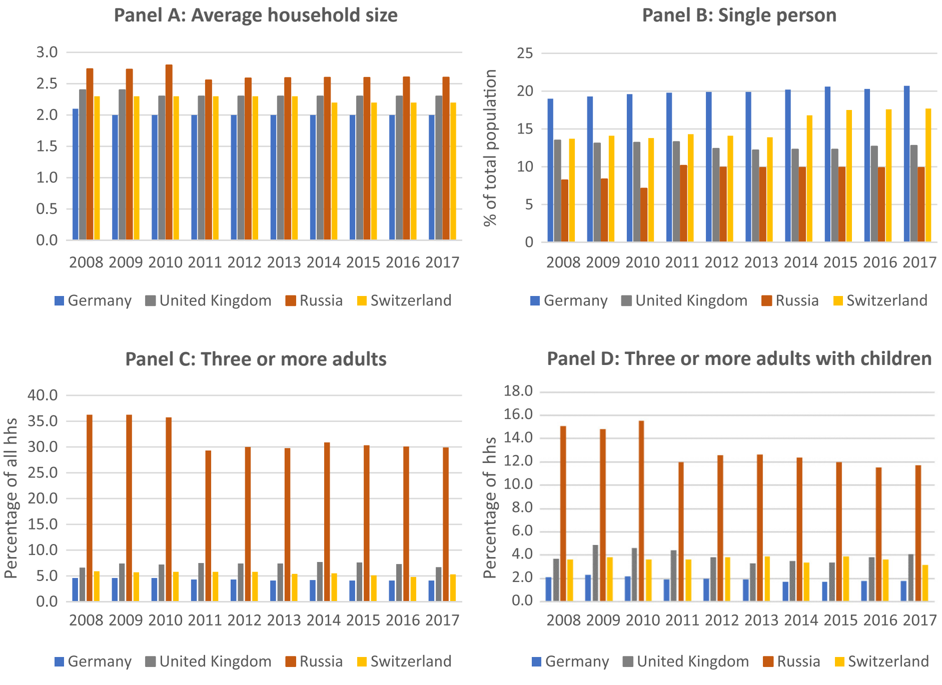

Figure 1. Distribution of Household Types in Germany, Russia, Switzerland, and the UK
Source: European Union Statistics on Income and Living Conditions (EU-SILC) and RLMS-HSE.
[Colour figure can be viewed at wileyonlinelibrary.com]

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 United Kingdom 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) and show a larger proportion of extended households in Russia. In particular, 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.[7]

[7]There are just a handful of studies that investigate the sensitivity of equivalence scales to poverty analysis for Russia, which offer inconclusive evidence. Using Engel's food share method, Ovcharova *et al*. (1999) estimate equivalence scales for the Volgograd region in Russia and find significant reductions poverty. Commander *et al*. (1999) experiment with a variety of adult equivalent scales using RLMS data and find the choices of scale parameters to significantly affect poverty and inequality. Yet, Dang *et al*. (2020) find their results to remain robust to two different scale adjustment methods with income mobility and growth. See also Ovcharova and Tesliuc (2006) for alternative consumption indicators and poverty lines that are adjusted for household size and composition using the cross-sectional household data NOBUS.

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3. Empirical Strategy

3.1. *Measuring Scale Elasticity*

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

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

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 such as age groups, gender, nationality, education levels, marital status, employment status, health status, and living space per capita. α_i is an individual-level unobserved component, ε_{it} is the i.i.d error term. It was expected that satisfaction positively depends on income and negatively depends on household size.[8] 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. 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.[9]

Different sizes of scale economies have important policy implications, since they lead to different profiles of the poor population. For example, lower values of the equivalence parameters (which imply more adjustments for larger family sizes) tend to portray the poor as primarily composed of older people as these are over-represented among single households in Russia. On the other hand, higher values of the ES parameters would shift the profile from the poor being primarily older people to the poor being primarily families with children.

Following Schwarze (2003), we also define e_a as the ES 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 effect of household size. 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.

[8]These results are supported by empirical evidence from both richer and developing countries such as Germany and Great Britain (Van Praag and Ferrer-i-Carbonell, 2004) and Mexico (Rojas, 2007). Also see Ravallion and Lokshin. (2002) for more discussion for Russia.

[9]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.

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

$$W_{it}^{*} = X_{it}'\theta + \beta \ln Y_{it} - \beta e_a \ln\left(a_{it} + k_{it}\right) + \beta b k_{it} \ln\left(a_{it} + k_{it}\right) + \alpha_i + \epsilon_{it} \tag{2}$$

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

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

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

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

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

If we assume that $\Lambda(.)$ has a cumulative logistic distribution and unobserved individual heterogeneity does not exist (*i.e.* $\alpha_i = 0$), 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 (see Appendix A, Table A.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, such heterogeneity can result in inconsistent estimates (Ravallion and Lokshin, 2002; Ferrer-i-Carbonell and Frijters, 2004; Ravallion, 2012).[10] The individual fixed-effects model is an appropriate model to deal with these issues.

For our estimations we apply the BUC fixed-effects model developed by Baetschmann *et al.* (2015).[11] Consistent estimations of parameters (θ, β) are performed by collapsing ordered variables (J levels of W_{it}) into binary outcomes for each choice ($0, \ldots, J-1$). Subsequently, the conditional maximum likelihood estimator by Chamberlain (1980) can be applied to each of these binary choice models. By copying each observation $J-1$ times in the data set (*i.e.* "blowing-up"

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

[11]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).

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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 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.[12] For example, empirical evidence for Germany suggests that the ES parameters in FE models are significantly reduced compared to the pooled regressions (Schwarze, 2003; Borah *et al.*, 2019), but the opposite result holds for Switzerland (Falter, 2006).

3.2. *Chronic Poverty and Income Mobility*

Following Jalan and Ravallion (2000), we define individuals as chronically poor if their permanent incomes are below a specified poverty line. Transient poverty is the difference between total poverty and chronic poverty aggregated over all individuals. In this approach, the intertemporal mean of poverty for each individual is defined as

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

where α is a measure of the sensitivity of poverty to inequality among the poor (*i.e.* poverty aversion indicator), $I(.)$ is the indicator function which is one if the condition is satisfied and zero otherwise. Total poverty is calculated by averaging across all individuals $P = \left(p_i \ldots\ldots p_N\right) = \frac{1}{N}\sum p_i$.

The aggregate chronic poverty index is defined as

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

In Equation (6), $\overline{y}_i$ is obtained by averaging all income of over the period for each individual, irrespective of the poverty status of the individual at any time. To provide robustness checks on estimation results, we also follow alternative approaches in measuring poverty. These include the spell approach, which defines individuals as chronically poor if they are poor in a certain number of periods, and the equally distributed equivalent approach by Duclos *et al.* (2010).[13]

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

[13] For the spell approach, we employ Foster's (2009) measure of chronic poverty, which considers 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 $p_{ci} = \frac{1}{T}\sum_{t=1}^{T} I[\sum_{t=1}^{T}(y_{it} < z) \geq \tau T]\left(1-\frac{y_{it}}{z}\right)^{\alpha}$, 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.

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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

$$M^{un} = \sum_{k=0}^{K} P\left(z_k \leq y_1 \leq z_{k+1} \quad \text{and} \quad y_2 \geq z_{k+1}\right) \tag{7}$$

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 Equation (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.[14]

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

4. Data and Country Background

4.1. *Data*

We analyze the Russian Longitudinal Monitoring Survey (RLMS), which is an annual and nationally representative panel household survey. Our analysis covers 24 years (22 survey waves) from 1994 to 2017. We restrict the estimation sample to working-age adults, who are 16 years of age or older. We also exclude households with an unusually large number of members (*e.g.* having more than five adults and three children).[15]

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

[14]See Dang *et al*. (2020) for more discussion on these measures of mobility.

[15]Such households represent less than 3 percent 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 a pooled model and even negative (but insignificant) when using fixed effect ordered logit. At the same time, the adult scale parameter is robust to using an unrestricted sample.

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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 distribution.[16] There is also a reasonable degree of churning over time, with only about 40 percent 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 positive incomes. 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.[17] 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 summary statistics for the control variables.

4.2. *Country Background*

The transition processes in the former countries of the Soviet Union have received much attention in the economic literature (Milanovic, 1999; Braithwaite and Grootaert, 2000; Forster *et al*., 2005). While large heterogeneity exists within the former Soviet Union countries regarding the speed of economic recovery and post-transition growth, the transition from a centrally planned economy to a market economy was characterized by widespread poverty and unemployment, high inequality and political instability in all these countries. Income structures and distributions changed significantly due to disruptions to the economic systems (Milanovic, 1998; Górniak, 2001).

But compared to the other formerly planned economies, the extent and severity of economic declines at the early stages of the transition in Russia are considered one of the worst, with a sharp increase of poverty incidence, severity and depth of poverty in the early 1990s (Klugman and Braithwaite, 1998; Svejnar, 2002; Bezemer, 2006). The subsequent periods witnessed major changes in living standards for the country, with poverty steadily decreasing from 34 percent in the early 1990s. After declining to around 20 percent in 1997, the (headcount) poverty rate peaked at 29 percent in 2000 following the August 1998 crisis (Figure 2).

[16]Since responses with a score of eight or nine account for less than 1 percent 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).

[17]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, 2009), we re-estimate our scale parameters without these variables and obtain similar results.

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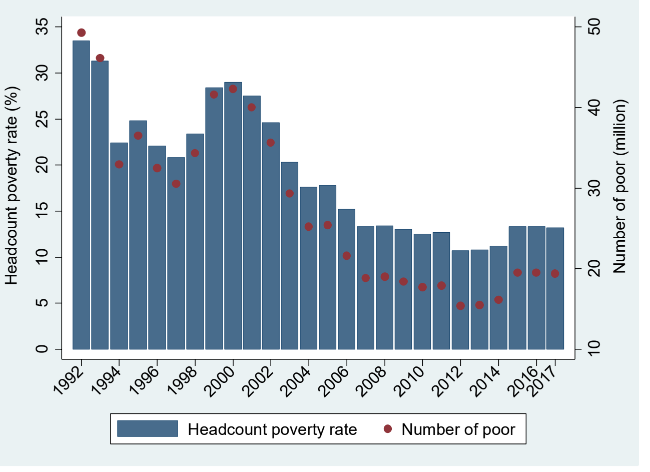

Figure 2. Trends in Poverty, 1992–2017
Source: Official data of the Russian Federal State Statistics Service (http://www.gks.ru/free_doc/new_site/population/urov/urov_51g.doc, accessed October 15, 2020). [Colour figure can be viewed at wileyonlinelibrary.com]

Between 2000 and 2012, economic growth led to a dramatic reduction of poverty by almost three times, with the poverty rate reaching 10.7 percent in 2012. This translates into 27 million people escaping poverty in this period. The subsequent period witnessed poverty slightly increasing to 13 percent in 2017, which was likely caused by the financial crisis in the early 2010s.[18]

Social protection programs, including pensions, have been an important component of the government's poverty reduction strategy since the early 2000s. The government increased social spending between 2003 and 2016, with social spending reaching about 12 percent of GDP in 2016 (Figure 3).

While this is still lower than the average social spending in OECD countries (20.5 percent), other programs such as pension account for almost 9 percent of GDP (Figure 3). For comparison, average pension spending in OECD countries in 2015 was 8 percent of GDP (OECD, 2020a, 2020b). As a result, social protection programs account for a significant share of household income, and they steadily increase to almost 20 percent of total household monetary incomes in 2016. On the other hand, other social assistance programs and subsidies account for less than 3.3 percent of GDP in the period 2003–2016.

Social assistance programs targeted to the poor include child allowances. Children from families with per capita incomes below the regional minimum subsistence level are qualified to receive monthly cash benefits until the child reaches 18 years old. The amount of benefits varies by region and is proportionate to the

[18]The official method of measuring poverty in Russia uses a minimum subsistence level as the poverty line, which was adopted in 1992 and revised in 1999 (see more detailed discussion in Ovcharova and Tesliuc (2006)). Individuals are classified as poor if their incomes are below the official minimum subsistence level established in each region by socio-demographic groups. This minimum subsistence level is also used to define eligibility for social welfare assistance. See also Abanokova and Dang (2021) for a recent discussion of general poverty trends in Russia.

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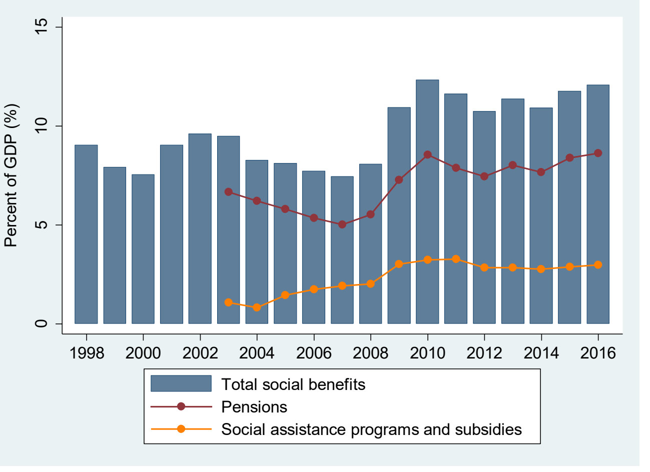

Figure 3. Social Protection Spending, 1998–2016

Notes: Category "Social assistance programs and subsidies" does not include scholarship expenditures.

Source: Official data of the Russian Federal State Statistics Service, authors calculations (https://rosstat.gov.ru/storage/mediabank/tab1(2).htm, https://rosstat.gov.ru/bgd/regl/b11_44/IssWWW.exe/Stg/d01/06-06.htm, https://rosstat.gov.ru/bgd/regl/B03_44/IssWWW.exe/Stg/d010/i011190r.htm, accessed October 15, 2020). [Colour figure can be viewed at wileyonlinelibrary.com]

number of children in the family. According to official statistics, children in Russia have a higher risk of falling into poverty. While 33 percent of all Russian households have children in 2017, the corresponding figure is more than twice higher at 81 percent for poor households. The risk of poverty rises with the number of children, but households with one or two children account for the majority (59 percent) of poor households (RFSSS, 2020). As such, interventions targeted at households with children are justified, but questions can be raised about the efficiency of such poverty programs since eligibility rules are not based on any set of estimated ESs.[19]

5. Estimation Results

5.1. *Scale Parameters*

In Table 1, we provide 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 by almost 13,000, since these individuals were observed only once in the RLMS, or their subjective welfare levels did not change 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

[19]The official poverty line does not capture the economies of scale that result from sharing the fixed costs for households (Ovtcharova and Tesliuc, 2006).

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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 more children bear higher costs and need more resources.

Using the estimates from Table 1, Table 2 calculates the ESs. 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 ES parameter for adults (from 0.6 to 0.4) and for children (from 0.08 to 0.05). While the marginal cost of a second child in two-parent households calculated with the BUC model is similar to the values calculated with the FE OLS model, the costs of a second child in three and four-adult households are slightly lower for the latter model. We switch to presenting results using the BUC model in the subsequent discussion since this is our preferred model for interpretation.[20]

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.*, 2019), which can be explained by more 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 4 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 poverty line scale, each normalized to a single adult.[21] 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 ES embedded in the official poverty line for Russia, particularly for large-size households.

5.2. *Adjusted Poverty Lines*

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 ESs, 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-thirds of the median income per adult equivalent for each household type, using the parameters that account for differences

[20]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.

[21]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.

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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).
***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

in economies of scale and composition in the household. To make Table 3 easier to read, we leave out the standard errors (see Appendix A, Table A.5 for the full results).

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TABLE 2
Scale Elasticity Parameters, RLMS 1994–2017

	Dependent Variable: *Subjective Wealth*		
Scale Parameters	Pooled Ordered Logit	FE OLS	BUC
Baseline elasticity $e_a = \beta e_d/\beta$	0.636***	0.399***	0.407***
	(0.032)	*(0.060)*	*(0.088)*
Additional child $b = \beta b/\beta$	0.078***	0.050**	0.048*
	(0.012)	*(0.021)*	*(0.026)*
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.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

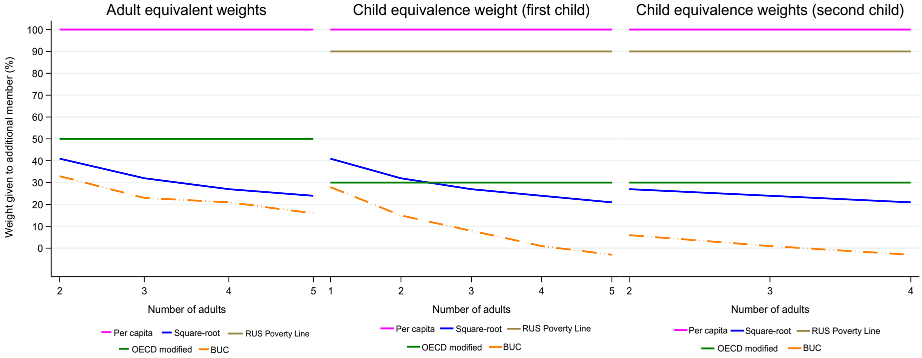

Figure 4. Comparison of Different Equivalence Scales [Colour figure can be viewed at wileyonlinelibrary.com]

Table 3 suggests that our proposed poverty lines are generally much lower than the official Russian poverty thresholds, in both absolute and relative terms. In particular, compared to 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 corresponding differences for our relative poverty lines are smaller but are still considerable. The official poverty thresholds are from about 20 percent to 90 percent higher and 40 percent to 100 percent higher for households without children and households with children, respectively.

We provide in Appendix A, Figure A.2, the poverty rates that correspond to the official poverty line adjusted with the estimated ESs in Table 2. Consistent with our previous discussion, the revised poverty rates based on the estimated ESs are lower than the official poverty rates.

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TABLE 3
ALTERNATIVE POVERTY THRESHOLDS BY HOUSEHOLD SIZE IN 2017 (IN RUBLES PER MONTH)

	Estimated with Absolute Line		Estimated with Relative Line		
Household Type	Pooled OL	BUC	Pooled OL	BUC	Official
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	16,908	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

Notes: Population weights are applied. Standard errors for poverty rates are adjusted for complex survey design. Poverty line for reference "one adult" is defined as an average of minimum subsistence levels for working-age individual and pensioners in 2017. The level of absolute poverty line is 10,899 rubles per month for working-age individual, is 8,315 rubles per month for pensioner and is 9,925 rubles per month for child in 2017. Relative poverty line is set on 60 percent of household size-weighted median equivalized income for each household type using RLMS data in 2017. Poverty lines of reference adult are adjusted with weights in Table 2 using BUC model (where baseline elasticity equals 0.407 and every child has a weight 0.048) and using Pooled Ordered Logit model (where baseline elasticity equals 0.636 and every child has a weight 0.078).

5.3. *Poverty and Income Dynamics*

In Figure 5, we start examining 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 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 size. When b increases from 0 to 0.1, it is a situation where for the same household size, households with children have a lower ES elasticity (*i.e.* a 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 provides the opposite scaling effects compared to the absolute poverty line.[22] Yet, Figure 5, Panel A shows that the poverty rate using the absolute poverty line can decrease by 9 to 15 percentage points (from 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 points if e_a decreases from 0.5 to 0.1. Figure 5, Panel B displays the opposite results where the poverty rate using the relative poverty line increases slightly by at most four

[22]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 percent of the national median equivalized disposable income.

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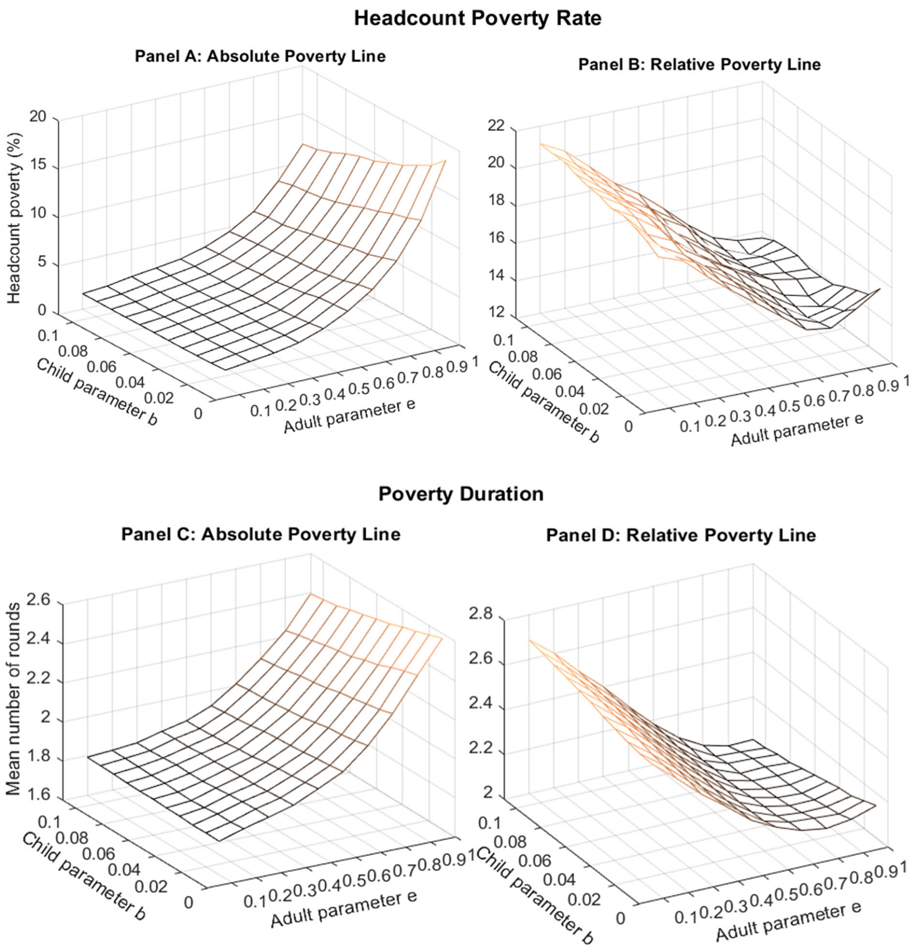

Figure 5. Scale Factors and Headcount Poverty Rate and Poverty Duration, RLMS 1994–2017

Notes: 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 percent 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. [Colour figure can be viewed at wileyonlinelibrary.com]

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. On the other hand, poverty is less sensitive to the choice of the child discount factor. It varies by at most 6 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.[23]

[23]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).

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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	0.085	0.1	0.119	0.142	0.17
Transient poverty	0.036	0.041	0.045	0.05	0.054
Chronic poverty	0.049	0.059	0.074	0.092	0.115
Share of chronic poverty (%)	*57.3*	*59.4*	*62.1*	*64.9*	*67.9*
Poverty gap					
Total poverty	0.03	0.035	0.042	0.05	0.06
Transient poverty	0.015	0.017	0.02	0.023	0.026
Chronic poverty	0.015	0.018	0.022	0.027	0.035
Share of chronic poverty (%)	*49.6*	*50.7*	*52.3*	*54.5*	*57.2*
Squared poverty gap					
Total poverty	0.016	0.019	0.022	0.026	0.032
Transient poverty	0.009	0.01	0.012	0.014	0.016
Chronic poverty	0.007	0.009	0.01	0.013	0.016
Share of chronic poverty (%)	*45.6*	*46.1*	*47.1*	*48.5*	*50.5*

Notes: Absolute poverty line is defined as a minimum regional subsistence level per person for each year. 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 A.6 in Appendix A shows that for the same child scale parameter of 0.1, households with children are less poor if the adult scale parameter falls in the range [0.1, 0.5], but are poorer if the adult scale parameter falls in the range [0.6, 1]. Clearly, selecting a larger child discount factor, say at 0.1, will result in households with children being less poor than households with children for most values of the adult scale parameter. But still, if we set the latter at 1, households with children are poorer.

We turn next to examining poverty duration, which is defined as the average number of consecutive survey years (rounds) a household spends in poverty. Figure 5, Panels C and D produce qualitatively similar results. Poverty duration is sensitive to changes in e_a, and ranges 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's (2000) 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 positively 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 almost 10 percentage points when e_a increases from 0.3 to 0.7. For the poverty gap and squared poverty gap, the corresponding figures are a-7-percentage-point and a 5-percentage-point increase. We plot the alternative chronic poverty measures (Foster, 2009; Duclos and Araar, 2010) against the scale factors in Appendix A, Figure A.3, which also shows that these measures are more sensitive to scale adjustments for adults than for children.

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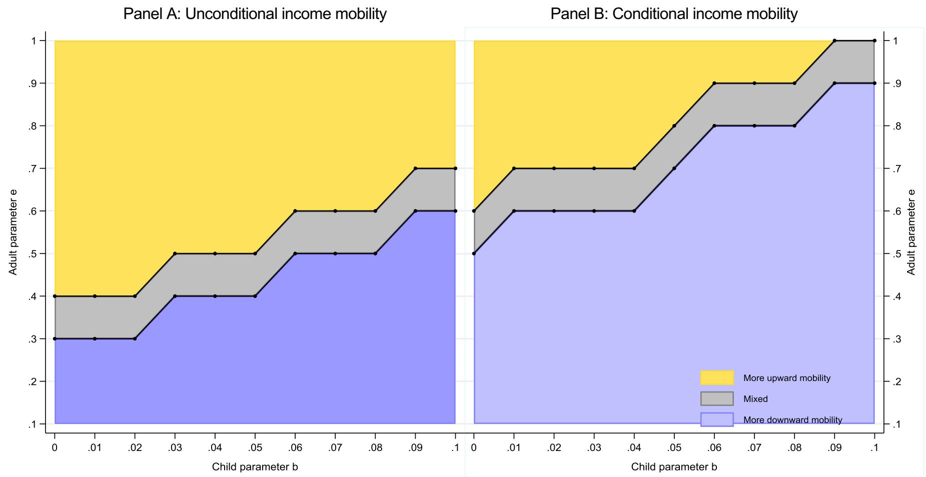

Figure 6. Scale Factors and Income Mobility, RLMS 1994-2017
[Colour figure can be viewed at wileyonlinelibrary.com]

Figure 6 examines the relationship between scale parameters and unconditional income mobility (Panel A) and conditional income mobility (Panel B) (see Appendix A, Figure A.4 for the corresponding three-dimensional graphs). Three possible scenarios can happen with income mobility: 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 nor 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 more upward conditional mobility, except when the child parameter falls in the interval [0.09, 0.1] (Panel B). 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 ESs have in determining estimation results with income dynamics.

6. Robustness Checks and Further Extensions

6.1. *Robustness Checks*

We examine several 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 well-being well before their actual realization. We control for income

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TABLE 5
The Effect of Alternative Specifications on Scale Parameters Estimates, RLMS 1994-2017

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

Note: Standard errors in parentheses are calculated using delta-method. All regressions include the same controls as in Table 1.
$^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$.

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 the pooled model (Table 5, row 1).[24]

Relative income rather than total income may affect satisfaction, and if ignored, may result in biased estimates (Borah *et al*., 2019). We include dummy variables to indicate the relative position of the household in the reference group`s distribution of household income quartiles (Appendix A, Table A.8). The reference group is determined for each year and consists of individuals living in households of 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).[25]

We also analyze the other satisfaction variables in the RLMS as alternative, dependent variables for the subjective wealth variables, which are 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.10). To save space, we only report the scale

[24]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 regression results are shown in Appendix A, Table A.7.

[25]The full regression results are shown in Table 1. Employing other definitions of the reference group provides similar results, as shown in Appendix A, Table A.9.

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parameters derived from the regressions for life satisfaction (Table 5, row 3). The estimation results of the BUC model are robust, with the adult scale parameter of about 0.6 and child scale parameter about 0.04.[26]

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.11). 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 the POL model (Appendix A, Table A.12). 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 high costs on the household. On the other side, pensioners often consume less than working-age adults and can contribute their pensions to the household income. Our estimates from the RLMS suggest that the share of individuals (in total population) who received any pension in the past month hovers around 30 percent over the period 1994–2017. The majority of these pensioners (more than 70 percent) 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: a 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

$$
\begin{aligned}
(9)\qquad W_{it}^{*} &= X_{it}'\theta + \beta_1 \ln\left(\frac{Y_{it}}{(h)^{e_a - bk - cp}}\right) + \beta_2 p_{it} + \alpha_i + \varepsilon_{it} \\
&= X_{it}'\theta + \beta_1 \ln Y_{it} - \beta_1 e_a \ln h + \beta_1 b k_{it} \ln h + \beta_1 c p_{it} \ln h + \beta_2 p_{it} + \alpha_i + \varepsilon_{it}
\end{aligned}
$$

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

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.13), the total effect of pensioners is statistically significant and positive in the BUC model (Appendix A, Table A.14). But the inclusion of pensioners does not change the estimated scale parameters significantly: the adult

[26]The adult scale parameter is still high when using satisfaction with economic conditions (0.8), but the child scale parameter decreases 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).

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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

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

where $f\left(a_{it}+k_{it}\right) = 1 * a_{it}1k_{it}0 + \beta_{a2ko} * a_{it}2k_{it}0 + \beta_{a2k1} * a_{it}2k_{it}1 + \ldots + \beta_{a5k1} * a_{it}5k_{it}1$, 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.15. 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. Further Discussion and Conclusion

We estimate ESs using unique subjective well-being 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.

In particular, we find that the ESs based on subjective wealth are lower, which suggests larger economies of scale and a decreasing marginal cost of additional children. These findings are different from the OECD scales, and these differences increase with household sizes. Our results are consistent with existing studies using a similar subjective well-being approach that generally find larger economies of scale (compared to commonly used expert scales) for Western and Eastern European countries (Schwarze, 2003; Bishop *et al.*, 2014; Kalbarczyk-Stecliket *et al.*, 2017; Mysíková *et al.*, 2020). We find that the costs of adding the first child are lower than the costs of adding an additional adult, which is similar to the findings for the Eastern and Western European countries. But we also find that the weights for adults are mostly higher and economies of

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scale are lower in most Eastern European countries except Czech Republic and Romania.

Our estimates based on panel data show that children have lower subjective equivalence weights than the estimates based on cross-sectional data provided by Takeda (2010) for Russia. In particular, Takeda (2010) finds that the marginal cost of the first child is approximately 22 percent of a couple's household income, and the corresponding figure for the second child is around 8 percent. The marginal costs of the first child and the second child in our paper are twice lower at 11 percent and 4 percent. This suggests that estimation results that are based on cross-section data may underestimate the role of economies of scale. This finding is consistent with those in Schwarze (2003) and Borah *et al*. (2019) that employ the German SOEP panel data to estimate subjective ESs.

Furthermore, we consider different modelling assumptions in estimating the ESs. In particular, our application of the fixed-effects ordered logit model ("blow-up and cluster" estimator) on panel data provides somewhat higher estimated weights for extended households with children than those offered in existing studies that use fixed-effects OLS models. This implies that ignoring the discrete nature of the dependent variable in estimating income elasticities may result in biased estimates for the role of economies of scale in extended households.

Our results suggest that the official poverty rates for Russia may be affected by the choices of the ESs. In particular, we showed that economies of scale are significant. These results stand out when we consider population subgroups such as children and when we compare the ESs derived by self-reported well-being with other commonly used ESs. We also estimate the marginal costs for extended households to be lower (based on the fixed-effects ordered logit model). Consequently, these results challenge the common view that large households with many children are poorer than small households. These results also offer some tentative evidence that the practice of providing more benefits for additional children may not represent the optimal poverty-reduction strategy for Russia, and that this practice may unnecessarily provide more benefits to larger households than smaller households. It is therefore essential to incorporate the scale effect into poverty assessments for the country.

There is significant heterogeneity in terms of economic growth and demographic composition among the regions of Russia caused by geographical differences in relative prices and consumption preferences. Since the RLMS data are not representative at the regional level, we are unable to offer this analysis. But given a larger panel survey that is representative at the regional level, a promising direction for further research would be to apply our scale adjustments to better understand the effects of equivalence of scale on the composition of poverty and poverty dynamics. Such knowledge is essential for regional poverty comparisons and the development of well-targeted policy interventions.

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