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Happiness functions with preference interdependence and heterogeneity: the case of altruism within the family

Adrian Bruhin · Rainer Winkelmann

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Abstract This study investigates the prevalence and extent of altruism by examining the relationship between parents' and their adult children's subjective well-being in a data set extracted from the German Socio-Economic Panel. To segregate the share of parents with altruistic preferences from those who are selfish, we estimate a finite mixture regression model. We control for various sources of potential bias by taking advantage of the data's panel structure. To validate our modeling approach, we show that predicted altruists indeed make higher average transfer payments.

Keywords Altruism · Subjective well-being · Finite mixture regression models

JEL Classification C23 · D64

1 Introduction

Happiness data are increasingly used to tackle important problems in economics, as reviewed by Frey and Stutzer (2002), Layard (2005), and Di Tella and MacCulloch (2006). Indeed, the recent surge in interest is quite

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Responsible editor: Deborah Cobb-Clark

A. Bruhin (✉) · R. Winkelmann
University of Zurich, Socioeconomic Institute, Zurichbergstrasse 14,
8032 Zurich, Switzerland
e-mail: adrian.bruhin@sts.uzh.ch

dramatic, as pointed out by Clark et al. (2006), who counted 417 happiness-related articles in Econlit between 1960 and 2005, 76% of which had been published since 1995 and 30% since 2003. Most of these papers use, in one way or another, responses to current happiness or life satisfaction questions in cross-section and panel survey data to study the factors motivating individual behavior, as well as the effects of behavior, policies, and institutions, on well-being. With the odd exception, much of the previous literature takes a purely individualistic approach to happiness.

The aim of this study is to broaden the existing literature by focusing on positive preference interdependence as in Becker (1981), which may result in altruistic behavior. The question of how widely and to what extent altruistic preferences are present in the population is important in various fields of economics. In public economics, the presence of altruism in a substantial fraction of the population may, by adjusting charitable giving and other voluntary transfers, neutralize governmental attempts at redistributing income between generations (Laferrere and Wolff 2006). In macroeconomic growth modeling, it is crucial to distinguish between two different motivations for intergenerational transfer payments, altruism or joy of giving (Barro 1974; Bertola et al. 2006). With altruism, individuals' preferences exhibit positive interdependence so that their current utility levels correspond to the discounted utility flows of all future generations, which results in an infinite planning horizon. Individuals motivated solely by joy of giving, however, do not care about the utility of their offspring and, consequently, their bequests will be driven solely by the utility obtained from donating per se. This supports an overlapping generation's point of view instead of an infinite planning horizon. Moreover, as Fehr and Fischbacher (2002) point out, when markets are imperfect, even a minority of people exhibiting some sort of social preferences, such as altruism, can have a major impact on the equilibrium.

In contrast to other studies on altruism, which rely on the analysis of consumption levels and transfers, we focus on subjective well-being as an immediate indicator of utility. Besides being straightforward, this approach allows us to identify altruistic preferences even in a case where the income gap between parents and their children is not wide enough to trigger transfer payments. Imagine a situation where the parents' and their children's marginal utilities of income are almost the same. In such a case, the parents' marginal disutility of reduced consumption associated with a transfer payment is likely to exceed the marginal utility gained from a transfer-induced increase in the children's happiness. So, even if these parents have altruistic preferences in the sense that they care for their children's happiness, this is not revealed in transfer or consumption patterns. However, by directly analyzing the dependence of the parents' utility on their children's subjective well-being, our approach allows us to still detect altruistic preferences even in the absence of any transfer payments.

Our analysis is based on data from the German Socio-Economic Panel (GSOEP), a representative annual panel survey initiated in 1984. As the panel population ages, children become adults, move out of their parental homes, and set up their own households. The GSOEP has the nice feature that it surveys these descendants' households as well, and thus allows us to generate linked parent–child observations. Between 2000 and 2004, we observe a total of 2,577 interviewed parents with at least one child living in a spin-off household. As these parents are observed in several waves of the panel, and some of them have more than just one adult child who has left home, the number of linkable parent–child pairs amounts to 11,330. Each of these pairs is observed on average for slightly more than 3 years.

Winkelmann (2005), using GSOEP data as well but a different sample including children still at home, reports a long-run correlation of 0.4 to 0.5 in subjective well-being between parents and children. In principle, there are at least three different explanations for this finding: First, attitudes towards well-being may be genetically transmitted. Second, parents and children may share, to some extent, the same environmental and socioeconomic attributes. Third, the correlation may be due to a direct, positive, and causal dependence of the parents' utility functions on the utility of their adult children, i.e., altruism. To isolate the latter effect, we suggest an estimation strategy based on panel data.

We know from experimental economic research that there exist several distinct social preference types, and at least a minority of people seem to exhibit altruistic preferences (see, for example, Fehr and Schmidt 2002). Besides reporting vast heterogeneity, Andreoni and Miller (2002), for example, find evidence based on a series of dictator games that about 23% of their participants treat their own and the other's payoffs as perfect substitutes, a behavior compatible with altruism. Phelps (2001) conducts thematic apperception tests, a battery of psychological tests aimed at identifying altruistic motivation, and finds that around 20% of the participants responded in an altruistic manner. We will compare our estimates of the prevalence of altruistic preferences, based on survey data, with these findings, gained by applying completely different methodologies in other fields of economic and psychological research.

By estimating a finite mixture regression model, we account for unobserved heterogeneity, i.e., the existence of different social preference types, and isolate the share of altruists in a representative household sample. Distinguishing between two preference types allows us to separate the fraction of altruistic parents from the remainder of the sample, which is assumed to behave selfishly.[1] As the finite mixture model endogenously assigns a group membership (altruistic/selfish) probability to each parent, we can test on an individual level how altruism corresponds to transfer payments. This allows us to check the plausibility of the endogenous group assignment, as we expect parents with altruistic preferences to pay – at least on average – higher transfers towards their children.

In Section 2, the structure of the data set is discussed in greater detail, and descriptive statistics are provided. Section 3 covers the basic econometric

[1] A related approach has been previously applied by Clark et al. (2005) in the context of estimating the responses of well-being to income changes.

model, an extension to account for household-specific effects, and estimation. Section 4 presents and interprets the results, while Section 5 concludes.

2 Data structure and descriptive statistics

The analysis is based on the GSOEP, an annual survey of households, which was started in 1984 in West Germany and extended to East Germany in 1990 (Wagner et al. 1993). As mentioned above, it is an important feature of the GSOEP that it follows up on adult children who moved out of their parental homes and may now live in their own families. In more recent waves of the GSOEP, the number of such children living in spin-off households has become large enough to permit empirical studies of parent–child pairs.

We analyze data for the years 2000–2004.[2] In a first step, we extract 2,577 distinct parents with at least one traced child living in a spin-off household. Note that, because for any given parent the number of these children varies between one and five, the number of observed parent–child pairs is higher than the actual number of parents in the data set. Table 1 summarizes the data structure for each wave of the panel. For example, among the 1,616 parents observed in the year 2000 wave, 1,205 parents have only one child living outside the parental household. The remaining 411 parents have several children, so that the total number of observed parent–child pairs adds up to 2,108. The panel is not balanced, as the number of both parents and parent–child pairs varies over time. In total, the data set contains 8,775 parent observations and 11,330 parent–child pair observations.

Besides a broad range of socioeconomic variables, the GSOEP provides information on subjective well-being, which can be interpreted as a direct measure of individual utility and, thus, is of central interest to this paper. All respondents are asked directly about their general life satisfaction by the following question: "How satisfied are you with your life, all things considered? Please answer according to the following scale: 0 means completely dissatisfied, 10 means completely satisfied." Because general life satisfaction is measured on an ordinal scale, it needs special consideration in regression models, with parent's well-being as dependent variable and children's well-being as explanatory variable. Section 3 discusses these issues in greater detail.

For both parents and children, we extract the following characteristics from the data set, which are generally thought of as being important determinants of subjective well-being (see, for example, Frey and Stutzer 2001): health, age, employment status, monthly disposable income, household size, marital status, and mean geographical distance between the parental household and the spin-off households. Health is measured on a self-reported, five-point scale that is, for simplicity, converted into an indicator variable of good health status for the highest two values. In contrast to other studies, such as Clark and

[2]The 2004 wave was the latest release when this research was started. Before 2000, the number of child spin-offs was relatively small, and we therefore took 2000 as our initial year.

Table 1 Data structure

Number of children living outside the parental household	Number of parent observations					
	2000	2001	2002	2003	2004	2000–2004
One	1,205	1,279	1,313	1,377	1,458	6,632
Two	341	334	363	373	370	1,781
Three	63	51	61	77	74	326
Four	3	3	7	5	4	22
Five	4	4	2	2	2	14
Total	1,616	1,671	1,746	1,834	1,908	8,775
Total number of parent–child pair observations	2,108	2,132	2,260	2,384	2,446	11,330

Source: GSOEP 2000–2004

Oswald (1994), who find evidence for a U-shaped effect of ageing on reported subjective well-being with a minimum around 35 years, age is included among the other regressors only in linear form. Because all the parents in the sample are at least 32 years of age, the effect of ageing is expected to be nearly monotonically and positively associated with general life satisfaction. We measure the mean distance in kilometers between the parents' households and their spin-off households based on the geographical coordinate of the country's midpoint, as discussed by Schwarze and Winkelmann (2005). As it is plausible that parents know less about their children the farther away they live, this provides a proxy measure for the parent's general knowledge about their children's living conditions.

Parents may exhibit paternalistic preferences, that is to say, they do not only care about their children's well-being but they may derive direct utility from other attributes of their children, such as education, marital status, and income, regardless of the effect of these attributes on their children's well-being, i.e., for a given level of well-being. If this is the case, adding the children's socioeconomic characteristics as controls is crucial for obtaining an unbiased estimator of the prevalence and extent of altruistic preferences.

Additionally, the data set contains information on the annual amount of monetary transfers paid to the children by their parents. This variable is interesting for two reasons: First, if the parents' motivation for paying transfers is joy of giving or reciprocity instead of altruism, we expect parents' well-being to be positively associated with these transfers ceteris paribus, i.e., for a given level of the child's well-being. Thus, we should include it among the other control variables. Second, after assigning each parent to one of the two groups, it allows us to compare the average transfer payments of the altruistic parents with the selfish ones.

Table 2 reveals that children report, on average, a much better health status than their parents, and the mean difference in age between parents and children is about 27 years. Due to their lower age, but possibly also because of secular trends in cohabitation, fewer children than parents are married. Standard errors are reported in parentheses, and we see that the mean differences are statistically significant.

Table 2 Descriptive statistics

Means (std. err. in parentheses)	Parents	Children
Subjective well-being[a]	6.573 (0.019)	7.055 (0.020)
Good health (yes=1/no=0)	0.311 (0.005)	0.697 (0.006)
Age	57.4 (0.093)	30.7 (0.075)
Unemployed (yes=1/no=0)	0.085 (0.003)	0.070 (0.003)
Monthly income (in EUR)	4,567 (32.78)	4,030 (25.97)
Female (yes=1/no=0)	0.542 (0.005)	0.513 (0.006)
Years of schooling	11.2 (0.026)	12.3 (0.031)
Household size	2.409 (0.011)	2.470 (0.015)
Married (yes=1/no=0)	0.822 (0.004)	0.460 (0.005)
Transfers paid per year (in EUR)	1,315 (60.14)	
Distance between households (in kilometers)	48.2 (1.137)	
Person-year observations	8,775[b]	6,606[c]

Source: GSOEP 2000–2004

[a]Measured on a 0, 1, . . . , 10 scale

[b]Excludes multiple person-year observations for parents with several children

[c]Excludes multiple person-year observations for children with two parents

3 Model

3.1 Basic model

Our basic modeling framework is an extension of the standard ordered probit model, which allows us to endogenously separate altruistic parents from those who are assumed to be selfish. Let $h_{it} = j$, $j = 0, 1, \ldots, 10$, denote the ordered response of parent i at time t on the 11-point happiness scale. Similarly, v_{it} is the ordered response of parent i's child at time t. If there is more than one child, v_{it} is taken to be the response of parent i's child at time t.

The main object of interest is $P(h_{it} = j|x_{it})$, the conditional probability model for the ordered response of the parents' happiness, where $x_{it} = (x_{it1}, \ldots, x_{itk})'$ is a $(k \times 1)$ vector of determinants of subjective well-being, discussed in the previous section, excluding a constant. If we assume an ordered probit formulation with a linear index function $x'_{it}\beta = x_{it1}\beta_1 + \ldots + x_{itk}\beta_k$, as in McKelvey and Zavoina (1975), we obtain

$$P\big(h_{it} = j|x_{it}\big) = \Phi\big(\kappa_j - x'_{it}\beta\big) - \Phi\big(\kappa_{j-1} - x'_{it}\beta\big)\,, \tag{1}$$

where $\kappa_j > \kappa_{j-1}$ are threshold values, and Φ denotes the cumulative density function of the standard normal distribution.

To account for heterogeneity in the parents' preference types, we introduce an indicator variable, a_i, such that $a_i = 0$ if parent i is selfish and does not care for the well-being of her adult child, and $a_i = 1$ if she is altruistic. For altruistic parents, their children's well-being, v_{it}, becomes one of the determinants of their own utility, and we therefore expect its coefficient, η, to be positive. However, for selfish parents, the children's well-being has no effect on their own general life satisfaction. This yields the conditional probability model's basic form

$$P(h_{it} = j|x_{it}, v_{it}, a_i) = \Phi(\kappa_j - x'_{it}\beta - a_i\eta v_{it}) - \Phi(\kappa_{j-1} - x'_{it}\beta - a_i\eta v_{it}) . \quad (2)$$

In this formulation, the child's well-being, v_{it}, enters as an explanatory variable. Because we treat the parents' happiness h_{it} as an ordinal variable, we should, by symmetry, make the same assumption on the child's well-being. It is not immediately obvious how this can be done in a regression context. Rather than including indicator variables for each possible response value (in which case we lose the ordering information), we follow Terza (1987) and replace v_{it} by a cardinalization that is compatible with the ordered probit assumption, i.e., an underlying normally distributed latent linear index v^*_{it}. The children's subjective well-being responses are replaced by their conditional expectations

$$\tilde{v}_{it} = E(v^*_{it}|v_{it} = j) = E(v^*_{it}|\mu_{(j-1)} \leq v^*_{it} < \mu_{(j)}) = \frac{\phi(\mu_{(j-1)}) - \phi(\mu_{(j)})}{\Phi(\mu_{(l)}) - \Phi(\mu_{(j-1)})} , \quad (3)$$

where $\mu_{(j)}$s denote the quantiles of the standard normal distribution for the sample cumulative relative frequencies of the 11 response categories $j = 0, 1, \ldots, 10$, and ϕ stands for the standard normal density. To test the robustness of our results, we modeled children's well-being as an indicator, which takes on the value 1 if $v_{it} > 4$ and zero otherwise, instead of applying Terza's cardinalization. Besides the obvious loss in efficiency, our estimates remained largely unaffected.

We include the well-being index of the representative (=average) child for parents with several children in the above expression. Therefore, we implicitly assume that parents weigh their children's well-being equally.[3] To simplify the interpretation of the model, $\tilde{v}_{it}$ is centered around zero, which ensures that its effect on the parents' happiness is captured solely by η and does not have any influence on the vector of threshold parameters κ_j.

3.2 Extensions

So far, the model assumes a pooled data structure and does not take advantage of the fact that the panel data set contains up to five observations on each parent over time. The data's panel structure, however, may help to resolve some of the potential endogeneity problems.

First, if there is unobserved variation in the parents' permanent consumption levels, which is correlated with the children's consumption due to some unobserved time-unvarying family-specific effects, α_i, the children's well-being, v_i, is endogenous. Second, imagine a situation where both parents and children share similar attitudes towards their life satisfaction, like being intrinsically happy or unhappy. Such a correlation, for example, due to genetic

[3] Schwarze and Winkelmann (2005) find that their results remain robust when running the analysis on a subset of parents having a single child. Therefore, the assumption of a representative child seems to be justified.

transmission, generates an endogeneity problem as well. By ignoring these potential sources of endogeneity, we would attribute the whole correlation between parents' and their children's happiness to altruistic preferences even when, say by genetic inheritance, intrinsically content parents may tend to have happier children. Consequently, we would overestimate the weight of altruistic preferences.

However, the data's panel structure allows us to isolate that part of the correlation between parents' and their children's happiness that is caused by altruistic preferences, as long as the unobserved other causes, i.e., the family-specific effects α_i, remain constant over time. In a linear regression model, we would eliminate α_i and obtain a fixed-effects estimator by either taking first differences or applying the within-transformation. Unfortunately, due the ordered probit's nonlinear form, neither is possible. A dummy variable approach is ruled out as well because it consumes too many degrees of freedom and leads to an incidental parameters problem with inconsistent maximum likelihood estimators.

To be able to address time-unvarying unobservable effects in probit formulations all the same, Mundlak (1978) proposed to model the correlation between the unobserved time-constant effects and the regressors directly. In our case, by assuming that the family-specific effects, α_i, are normally distributed conditional on the individual means, $\bar{x}$ and $\bar{\tilde{v}}$, such that

$$\alpha_i|\bar{x}_i, \bar{\tilde{v}}_i \sim \mathrm{N}\left(\bar{x}_i'\delta_1 + \delta_2\bar{\tilde{v}}_i, \sigma_\alpha^2\right), \tag{4}$$

their long-run correlation with the dependent variable, h_{it}, can be segregated from the effect of altruistic preferences. As the sum of two normal distributions is again normally distributed, we obtain the following conditional probability model, which accounts for family-specific effects:

$$\begin{aligned} P(h_{it} = j|x_i, v_i, a_i) = \Phi\left(\kappa_j - x_{it}'\beta - a_i\eta\tilde{v}_{it} - \bar{x}_i'\delta_1 - \delta_2\bar{\tilde{v}}_i\right) \\ -\Phi\left(\kappa_{j-1} - x_{it}'\beta - a_i\eta\tilde{v}_{it} - \bar{x}_i'\delta_1 - \delta_2\bar{\tilde{v}}_i\right), \end{aligned} \tag{5}$$

where η measures the causal effect of the children's on their parents' happiness. Note that all parameters are now scaled by an unidentified but constant factor $\left(1+\sigma_\alpha^2\right)^{-1/2}$. This scaling can be safely ignored, as it cancels out, as long as we base our inference on standard errors obtained by the bootstrap method and interpret the parameter estimates either in terms of marginal probability effects or relative sizes.

3.3 Estimation of the model

To estimate the model, we have to deal with the fact that we cannot directly observe a given parent's preference type, i.e., a priori, we do not know whether he/she is selfish or altruistic. In the following, we discuss our estimation strategy, which allows us to overcome this kind of incomplete-data problem. We also briefly address some issues that typically arise during the maximum likelihood estimation of a finite mixture model.

The conditional probability model directly translates into the parent's type-specific density, which can be written as

$$f(h_i|x_i, v_i, a_i) = \prod_{t=1}^{T_i} f(h_{it}|x_i, v_i, a_i)\,. \tag{6}$$

As we do not observe the indicator a_i directly, parent i's preference type is unknown a priori. Therefore, we have to weigh his/her type-specific density by the probability that he/she belongs to the corresponding type, which equals this type's relative size. This yields the model's log likelihood function

$$\ln L(\Psi; x, v) = \sum_{i=1}^{N} \ln\left[\pi_a f(h_i|x_i, v_i, a_i = 1) + (1 - \pi_a)\ f(h_i|x_i, v_i, a_i = 0)\right], \tag{7}$$

where π_a is the share of altruists in the population and $\Psi = (\beta', \delta', \kappa', \eta, \pi_a)'$ denotes a vector containing all the unknown parameters of the model that need to be estimated. As in any finite mixture model (for a general treatise, see McLachlan and Peel 2000), the relative size of the altruists's group, π_a, cannot be estimated separately from the remaining parameters of the conditional probability model. It is well known that this highly nonlinear form and the potential multimodality, the existence of several local maxima, of the log likelihood function affect the speed of the optimization algorithm negatively, or even prohibit locating the global maximum.

However, if individual group-membership a_i were observed, Dempster and Laird (1977) show that the so-called complete data log likelihood function would take on the much simpler form

$$\begin{aligned}\ln \tilde{L}&(\Psi; x, v, a)\\ &= \sum_{i=1}^{N} a_i \left[\ln \pi_a + \ln f(h_i|x_i, v_i, a_i{=}1)\right]\\ &\quad + (1 - a_i)\left[\ln(1{-}\pi_a){+}\ln f(h_i|x_i, v_i, a_i{=}0)\right].\end{aligned} \tag{8}$$

In this case, the estimated share of altruists, $\hat{\pi}_a = 1/N \sum_{i=1}^{N} a_i$, would be given analytically and the maximum likelihood estimates of the remaining parameters could be obtained separately by numerically maximizing the corresponding type-specific densities.

Dempster and Laird's expectation maximization (EM) algorithm now proceeds iteratively in two steps, E and M. During the E step, given the actual fit of the data, an a posteriori probability of being an altruist is obtained for each parent according to Bayes' law by

$$\tau_{a,i} = \frac{\pi_a f(h_i|x_i, v_i, a_i = 1)}{\pi_a f(h_i|x_i, v_i, a_i = 1) + (1 - \pi_a)\ f(h_i|x_i, v_i, a_i = 0)}\,. \tag{9}$$

In the M-step, the complete data log likelihood is maximized, where the unobserved indicator a_i is replaced by these a posteriori probabilities of belonging to the altruistic group. Note that, besides being able to deal with the nonlinearity of the log likelihood function, the EM algorithm also allows us, based on these $\tau_{a,i}$, to endogenously classify each parent as being either altruistic or selfish.

The problems caused by multimodality can be addressed by implementing a stochastic version of the EM algorithm, such as the simulated annealing expectation maximization (SAEM) algorithm developed by Celeux et al. (1996). In each iteration, it has a positive probability of leaving a once-taken path to convergence and starting over in a different region of the log likelihood function. This results in much higher chances of converging to the global maximum but comes at the cost of even higher computational demands than the standard EM algorithm. The estimation routine, which we programmed in the R environment (R Development Core Team 2005), therefore uses a hybrid form (Render and Walker 1984) of the SAEM algorithm, which is more reliable in the detection of the global maximum, and the much faster Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm.[4]

The lowest five categories of parents' subjective well-being responses are only sparsely populated, with 11.4% of all responses overall. For practical reasons, we collapsed those five responses into a single category, ensuring that, during the bootstrap estimation of the standard errors, all response categories contain at least one observation in each subsample, a requirement for estimation of the full model, with a sufficiently high probability. Moreover, in a single index model such as ours, combining categories does not affect the estimator's consistency. The only costs are some loss in efficiency and the impossibility of predicting conditional outcome probabilities for the single components (which is not essential for our research question). As several randomly generated start values all led to the same maximum likelihood estimates, the model seems to be well identified.

4 Results

In this section, we present the results of four total finite mixture regressions. The first part deals with model selection issues and therefore addresses the question of whether we need to control for family-specific effects and alternative motivations for paying transfers, such as paternalistic preferences, joy of giving, and reciprocity. The second part sheds light on our main research question by discussing the prevalence and extent of altruistic preferences. Finally, we investigate whether parents who get assigned to the group of altruists actually pay higher average transfers to their children.

[4]The BFGS algorithm is a quasi-Newton method that allows solving unconstrained nonlinear optimization problems (see, for example, Broyden 1970). It is one of the standard hill-climbing optimization routines implemented in the R environment, as well as other statistical packages such as STATA.

4.1 Model selection

Table 3 shows the maximum likelihood estimates of four different finite mixture ordered probit models, which all discriminate between selfish and altruistic parents by analyzing the direct dependence of parental utility on children's well-being. The standard errors, in parentheses, are based on the bootstrap method and clustered by individuals to control for possible serial correlation. Not shown in the table are coefficients on four time dummies in each model that capture a potential time trend in happiness, as well as the Mundlak parameter estimates $\hat{\delta}_1$ and $\hat{\delta}_2$ in the family-effects models.

Model 1 represents the baseline as it only uses the parents' socioeconomic characteristics as controls and makes no use of the data's panel structure. While still assuming the data to be pooled over time, Model 2 includes the children's socioeconomic characteristics as well. Thus, it takes into account that parents may not only care about their children's happiness but obtain utility directly from their offsprings's socioeconomic status, too. In such a case, we should control for these paternalistic preferences and prefer model 2 over model 1 to avoid omitted variable bias. As mentioned in Section 3.2, there may exist unobserved family-specific effects that result in an endogeneity problem and lead to biased estimators as well. In contrast to their pooled counterparts, 1 and 2, models 3 and 4 use the data's panel structure to control for such time-unvarying unobserved effects by applying Mundlak's formulation. They therefore take the potential correlation between the regressors and these effects into account. Consequently, they consistently identify parents with altruistic preferences even when correlated family-specific effects are present. Because the family-effects models include the individual means over time of all regressors, $\bar{x}$ and $\bar{\tilde{v}}$, we have to exclude the variables age, years of schooling, and gender (but not their means over time) to avoid perfect multicollinearity. The number of parameters therefore rises by 8 if we go from model 1 to model 3, and by 13 from model 2 to model 4, respectively.[5]

Looking at the estimated parameters in Table 3, we find the results of all four models to be in line with prior findings in the happiness literature. Health and income both show a significant positive effect on parent's subjective well-being, whereas the impact of unemployment is highly significantly negative. As expected, the effect of good health is very large in relative size.[6] With the exception of log-household size, which is insignificant in the family-effects

[5] A further potential source of bias, not explicitly considered so far, can arise due to simultaneity, if children's utility depends on their parents' utility as well. To consider the empirical relevance of such a possibility, we performed a Rivers–Vuong test (Rivers and Vuong 1988) in a pooled standard ordered probit model with the children's age and gender as instruments. The fact that the estimated residuals from the first-stage linear regression of the test were not significant in the ordered probit estimation of the second stage (p value=0.37) means that the absence of simultaneity bias could not be rejected.

[6] The absolute size of the coefficients in the family-effects model cannot be compared directly to their pooled models' correspondents, as they are scaled by an unidentified, but constant factor $(1+\sigma_{\alpha}^{2})^{1/2}$.

Table 3 Finite mixture estimates of parental well-being ($N = 8{,}775$ observations)

Coefficients and (Std. err.[a])	Pooled over time		Family Effects	
	Model 1	Model 2	Model 3	Model 4
Fraction of altruists $\hat{\pi}_a$	0.277 (0.026)	0.274 (0.032)	0.210 (0.033)	0.214 (0.033)
Children's well-being in the group of altruists $\hat{\eta}$	0.865** (0.064)	0.873** (0.068)	0.918** (0.094)	0.912** (0.083)
Good health	0.762** (0.033)	0.760** (0.034)	0.299** (0.031)	0.300** (0.031)
Log-income	0.480** (0.039)	0.471** (0.046)	0.146** (0.057)	0.140* (0.056)
Unemployed	−0.384** (0.065)	−0.382** (0.059)	−0.222** (0.062)	−0.224** (0.061)
Married	0.050 (0.060)	0.037 (0.059)	0.244 (0.139)	0.247 (0.143)
Log-household size	−0.223** (0.063)	−0.206** (0.066)	0.177 (0.091)	0.185 (0.095)
Distance between households	−0.054** (0.015)	−0.058** (0.015)	−0.003 (0.031)	−0.004 (0.035)
Transfers paid (in 1,000 EUR)	0.005** (0.002)	0.006* (0.002)	0.005* (0.002)	0.005* (0.002)
Age[b]	0.185 (0.023)	0.147** (0.036)		
Good health of the average child		0.009 (0.038)		−0.041 (0.032)
Log-income of the average child		−0.049 (0.041)		0.032 (0.045)
Unemployment of the average child		0.013 (0.059)		0.054 (0.053)
Average child is married		0.036 (0.053)		−0.012 (0.055)
Log-household size of the average child		0.016 (0.056)		0.009 (0.064)
Age of the average child[b]		0.068 (0.055)		
Years of schooling of the average child[c]		0.018 (0.010)		
Average child is female[c]		0.019 (0.042)		
Log-likelihood	−14,442.63	−14,434.04	−14,299.88	−14,288.39
Number of parameters	20	28	28	41
BIC	29,067	29,122	28,854	28,949

All models additionally contain six threshold parameters and four time dummies. Models 3 and 4 contain additional parameters for the individual means over time.
Source: GSOEP 2000–2004

BIC Bayesian information criterion

*significant at $\alpha = 5\%$; **significant at $\alpha = 1\%$

[a] All standard errors are clustered and obtained on the basis of 300 bootstrap replications

[b] Only individual means over time are included in models 3 and 4 due to perfect time-dependence

[c] Only individual means over time are included in model 4 due to time-invariance

model, all coefficients preserve the same sign. Furthermore, as the parameter estimates in the family effects models only rely on variation within the individuals over time, it comes at no surprise that their standard errors are generally larger than these estimated from the pooled models.

While our main interest is in patterns regarding altruism, to be discussed in detail below, the regressions also provide some evidence for the presence of paternalistic preferences, joy of giving, and reciprocity. A test for the presence of paternalistic preferences comes down to the question of whether the coefficients of the children's socioeconomic characteristics are jointly significant. Two likelihood ratio tests (model 2 against model 1 and model 4 against model 3) show that the null-hypothesis of the absence of paternalistic preferences has to be rejected (the p values are 0.028 and 0.042, respectively). Thus, we conclude that parents care directly for their children's socioeconomic standing, which rules out models 1 and 3. Because the remaining two models, 2 and 4, are not nested, they cannot be tested against each other. A comparison based on the Bayesian information criterion reveals a slight advantage for the family effects model.

With regards to joy of giving, a necessary condition for such an effect is that transfers increase a parent's happiness ceteris paribus, i.e., for a given happiness of the child. This condition is not sufficient, though, as there may be other explanations as to why transfers can be associated with increased happiness. One is that parents in a better financial situation give more to their children, and they may be happier for that very reason, i.e., the better financial situation, rather than the transfers per se. Therefore, it is important to eliminate this potential confounding effect by controlling for parental income. Second, the observed transfers could be a "pay-back" for received or anticipated future services that children provide for their parents. We do not observe such services in the data. Hence, we cannot exclude that part of the transfer effect is due to reciprocity rather than joy of giving proper. From model 4, with family effects (p value=0.028) or model 2 for the pooled panel (p value=0.015), there is evidence that transfers have a statistically significant positive effect on well-being, after controlling for income, as well as the child's utility. Thus, joy of giving and/or reciprocity appear to be motives for transfers as well.

4.2 Prevalence and extent of altruistic preferences

The main parameters of interest, $\hat{\pi}_a$, the estimated fraction of altruists, and $\hat{\eta}$, the extent of interdependence in the altruists' preferences, are highly significant with p values close to zero in all models. The estimated fraction of altruists is larger (27.4%) in the pooled model than in the model that accounts for family-effects (21.4%), although the difference is not statistically significant.

Table 4 Average predicted change in happiness distribution of altruistic parents for a standard deviation increase in child happiness index

Response category	Model 2		Model 4	
	Estimates	(Std. err.[a])	Estimates	(Std. err.[a])
Zero to four	−0.155	(0.015)	−0.163	(0.017)
Five	−0.052	(0.007)	−0.045	(0.009)
Six	−0.017	(0.005)	−0.012	(0.006)
Seven	0.009	(0.006)	0.011	(0.008)
Eight	0.087	(0.008)	0.078	(0.012)
Nine	0.060	(0.005)	0.055	(0.005)
Ten	0.069	(0.011)	0.075	(0.013)

[a] All standard errors are clustered and obtained on the basis of 300 bootstrap replications.
Source: GSOEP 2000–2004

All in all, the estimated share of altruists is comparable in magnitude to the 20% reported by Phelps (2001), who relies on psychological tests in a US survey. So, even if we apply a completely different methodology and examine members of the same family instead of strangers, we obtain results that are qualitatively similar to those of Phelps. Furthermore, our estimates for the spread of altruism are also similar to the fraction of people who treat their own and others' payoffs as perfect substitutes in dictator games (Andreoni and Miller 2002). This indicates that, after controlling for children's socioeconomic characteristics and parents' income, as well as applying a family-effects estimator, survey-based estimates can provide some meaningful information on preference interdependence and altruism.

As in any other standard ordered probit model, only the signs of the coefficients within a certain group of the finite mixture ordered probit model have a direct interpretation (Boes and Winkelmann 2006). Arguably, the most intuitive way of interpreting the quantitative effect of the representative child's well-being in the group of altruistic parents is to compute its average marginal probability effect (AMPE) of observing a certain parental response with regard to well-being. To compute the AMPE, each parent has to be classified either as being altruistic or selfish. This is achieved by assigning each parent to the altruists whose a posteriori probability, $\tau_{a,i}$, is greater than 50%. By definition, marginal probability effects are zero in the group of selfish parents.

Table 4 shows the AMPE of the child's well-being in the group of altruistic parents.[7] For example, a permanent unit increase in $\tilde{v}_{it}$ (i.e., a one-standard-deviation increase) would, ceteris paribus, boost the probability of observing the most frequent subjective well-being response, $h = 8$, by 8.7 percentage points in model 2 and 7.8 percentage points in model 4.

[7] By definition, the AMPEs have to sum up to zero in both models. The small differences (0.001) from zero in the results reported in Table 4 are due to rounding error.

4.3 Transfer payments by preference type

If the model correctly identifies the parents with altruistic preferences, we expect them to be, on average, more likely to make transfers to their children. Even though, as argued before, not all the parents in the altruistic group necessarily need to pay actual transfers. As we have both the transfer payments and the individual probabilities of being an altruist, we can run a regression to check and quantify this association.

Table 5 shows the results of two ordinary least squares regressions of the annual transfer amount, paid by the parents to their representative child, on the a posteriori probabilities $\tau_{a,i}$ from models 2 and 4. These regressions control for various socioeconomic characteristics of the parents and their children.

Table 5 Regressions of transfer amount ($N = 8,775$ observations)

Coefficients and (std. err.[a])	OLS regression of transfers (in 1,000 EUR)	
	Model 2b	Model 4b
A posteriori probability of being an altruist $\tau_{a,i}$	0.905* (0.400)	1.000* (0.490)
Good health	−0.128 (0.135)	−0.122 (0.132)
Log-income	1.616** (0.178)	1.619** (0.219)
Unemployed	−0.056 (0.139)	−0.053 (0.143)
Married	0690** (0.166)	0.686** (0.160)
Log-household size	−1.634** (0.213)	−1.636** (0.228)
Years of schooling	0.251** (0.038)	0.251** (0.043)
Good health of the average child	−0.128 (0.176)	−0.124 (0.180)
Log-income of the average child	−0.509** (0.178)	−0.509** (0.179)
Unemployment of the average child	0.480 (0.532)	0.481 (0.533)
Average child is married	0.690 (0.190)	0.221 (0.195)
Log-household size of the average child	0.087 (0.170)	0.085 (0.180)
Years of schooling of the average child	0.047 (0.037)	0.047 (0.037)
Intercept	−10.901** (1.933)	−10.883** (1.780)
R^2	0.049	0.049

Source: GSOEP 2000–2004

OLS ordinary least squares

*significant at $\alpha = 5\%$; **significant at $\alpha = 1\%$

[a] All standard errors are clustered and obtained on the basis of 300 bootstrap replications

As expected, parents' income shows a significant positive sign, whereas the average child's income is negatively correlated with transfers paid by the parents. Parental household size also shows the expected negative sign, and parents with higher education seem to be more willing to pay transfers to their children. Most interestingly, the results show a significant positive relationship between transfer payments and the individual a posteriori probabilities of having altruistic preferences.[8] In both models, the estimated transfer amount is roughly 1, 000 Euros higher for altruistic parents than it is for the rest of the population. The fact that parents to whom the model assigns a high probability of having altruistic preferences indeed pay, on average, much higher transfers to their children gives us a strong indication that the econometric model is capable of identifying the altruists in the data set.

5 Conclusion

In this paper, we estimate the share of parents with altruistic preferences in a data set stemming from a representative annual survey, the GSOEP. The panel structure of the data allows us to control for various sources of bias, such as paternalistic preferences, genetically transmitted inclinations towards general life satisfaction, or any other sort of time-invariant, family-specific effects. The estimated share of altruists lies between 21% and 27% of the population, depending on whether the model accounts for family-specific effects or not. When we control for family-specific effects, the estimated fraction of altruists, which lies around one fifth, coincides roughly with the findings of two recent studies relying on different psychological (Phelps 2001) and experimental (Andreoni and Miller 2002) methodologies and data sets.

The estimated size of the effect of the children's reported life satisfaction on their altruistic parents' subjective well-being is both robust and relatively large in terms of marginal probability effects. Besides altruism, we find evidence that joy of giving and/or reciprocity provide an additional motivation for parents to pay transfers to their children.

Furthermore, we have shown that actual transfers to the children are, on average, considerably larger for parents who get, with a high probability, assigned to the altruistic group. This provides strong evidence that the econometric model, on average, correctly identifies the parents with altruistic preferences, as these individuals show a consistent behavior in their transfer payments. Our approach, which is based on a finite mixture model to account for heterogeneity in preference types and relies on subjective well-being as immediate proxy for utility, seems therefore to be well suited to estimate the share of altruists in panel surveys such as the GSOEP.

[8]If we exclude transfers in models 2 and 4, the classification and, consequently, the results remain stable. Therefore, the dependence of $\tau_{a,i}$ on transfers paid seems negligible.

Finally, the finding that some parents' subjective well-being positively depends on the happiness of their children living in spin-off households confirms the results of other studies that altruistic preferences are present in at least a minority of the population. While this study focuses on altruism, further research has to show whether other cleanly segregated social preference types exist and how they relate to existing theories of other-regarding preferences. Such a deeper understanding of the heterogeneity in preferences may be crucial in determining equilibria, especially when markets are imperfect. So far, we conclude that altruistic preferences are substantial in their prevalence, as well as their extent, and they are likely to play an important role in public economics.

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