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Reconstruction of the Social Cash Transfers System in Poland and Household Well-being: 2015 – 2018 Evidence

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Session 4D-2, Fighting Inequality and Poverty: Exploiting within and across Country Variations to Evaluate Distributive Impacts of Policy II

Time: Wednesday, August 24, 2022 [16:00-17:30 CEST]

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Abstract

In this study, the impact of social benefits on poverty, and economic activity in Poland is examined. In 2016 a huge programme of cash transfers, referred to as Family 500+, was introduced. It was intended to support families with children, especially the poorest ones, and to foster fertility. The impact of the transfers is examined through the observation of changes in monetary and multidimensional poverty following the reconstruction of the social benefits system. Changes in the recipients' behaviour are also investigated using estimates of regression models and treatment effects. The Family 500+ programme appeared to be successful as an anti-poverty tool and also resulted in average well-being increases for the whole population. However, it was also followed by the reduction of the economic activity of some recipients, especially in 2016 and 2017. The abovementioned trends partly reversed in 2018. As some income data in lower parts of the distribution seem to be flawed, income imputations, based on regression on income correlates, are employed.

Keywords: family benefits, monetary and multidimensional poverty, data imputation
JEL codes: D1, I3, H8

1. Introduction

In this study, the effects of the changes in the system of social cash transfers in Poland between 2015 and 2018 are examined. In April 2016, the state family support programme, which seriously changed the volume and structure of social benefits, was launched. It is known as “Family 500+” and ensures the monthly unconditional support of tax-free 500 PLN (złoty) per each child in families with two or more children and means-tested support of the same amount for families with one child. In 2016, 500 PLN was equal to 26% of the mean equivalent income. Total spending in 2017 was equal to 6% of the state budget. Family 500+ also changed the composition of the social transfers – the contribution of all family benefits to their total amount (excluding retirement and invalid pensions) increased from 63% in 2015 to 86% in 2018. For more details on Family 500+, see Brzeziński and Najsztub (2017), Michoń (2021) and Ministerstwo Rodziny i Polityki Społecznej (2021). The effects of the abovementioned social policy reconstruction are examined by observing resulting changes in the standards of living, especially monetary and multidimensional poverty. The impact of the benefits on the economic activity of the recipients is also explored.

In October 2015, the United Right (an alliance of three parties with the Law and Justice party as the dominating one) won the parliamentary election, reaching an absolute majority in the Parliament. Their programme was a combination of conservative rhetoric and social pledges, especially those supporting family values, with Family 500+ as a flagship programme. Its declared main goals were: (i) to reduce child poverty, and (ii) to increase fertility (which was among the European lowest in 2015 in Poland). The opponents argued that there would be a negative impact on the labour supply and a low efficiency resulting from also covering non-poor families with at least two children through the programme. Michoń (2021) presents a review of Internet debates on Family 500+ (in Polish). Though the majority of them are more political or ideological than economic, they reflect the general climate of the debate. Among several analyses using formal quantitative methods, most of them claim or anticipate negative effects from Family 500+. Using microsimulation models, Brzeziński and Najsztub (2017) anticipated a low efficiency of the program due to its structure. Magda et al. (2021) estimated, using the difference-in-difference method, its negative impact on the female labour supply. Wilk (2021) reported a low response to the programme in terms of the fertility rate. On the other hand, it is not surprising that Family 500+ has been effective in reducing the economic hardship of the families with children (Milovanska-

Farrington, 2021). This is also claimed by simulation results presented by Brzeziński and Najsztub (2017).

In the present study, the abovementioned issues, excluding demographic ones, are analysed further, using data for 2015-2018. The findings confirm many of the observations described above for the 2016-2017 period. However, in 2018 some trends reversed. The analysis reported here covers the effects of all social benefits not related to the social insurance system, i.e., retirement and invalid pensions. The effects do not differ much from those obtained for Family 500+. This suggests that this type of child allowance did not lead to unpredictable results and has generally been in line with the effects of the cash transfers observed for some post-communist countries (Fialová and Mysíková, 2009; Szulc, 2012; Harumová, 2016).

The remaining part of the paper is organised as follows. In Section 2, the theoretical concepts employed in the study are discussed. In Section 3, basic statistics on the Polish social transfers system are provided. Section 4 is devoted to the impact of the transfers on monetary and multidimensional poverty, together with the data quality issues. In Section 5, other changes due to reconstruction of the social transfers are examined. Section 6 concludes the paper.

2. Conceptual framework

2.1. Data

The individual data on households and persons employed in this research come from the household budget surveys collected annually by the central statistical office – Statistics Poland. The yearly samples cover from 37,148 (2015) to 36,166 (2018) households. The reference period of observation is one month. Basic methodological details may be found in Główny Urząd Statystyczny – Statistics Poland (2018). The household data include a wide set of economic, demographic and sociological variables, allowing the evaluation of various aspects of households' and individuals' economic positions. Those utilised in the present study encompass, inter alia, information on household disposable income and its components, expenditures, assets, durables, dwelling conditions, demographic and socio-economic attributes, and answers to subjective income questions. There are two-year panel components covering from 15,635 (2015–2016) to 15,155 (2017–2018) households included in the samples.

2.2. Income imputation

There are reasons to assume that for some households their incomes are misreported, especially at their lows and highs. This may be caused by several reasons, including (i) allocating too large a portion of revenues to production in the questionnaires (for self-employment incomes), (ii) seasonality, and (iii) intentional misreporting. There have been numerous attempts to adjust for high income distribution using administrative data (for Poland this was performed by Brzeziński et al., 2021), but for this study underreporting incomes at bottom tail of distribution is a concern. Hlasny et al. (2021) proposed an algorithm based on a similar concept using survey data only based on the estimation of the distribution function performed on middle-range incomes. In the present study, the problem of "contaminated" data is tackled by informal income imputations using methods created primarily for missing data estimations. Consequently, the "suspicious" incomes are replaced by imputed ones. Some observable variables that may be assumed to be more reliable and stable in time are used to provide the estimates. They capture information on housing, consumer durables, education and some expenses related to standards of living.

A formal algorithm for missing data imputation based on the general Rubin (1987) concept and developed in numerous studies later on (e.g., Carlin et al., 2003; Carpenter and Kenward, 2013) may be applied if the data are missing at random or if the process that produces the missing data is ignorable (for details, see Rubin, 1987, pp. 50–53). Unfortunately, none of these conditions is held if "contaminated" data are to be replaced by corrected ones, at least when the intentional underreporting of incomes occurs. Therefore, formal statistical inference for models with imputed data is not possible in the present study, although the estimated incomes may be still unbiased. Two methods of estimation were attempted in this research. They are based on (i) linear regression and (ii) predictive mean matching. As the final results are very similar for both methods, only regression estimates are utilised. The estimation is performed according to the steps below:

- preliminary estimates of the household equivalent income on covariates are obtained for incomes between the first quintile and the median (which are assumed to be more reliable than extreme ones),
- incomes below the first quintile for which the discrepancy between the survey incomes and estimated ones exceeds 50% of the previous ones are removed from the sample, creating missing observations,

- the missing observations are replaced by incomes imputed with the use of the STATA ‘mi impute regress’ algorithm; the estimates are obtained by means of simulations from the predictive distribution of the missing incomes (for details, see the Stata 16 Multiple-Imputation Reference Manual, pp. 258–259).

2.3. Well-being measurement

Household equivalent disposable income is used as a monetary well-being indicator. Though modified OECD 50/30 equivalence scales are recommended for all European Union countries by Eurostat, they seem to be too flat (i.e., assume too high an economy of scale) for Poland and many other post-communist countries. Hence, OECD 70/50 equivalence scales are applied here to produce the equivalent income, i.e., one additional adult is assumed to increase the cost of living of a single person by 70% while one child increases it by 50%. More precisely, some empirical studies for Poland (e.g., Szulc, 2009; Szulc, 2014) show that a weight of 0.7 slightly overestimates the cost of living for adults, while a weight of 0.5 underestimates the cost of children. The multidimensional poverty/well-being indicator comprises three dimensions, (i) income, (ii) housing (including the dwelling size and quality as well as equipment), and (iii) subjective evaluations of one’s own standard of living. The first one is represented by a function of equivalent income defined by eqn. (1), while the two remaining are composed of one-dimension variables aggregated in one indicator. The final scalar indicator is defined as a weighted mean of indicators calculated for all three dimensions separately. The whole concept is based on the fuzzy sets approach to multidimensional poverty measurement (Cheli and Lemmi, 1995).

If a variable describing poverty at the lowest level of aggregation is binary, it is equal to 1 when as a symptom of poverty (e.g., a lack of some consumer goods) it is not observed and 0 otherwise. For continuous (e.g., the equivalent income or dwelling size) and discrete ordinal (e.g., subjective evaluation of own economic conditions) variables, the concept of well-being indicator is derived from the “Totally Fuzzy and Relative” (TFR) approach to multidimensional poverty measurement proposed by Cheli and Lemmi (1995). In the “fuzzy” approach, as opposed to the dichotomous approach, no single poverty line is set. Instead, for a variable y used as a single dimension well-being measure, the degree of poverty based on preselected interval, say [y*, y**], is calculated for each unit (individual or household). A poverty measure for the *i-th* unit is equal to 1 when $y \leq y^*$ and equal to 0 when $y \geq y^{**}$. There are several concepts of poverty measurement for $y \in (y*, y**)$, and the one applied in the present study is the original Cheli and Lemmi (1995) TFR function. It yields the following “fuzzy” poverty indicator for an individual/household ranked as *i-th* in non-descending order:

$$p_i = p(y_i) = \begin{cases} 0 & if\ y \ \geq \ y** \\ p(y_{i-1}) + \frac{F(y_i) - F(y_{i-1})}{1 - F(y*)} & if\ y \in (y*, y**) \\ 1 & if\ \leq \ y \ y* \end{cases} \quad (1)$$

where *F* stands for a cumulative distribution function. By definition, p_i fits the interval [0; 1]. When *y* is a discrete ordinal variable, it is natural to set $y* = y_{min}$ and $y** = y_{max}$. Formally, the same choice may be applied to a continuous variable, like income, but it seems to be more rational to set $y* > y_{min}$ and $y** < y_{max}$. This is firstly to relax the impact of outliers. Second, when $y* = y_{min}$ and $y** = y_{max}$, the indicator p_i is “totally relative” and its value depends on the shape of the distribution function only. In this study, comparisons between years are also performed and fixing y* and y** over time is necessary. For income, the bottom limit is equal to the 2015 existence minimum, while the upper limit is three times the social minimum (both thresholds are calculated by the Institute of Labour and Social Affairs, 2020). For other (nearly) continuous variables, like dwelling size, *y** and *y*** are set at the 0.05 and 0.95 percentiles obtained for the year 2015, respectively.

Once individual measures are defined, they should be aggregated to mid-level dimensions, i.e., equivalent income, housing and equipment, and subjective evaluations of the own economic position. As the first one is represented by a single variable, the problem of aggregation is relevant for the two remaining dimensions only. The weighting system within those dimensions was proposed by Cheli and Lemmi (1995). For the *j-th* item it is calculated as:

$$w_j = ln\left(\frac{1}{\overline{H_j}}\right)$$

where $\overline{H_j}$ denotes the proportion of units that are poor with respect to the *j-th* item. In such a concept of weights, it is presumed that a more frequent poverty syndrome (e.g., the lack of a passenger car) is a less important symptom of poverty than a less frequent one (e.g., the lack of a refrigerator). However, the abovementioned form of weighting is problematic when three mid-level components are to be aggregated in one well-being indicator, as it assumes the equal importance of all dimensions. Hence, at the highest level of aggregation arbitrary weights are applied: 0.5 for income and 0.25 for both remaining dimensions.

In the present study, the impact of social transfers on the standard of living is one of the main goals. Therefore, it is more convenient to define a multidimensional well-being measure instead of a poverty measure to make it compatible with equivalent income. This may be easily done by defining the multidimensional well-being indicator $F = 1 - P$ where P is an aggregate poverty indicator. Formally, it is acceptable to use eqn. (1) to produce well-being indicators at the lowest level. However, the approach to weighting applied in the poverty measurement does not seem correct in that case: rare consumer goods (e.g. electric bicycle) do not necessarily increase well-being to a higher extent than more frequent goods (e.g., a passenger car).

2.4. Measurement of the transfers' effects

The final effect of the transfers depends on their volume and allocation. Comparing actual poverty indices and pre-transfer (simulated) ones allows for the evaluation of the simultaneous effect of both abovementioned attributes. Indices gauging poverty incidence ("how many poor?") and depth ("how poor the poor are?) are used for that purpose and the poverty lines are set at the first decile and first quartile. Moreover, the elasticity of the effect with respect to the poverty threshold is evaluated using graphical methods. Poverty indices are calculated for each year separately, for all types of households together. Simulated indices of income poverty are calculated by means of actual incomes diminished transfer values. For multidimensional poverty, regression models are estimated to predict changes in well-being levels due to changes in incomes. The calculations are also performed using imputed incomes.

A static evaluation of the transfers is supplemented by a dynamic one aimed at answering two questions: how well the non-poor are protected from falling into poverty and to what extent transfers allow the poor to leave the poverty zone. For that purpose, joint (two year) well-being distribution is constructed using panel data. Both income and multidimensional poverty are included in the analyses. The concept applied in the present study follows the idea of protection and promotion effects proposed by Ravallion et al. (1995). If the analysis is restricted to transitions to and out of poverty, the effects may be estimated as follows. A protection effect takes the form of a relative difference between the simulated number (subscripted by S) of new poor and the actual one (subscripted by A)

$$PROT = \frac{N[y_S(0) \geq z_0 \ \& \ y_S(1) < z_1] - N[y_A(0) \geq z_0 \ \& \ y_A(1) < z_1]}{N[y_S(0) \geq z_0 \ \& \ y_S(1) < z_1]} \quad (2)$$

where $N[y_{A/S}(0) \geq z_t \text{ \& } y_{A/S}(1) < z_t]$ is the number of individuals who were not poor in period 0 and became poor in period 1. Similarly, the promotion effect takes a form of a relative difference between the actual number of new non-poor and the corresponding simulated number

$$PROM = \frac{N[y_A(0)<z_0 \text{ \& } y_A(1)\geq z_1]-N[y_S(0)<z_0 \text{ \& } y_S(1)\geq z_1]}{N[y_A(0)<z_0 \text{ \& } y_A(1)\geq z_1]} \quad (3)$$

where $N[y_{A/S}(0) < z_t \text{ \& } y_{A/S}(1) \geq z_t]$ is the number of individuals who were poor in period 0 and non-poor in period 1. The simulations applied here are employed in order to answer two questions: (i) what would happen if the transfers were terminated, and (ii) what would happen if the transfers observed for period 0 remained unchanged in period 1?

Finally, the impact of the transfers on mean well-being and economic activity is gauged. This is also performed in a static and a dynamic version. The static one is based on two treatment effect evaluation methods: matching estimation and inverse probability weighted regression adjustment (hereafter: IPWRA). In a dynamic approach, changes in outcome variables of interest are regressed on changes in transfers using two-year panels. Both matching estimation and IPWRA are intended to produce unbiased estimates of a treatment effect, which in the present case is defined as receiving a certain type of benefits. Potential bias in observational studies results from a non-random selection of the recipients who are, on average, in a worse economic position and less economically active than non-recipients. To obtain an unbiased estimate the concept of average treatment effect may be employed. One of the possible estimates referred to as an average treatment effect on the treated takes the form

$$\hat{\tau} = E[Y(1)|D = 1] - E[Y(0)|D = 1] \quad (4)$$

where *Y(1/0)* stands for an outcome variable among receiving treatment (1) and in control group (0) and *D(* = 0/1) is a variable describing receiving a treatment. To calculate $\hat{\tau}$, one has to estimate the counterfactual component $E[Y(0)|D = 1]$ which may be interpreted as a potential expected value of *Y* among recipients for whom benefits were denied. In the present study a propensity score matching (see Abadie and Imbens, 2012, or Wooldridge, 2010, pp. 903–936) is applied for that purpose. An alternative to the matching estimation method is IPWRA, combining regression adjustment with propensity score weighting. At the first stage, the probabilities of the treatment are estimated using a probit model. In the second one, their reciprocals are used as weights in a regression model with *Y* as a dependent variable and the treatment as one of explanatory variables (for details, see Wooldridge, 2007, or Cattaneo et al., 2013). There are at least two advantages of IPWRA over the matching estimation method. First, it allows for multilevel treatment. Second, it is more robust to the misspecification of those models. The drawback is the possibility of not achieving the convergence of the iterative algorithm.

Using panel data in both static and dynamic analysis gives an opportunity to reduce the bias caused by endogeneity (regression models) or violating the unconfoundedness assumption (the estimation of treatment effect). Both types of bias result from the occurrence of omitted variables in the model. When the outcome variable is a well-being indicator, some potentially significant explanatory variables cannot be observed. The capability to earn income related to psychological attributes or hidden skills is a typical example of such variables. Omitting them in the model usually results in a downward bias in the estimation of the effect of benefits if they are means-tested. When panel data are available it is possible to use benefits received in the basic period as proxies for control variables for the abovementioned unobservable ones.

3. General review of the social benefits in Poland: descriptive statistics

Between 2015 and 2018, the relatively fast growth of mean standards of living could be observed, as reported in Tab. 1. During this period, the mean equivalent income rose by 19.8%, while the Gini index dropped by 8.3%. A similar tendency could be observed for the multidimensional well-being indicator, although the changes were less intense: the well-being increased by 2.8% and Gini index dropped by 5.4%. The strong growth of the income component was mitigated by worsening subjective evaluations between 2017 and 2018. However, the latter was more an effect of changes in the distribution than of a drop in the mean level. In 2016 and 2017, but not in 2018, the recipients of social benefits experienced higher than average well-being increases. At the same time, due to the growing number of children, for recipients of Family 500+ the growth rate was lower than for all the beneficiaries of social transfers. As mentioned in the Introduction, between 2015 and 2018 significant changes in the system of social cash transfers took place (for basic statistics, see Tab. 2). Their main feature was the huge increase of family benefits under the relative stability of the remaining ones. For the whole sample, the mean real value of the first rose by 291%, while the mean value of the latter by 10%. The mean value of all transfers increased by 188% for the whole sample and among recipients of the benefits by 99% and by 222% among households with children. The huge growths of means were accompanied by relatively moderate increases in the proportion of recipients of all types of transfers: from 29% to 33%. As might be expected, the proportion of family benefits recipients extensively increased, at the cost of the remaining benefits. Huge growth was also observed for households with children. Changes in the composition of the social benefits are displayed in Tab. 3.

Though expanding the value of social benefits usually results in easing the economic hardship of recipients, it may also lead to a dependency on the social system (see, e.g., Kotlikoff et al., 2006 and Shepherd et al., 2011). As displayed in Tab. 4, the average proportion of social benefits in the household income between 2015 and 2018 rose from 6.6% to 11.8% for the whole sample and from 19.4% to 24% for the recipients. Moreover, the proportion of households for which social benefits contribute more than 50% to the whole income increased from 8.4% to 10.4%. Other side effects of the social transfers, especially the reduction of economic activity, are analysed in Section 5.

The distribution of the social transfers is explored by means of concentration curves and coefficients. Both answer the general question of to what extent (if any) social benefits are negatively correlated with well-being. In other words, to what extent are they pro-poor. The concentration curve is defined as a cumulative share of the benefit(s) going to a particular well-being range. It is similar to the Lorenz curve, but units are ranked in non-descending order by their well-being, not by the amount of the benefit, as would be in the case of the Lorenz curve for benefits. A summary measure of benefit(s) distribution is the concentration coefficient, defined as an area between the concentration curve and the diagonal (the line of perfectly equal distribution). As the concentration for social benefits usually lies above the diagonal, the concentration coefficient is usually negative. It is also negative when the concentration curve crosses the equal distribution line but the area above the diagonal is greater than area below. In practice, the more negative the concentration coefficient, the more pro-poor distribution. Fig. 1a.–Fig. 2b. display concentration curves constructed for the years 2015 and 2018 for family and for remaining types of benefits. For both methods of ranking people, by equivalent income and by multidimensional well-being, the results are inconclusive, to some extent, since there is a crossing of the curves. However, when the latter type of ranking is applied, the curve representing the remaining benefits dominates the family benefits curve at the lower ranges of distribution, which is especially true for 2018. This may be explained by the fact that family benefits are only partly means-tested, while the remaining benefits include, inter alia, means-tested social assistance and unemployment

Tab. 1 Monthly equivalent incomes (means in 2015 prices) and multidimensional well-being indicators.

Well-being indicator	2015		2016		2017		2018	
	mean	Gini	mean	Gini	mean	Gini	mean	Gini
Income – all households	1772	0.303	1906	0.281	2027	0.277	2122	0.278
Multidimensional – all dimensions	0.651	0.166	0.660	0.160	0.668	0.156	0.669	0.157
Multidimensional - income	0.514	0.357	0.530	0.344	0.541	0.337	0.550	0.335
Multidimensional - subjective	0.669	0.146	0.671	0.140	0.674	0.134	0.655	0.143
Multidimensional - housing	0.912	0.055	0.916	0.053	0.920	0.050	0.924	0.045
Income – all beneficiaries	1432	0.299	1664	0.270	1829	0.271	1904	0.274
Income - 500+ beneficiaries	-	-	1707	0.251	1827	0.273	1895	0.276
Multidimensional – all beneficiaries	0.573	0.055	0.609	0.170	0.629	0.162	0.628	0.164
Multidimensional – 500+ beneficiaries	-	-	0.626	0.152	0.629	0.157	0.626	0.162

Note: own calculations based on the household budget surveys

Tab. 2. Social benefits: basic statistics (means in 2015 prices)

Type of the benefit	2015	2016	2017	2018
mean benefits				
All types	430	563	550	430
Family	353	488	473	353
Other	78	75	77	78
All types – recipients only	996	1092	1116	996
All types – hh with children only	1220	1281	1271	1220
proportion of the recipients				
All types	0.287	0.328	0.369	0.331
Family	0.101	0.167	0.224	0.213
Other	0.186	0.161	0.146	0.118
All types – hh with children only	0.367	0.529	0.682	0.680
proportion of the households with children				
-	0.338	0.333	0.326	0.316

Note: own calculations based on the household budget surveys

Tab. 3. Composition of the social benefits

Type of the benefit	2015	2016	2017	2018
Family – all	0.632	0.819	0.866	0.861
Family 500+	-	0.510	0.625	0.607
Social assistance	0.181	0.081	0.053	0.050
Unemployment	0.069	0.029	0.022	0.015
Other	0.117	0.070	0.059	0.075

Note: own calculations based on the household budget surveys

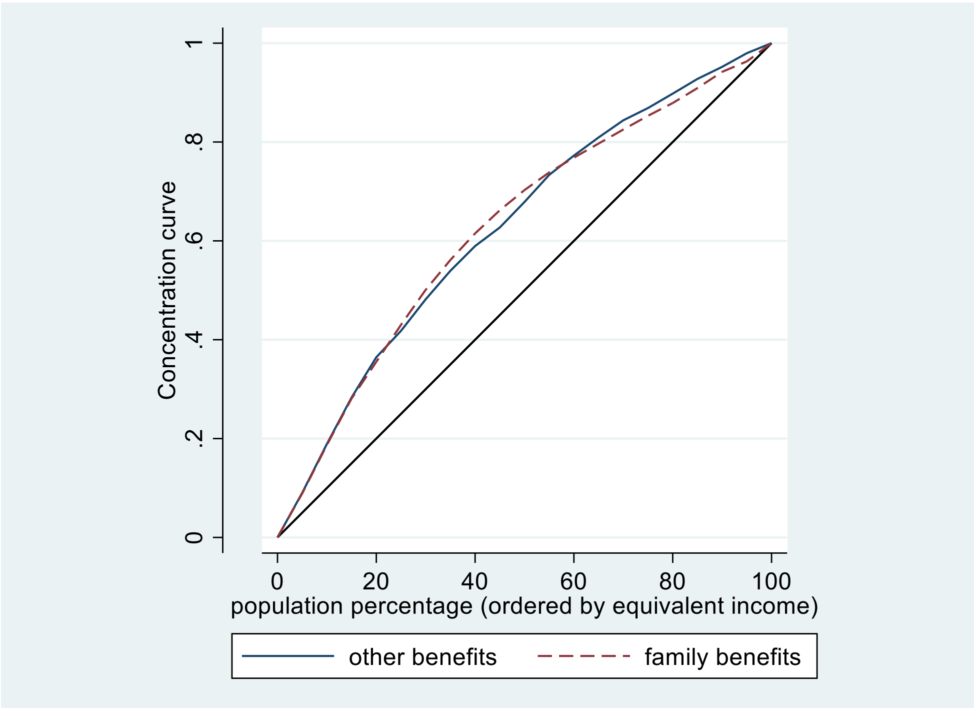
benefits that are strongly negatively correlated with well-being. Summary results on the concentration of various types of benefits in the form of concentration coefficients are reported in Tab. 5. As might be expected, all of them are negative and the highest absolute values may be observed for social assistance and for unemployment benefits. Absolute values for family allowances dropped considerably in 2016. Benefits included in the category “other” are characterised by lowest absolute values, as they comprise, inter alia, transfers received from abroad and preretirement benefits.

Tab. 4. Contribution of the social transfers to household income

	2015	2016	2017	2018
Share of the transfers: all households	0.066	0.102	0.126	0.118
Share of the transfers: all recipients	0.194	0.237	0.244	0.240
Share of the transfers: households with children	0.094	0.161	0.204	0.193
Share of the transfers < 0.2	0.730	0.656	0.641	0.646
0.2 < share of the transfers < 0.5	0.186	0.240	0.253	0.251
Share of the transfers > 0.5	0.084	0.103	0.106	0.104
% of poverty gap, poverty line at the first quartile	79	140	170	148
100% of poverty gap if poverty line at centile	21	31	35	33

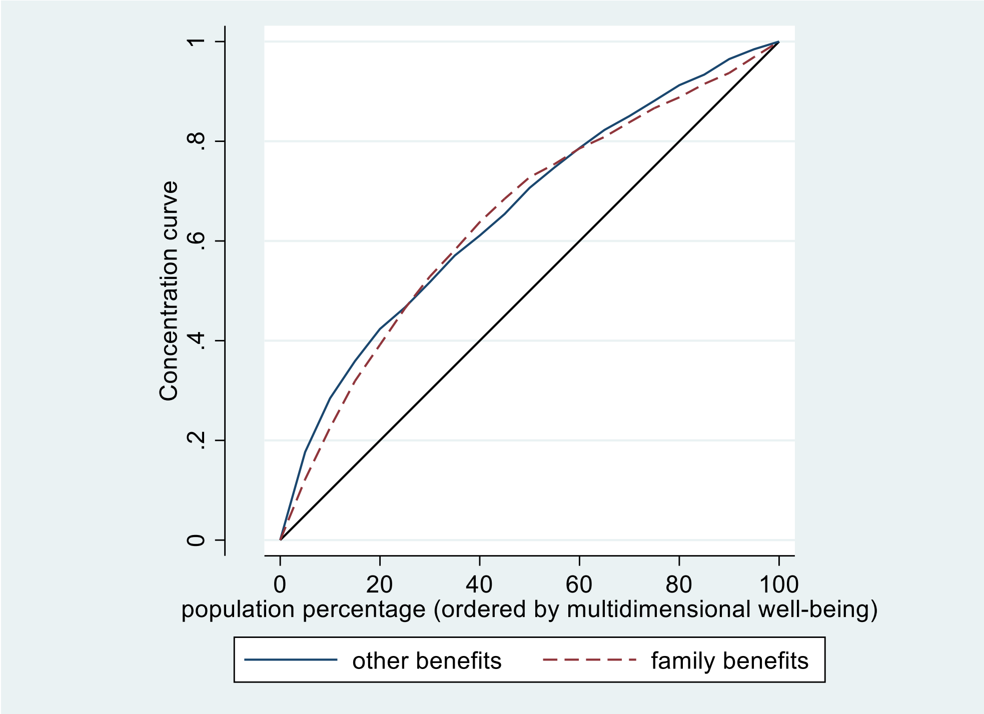
Note: own calculations based on the household budget surveys

Fig. 1a. Concentration curves for family and other benefits, ranking by equivalent income, 2015



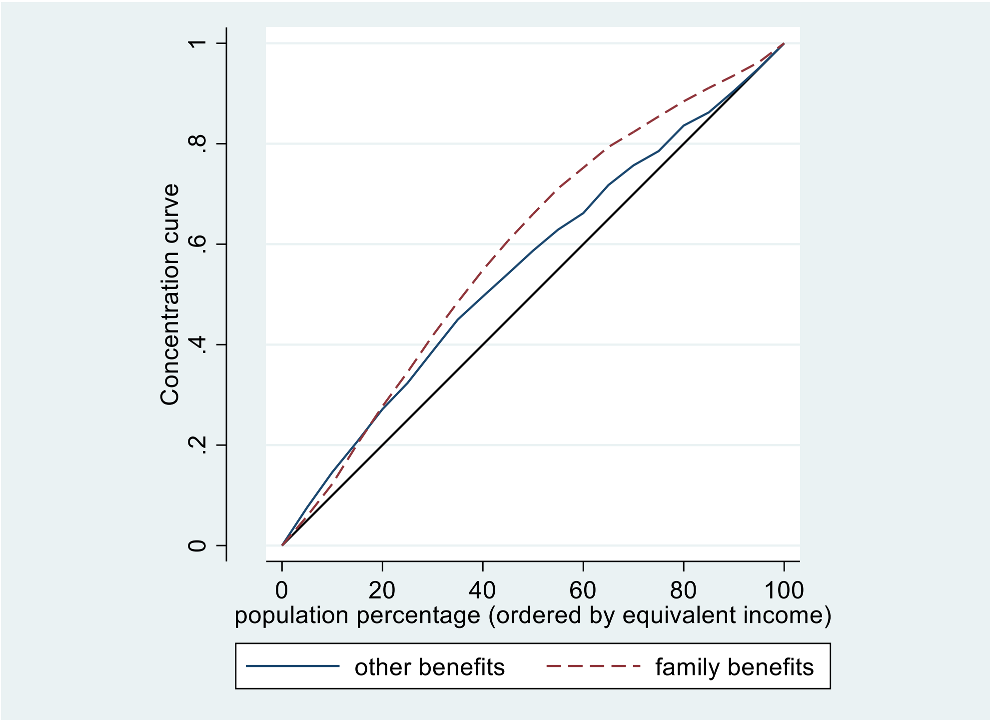
Note: own calculations based on the household budget surveys

Fig. 1b. Concentration curves for family and other benefits, ranking by multidimensional well-being, 2015



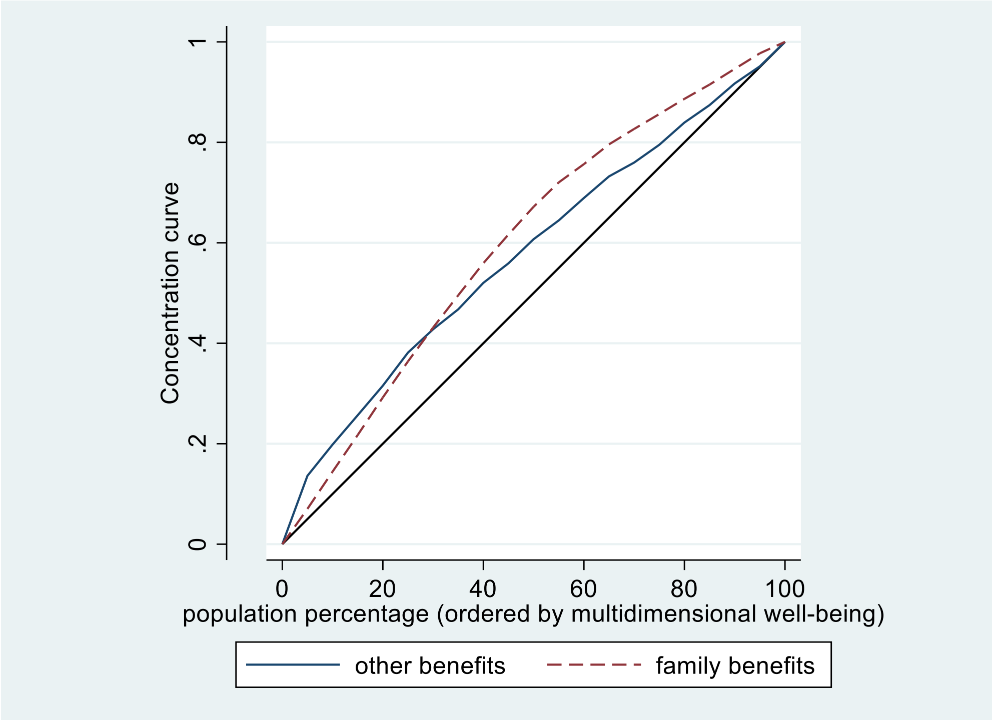
Note: own calculations based on the household budget surveys

Fig. 2a. Concentration curves for family and other benefits, ranking by equivalent income, 2018



Note: own calculations based on the household budget surveys

Fig. 2b. Concentration curves for family and other benefits, ranking by multidimensional well-being, 2018



Note: own calculations based on the household budget surveys

Tab. 5. Concentration coefficients for various types of social benefits

Type of the benefit	2015	2016	2017	2018
	Ranking by equivalent income			
Family	-0.2560	-0.1510	-0.1718	-0.1854
Social assistance	-0.4248	-0.3457	-0.1509	-0.1252
Unemployment	-0.2798	-0.2762	-0.2659	-0.1767
Other	-0.0954	-0.0652	-0.0754	-0.0084
	Ranking by multidimensional well-being			
Family	-0.2947	-0.1792	-0.1863	-0.2045
Social assistance	-0.5188	-0.4289	-0.2203	-0.1732
Unemployment	-0.3052	-0.2910	-0.2720	-0.2034
Other	-0.1039	-0.0784	-0.0821	-0.0499

Note: own calculations based on the household budget surveys

4. Impact of the transfers on incidence and depth of the poverty

4.1. Static analysis

A conventional measure of an effect of social transfers takes the form of the difference between poverty indices calculated with the use of actual and before-transfer incomes. When income poverty is the object of interest, such a difference may be obtained just by subtracting cash transfers from actual incomes and then calculating simulated indices of poverty. When multidimensional poverty is considered, changes in indices should be predicted conditionally on changes in income. In the present study, this measure is implemented using regression models with a multidimensional well-being indicator as a dependent variable and a quadratic polynomial of equivalent income producing explanatory variables. To estimate this model, the sample was restricted to the area between the first equivalent income decile and the median. Censoring the lowest incomes is intended to reduce the impact of data errors mentioned in Section 2.2. They result, inter alia, in nonsensical relations between equivalent income and multidimensional poverty. As may be observed in Fig. 3a, displaying results of the LOWESS[1] nonparametric regression, for the lowest incomes this type of poverty increases with respect to income. This relationship is reported for 2018 only, but the curves estimated for the remaining years do not differ much from this one.

To check the bias resulting from the data errors, identical estimates were obtained for incomes corrected with the use of the imputation described in Section 2.2. The shape of the multidimensional poverty curve (see Fig. 3b.) demonstrates a decreasing, therefore more acceptable, relation between such a type of poverty and equivalent (corrected) income. Hence, evaluations of the impact of transfers on poverty are also performed for corrected incomes. Eventually, indices measuring income and multidimensional poverty incidence and depth are calculated for both types of incomes. The results are reported in Tab. 6 (income poverty), and in Tab. 7 (multidimensional poverty). Poverty lines are set at the first deciles and the first quartiles of the equivalent income. Comparisons based on the declared (uncorrected) income data lead to two general conclusions: (i) the impact of the transfers increased sharply in 2016 and then in 2017, and (ii) the lower the poverty line, the stronger the impact. This finding is valid for both poverty incidence and depth. All estimates of the effects are significant at the 0.001 level. Comparing the abovementioned results with those obtained by means of

[1] Locally weighted scatterplot smoothing, for details, see Cleveland (1979).

Tab. 6. Income poverty incidence and depth: after and before transfers, declared incomes

Poverty measure	2015	2016	2017	2018	2015	2016	2017	2018
	declared incomes				corrected incomes			
	poverty line at the first quartile							
Incidence, after	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
Incidence, before	0.289	0.336	0.355	0.349	0.292	0.338	0.357	0.350
Difference	**0.039**	**0.086**	**0.105**	**0.099**	**0.042**	**0.088**	**0.107**	**0.100**
Depth, after	0.268	0.245	0.226	0.235	0.186	0.165	0.160	0.159
Depth, before	0.340	0.345	0.349	0.345	0.264	0.284	0.300	0.290
Difference	**0.071**	**0.100**	**0.123**	**0.110**	**0.078**	**0.119**	**0.140**	**0.131**
	poverty line at the first decile							
Incidence, after	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
Incidence, before	0.147	0.189	0.219	0.210	0.155	0.203	0.228	0.220
Difference	**0.047**	**0.089**	**0.119**	**0.110**	**0.055**	**0.103**	**0.128**	**0.120**
Depth, after	0.247	0.237	0.225	0.240	0.130	0.114	0.110	0.101
Depth, before	0.343	0.347	0.345	0.343	0.252	0.279	0.292	0.275
Difference	**0.096**	**0.110**	**0.120**	**0.103**	**0.122**	**0.164**	**0.183**	**0.174**

Note: own calculations based on the household budget surveys

corrected incomes yields similar general conclusions, although the numerical results are not identical: estimates of the effects are greater in that case. It may be assumed that due to removing some “fake poor” from the sample (more precisely: moving them to higher ranges of the distribution), those estimates of the effects are more reliable. To display changes in the effects of the transfers not attached to a fixed poverty line, the effects are plotted over a variable poverty line for 2015 and 2018. It may be observed in Fig. 4a and Fig. 5a that for poverty lines set below the first decile, the impact on the poverty depth do not necessarily decrease with respect to the poverty threshold, which is rather a counterintuitive result. Considering, inter alia, the relations presented by Fig. 3a, there are reasons to believe that this may be an effect of income data errors: the “fake poor” less frequently receive benefits and therefore after-transfer poverty is reduced to low extent. Corresponding plots (see Fig. 4b and Fig. 5b) produced with the use of corrected incomes support this hypothesis: observed changes in the effects due to the poverty line are much more reliable. counterintuitive result. Considering, inter alia, the relations presented by Fig. 3a, there are reasons to believe that this may be an effect of income data errors: the “fake poor” less frequently receive benefits and therefore after-transfer poverty is reduced to low extent. Corresponding plots (see Fig. 4b and Fig. 5b) produced with the use of corrected incomes support this hypothesis: observed changes in the effects due to the poverty line are much more reliable.

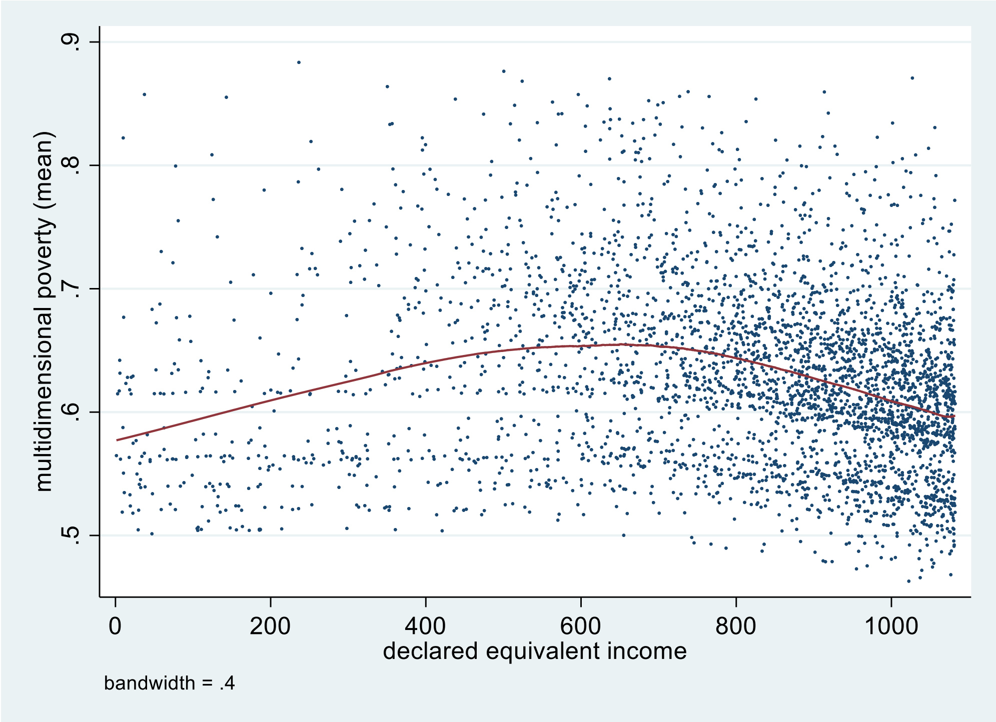
Conclusions on multidimensional poverty do not differ much from those derived from the estimates obtained for corrected incomes: considerable increases of the effects in 2016 and in 2017 and decreases of the effect due to the increase in the poverty line may be observed. This is true for results attained by means of both declared and corrected incomes. The impact of the transfers on poverty depth is noticeably stronger when corrected incomes are applied.

Tab. 7. Multidimensional poverty incidence and depth: after and before transfers, declared incomes

Poverty measure	2015	2016	2017	2018	2015	2016	2017	2018
	declared incomes				corrected incomes			
	poverty line at the first quartile							
Incidence, after	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
Incidence, before	0.291	0.338	0.354	0.347	0.302	0.357	0.371	0.363
Difference	**0.041**	**0.088**	**0.104**	**0.097**	**0.052**	**0.107**	**0.121**	**0.113**
Depth, after	0.201	0.191	0.182	0.179	0.197	0.188	0.185	0.179
Depth, before	0.279	0.291	0.304	0.282	0.275	0.346	0.365	0.350
Difference	**0.077**	**0.100**	**0.121**	**0.103**	**0.079**	**0.158**	**0.180**	**0.171**
	poverty line at the first decile							
Incidence, after	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
Incidence, before	0.158	0.203	0.229	0.216	0.153	0.230	0.255	0.248
Difference	**0.058**	**0.103**	**0.129**	**0.116**	**0.053**	**0.130**	**0.155**	**0.148**
Depth, after	0.174	0.170	0.165	0.148	0.170	0.163	0.165	0.146
Depth, before	0.268	0.276	0.284	0.253	0.293	0.352	0.366	0.344
Difference	**0.094**	**0.105**	**0.119**	**0.105**	**0.122**	**0.189**	**0.201**	**0.198**

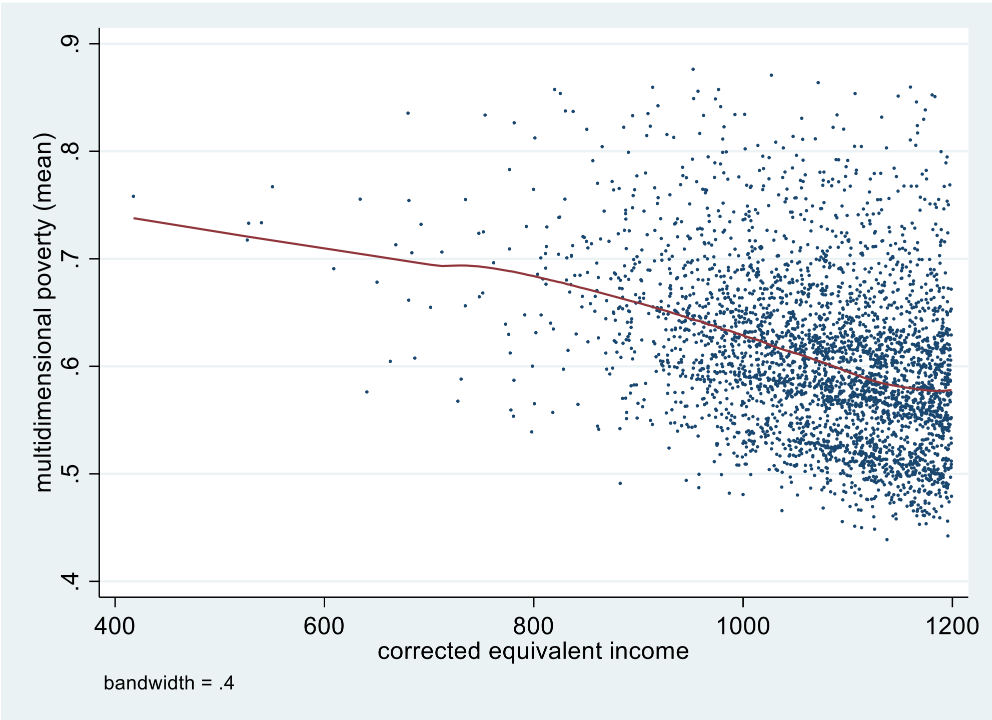
Note: own calculations based on the household budget surveys

Fig. 3a. Relation between equivalent income and multidimensional poverty below the first decile for declared incomes, 2018 (LOWESS smoothing)



Note: own calculations based on the household budget surveys

Fig. 3b. Relation between equivalent income and multidimensional poverty below the first decile for corrected incomes, 2018 (LOWESS smoothing)



Note: own calculations based on the household budget surveys

4a. Difference between after and before transfer income poverty incidence and depth, declared incomes, 2015

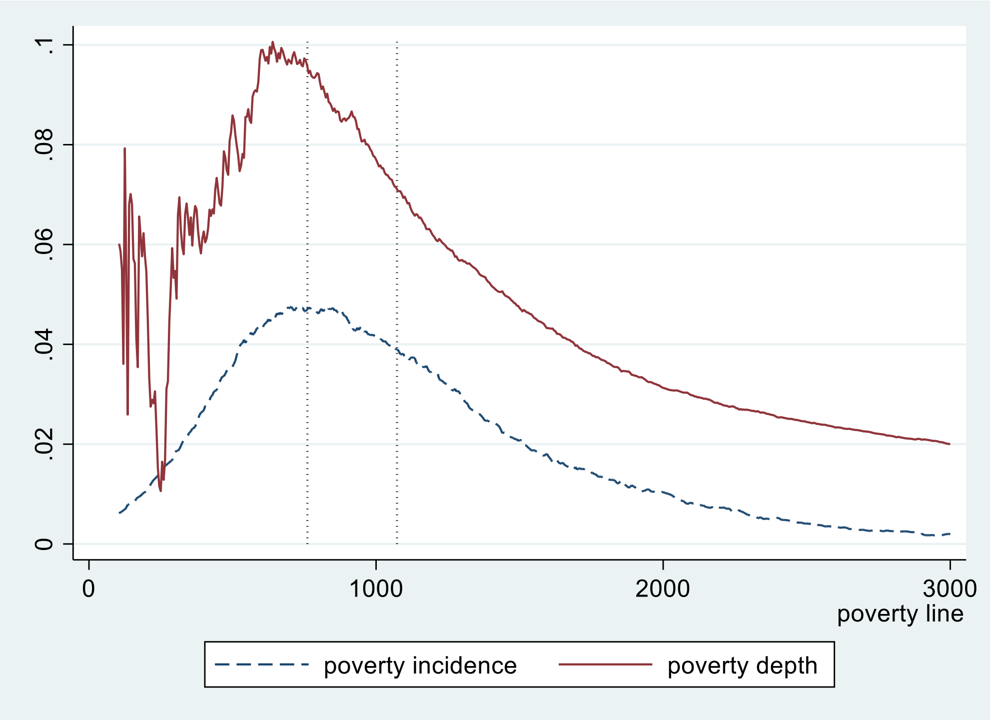
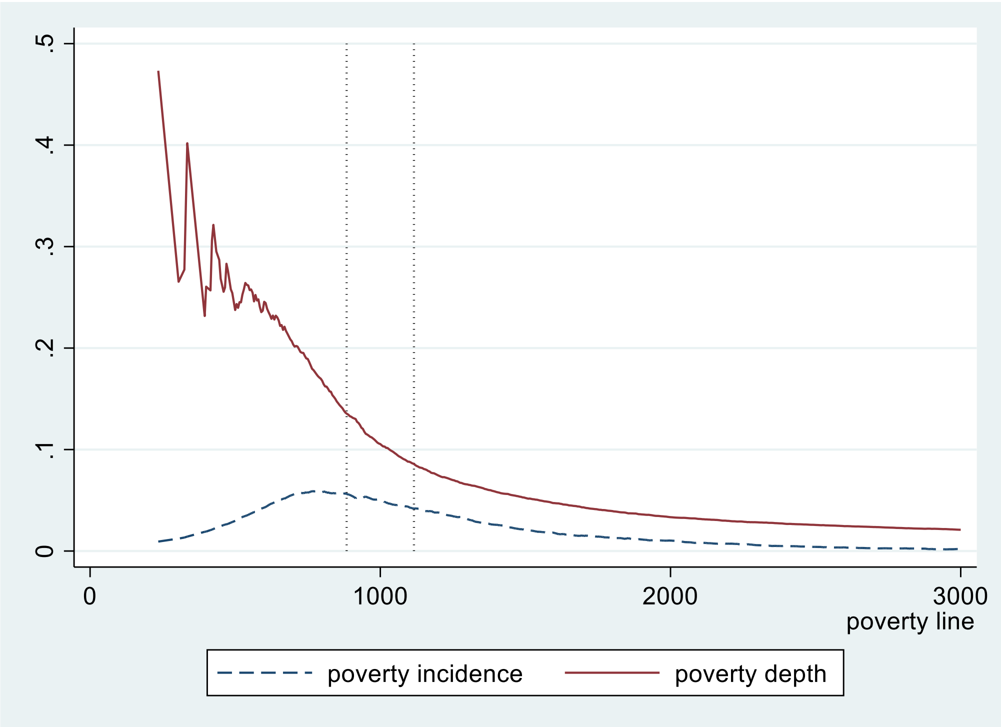


Fig.

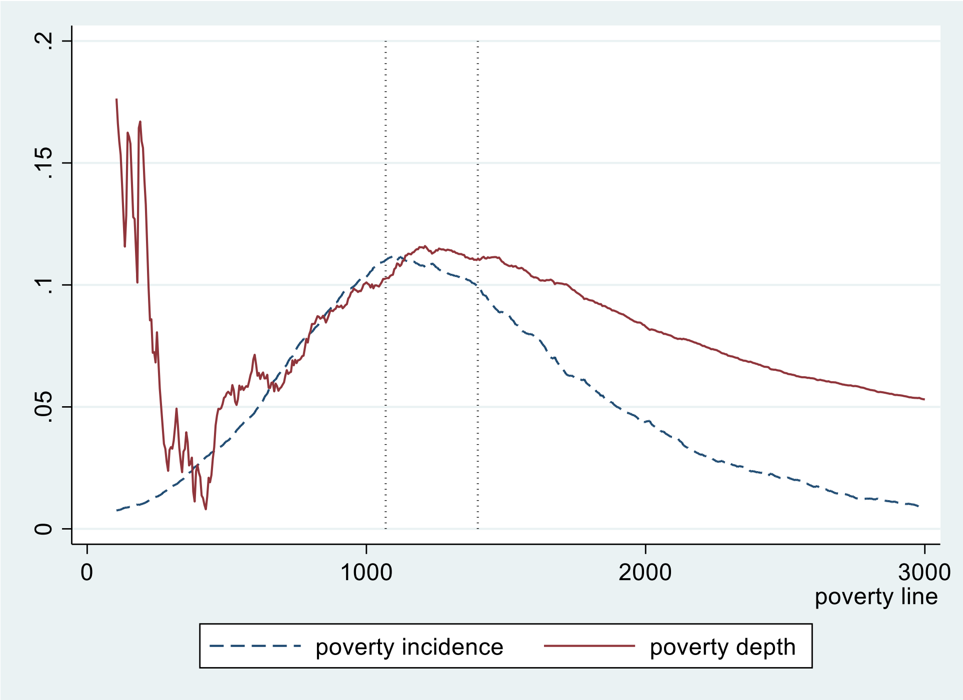
Note: own calculations based on the household budget surveys; vertical dotted lines at the first decile and the first quartile

Fig. 4b. Difference between after and before transfer income poverty incidence and depth, corrected incomes, 2015



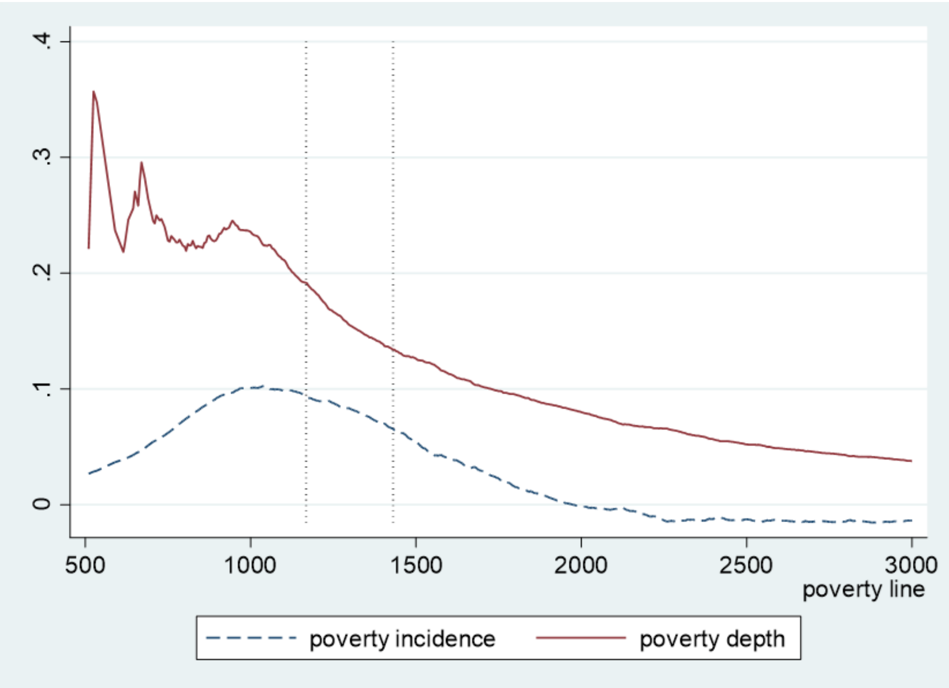
Note: own calculations based on the household budget surveys; vertical dotted lines at the first decile and the first quartile

Fig. 5a. Difference between after and before transfer income poverty incidence and depth, declared incomes, 2018



Note: own calculations based on the household budget surveys; vertical dotted lines at the first decile and the first quartile

Fig. 5b. Difference between post- and pre-transfer income poverty incidence and depth, corrected incomes, 2018



Note: own calculations based on the household budget surveys; vertical dotted lines at the first decile and the first quartile

4.2. Dynamic analysis

Due to using two-year panel data, it is possible to estimate the protection and promotion effects of the transfers, as described in Subsection 2.4. Both these measures display simulated transitions between the poverty and non-poverty zones due to changes in social transfer patterns. Two types of those changes are considered: (i) removing all social benefits, and (ii) leaving them unchanged in the succeeding year. In Tab. 8a and Tab. 8b, the effects of the previous type of changes are reported. Unlike in the case of static effects, negative protection/promotion effects are likely and they occurred in the 2017–18 period. Naturally, this does not mean that the benefits had a counterproductive effect, as simulated poverty rates are still much higher than actual ones (see Tabs. 6–7). Rather, the negative value suggests that there are sources for successfully coping with poverty other than social benefits. The increases in economic activity observed between 2017 and 2018 (see Tab. 10) support this hypothesis. Nevertheless, most of the protection/promotion effects appeared to be positive and significant, usually below the 0.01 level. As might also be observed in the case of static effects, the lower the poverty line, the stronger the effect. Not surprisingly, removing all benefits would result in a stronger decline of protection/promotion effects than if there had been no change in benefits between years under comparison. This is especially true when the poverty line is set at the first decile. The effects for multidimensional poverty (see Tabs. 9a and 9b) are stronger than those for income poverty.

Tab. 8a. Protection and promotion effect for income poverty, benefits removed

	2015/16	2016/17	2017/18
	poverty line at the first quartile		
Protection	0.171***	0.019	-0.166**
Promotion	0.278***	0.134***	-0.023
	poverty line at the first decile		
Protection	0.562***	0.629***	0.642***
Promotion	0.430***	0.444**	0.304***

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1 (bootstrap standard errors)

Tab. 8 b. Protection and promotion effect for multidimensional poverty, benefits removed

	2015/16	2016/17	2017/18
	poverty line at the first quartile		
Protection	0.430***	0.490***	0.469***
Promotion	0.322***	0.344***	0.236***
	poverty line at the first decile		
Protection	0.669***	0.706***	0.685***
Promotion	0.396***	0.371**	0.221***

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1 (bootstrap standard errors)

Tab. 9a. Protection and promotion effect for income poverty, benefits unchanged

	2015/16	2016/17	2017/18
	poverty line at the first quartile		
Protection	0.308***	0.158***	-0.028
Promotion	0.260***	0.186***	-0.010
	poverty line at the first decile		
Protection	0.431***	0.263***	-0.020
Promotion	0.216***	0.237***	-0.006

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1 (bootstrap standard errors)

Tab. 9b. Protection and promotion effect for multidimensional poverty, benefits unchanged

	2015/16	2016/17	2017/18
	poverty line at first quartile		
Protection	0.380***	0.256***	0.017
Promotion	0.144**	0.108**	-0.122***
	poverty line at first decile		
Protection	0.692	0.622	0.225
Promotion	0.126	0.099	-0.133*

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1 (bootstrap standard errors)

5. **Changes following the cash transfers**

Examining the household response to receiving Family 500+ is one of the main goals of the present study. In this section, reactions to receiving this type of cash transfer are investigated using two-year panel data. In Subsection 5.1 changes in well- being are observed, while Subsection 5.2 is devoted to economic activity. In both cases univariate and multivariate analyses are performed. The latter ones employ regression methods (with a Heckman correction, when necessary) and the estimation of treatment effects (matching estimation and IPWRA). Regression models for *i-th* unit take a general form:

$$\Delta Y_i = \alpha_0 + \alpha_1 \Delta X_i + \alpha_2 \boldsymbol{Z_i} + \varepsilon_i \quad (5)$$

where ΔY_i stands for a change in indicator of well-being or economic activity, ΔX_i is a change in the benefit value, and $\boldsymbol{Z_i}$ represents a set of control variables assumed to be correlated with a response variable.

5.1.Changes in well-being

In Tab. 10, changes in real equivalent incomes, its components and multidimensional well-being indicators for the whole sample and for households

Tab. 10. Changes in well-being and economic activity: whole sample vs new Family 500+ recipients

Change in:	2015/16	2016/17	2017/18
income	0.097	0.102	0.084
income, new 500+	0.222	0.206	0.045
multidimensional	0.039	0.028	0.013
multidimensional, new 500+	0.116	0.102	-0.023
income from economic activity	0.069	0.094	0.074
income from economic activity, new 500+	0.045	0.028	-0.135
non-social income	0.071	0.092	0.097
non-social income, new 500+	0.018	0.040	-0.117
no. of active women	-0.026	-0.023	-0.023
no. of active women, new 500+	-0.024	-0.016	0.095
no. of active men	-0.034	-0.031	-0.025
no. f active men, new 500+	-0.034	-0.036	0.119

Note: own calculations based on the household budget surveys

receiving Family 500+ for the first time (i.e., not receiving benefits in a basic year) are reported. For the 2015–16 and the 2016–17 periods, the incomes of the new recipients were growing at twice as high a pace than for the whole sample. However, between 2017 and 2018 this trend was reversed. It is not surprising that the recipients' incomes originating from economic activity (employment and self-employment, including agriculture) were growing at a slower pace, as compared to the whole sample, and even dropped in 2018. Similar trends can be observed for all non-social incomes (including old age and invalid pensions). The trends in multidimensional well-being are similar to those revealed by changes in equivalent incomes, though relative differences between the recipients and the whole sample are more sizable. Due to the low number of new Family 500+ recipients in 2018 (1.7% of the whole sample), the results for the 2017–2018 period are not very informative. This problem is resolved in the succeeding paragraphs by reporting the results of estimations on the whole panel sample. Supplementary to the results reported in Tab. 10, changes for a subsample of the households receiving Family 500+ in both years were calculated[2]. In some aspects, the conclusions vary from those based on figures displayed in the last column of Tab. 10. A slight drop in multidimensional well-being among the recipients could be observed, while the growth of the income derived from economic activity was positive. The number of active people among the recipients dropped, but at twice as low a rate than that observed for the whole sample.

In the regression models presented in this subsection the yearly change in well-being (equivalent income or multidimensional indicator) is a dependent variable and the yearly change in Family 500+ is an independent one. The control variables comprise a change in remaining benefits, demographic and other household attributes, and the number of economic active men and women, as well as the values of Family 500+ and equivalent income in the basic year. The latter set is not fixed for all types of the dependent variable and changes in some details (for instance, when the change in economic activity is a response variable). All estimates are performed on a sub-sample of the households with children. There are at least two potential problems with the estimation of such a model. First, omitted unobservable variables, like people's attitudes, may result in endogeneity which, in a scarcity of potential instrumental

[2] Unpublished, available upon request.

variables, is a serious problem. As Family 500+ for households with one child is means-tested, the recipients' earning income ability is likely to be lower than that of the non-recipients. Using panel data seems to be a good alternative to the instrumental variables estimation. It is possible to overcome, at least partly, the problem of omitted variables by including the values of income and benefits during a basic year as proxy variables for the earning ability. Another problem with the estimation stems from the selection of the subsample of recipients, which is most probably non-random. As households with children are more likely to pay more attention to family values at the cost of economic activity, they are also more likely to reach a lower income which is not necessarily a side effect of receiving benefits. In other words, people bearing children may be more likely to stay at home rather than enter the labour market if their potential earnings are lower than their reservation wage. This may result in biased estimators of eqn. 5. A typical solution to this problem is a regression model with a Heckman correction (Heckman, 1976). This requires additional variables that affect selection but not the dependent variable. The variables utilised for that purpose include the type of residence, food ratio in consumer expenditures, and age and education of the household head. The Heckman regression should replace the standard model if the correlation between the stochastic disturbances of the estimated equation and selection equation is significantly different from zero. This occurred for all dependent variables under consideration, for all years.

In the first three rows of Tab. 13, estimates of the marginal effects for change in Family 500+ are reported. For the convenience of the presentation they are multiplied by 100. There is a strict correspondence between trends in equivalent income and multidimensional well-being. The estimates are positive in the 2015–2016 period and negative for the two succeeding ones, with higher absolute values for 2017–2018 period. The relative impact of Family 500+ on income, both positive and negative, is relatively stronger for income than for multidimensional well-being. It is hardly surprising that estimates for labour/self-employment income are all negative, with the lowest absolute values in the 2015–2016 period. Nevertheless, even those estimates demonstrate that increasing the Family 500+ value by 100 PLN results in a decrease in the mean labour/self-employment income by 25 PLN. It seems that there are no differences between the responses to Family 500+ and social transfers of any type, though some estimates are not statistically significant.

The impact of the social benefits is also evaluated by means of estimates of the treatment effects. For that purpose, it is possible to use one year of data, but in the present study panel data sets are also employed to provide more complete information on household earning ability. Omitting this information would probably result in violating the unconfoundedness assumption in the matching estimation. As in the regression models presented above, some information, especially on transfers, of the basic year is included in the estimation. Two methods of estimation are employed: propensity score matching and inverse probability weighted regression adjustment (IPWRA). The results of the estimations are displayed in Tab. 12. In general, there are several differences as compared to the estimates obtained by means of regression method and reported in Tab. 12. This especially applies to changes in income and in multidimensional well-being. On the other hand, many of the estimates are not statistically significant, so the only significant differences arise for the 2015–2016 period. Conclusions on the impact of the transfers on labour/self-employment income are consistent with the findings based on the regression models. Although some estimates are not significant at 0.1, the p-values in that case are close to this level.

The natural question is which results, based on regression or on treatment effects estimates, are more reliable. The previous method is more sensitive to the specification of the model, but using panel data allows for controlling for non-observable variables if they are constant over two years. Moreover, in regression models the variables representing transfers may be continuous. This restriction may be partly overcome by applying multilevel treatment effect IPWRA models. In the present study the transfers are measured by a discrete variable V defined as follows:

$$V = \begin{cases} 0 & if\ no\ transfers\ received \\ 1 & if\ transfers\ without\ 500+\ received \\ 2 & if\ transfers\ including\ 500+ received \end{cases}$$

The respective estimates are displayed in Tab. 13. When the estimates are statistically significant they are close to those obtained by means of regression, with the exception of income effects in the 2015–2016 period. As compared to non-recipients, the effect is negative and the absolute value is higher for Family 500+ recipients than for other beneficiaries of social transfers.

5.2.Changes in economic activity

Changes in the number of men and women that are economically active are reported in four last rows of Tab. 10. They were calculated for the whole sample and for the people living in the households of recipients of Family 500+. Due to the ageing society and the increasing number of pensioners (which grew by 9.2% between 2015 and 2018), the number of economically active persons decreased over that period. Nevertheless, the number of economically active women decreased at a lower-than-average pace between 2015 and 2017 and rose substantially in 2018 (by 9.5%). The corresponding indicators for the men were slightly above the average, but the increase in 2018 was even higher than that for the women (by 11.9%). On the other hand, a small sample of the new Family 500+ recipients in 2018 probably resulted in large sampling errors, as mentioned in the previous subsection. Relatively minor declines in economic activity may be easily explained by the fact that adults in household bearing children are usually below retirement age. This suggests that the abovementioned changes might be related to changes in social transfers. As in the previous section, this issue is analysed further by means of the estimation of regression models and treatment effects. The results are reported in last six rows of Tab. 11 (regression), Tab. 12 (matching estimation) and Tab. 13 (IPWRA).

Regression analysis based on Heckman models yields negative estimates on Family 500+ for the 2015–2017 period, although the absolute values are rather small and reveal a decreasing trend. Estimates for the 2017–2018 period are not significant. The results obtained for all types of social benefits are similar for the 2015–2016 period (using the IPWRA method), and for the two remaining ones are not statistically significant. As in the case of estimates for well-being presented in the previous subsection, the results obtained by means of treatment effect estimates are dissimilar at some points. Only estimates for the 2015–2016 period are negative and significant, and the remaining ones are, with one exception, positive and/or not significant. The estimates obtained for all types of social benefits are also negative and significant for the 2015–2016 period, but positive and significant for the men in the succeeding period and then negative and

significant. Multilevel IPWRA estimation suggests, with one exception (women, 2015–2016, not significant estimate) a discouraging impact of the transfers and the effect is stronger for “all transfers” than for sole Family 500+ transfers.

Tab. 11 Effects of social benefits using regression: on Family 500+ and on all transfers

	2015/16		2016/17		2017/18	
	LSQ	Heckman	LSQ	Heckman	LSQ	Heckman
Income on:						
500+	9,8087***	6,8407**	-6,4159	-7,0730	-9,7957	-12,7012**
all transfers	7,0376***		-2,7801		1,1462	
Multidimensional well-being on:						
500+	0,0026***	0,0027***	-0,0028**	-0,0025**	-0,0034***	-0,0034***
all transfers	0,0015***		0,0009**		0,0002	
Income from economic activity on:						
500+	-25,8918***	-25,785***	-41,6076***	-41,7375***	-41,5312***	-43,2491***
all transfers	-24,4548***		-35,1543***		-28,4337***	
No. of active women on:						
500+	-0,0066***	-0,0051***	-0,0041**	-0,0033**	0,0009	0,0017
all transfers	-0,0037***		-0,0009		0,0009	
No. of active men on:						
500+	-0,0061***	-0,0045***	-0,0052**	-0,0037**	-0,0008	-0,0008
all transfers	-0,0035**		-0,0004		0,0010	

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1

Tab. 12 Impact of social benefits using treatment effect estimation: on Family 500+ recipients and on all transfers

	2015/16		2016/17		2017/18	
	matching	IPWRA	matching	IPWRA	matching	IPWRA
Income on:						
500+	80,6042***	-48,7027*	-8,4052*	x	83,5472	x
all transfers	-142,81***	-133,53***	-26,4973	15,3867	-10,1334	11,4196
Multidimensional well-being on:						
500+	-0,0278***	0,0021	0,0099**	0,0184	-0,0038	0,0176
all transfers	0,0344***	0,0173**	0,0199	0,0127*	0,0070	0,0019
Income from economic activity on:						
500+	-185,2416***	x	-184,5467	x	-156,2497	x
all transfers	-327,35***	x	-89,2194	-227,03***	-212,18***	-256,84***
No. of active women on:						
500+	-0,0391**	-0,0307**	-0,1843**	-0,0366	0,0659	-0,0481
all transfers	-0,0794**	-0,0510***	-0,0200	-0,0899***	0,0097	-0,1396**
No. of active men on:						
500+	-0,0146	-0,0547***	0,1078	0,0393	0,2122**	0,1386
all transfers	-0,0217	-0,0416***	0,2924***	0,0633**	0,0862	-0,0963**

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1 (bootstrap standard errors); x: convergence not achieved

Tab. 13 Impact of social benefits using 3 level treatment effect estimation (IPWRA): on Family 500 and on all transfers

	2015/2016	2016/2017	2017/2018
Income on:			
500+	-114,5620***	x	x
all transfers	-234,1759***	x	x
Multidimensional well-being on:			
500+	0,0239***	0,0189***	0,0139***
all transfers	0,0324**	0,0900***	-0,0962***
Income from economic activity on:			
500+	x	-141,4552***	x
all transfers	x	-431,4383*	x
No. of active women on:			
500+	-0,0250***	-0,0126	-0,1049***
all transfers	0,0362	-0,0798	-0,2115*
No. of active men on:			
500+	-0,0253***	-0,0190**	-0,0799***
all transfers	-0,1084*	-0,0391	-0,9569***

Note: own calculations based on the household budget surveys; ***: significant at 0.01, **: significant at 0.05, *: significant at 0.1 (bootstrap standard errors); x: convergence not achieved

6. Concluding remarks

Changes in the system of social cash transfers caused by the introduction of Family 500+ in 2016 increased their total amount enormously. The value was equal to 79% of the poverty gap calculated with the use of poverty line at the first income quartile, to 140% in 2016 and to 170% in 2017. Therefore, it is not surprising that the reduction of monetary and multidimensional poverty as well as increases in the mean incomes of the recipients were meaningful. Although Family 500+ is means-tested for households with one child only, the concentration curves and coefficients also indicate the strongly pro-poor nature of the transfers after 2015. On the other hand, the growth of the transfer volume and coverage resulted in a reduction in the economic activity of the recipients. The abovementioned trends were especially visible in 2016 and 2017, although some of them reversed in 2018. This may be partly attributed to the relative decrease in Family 500+ values, resulting from increases in mean incomes and from the inflation.

Distinguishing between monetary (income) and multidimensional poverty and/or well-being generally does not lead to opposite results, with few exceptions. Concentration curves and coefficients indicate a better targeting of the transfers when people are ranked with respect to the multidimensional well-being indicator. This suggests that the administration does not employ only an income criterion when addressing benefits (see Ravallion, 2009, for a wider discussion of the issue and for empirical results for China). Consequently, the impact of the transfers on multidimensional poverty is usually stronger than that on income poverty. This applies also to estimates of the protection and promotion effects in a dynamic analysis of poverty. Moreover, for some years the estimates of the behavioural responses of the recipients appeared to be different for both types of well-being indicators.

As might be expected, increases in the transfers' volume resulted in a reduction of the economic activity of the recipients, especially in the first two years of the Family 500+ programme. Univariate analysis revealed minor drops in the numbers of economically active people, both men and women, in 2016 and 2017 followed by massive increases in 2018 (though the latter may be attributed to sampling errors due to a very small sample size). Nevertheless, the benefits were large enough to compensate for the reduction in economic activity and the incomes of the recipients were increasing at a higher pace between 2015 and 2017. In 2018 this trend reversed, partly due to a lack of indexation of the Family 500+ (under inflation 3.5% between 2016 and 2018). However, multivariate analysis, based on regression models and on estimates of the treatment effect, did not provide univocal conclusions. The only robust result is a strong and negative impact of the benefits, of any type, on employment and self-employment incomes. The impact on the total incomes is also negative when the set of control variables is applied, but evaluations of its intensity vary between the methods. Comparing the impact of Family 500+ and the social benefits altogether yields very similar conclusions.

One of the problems in analyses using household surveys is the quality of declared income data, especially at the tails of the distribution. This problem was tackled by means of income imputation methods based on regressions on selected income correlates performed for middle ranges of incomes. Applying descriptive methods suggest the underestimation of the transfer impact on poverty when declared, uncorrected incomes are utilised. Since the non-random selection of observations was replaced by the estimated incomes, formal statistical inference on imputed values was not performed.

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