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The Development of Public Demand for Redistribution. A Pseudo-Panel Model for Decomposing Within- and Between-Effects

Alexander Schmidt
GK SOCLIFE
University of Cologne

GK SOCLIFE is a Research Training Group affiliated to Cologne Graduate School, University of Cologne

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Alexander Schmidt

Abstract

Public demand for redistribution has been a subject to research for the last couple of decades. While research has identified quite robust individual-level effects, we are still lacking solid evidence on the effects of country-level variables. In this paper I investigate the influence of macro-economic conditions on public demand for redistribution. I use data from the European Values Study (1990-2009). I argue that most cross-sectional research suffers from omitted variable bias. I propose a pseudo-panel model that makes use of longitudinal variation to draw better causal inference. The proposed model makes use of the hybrid-approach and allows disentangling within- and between-unit effects. The results show that within- and between-unit effects can be substantially different. I argue that within-unit effects should generally be better estimates than between-unit effects. Therefore, the analysis casts general doubt on the validity of cross-sectional analysis of country-level effects. My results suggest that increasing social spending leads to less demand for redistribution after a certain level of redistribution is reached (saturation effect). This result contradicts many results published in previous cross-sectional research. I also find a significant positive within-effect of unemployment rates on public demand for redistribution. I find a negative within-effect of economic inequality, which casts doubt on the median voter hypothesis. Finally, I find that increasing economic wealth has a positive but diminishing effect on public demand for redistribution.

Introduction*

Public demand for redistribution has been a subject of research for the last couple of decades. Research on the individual-level determinants of demand for redistribution has identified a wide range of determinants that explain the variance in individuals' demand for redistribution. For instance, it has been shown that the amount of redistribution preferred by individuals is related to their exposure to social risks and their values and attitudes.

However, we find variance in the demand for redistribution not only between individuals but also between countries. The redistribution of resources is a constituting characteristic of all welfare states, but the actual level of redistribution varies remarkably between countries, and so does public support for redistribution. The welfare regime theory provides a theoretical explanation for this phenomenon (Esping-Andersen 1990). However, empirical investigations of the causal relationship between country-level characteristics and individual attitudes still lack solid evidence.

The problems in current research result mostly from a lack of good comparative data, particularly genuine panel data. A panel study, which follows individuals in a large number of countries, would provide the opportunity to draw causal inferences about country-level effects on the demand for redistribution. Unfortunately, such a data set is not available.[1] Two types of empirical studies try to circumvent this data availability problem.

One type of studies, originating mostly from sociology, makes use of comparative cross-sectional data and employs multilevel (random effects) models (for instance, Dallinger 2010). Another type of studies, originating mostly from political science, makes use of time-series data on the country level, often called pooled time-series cross-section data (for instance, Blekesaune 2007). Both approaches have advantages and drawbacks.

Multilevel models for cross-sectional data use individuals as units of analysis. In this sense, multilevel models are in line with the logic of Coleman's methodological individualism (1990). On the other hand, multilevel models suffer from a high risk of omitted variable bias because they rely solely on the observation of cross-sectional variation. In other words, there

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[1] Actually, there are two comparative panel data sets: first are the data sets provided by the CNEF project (Cross National Equivalence File). These data sets contain harmonized variables from 7 different national panel studies. However, the N=7 macro units is, by far, not large enough to estimate the effects of country-level characteristics. Second, the EU-SILC data set (European Union Statistics on Income and Living Conditions) contains information about 27 countries (in the most recent wave). In principle, this number might be large enough to estimate the effects of country-level characteristics (though the participating countries are obviously not a random sample). However, the EU-SILC does not contain the standard questions used in research on attitudes toward redistribution and, thus, cannot be used for research on public opinions regarding redistribution.

is a considerably high risk of drawing invalid causal inferences if multilevel models for cross-sectional data are misspecified.

Regression models for pooled time-series cross-section data (TSCS) control for unobserved heterogeneity at the country level through the inclusion of country fixed effects. This is possible because the units of analysis (countries) have been observed several times. On the other hand, from the perspective of methodological individualism, it might be critical to draw conclusions about individual logics on the basis of evidence resulting from observations of countries.

Additionally, we cannot decompose the observed differences between countries (country-time points) into differences explained by compositional effects and differences that actually result from differences between country-level characteristics. In multilevel analysis, we can use the variance components to test whether country differences are explained by variables located at the country level or whether they can be explained by individual-level variables.

The following paper aims to combine both approaches to draw better causal inferences about the influence of country-level characteristics. In the following section, I will present an overview of theoretical approaches used to explain public demand for redistribution. I will derive a number of hypotheses based on the self-interest approach. Then, I will discuss the methodological problems in recent research and present a model based on two approaches developed (or, rather, used by) Mads Meier Jaeger (2011) and Malcom Fairbrother (2011). Finally, I will present the results of my own analysis and compare them to those of other studies. A paper by Mads Meier Jaeger (2011) will provide the ultimate reference for my study, as it uses a similar method and tests the same hypothesis but with different data.

Theoretical Considerations

The literature on welfare state attitudes addresses a variety of individual- and contextual-level factors that influence public demand for redistribution. Two main lines of argumentation can be identified (Andress and Heien 2001; Bowles and Gintis 2000; Jaeger 2006a; Rehm 2009). One line of argumentation relies on the idea of the *homo economicus* and argues that individuals' demand for redistribution results from their utility-maximizing behavior. This approach is referred to as the self-interest hypothesis. The second line of argumentation relies on the idea of the *homo sociologicus* and argues that individuals' demand for redistribution results from their ideological orientations (ideology hypothesis).

Research has found evidence for both arguments. A large number of studies support the self-interest hypothesis. It has been shown that not only present but also past and expected future exposure to risks has an influence on demand for redistribution (Benabou and Ok 2001; Linos and West 2003; Piketty 1995; Rehm 2009; Svallfors 1997). Research also has found evidence supporting the ideology hypothesis (Andress and Heien 2001; Shirazi and Biel 2005). Fong (2001) argues that justice beliefs are at least as important as self-interest when we want to explain attitudes toward income redistribution.

The subject of this paper is the influence of macro-level characteristics on individuals' support for redistribution. In comparative welfare state analysis, the two approaches discussed above are also used to link the macro- and micro-level. A wide range of literature originating from the welfare regime theory argues that country differences in public demand for redistribution can be explained by differences in their ideological settings. The institutional settings in welfare regimes foster a certain logic of solidarity that, then, emerges as a social norm (Larsen 2006; Mau 2004).

Indeed, we find high support for redistribution in countries with strong redistribution and low support for redistribution in countries with low amounts of redistribution (Dallinger 2010; Jaeger 2006b; Jakobsen 2011). Sabbagh and Vanhuysse (2006) show that justice-related attitudes differ systematically between welfare regimes. However, in the following study, I will focus on self-interest-related approaches and ignore the question of ideological influences resulting from the country level.

Scholars have proposed a variety of hypotheses relating macro-level characteristics to the self-interest hypothesis. The well-known median voter hypothesis, for instance, claims that increasing inequality is associated with a higher demand for redistribution (Meltzer and Richard 1981). The logic of this hypothesis is quite simple. The greater inequality is, the more people will benefit from greater redistribution. Consequently, the average demand for redistribution should rise if inequality increases.

A variety of hypotheses relate the economic situation to public demand for redistribution. In general, scholars have hypothesized that individuals will demand more redistribution in economic hard times and less redistribution in times of economic prosperity (Blekesaune 2007; Dallinger 2010; Jaeger 2011). An often-tested hypothesis states that an increasing risk of unemployment leads to increasing demand for redistribution. This is true for the individual level (Rehm 2009) and is also hypothesized to be true for the country level (often called the governemtnal protection hypothesis, Blekesaune 2007).

With regard to economic growth, predictions are less straightforward. Some scholars argue that small (or zero) growth rates lead to lower demand for redistribution because people claim compensation for their forgone income gains (Andress and Heien 2001; Pontusson 2005). Others claim that people demand more redistribution if economic risks increase. This argument is basically the same as the one used to explain a positive relationship between unemployment rates and support for redistribution (Blekesaune 2007; Dallinger 2010).

Finally, one can also hypothesize a relation between the level of wealth (usually measured by *GDP per capita*) and public support for redistribution. By redistributing resources, societies aim to provide an adequate standard of living to all citizens. If economic wealth increases, a saturation effect can emerge because the basic needs of the net receivers are well satisfied and people will not support more redistribution of resources (Haller, Höllinger, and Raubal 1990).

Nevertheless, empirical evidence regarding the influence of macro-level characteristics on individuals' demand for redistribution is rather ambiguous. As I will argue later, this might result from problems in model specifications and/or data availability. In two recent articles, Dallinger (2010)[2] and Finseraas (2009) report a positive impact of inequality on demand for redistribution. These results support the median-voter hypothesis. Other studies find insignificant (Lübker 2007) or even negative effects (Roller 1995). Jaeger (2011) finds a u-shaped effect, i.e. an effect that is negative when inequality is low and positive when inequality is high.

Some studies find a positive effect of unemployment on public demand for redistribution (Blekesaune 2007; Dallinger 2010; Fraile and Ferrer 2005), while others find no effect (Jaeger 2011). Some studies report a negative effect of economic wealth (mostly measured by *GDP per capita*) on demand for redistribution (Dallinger 2010; Jaeger 2011). Empirical studies also identify a strong positive relationship between the amount of social spending (as a percentage of GDP) and public demand for redistribution (Dallinger 2010; Finseraas 2009; Jaeger 2006b; Jakobsen 2011). This association is typically assumed to reflect the socializing effect of welfare states (Jaeger 2011; Larsen 2006).

Hypotheses

As this paper aims to retest established hypothesis with a new method, I will test for the well-known contextual-level hypotheses described above:

[2] Dallinger reports different models. In some models, she estimates a positive and a negative effect in others. In her final model, she estimates a non-linear effect that is positive for countries with average or above-average levels of inequality.

H_1: An increase in economic inequality leads to an increase in the demand for redistribution (median-voter hypothesis).

H_2: Increasing unemployment leads to an increase in the demand for redistribution (governmental protection hypothesis).

H_3: Increasing economic growth lowers the demand for redistribution (governmental protection hypothesis).

H_4: The level of wealth has a negative impact on demand for redistribution (saturation hypothesis).

H_5: Demand for redistribution increases with social spending (socialization hypothesis).

Estimating Country-level Effects in Empirical Analyses

In econometrics, it is widely accepted that one needs panel data to draw causal inferences (Andress, Golsch, and Schmidt 2012). With panel data, we can control for unobserved heterogeneity by including fixed effects. However, the problem in comparative welfare state research is that there are no cross-national comparative panel data sets that include the variables typically used for the analysis of welfare state attitudes.

All available data sets for the analysis of welfare state attitudes are cross-sectional. In recent research, two approaches have been used to draw causal inferences on the basis of cross-sectional data: (1.) multilevel random effects models that make use of cross-sectional data on the individual level and (2.) fixed effects regression that uses (aggregated) pooled TSCS data. The dependent variable in multilevel models is located at the individual level, which means that we actually model individual outcomes. From a theoretical point of view this is a great advantage over the analysis of aggregated data, although, in practice, adequate modeling of theoretically relevant relations is often missing (Nonnenmacher and Friedrichs 2011).

On the other hand, multilevel models cannot control for unobserved heterogeneity at the country level. This, however, can be done in the analysis of pooled TSCS data. In the following two subsections, I will discuss the disadvantages of both approaches. Then, I will discuss the model proposed by Jaeger (2011) and propose an extension of this model. The proposed model will combine the advantages of random effects multilevel models and fixed effects regression with polled TSCS data.

The problem of omitted variables in multilevel models

A simple (random intercept) multilevel model for cross-national data can be written as

$$y_{ij} = \alpha + \beta x_{ij} + \gamma z_j + u_j + e_{ij} \qquad (1)$$

with *i=1,…,n* individuals, nested in *j=1,…N* countries. Additionally, x_{ij} is a vector of variables that vary between and *within* countries, with β being the corresponding vector of coefficients. Moreover, z_j is a vector of variables that vary only *between* countries, with γ being the vector of coefficients for these variables. The error term u_j constitutes the *random* intercept by capturing unobserved between-country variation, i.e. the differences between countries that cannot be explained by z_j and x_{ij}.

The problems in applied research basically result from violations of the assumptions that we have to make to draw causal inferences from regression analysis. First, as in ordinary least square regression, one has to assume that the error component is independent from the variables in the model (assumption of exogeneity), i.e. ($E(e_{ij}|z_{j,}x_{ij}) = 0$, $E(u_j|z_{j,}x_{ij}) = 0$). In other words, the model has to include all relevant variables to yield unbiased estimates. This is a well-known problem that also exists in ordinary least square regression and is called "omitted variable bias" (see Kim and Frees 2006, for a detailed discussion of omitted variable bias in multilevel analysis).

Second, the error terms have to be randomly distributed. This means that the samples at both levels have to be random samples that are large enough to guarantee that the error terms are randomly distributed: $u_j \sim N\left(0, \sigma^2_{u_j}\right), e_{ij} \sim N\left(0, \sigma^2_{e_{ij}}\right)$. Obviously, this assumption is very problematic for social science applications because we have neither random country samples nor large samples at the country level. However, in this paper, I will not discuss the problem of non-random country samples, but I will consider the small-N problem.

In most social science applications, the number of macro-level units is about 30, sometimes even smaller. Thus, the degrees of freedom available for estimating country-level effects are quite limited anyway, and the power of the statistical tests is generally low (Hox 2010; Maas and Hox 2005). Additionally, it is a fact that many country characteristics are highly dependent on each other. Given the low number of cases and the problem of multi-colliniarity, estimation can be very difficult. In many applications, one does not find a single significant effect when all theoretically relevant variables are included in the model. Therefore, researchers often end up testing country-level variables separately (for instance, see Pichler and Wallace 2009; Semyonov, Raijman, and Gorodzeisky 2006). As explained above, this procedure involves a high risk of biased estimates.

To sum up, models for cross-sectional data always pose the risk of yielding biased estimates because the inclusion of all relevant variables might be impossible. Therefore, we can never be sure whether the observed differences between the units actually result from differences in the explanatory variables or whether they result from some unobserved background characteristic underlying all the observed variables (this is the problem of endogeneity). In multilevel analysis, the number of variables that can be tested is even smaller than in individual-level analysis due to the small number of cases at the country level. Therefore, multilevel (random effects) models for cross-section data should be viewed very critically when it comes to causal inference (Fairbrother 2011; Jaeger 2011).

Country fixed effects analysis with aggregated pooled TSCS data

The problem of correlated error terms (or unobserved heterogeneity in the panel language) can be solved with panel data. Panel data contain repeated observations of the same units. By including fixed effects for the units of analysis, we can control for unobserved heterogeneity, and the estimated effects can be interpreted as causal effects (Andress, Golsch, and Schmidt 2012). As individual-level panel data are not available for cross-national analysis, researchers usually apply models with aggregated country-level data. A simple panel regression model can be written as:

$$y_{it} = \alpha + \beta x_{it} + \gamma z_i + u_i + e_{it} \qquad (2)$$

with $i=1,\ldots,n$ units (individuals or countries) that have been observed $t=1,\ldots T$ times. This model has the same basic structure as the multilevel model presented in Equation 1, but here, we have time points (t) nested in units (i). As in the multilevel model, we have an error term u_i that captures the heterogeneity between the units i, a vector of variables that varies only between units (z_i), and a vector of variables that varies *within* and between units (x_{it}). A fixed effect model is a model that controls for all unobserved characteristics of the units. This is achieved by the elimination of the unit-specific error term u_i. To that end, we subtract the unit-specific mean of all variables from the original variable (so-called fixed effects transformation). Due to this subtraction, we eliminate all *time-constant* variables from the model (z_i and u_i). The variance that remains for analysis after this transformation is the so-called *within* variance:

$$(y_{it} - \bar{y}_i) = \beta(x_{it} - \bar{x}_i) + (e_{it} - \bar{e}_i) \quad (3)$$

The resulting model is supposed to analyze how a change in x_{it} influences a change in y_{it}. In principle, a fixed effects approach could be applied to all useful units of analysis that have been observed over time. The important question is that of whether countries are a useful unit of analysis in the context of public opinion research.

Obviously, there is no one public opinion pertaining to a country. In contrast, the variables that we use for the analysis of PTCS data are aggregated variables based on thousands of opinions surveyed at the individual level. Hence, the subject of analysis in these kinds of analysis is the *mean* opinion. We ask whether the *mean* opinion changes when a certain country-level variable changes. We ask, for instance: Does the *mean* level of support for redistribution change if the unemployment rate changes? In principle, one can, of course, ask these questions, but as sociologists, we are interested in the behavior and attitudes of individuals. In other words, we should aim to explain a change in the mean level of support for redistribution through changes at the individual level.

Let us think about the example of unemployment rates to pinpoint the problems of aggregated data analysis. Assume that we observe increasing demand for redistribution resulting from rising unemployment rates. There are different explanations for this observation. First, it is possible that only those individuals who are directly affected by unemployment respond to their situation with increasing demand for redistribution. As a result, the mean level of demand for redistribution will rise.

Another explanation could be that all individuals in a country with rising unemployment rates perceive a rising risk of becoming unemployed and respond to this situation with increasing demand for redistribution. The latter refers to a situation where we actually have an effect of a country-level characteristic. The first case refers to a situation where the observed country-level changes result solely from individual-level effects. Multilevel analysis allows the disentangling of these two kinds of effects, but aggregated data gives us no chance to test for this.

To summarize, to draw causal inferences, we have to deal with unobserved heterogeneity. In fixed effects analysis, we control for unobserved heterogeneity through elimination of the error term u_i from the regression function. Therefore, we need longitudinal data, which is, unfortunately, not available for individuals. In multilevel (random effects) models for cross-sectional data, we estimate the error term. This implies that the regression function needs to include all relevant variables. Misspecified regression functions will yield biased results.

A third approach, taking a middle ground between multilevel analysis and the analysis of pooled TSCS data has just been proposed by Mads Meier Jaeger (2011). His model aims to overcome the problems that result from the lack of genuine panel data. In the next section, I will propose a model that extends Jaeger's approach.

A multilevel pseudo-panel approach for decomposing within and between effects

Mads Meier Jaeger (2011) proposed a (modified) pseudo-panel approach to deal with the lack of genuine panel data for cross-national analysis of public opinions.[3] A pseudo-panel is a panel data set that has been generated on the basis of independent cross-sections. The original pseudo-panel approach goes back to Deaton (1985) and is based on the idea of generating a panel data set with cohorts as units of analysis. In other words, in a pseudo-panel, we do not track individuals over time; rather, we track groups of individuals. The average group characteristics are treated as observations. Including group fixed effects, then, allows testing for causal relationships between changing group characteristics and changes in the dependent variable.

In principle, this approach is very similar to the fixed effects analysis of aggregated data that we use for the analysis of pooled TSCS data because it is also based on the analysis of aggregated data. However, the level of aggregation is different. We do not treat all individuals within a country as one group but, rather, we construct a number of groups within each country. In other words, the level of aggregation is much closer to the individual level than it is to the country level.

In Deaton's original approach (1985), the groups are defined on the basis of time-constant and randomly distributed characteristics, typically year of birth and gender. This procedure ensures that the *same* individuals are included in each of the groups. However, the critical assumption for the grouping variable is that it is strictly exogenous and that the group means vary across groups and time (Inoue 2008).[4] In Jaeger's approach, the grouping variables are not strictly time-invariant. Jaeger defines groups on the basis of the most important socio-demographic variables, including education and social class. Therefore, he has to assume (!) that these variables are strictly exogenous.

[3] The so-called pseudo-panel approach basically goes back to Deaton (1985) and has been further developed by Verbeek (2008) and other authors. However, Jaeger (2011) proposes a modification of the approach and an adaption of the model for multilevel data.

[4] If these assumptions are met, the pseudo-panel approach can be viewed as an instrumental variable estimation (for more details, see Moffit 1993, Inoue 2008, Verbeek 2008).

In principle, the basic pseudo-panel data model has the same structure as the model in Equation 2 with *i* now indicating groups:

$$y_{it} = \alpha + \beta x_{it} + \gamma z_i + u_i + e_{it}$$

In the original pseudo-panel approach, as in the analysis of Jaeger, this equation is transformed into a fixed effects model aiming to control for unobserved heterogeneity. Before I will propose a different way to specify the model, we will extend this model for cross-national data and include an additional level for the countries:

$$y_{jit} = \alpha + \beta x_{jit} + \gamma_1 z_{1ji} + \gamma_2 z_{2jt} + u_{1j} + u_{2ji} + e_{jit} \tag{4}$$

The model in Equation 4 has three levels: single observations at time point t (*t*), which are nested in groups (*i*), which are, in turn, nested in countries (*j*). It includes two random effects: the random effect u_{1j}, which captures unobserved heterogeneity at the country level, and the random effect u_{2ji}, which captures unobserved heterogeneity between the groups (within each country). It also includes one additional vector of variables. The vector x_{jit} includes variables that vary across countries, groups, and time. The vector z_{1ji} includes variables that vary across countries and across groups. Finally, the vector z_{2jt} includes those variables that vary across-countries and across time. Thus, z_{2jt} is the vector of variables that captures the (time-variant) country characteristics. Including fixed effects for countries and groups (subtracting cross-time means of all variables) reduces the function to:

$$(y_{jit} - \bar{y}_{ji}) = \beta\left(x_{jit} - \bar{x}_{ji}\right) + \gamma_2(z_{2jt} - \bar{z}_{2j}) + (e_{jit} - \bar{e}_{ji}) \tag{5}$$

The variance of the dependent variable left for the analysis is the within-groups variance. This variance can be explained either by the within-group variation of group-level variables $(x_{jit} - \bar{x}_{ji})$ or by the within-country variation of country-level variables $(z_{2jt} - \bar{z}_{2j})$. This is the model estimated by Jaeger (2011). One drawback of this approach is that it cannot be used to investigate country differences. We cannot decompose observed country differences into differences explained by country characteristics and differences explained by group characteristics because the fixed effects transformation, applied to draw better causal inferences, eliminates these differences.

I propose applying a so-called hybrid approach to the model from Equation 4. A hybrid approach is a model that estimates within- and between-unit effects simultaneously (Andress, Golsch, and Schmidt 2012; Rabe-Hesketh and Skrondal 2005). In other words, hybrid models estimate fixed effects parameters (relying on the within-unit variance) and parameters that result from the analysis of the variance between units. A hybrid model for panel data looks like this (derived from Equation 2):

$$y_{it} = \alpha + \beta^{W}(x_{it} - \bar{x}_i) + \beta^{BE}\bar{x}_i + \gamma z_i + u_i + e_{it} \tag{6}$$

This random effects model includes two vectors of variables derived from the vector of time-varying variables (x_{it}). The variables ($x_{it} - \bar{x}_i$) have been transformed according to the fixed effects transformation rule. The corresponding vector of coefficients (β^{W}) will give the fixed effects estimates (within-unit effects). Additionally, the model includes the cross-time mean of the time-varying variables x_{it} ($\bar{x}_i$). The coefficients in β^{BE} will give estimates based on the between-unit variance.

In a recent paper, Malcom Fairbrother (2011) proposes using the hybrid approach for multi-level models with pooled cross-section data. He decomposes the country-level effects into a within-country and a between-country effect. As the pseudo-panel data that I use include repeated observations at the country level *and* at the group level, I can apply the decomposition to both levels. This is not possible with a series of pooled cross sections, like Fairbrother uses. The advantage of this approach over the original model proposed by Fairbrother (2011) is that I have panel data observing the same groups within countries. Therefore, causal inferences should be more convincing because I can control for unobserved heterogeneity between the units of analysis.

The advantage over the approach taken by Jaeger (2011) is that I can estimate fixed effects parameters without discarding the between variance. I can use country- and group-level variables to explain between-country and between-group differences. Hence, I can exploit the advantage of multi-level analysis and make statements about the relative importance of group-level and country-level characteristics. In other words, I can analyze the extent to which country differences are explained by compositional effects (effects from the group level). The complete model that I estimate can be written as (a hybrid model derived from the multi-level model in Equation 3):

$$y_{jit} = \alpha + \beta^{W}\left(x_{jit} - \bar{x}_{ji}\right) + \beta^{BE}\bar{x}_{ji} + \gamma_1 z_{1ji} + \gamma_2^{W}(z_{2jt} - \bar{z}_{2j}) + \gamma_2^{BE}\bar{z}_{2j} + u_{1i} + u_{2ji} + e_{jit} \tag{7}$$

The model in Equation 7 decomposes the effect of all time-varying variables (x_{jit} at the group-level and z_{2jt} at the country level) into a within- and a between-effect. As the variables z_{1ji} are constant within groups, they are not transformed. The variables contained in this vector are the group-constituting variables, which are, by definition, time-constant. These variables are included in the model to control for unobserved heterogeneity at the group level. This can be done using the variables that constitute the groups and does not necessarily have to be done with the original group dummies (Moffit 1993). For example, if groups are defined on the basis of age (year of birth), one can control for unobserved heterogeneity with a function of age and does not need to use the full set of group dummies (Verbeek 2008).

Data

Individual-level data used for the pseudo-panel

The data source for the pseudo-panel is the European Values Study (2nd [1990], 3rd [1999/2000] and 4th [2009] waves). The data for some countries has been imputed from the World Values Study, a replication of the EVS. In total, I have data for 29 countries.[5] For 23 countries, I have individual-level data from all waves. However, some countries did not participate (or did not conduct the necessary variables) in all waves. For Estonia, Finland, Latvia, and Luxembourg, I do not have data for the 2nd wave. Denmark and Portugal did include the item that I need for my dependent variable in the 3rd wave. In sum, I have individual level data for 81 country-time points.

I used a 3x3x3 classification to construct the socio-economic groups that make up the units of analysis. The typology is taken from Jaeger (2011) and is designed to capture the most important socio-demographic cleavages. Following Jaeger (2011), I use three educational groups (primary, secondary, and tertiary), three age groups (15-35, 36-54, 55-max), and three social classes (manual workers, non-manual service workers, professionals). The social classes are grouped on the basis of the EGP classification (Erikson and Goldthorpe 1992). In principle, I construct 27 (3x3x3) groups per country-time point. However, not all groups are represented in all countries. The average number of observations per country-time point is 26.3. The total pseudo-panel consists of 2133 single observations, nested in 782 socio-demographic groups, nested in 29 countries.

[5] Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, East Germany, West Germany, Great Britain, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, the Russian Federation, Slovakia, Spain, Sweden, Turkey, and the United States.

However, in the multivariate analysis, I can use 1501 observations, nested in 593 groups, nested in 22 countries. The decrease in the number of countries is due to a lack of comparable country-level data. Table A1 in the appendix gives an overview of the countries, time points, and numbers of groups per country-time point used for the multivariate analysis.

The dependent variable is the mean demand for redistribution in the socio-demographic groups. The mean demand for redistribution was measured through an item that asks people to state their view on a ten-point scale with the end poles:

- "Incomes should be made more equal" [1] and
- "We need larger income differences as incentives" [10].

On the level of groups, I control for the ideological dimension by including the mean score on a ten-point left-right scale. Furthermore, I include the share of men to control for the composition of the groups. I also include the mean of the relative income position to control for the average income positions of the groups.

Country-level data

On the country level, I use five variables to test my hypotheses. To test the median-voter hypothesis, I measure economic inequality with the *Gini index*. The values have been taken from the World Income Inequality Data Base (WIID, V2.0c).[6] All the *Gini* indices used are based on disposable household incomes. Within each country, all values are calculated from household incomes based on the same equivalence scales. However, the equivalence scales used are not the same across countries.[7] Unfortunately, the WIID did not always provide a (suitable) value for the exact years in which the EVS surveys were conducted. In these cases, the nearest values were chosen. Generally, I opted for qualitatively good measures over measures that were closer in time but of bad quality.

The level of wealth is operationalized through *GDP per capita*. The values are taken from the Pen World Table (Heston, Summers, and Aten 2011). Furthermore, the economic situation of a country is measured with the average *growth rate*. The data comes from the OECD online database. The amount of *social spending* is measured as a percentage of GDP.

[6] Exceptions: values for the 3rd wave in Canada, Turkey, and the USA are taken from the OECD Factbook 2009: Economic, Social and Environmental Statistics.

[7] Therefore, the within-variation might be a more valid measure than the between–country variation. On the other hand, one can argue that the Gini index based on household incomes might not be very sensitive to the use of different equivalence scales (Buhmann et al. 1988). This is true if the scales are not strongly elastic to family size.

The data is taken from the OECD online database. Finally, *unemployment rates* are used to measure the risk of becoming unemployed. The data is also taken from the OECD database.[8]

Results

I start with a simple model that identifies the variance components. The model includes dummy variables for each wave; i.e., it allows the fixed part of the intercept to vary between waves. For two reasons, the variance components cannot be compared to those of other studies. First, the structure of the data set differs from those of previous studies [observations (t) nested in groups (i), nested in countries (j)]. Second, the units of analysis are socio-demographic groups, and the dependent variable is the mean level of support for redistribution in each group.

Therefore, the variance between the units of analysis (between the groups) is much smaller than the variance usually estimated in individual-level analysis because the number of units is smaller (27 per country-time point compared to thousands of individuals in other studies) and because the use of mean levels as a dependent variable averages out extreme values.

However, the variance components estimated in model M_1 (Table 1) give the following intra-class-correlation coefficients: $ICC_{country}$= .29, ICC_{groups}=.03, and ICC_{time}=.67. Most of the variance (about 70%) is due to within-group variation between waves. A very small part of the variance (3%) is observed at the group level. About 30% of the variance results from differences between countries.

Model M_2 includes the variables that constitute the socio-economic groups. These variables control for differences between the groups. As indicated in the methodological section, one does not necessarily need to include dummy variables for each group to control for unobserved heterogeneity (27 dummy variables). Instead, one can use different functional forms of the group-constituting variables. In model M_2, I included dummy variables for *class* and *education* and a linear function of *age*. I also tried different functional forms of the age variable (quadratic, cubic, etc.), but the models were not significantly better than the one with a linear age function.

[8] Exceptions: Austria 1990, Estonia 1990, Turkey 1990, Turkey 2000; data is taken from the United Nations Data Base (International Development Indicators).

Table 1: Multilevel random effects models of support for redistribution

	M1	M2	M3	M4	M5	M6
Prim. Educ. (BE)		Ref.	Ref.	Ref.	Ref.	
Secon. Educ. (BE)		-0.160 ***	-0.065	-0.066	-0.065	
Tert. Educ. (BE)		-0.275 ***	-0.161 **	-0.162 ***	-0.162 ***	
High Class (BE)		Ref.	Ref.	Ref.	Ref.	
Middle Class (BE)		0.318 ***	0.199 ***	0.200 ***	0.201 ***	
Low Class (BE)		0.547 ***	0.318 ***	0.321 ***	0.323 ***	
Age (BE)		0.020	-0.001	-0.001	-0.000	
Left-Right (BE)			-0.176 ***	-0.174 ***	-0.172 ***	
Left-Right (W)			-0.112 ***	-0.112 ***	-0.096 ***	-0.098 ***
Income (BE)			-0.179 ***	-0.176 ***	-0.176 ***	
Income (W)			-0.087 **	-0.087 **	-0.065 *	-0.071 *
GDP/C (BE)				-0.157 +	-0.191	
GDP/C^2 (BE)				n.s.	0.012	
GINI (BE)				0.215 +	0.203	
GINI^2 (BE)				0.149 *	0.147 *	
Social Spend. (BE)				0.337 **	0.294 *	
Social Spend.^{2}(BE)				n.s.	-0.044	
Unempl. (BE)				0.117	0.151	
Growth (BE)				-0.015	-0.051	
GDP/C (W)					0.381 **	0.464 **
GDP/C^2 (W)					-0.053 **	-0.065 **
GINI (W)					-0.268 ***	-0.253 ***
GINI^2 (W)					0.077 *	0.075 +
Social Spend. (W)					-0.180 *	-0.167 *
Social Spend.^{2} (W)					-0.089 ***	-0.081 ***
Unempl. (W)					0.155 ***	0.163 ***
Growth (W)					0.017	0.003
Wave 1	-0.371 ***	-0.516 ***	-0.437 ***	-0.538 ***	-0.318 *	-0.171
Wave 2	0.071	-0.071	-0.007	-0.105	-0.019	0.077
Wave 3	0.293 **	0.148	0.180	0.082	-0.051	0.075
Group fixed eff.	no	no	no	no	no	yes
Variance Components						
Country	0.252 ***	0.255 ***	0.255 ***	0.145 ***	0.148 ***	no
Groups	0.025 ***	0.000 ***	0.000	0.000	0.000	no
Waves	0.566 ***	0.525 ***	0.497 ***	0.497 ***	0.481 ***	no
N (Country)	22	22	22	22	22	22
N(Groups)	593	593	593	593	593	593
N (Waves)	1501	1501	1501	1501	1501	1501
AIC	3552.5	3391.9	3317	3317.1	3290.4	2499
BIC	3584.4	3450.4	3397	3428.7	3455.1	2568

Notes: + p<.1, * p<.05, ** p<.01, *** p<.001. The significance level of 10% (+) is indicated only for country-level indicators, as the *df* for these tests are quite low. All continuous variables are *z*-standardized. The models are estimated with full maximum likelihood.

Source: Own calculations with Stata; Data: EVS and WVS (weighted data), macro-level data from different sources.

The model explains almost all variance at the group level, which is exactly the desired result. Remember that the reason for using a pseudo-panel approach is to control for unobserved heterogeneity between the units of analysis. Model M_1 tells us that there is unobserved heterogeneity between the groups. Obviously, model M_2 explains almost all the unobserved heterogeneity between groups, though the variance component is still significant. Consequently, we can conclude that the effects introduced in the following models should not suffer from omitted variable bias at the group level.

Model M_3 includes two additional group-level variables: *income* and *political orientation.*[9] In contrast to the group constituting variables from model M_2, which are, by definition, constant within groups, the variables *income* and *political orientation* can vary between and *within* groups. Therefore, I can decompose the effects into a within- and a between-unit effect. *Income (BE)* and *left-right (BE)* give the between-unit effects, and *income (W)* and *left-right (W)* give the within-unit effects. The between-units effects explain the variance at the group level, and the within-unit effects explain the variance between waves, i.e. the development of demand for redistribution over time. At the group level, the model now explains all variance. The variation over time (the within-group variation) is partly explained by the model. The residual variance is reduced by 5.3%; i.e., changes in political orientation and income can explain 5.3% of the within-group variance in demand for redistribution.

The estimated effects in Model M_3 are generally in line with the empirical evidence from individual-level analysis. Education and income have negative effects on the demand for redistribution. The demand for redistribution decreases the higher the social class of an individual (a group in my analysis) is. The ideological orientation also has the expected effect. However, an important observation is that the within-unit effects of income and political orientation are much smaller than the between-unit effects. With regard to causality, this result indicates that the effects estimated with cross-sectional data are overestimated because they suffer from omitted variable bias.

Model M_4 introduces the between-unit effects at the country level. I tested for quadratic terms of all country-level variables but excluded the non-significant ones (marked with n.s. in Table 1). With regard to the variance components, we can see that the introduced variables explain variance only at the country level. The variance between waves is unaffected by this variables (as it should be). The variance at the country level is reduced by 43%.

[9] I also tested for an effect of gender, but the effect was not at all significant.

The effect of GDP/C is significant at the 10% level and negative. This result is in line with those of other research. The model identifies a positive and non-linear effect of economic inequality: The higher the *Gini* index is, the higher the demand for redistribution will be. The effect size increases with the *Gini* index. This result supports the median voter hypothesis, similar to the results found by Dallinger (2010) and Finseras (2009). The model also identifies a significant association between social spending and public support for redistribution: The higher *social spending* (as a percentage of GDP is), the higher the demand for redistribution will be. This result is also in line with evidence from previous research. Unemployment and growth rates have no significant effects.

Model M_5 , finally, includes the within-country effects. Again, I tested for quadratic terms of all variables and present only the significant parameters.[10] I find a significant non-linear effect of economic wealth (Figure A1 in the appendix gives a graphical presentation of the between- and the within-effect). Demand for redistribution rises with economic wealth when economic wealth is low; if a certain level of wealth is reached, support for redistribution decreases with wealth. This result is in line with the saturation hypothesis and contradicts the estimated between-unit effect.

For economic inequality, I find a non-linear effect that is also quite different from the between-country effect. Demand for redistribution decreases with economic inequality when inequality is low. The higher economic inequality is, the less negative the effect of a change in economic inequality on support for redistribution is. If a certain level of inequality is reached, additional increases in inequality lead to an increase in the demand for redistribution (see Figure A1 in the appendix).

Social spending also has a significant effect that is particularly interesting. In contrast to previous research, I find a non-linear effect of social spending (see Figure A1). If social spending is low, demand for redistribution increases with social spending. If social spending is high, demand for redistribution decreases with social spending. Note that the between-country effect is positive. Thus, between countries, we observe high demand for redistribution in countries with high amounts of social spending. Within countries, we observe the opposite when social spending has reached a certain level. This might be some kind of counter-reaction to strong governmental expenses and can also be explained by the self-interest hypothesis: if social expenditures rise, net payers should demand less redistribution to lower their tax burden.

[10] I also included the quadratic terms of the between variables because the hybrid approach requires controlling for the mean levels of all variables in the model. Thus, I needed to include the quadratic terms of the between-variables when the quadratic terms of the within-variables were significant.

Finally, I also find a significant positive effect of unemployment rates on the demand for redistribution: the higher the rise in unemployment rates is, the higher the demand for redistribution is. This result supports the self-interest hypothesis and is in line with evidence from other research.

Model M_6 is a fixed effects model like the one used by Jaeger (2011). It includes fixed effects for each country and all 593 socio-demographic groups. Therefore, the effects of time-constant group-level variables and the between-country effects cannot be estimated. Obviously, the within-unit and the within-country parameters estimated in the fixed effects model M_6 are not identical to the ones estimated in the random effects model M_5. Why? A complete hybrid model, i.e. a model replicating exactly the within-estimates from a fixed effects model, would require including the cross-time means of *all* variables in the model.

My random effects model M_5 does not include the cross-time means of all variables in the model. For instance, I did not include the cross-time mean of the variable wave. I chose this model to get a model that is easy to interpret. The drawback of this modification is that the model does not exactly replicate the estimates from a fixed effects regression. However, I compared all effects estimated in model M_6 to the respective estimates in model M_5. There is no significant difference between the estimates; therefore, I chose the model that was easier to interpret. Nevertheless, a complete replication of the fixed effects estimates from model M_6 is possible.

Discussion

The model developed in this paper aimed to estimate country-level effects on public demand for redistribution. Therefore, a pseudo-panel data set was constructed. The units in this panel are socioeconomic groups that have been observed over a period of nearly 20 years (1990-2009). The groups are nested in countries. The structure of the data set allowed the decomposition of within- and between-unit effects at the group-level *and* at the country level. The purpose of this exercise was to disentangle causal effects (fixed effects based on the within-country/-unit variance) and effects based on cross-sectional "snapshots."

The group-level effects are not of direct interest in this paper but are control variables. Nevertheless, an important observation is that within- and between-effects at the group level are substantially identical. The within-effects are smaller, but the direction of the effects is the same. This observation meets the expectations, as we would expect that the effects based on cross-sectional variation are likely to be overestimated while the fixed effects should be unbiased. Nevertheless, we may conclude that observed cross-sectional differences between individuals are at least partly useful for drawing causal inferences; i.e., within- and between-unit effects are at least substantially similar.

When it comes to the country-level indicators, the results of my analysis suggest a different conclusion. Most of the between-country effects have the opposite sign from the respective within-country effect. This means that the results based on cross-sectional observations lead to substantially different conclusions than the results based on within-units (longitudinal) variation. The effect of social spending is a particularly interesting example to illustrate this.

The between-estimate suggests a positive relationship between demand for redistribution and social spending. This relationship is well-known from previous research. It is often interpreted as the socializing effect of welfare states: people who are used to high levels of redistribution support high levels of redistribution. Can this be called a causal effect? Probably not! It is quite likely that some cultural background characteristic might influence both support for redistribution and the realized level of redistribution. Perhaps it is the culturally determined preference for equality that affects the actual level of redistribution and support of redistribution.

The within-estimator of social spending suggests a different relation between social spending and support for redistribution. Controlling for the level of redistribution, we find that an increase in social spending lowers support for redistribution. This effect might be some kind of counter-reaction to increases in governmental expenditures. However, the important point is that the relationship within units is quite different from the relationship between units. Hence, the evidence from previous cross-sectional analysis (more social spending = more support for redistribution) probably suffers from omitted variable bias.

Comparison with other studies

I will now briefly discuss how my results relate to the results of previous research. Concerning the individual-level determinants (income and political orientation) I found the same effects as in the pseudo-panel data analysis by Jaeger (2011). The results of our analysis are also in line with evidence from other research.

I found a positive between-country effect of economic inequality. This result supports the median voter hypothesis and is in line with the results found by other researchers (Dallinger 2010; Dion and Birchfield 2010; Finseraas 2009). However, the within-country effect is negative; i.e., an increase in inequality leads to lower support for redistribution. The within-effect of economic inequality will become positive only if a country experiences a very strong increase in inequality (see Figure A1). The u-shaped effect is similar to the effect estimated in Jaeger's (2011) pseudo-panel model.

With regard to economic wealth, I found a negative between-country effect, reflecting a well-known relationship from previous research (Dallinger 2010; Jaeger 2011). However, the within-country effect of economic wealth that I found in my analysis is positive with a diminishing effect as wealth increases (see Figure A1). The results of my analysis, therefore, support the saturation hypothesis: increases in economic wealth are accompanied by greater demand for redistribution, but the effect diminishes as wealth keeps growing. However, it must be mentioned critically that the within-estimates from Jaeger's analysis are different from my estimates.[11]

The results achieved via the pseudo-panel approach seem to be particularly promising with regard to the effect of social spending. The between-country effect of social spending is positive in my analysis. This is a result that is well-known from previous research (Dallinger 2010; Finseraas 2009; Jaeger 2006b; Jakobsen 2011). The within-country effect in my analysis is negative, which is the same result that Jaeger (2011) reported in his pseudo-panel data analysis. The identical effect in my analysis and Jaeger's might be a good indicator that the identified relationship is a good estimator. Hence, we have to rethink the causal relationship between social spending and support for redistribution. The level of social spending might be positively correlated with support for redistribution, but an increase in the amount social spending is accompanied by a decrease in the demand for redistribution.

Finally, I also found a significant positive within-effect of unemployment rates. In the pseudo-panel data analysis from Jaeger (2011), he did not find a significant effect of unemployment. However, my result is in line with the results from Blekesaune (2007), who also indentify a positive within-country effect of unemployment rates on demand for redistribution, and with the results from Dallinger (2011) based on cross-sectional data.

Summary and Conclusion

In this paper, I extended the pseudo-panel approach applied by Mads Meier Jaeger. My model allows the estimation of within-unit (fixed) effects, which can be interpreted as causal effects. At the same time, I can make use of the advantages of multi-level analysis to explain the differences between countries. Therefore, I am able to investigate whether country differences

[11] One explanation for differences in the results might be the time period under investigation and the countries used for the analysis. Jaeger analyzes the period from 2002-2008, while I analyze the period from 1990-2009. The countries included in the data sets are also not identical, particularly as I included countries outside of Europe.

can be explained by compositional effects or whether they are actually explained by country-level characteristics.[12]

To employ a model like the one presented here, one needs a – preferably long – series of cross-sections for a sufficiently large number of countries. A pseudo-panel can be employed only if there is variance between the units of analysis (the socio-demographic groups) and if the changes in the dependent variable differ between these groups. Furthermore, the variables used to construct the socio-demographic groups have to meet the assumption of exogeneity.

The analysis showed that evidence based on cross-sectional data analyses will often lead to different conclusions than analyses with longitudinal data. One should conclude that causal inferences about the influence of country-level characteristics cannot be drawn from cross-sectional analysis. The proposed method offers the possibility of testing for longitudinal (causal) relationships without using data that has been aggregated to the country level.

With one exception, my results are identical to the results presented by Jaeger (2011). This might be a good indicator of the reliability of the proposed method because the database used and the time period analyzed in the two studies are quite different (Jaeger uses the ESS 2002-2008, I use the EVS/WVS 1990-2009). All in all, the pseudo-panel approach seems to be a promising way to overcome the problems resulting from a lack of genuine panel data for comparative research.

The negative effect of social spending, which has been identified in my analysis and in the analysis of Jaeger (2011), seems to be particularly interesting because it contradicts the results of previous research.

[12] An additional extension of the model would be the use of group-size weights. Weighting each group by its relative weight (in the respective country) would allow the consideration of compositional effects that result from different distributions of the group-constituting variables between countries.

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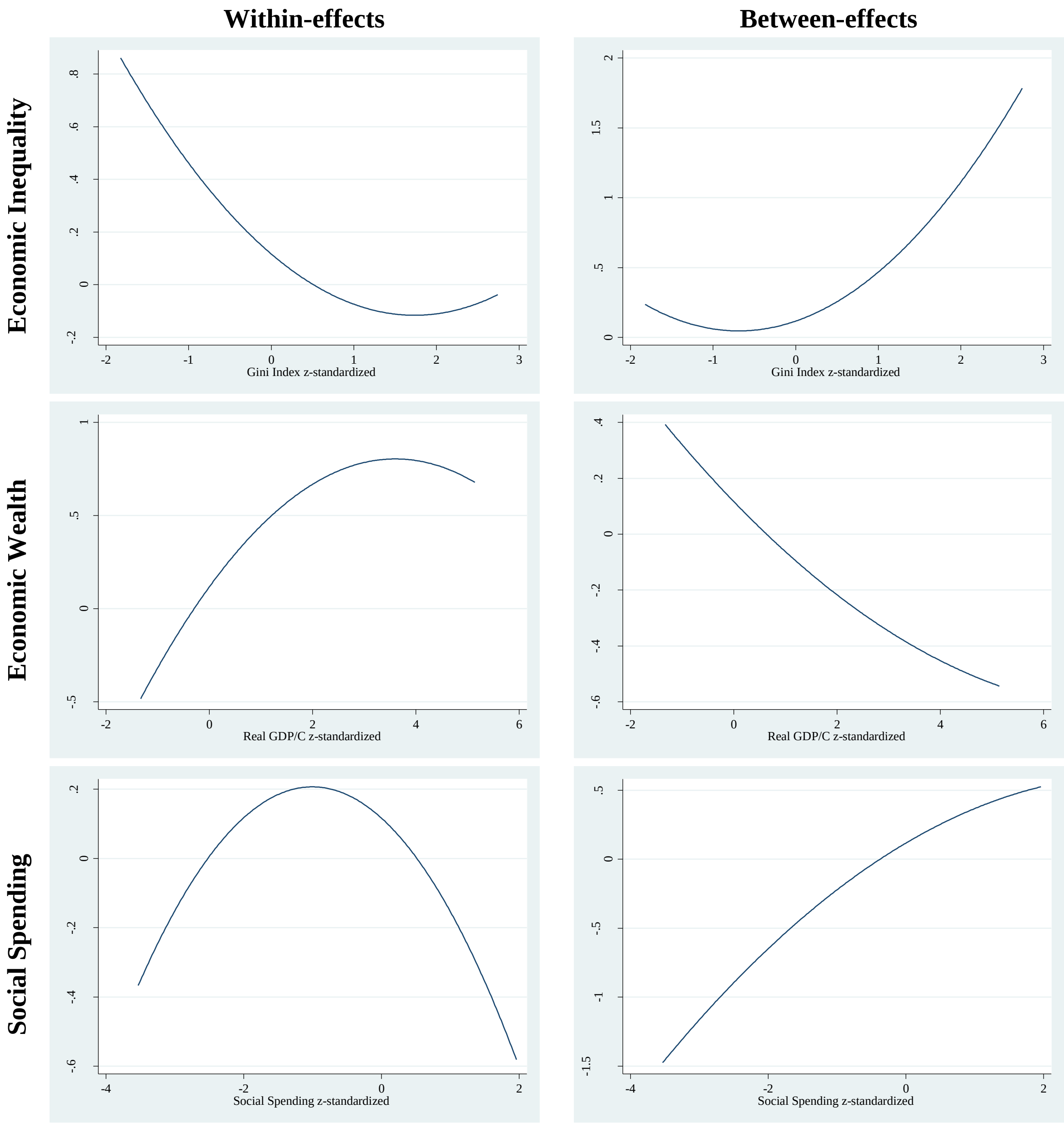
Appendix

Table A1: Number of socio-demographic groups by wave and country

Country	Wave			Total
	2	3	4	
Austria	27	27	27	81
Belgium	27	27	26	80
Czech Republic	27	27	26	80
Denmark	26		27	53
Estonia		23	26	49
Finland		27	24	51
France	26	26	27	79
Hungary			27	27
Ireland	26	25	27	78
Italy	27	27	26	80
Luxembourg		24	27	51
Netherlands	27	27	27	81
Norway	27	24	26	77
Poland	26	26	26	78
Portugal	26		26	52
Slovakia		26	25	51
Spain	27	27	27	81
Sweden		27	25	52
Turkey	27	27	27	81
Great Britain	27	27	27	81
United States	27	25	26	78
West Germany	27	26	27	80
Total	427	495	579	1,501

Figure A1: Within- and Between-effects of Country-level Variables



Notes: The tables give the predicted support for redistribution for average individuals (education = secondary, social class = middle, wave=2, all other variables = mean).
Source: Own calculations with Stata, predictions based on model M_5.

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