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Abstract

This study examines empirically the impact of income polarization on economic growth in an unbalanced panel of more than 70 countries during the 1960–2005 period. We calculate various polarization indices using existing micro-level datasets, as well as datasets reconstructed from grouped data on income distribution taken from the World Income Inequality Database. The results garnered for our preferred sample of countries suggest that income polarization has a negative impact on growth in the short term, while the impact of income inequality on growth is statistically insignificant. Our results are fairly robust to various model specifications and estimation techniques.

Keywords: economic growth, polarization, inequality, income distribution

JEL Classification: O11, O15, O4, D31.

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1. Introduction

In the last two decades, we have witnessed the emergence of an extensive body of theoretical and empirical literature on the impact of income distribution on economic growth. The theoretical literature has proposed numerous transmission channels through which income distribution — and in particular, income inequality — may affect growth, both positively and negatively. However, the empirical literature estimating the impact of income distribution on growth has not reached a consensus to date (for recent reviews, see Ehrhart, 2009 and Voitchovsky, 2009). Despite there being a large number of empirical studies, the substantive conclusions reached therein seem to be very sensitive to the quality or comparability of data used, to the sample coverage, and to the econometric specification (de Dominicis et al., 2008).

Voitchovsky (2009) examines theories postulating that income distribution affects growth, and usefully categorises them into two main groups. The theories belonging to the first group ('group-specific' theories) suggest that the origin of the mechanism through which distribution has an effect on growth is a situation of a specific income group (e.g. the poor, the rich, or the middle class). Growth-affecting mechanisms that originate from the situation of the poor include credit constraints, indivisibilities in investment, engagement in property crimes, and high fertility rates (see, e.g. Galor and Zeira, 1993; de la Croix and Doepke, 2003; Josten, 2003). Theories implying that the middle class plays an important role in linking distribution and growth include those modelling the level of redistribution through the median voter mechanism (see, e.g. Saint Paul and Verdier, 1996) and those stressing the size of domestic demand for manufactured goods (see, e.g. Zweimüller, 2000). Finally, there are theories suggesting that the rich may have a higher propensity to save, which boosts aggregate savings and capital accumulation within the economy (Bourguignon, 1981).

The second group of theories ('intergroup' theories) link distribution and growth and suggest the distance between different social or economic groups in society serves as the origin of the growth-influencing effect. One approach belonging to this group argues that distribution may have an adverse effect on trust and social capital (Josten, 2004). Another strand of this literature postulates that increasing social disparities, and in particular, rising social or economic polarization, lead to social discontent and create or intensify social conflicts (manifested in strikes, demonstrations, riots, or social unrest) and political instability (Esteban and Ray, 1994, 1999, 2011; Alesina and Perotti, 1996). This has direct and negative consequences for growth by disrupting market activities and labour relations and by reducing the security of property rights (Benhabib and Rustichini, 1996; Svensson, 1998; Keefer and Knack, 2002).

Voitchovsky's (2009) classification suggests that, in order to test empirically the different groups of theories that link distribution to growth, one should use appropriate distributional statistics that would capture distributional changes in appropriate parts of the distribution that relate to the growth-affecting mechanisms studied.[1] Nonetheless, the existing empirical literature has rarely conformed to this requirement, given the limited availability of distributional data. Most empirical studies have relied on the most popular inequality measure — namely, the Gini index — which is most sensitive to changes in the middle of the distribution.[2] One significant exception is a study of Voitchovsky (2005) that investigates how inequality at the top of the distribution (using the 90/75 percentile ratio) and at the bottom of the distribution (using the 50/10 percentile ratio) affects growth in a sample of micro-level data for 21 developed countries. Perhaps more importantly, some of the 'intergroup' theories linking distribution to social conflicts (Esteban and Ray, 1994, 1999, 2011) argue explicitly that the relevant distributional phenomenon that is growth affecting is not inequality, but polarization. Intuitively, polarization (defined formally below) is related but distinct from inequality and aims to capture the distance or separation between clustered groups in a distribution. Starting with the contributions of Foster and Wolfson (1992), Esteban and Ray (1994), and Wolfson (1994), a number of different polarization measures have been conceptualised.[3] Esteban (2002), Duclos et al. (2004), and Lasso de la Vega and Urrutia (2006) provide evidence that inequality and polarization indices differ empirically and in significant ways. For these reasons, using standard inequality indices like the Gini index in the empirical testing of at least some of the 'intergroup' theories to describe those mechanisms that link distribution and growth may lead to misleading conclusions.

The major aim of this study is to test directly if income polarization, as measured by the most popular polarization indices of Wolfson (1994) and Duclos et al. (2004), has an impact on economic growth. A major obstacle for such a study is the limited availability of cross-country data on income polarization, as polarization indices must be calculated from micro-level data pertaining to individual incomes. Relatively rich micro-level datasets — such as the Luxembourg Income Study (LIS) database — usually include only data for a small number of high-income economies. The present study removes the barrier of data availability

[1] See also Gobbin et al. (2007), who use simulation methods to show that inequality indices used in inequality-growth regressions should be theory-specific.
[2] A small number of studies perform robustness checks using the ratio of the top and bottom quintiles as an inequality measure (see, e.g. Barro, 2000; Forbes, 2000). In addition, Voitchovsky (2005) investigated how inequality at the top of the distribution (using the 90/75 percentile ratio) and at the bottom of the distribution (using the 50/10 percentile ratio) affects growth in a sample of micro-level data for 21 developed countries.
[3] The major contributions include Wang and Tsui (2000), Chakravarty and Majumder (2001), Zhang and Kanbur (2001), Anderson (2004), Duclos et al. (2004), Esteban et al. (2007), and Chakravarty and D'Ambrosio (2010).

by using a rich dataset consisting of grouped data (in the form of income quantile shares) taken from the UNU-WIDER (2008) World Income Inequality Database (WIID). The grouped data from the WIID are 'ungrouped' into individual income observations using the recently introduced 'ungrouping' algorithm of Shorrocks and Wan (2009). The polarization indices are then calculated and used in the empirical modelling of the impact of income polarization on economic growth. This procedure of constructing data allows us to obtain a relatively rich unbalanced panel of more than 70 countries (including not only high-income but also lower-middle-income and upper-middle-income economies) with observations from 1960 to 2005.

The only existing empirical work to estimate the impact of income polarization on economic growth is that of Ezcurra (2009), which used a family of polarization indices introduced by Esteban et al. (2007). It used regional data for 61 regions in the European Union and found that regional income polarization as measured in 1993 had a statistically significant and negative impact on the regional rate of economic growth over 1993–2003. The major advantage of the current study is its construction of a relatively rich panel dataset, which allows the study of the impact of polarization on growth in a standard framework for measuring growth determinants in a panel of countries.

This paper is structured as follows. The three strands of economic literature to which the paper is related are briefly reviewed in Section 2. The measures of polarization are introduced in Section 2.1. Section 2.2 gives an overview of the empirical literature on estimating the impact of inequality on growth, while Section 2.3 presents the main theoretical reasons for which we may expect income polarization to be inversely related to growth. Section 3 introduces the data and the methods used in constructing our income polarization observations. Section 4 reports empirical results, while Section 5 provides concluding remarks.

2. Theoretical and empirical background

2.1. What is the difference between 'polarization' and 'inequality'?

There are two main approaches to conceptualizing and measuring income polarization.[4] The first approach assumes that there may be an arbitrary number of groupings (or poles) in a dis-

[4] For a more complete overview of various polarization measures, see Esteban and Ray (2012). For a measurement of polarization along other than income dimensions like education, occupation, region, and others, see Gradín (2000). Reynal–Querol (2002) and Montalvo and Reynal–Querol (2005) analyse religious and ethnic

tribution; this approach was pioneered by Esteban and Ray (1991), and it was fully axiomatized and operationalized by Duclos et al. (2004) in the case of continuous distributions, and by Esteban and Ray (1994) and Estaban et al. (2007) in the case of discrete distributions. The second approach to measuring polarization essentially measures bipolarization as it is focusing on a division of a society into two groups with the median value (i.e. median income) as a cut-off. Measures of this type were first introduced in Foster and Wolfson (1992) and Wolfson (1994).[5] As stressed by Esteban and Ray (2012), all measures of polarization share some basic characteristics:

a) the impact of single individuals on polarization measures is negligible, since polarization describes the features and relative positions of social groups
b) with two or more groups, polarization increases when intragroup inequality is reduced
c) polarization rises when distances between groups are increased.

The conceptual difference between 'polarization' and 'inequality' is most evident when considering property b), which is violated by all standard inequality measures.

The first approach to measuring polarization, presented in its most complete form in Duclos et al. (2004), is formulated in the so-called identification–alienation framework. This framework suggests that polarization can be understood as the effect of two interrelated mechanisms: (1) alienation, which is felt by individuals from a given group (defined by income class, religion, race, education, etc.) toward individuals belonging to other groups, and (2) identification, which unites members of any given group. This approach assumes that polarization requires that individuals identify with other members of their socioeconomic group and feel alienation to members of other groups. By imposing a set of axioms, Duclos et al. (2004) derive the following family of polarization measures:

$$DER(\alpha) = \frac{1}{2\mu^{1-\alpha}} \iint f(x)^{1+\alpha} f(y)|y-x|dydx, \quad (1)$$

where $f(.)$ is the density function of the relevant distribution, μ is the mean income, and α is an ethical parameter expressing the weight given to the identification part of the framework. The DER family of indices assumes that the identification at income y is measured by $f(y)^{\alpha}$, while alienation between two individuals with incomes y and x is given by $|y - x|$. The axioms introduced by Duclos et al. (2004) require that α must be bounded in the following way: $0.25 \leq \alpha \leq 1$. When $\alpha = 0$, the DER index is equal to the popular Gini coefficient of inequality, which for a density f can be written as:

polarization; see also Permanyer (2012). Woo (2005) explores the consequences of polarization in terms of policymakers' preferences in collective decision-making.

[5] Foster and Wolfson's (1992) study has been published as Foster and Wolfson (2010).

$$G = \frac{1}{2\mu} \iint f(x) f(y) |y - x| dy dx. \quad (2)$$

Taking into account this relationship between the DER family and G, we may expect that the lowest admissible value for the DER index of $\alpha = 0.25$ should produce the values of the DER indices that are close in practice to the values of G, while setting α to 1 leads potentially to the highest disparity between G and the DER indices.

The second approach to constructing polarization indices — that is, the bipolarization approach of Wolfson (1994) and Foster and Wolfson (2010) — measures polarization as a distance from a given distribution to the degenerate symmetric bimodal distribution located at the extremes of the distribution support. In particular, the polarization measure proposed by Wolfson (1994) is defined as follows:

$$W = \frac{2\mu}{m} \left[\frac{\mu_H - \mu_L}{\mu} - G \right], \quad (3)$$

where m is the median income, while μ_H and μ_L are the means of incomes, respectively, above and below the median income.

The major empirical studies using the DER family of indices, the W index, and other polarization measures include analyses for Spain (Gradín, 2000, 2002), China (Zhang and Kanbur, 2001), Uruguay (Gradín and Rossi, 2006), Russia (Fedorov, 2002), Italy (Massari et al., 2009), the European Union (Ezcurra et al., 2006), the Central and Eastern European countries (Ezcurra et al., 2007), cross-country analyses (Ravallion and Chen, 1997; Seshanna and Decornez, 2003; Duclos et al., 2004; Esteban et al., 2007), and a kernel density estimation study for the UK (Jenkins, 1995).

2.2. Evidence on the impact of income inequality on growth

Most of the early empirical studies using cross-sectional ordinary least squares (OLS) estimation has found a negative effect of inequality on growth (see, e.g. Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Clarke, 1995; Deininger and Squire, 1998). On the other hand, studies using cross-country panel data and panel data estimation techniques have often found, rather, a positive effect (Li and Zou, 1998; Forbes, 2000). More recent studies suggest that changes in inequality in both directions may be associated with lower growth (Banerjee and Duflo, 2003), or that the effect of inequality on growth is nonlinear — that is, positive for high-income countries, but negative for low-income countries (Barro, 2000; Lin et al., 2009).

Using a sample of micro-level data for 21 developed countries, Voitchovsky (2005) found that inequality in the upper part of the distribution associates positively with growth, while inequality at the lower end adversely relates to growth. Herzer and Vollmer (2012) used heterogeneous panel cointegration techniques to estimate the long-term relationship between inequality and growth and found the effect of inequality to be negative. Andrews et al. (2011) found that there is no relationship between income inequality as measured by top income shares and economic growth in a panel of 12 developed countries, analysed in the period covering almost all of the 20th century; however, they also found that after 1960, there is a positive association between top income shares and economic growth.

Potential explanations for these conflicting results include the sensitivity of empirical outcomes to the sample used and econometric methods employed, poor quality or comparability of inequality data, and the inability of empirical literature to capture the complex inequality–growth interrelations postulated by theory (Voitchovsky, 2009).

2.3. How might polarization affect economic growth?

The recent theoretical literature has linked polarization to intensity of social conflicts (Esteban and Ray 1994, 1999, 2011). In particular, Esteban and Ray (2011) propose a behavioural theory of conflict across social groups, which implies that the equilibrium intensity of conflict is linearly related to three distributional measures: a polarization index of Esteban and Ray (1994), the Herfindahl–Hirschman fractionalization index (Hirschman, 1964), and the Gini index of inequality. Esteban et al. (2012) used the theory to test the impact of ethnic divisions on conflict and found ethnic polarization to relate positively to the intensity of social conflicts as measured by the death toll in civil wars.[6] However, as stressed by Esteban and Ray (2011), their model can be used not only to study the impact of ethnic polarization, but also of polarization in other domains (in particular, strictly economic ones), which can manifest in strikes, demonstrations, riots, assassinations, and political instability. This link between economic polarization and conflict has direct consequences for growth, as several theories suggest that social conflicts and political instability may affect growth negatively by disrupting market activities and labour relations and by reducing the security of property rights (Benhabib and Rustichini, 1996; Svensson, 1998; Keefer and Knack, 2002).

[6] The effect of fractionalization is also positive, but less statistically significant. On the other hand, the Gini index appears to affect conflicts negatively. In general, the empirical evidence on the impact of inequality between individuals on social conflict is at best mixed (Østby, 2011).

From another point of view, polarization has often been associated with the ‘disappearing of the middle class’ — a phenomenon observed in the US and the UK in the 1980s (Wolfson 1994; Jenkins, 1995). Indeed, if incomes concentrate around two opposite distributive poles, then the size of the middle class has to decrease. Various economic theories suggest that a stable and sizable middle class is a source of new entrepreneurs, transmits ‘middle class values’ associated with increased savings and promoting human capital, and creates demand for quality consumer goods, which boosts the overall level of investment and production (Banerjee and Duflo, 2008). Therefore, high or increasing level of bi-polarization may affect growth in a negative way.[7]

3. Data

3.1. Income polarization data

The paper uses two samples of income polarization observations. The smaller sample (LIS sample) comes from the Luxembourg Income Study (LIS) database, which provides internationally comparable micro-level data for a number of mostly high-income countries. Using LIS data, we can directly compute polarization measures for 35 countries in five-year intervals over 1970–2005.[8] The total number of polarization observations computed from the LIS data is 152; however, for most countries, the number of observations is rather small: for 17 countries, we have fewer than five observations.[9] We computed our polarization measures (the DER indices for a range of values of α and W index) for household disposable income, equivalised using the square-root scale, and weighted with LIS household sample weights multiplied by the number of persons in the household. Following common practice (see, e.g. Duclos et al., 2004), we excluded negative incomes and incomes more than 50 times larger

[7] A small number of empirical studies examine the impact of middle class size on growth, using income shares of the third or the third and fourth quintiles (see, e.g. Alesina and Perotti, 1996; Panizza, 2002). However, as shown by Wolfson (1994), the income shares of the middle quintile groups are not necessarily consistent with the concepts of polarization and the ‘disappearing middle class’.

[8] When there is no LIS data for a given year (e.g. 1995), we use data for the last available year over the previous period (i.e. 1991–1995). In a few cases, we obtain polarization indices using linear interpolation (see Appendix C).

[9] In our empirical models in Section 4.2.2, we exclude countries that have only a single polarization observation. For this reason and owing to the limited availability of data for our control variables, the number of observations used from the LIS sample was reduced to 132.

than the average income. The values of the polarization indices used in our empirical models are presented in Appendix C.

Compared to most studies that estimate the impact of income distribution on growth, the size of our LIS sample is rather small. Further, the sample contains mostly advanced Western economies for which the theoretical mechanisms linking polarization and growth described in Section 2.3. may be less relevant. For these reasons, we extend the LIS sample by using information from the UNU-WIDER (2008) World Income Inequality Database (WIID). The WIID database contains income distribution data on 161 countries over the 1960–2005 period. The Gini index of inequality is available for 5,313 observations in the WIID, but in 2,742 cases, we have also additional information on quintile or decile shares. We use these grouped data to reconstruct individual income observations from which polarization indices can be computed. To this end, we use an 'ungrouping' algorithm introduced recently by Shorrocks and Wan (2009), which allows us to construct synthetic samples of individual incomes from grouped income distribution data such as income quintile shares.[10] As shown by Shorrocks and Wan (2009), synthetic samples constructed using their algorithm allow for a very precise estimation of some of the popular inequality indices, including the Gini index. In Appendix B, we present a simulation study showing that the values of polarization indices DER and W can be estimated with satisfactory precision from individual-level data obtained via the Shorrocks–Wan method.

We used information from the WIID database, as per the following criteria. Only data for countries or periods not available in the LIS database were retained. We excluded all information of the lowest quality according to the WIID ranking and retained only those quantile shares based on disposable incomes. If data on both quintile and decile shares were available, we used decile shares. Finally, if there were no data for a given year we used data for the last available year in the preceding five-year period. Using these criteria and applying the Shorrocks–Wan 'ungrouping' algorithm, we were able to construct an additional 254 polarization observations. The values of polarization measures computed through our approach are presented in Appendix C.

Our larger sample (LIS + WIID) adds the estimates based on data constructed from the WIID database to the estimates from the LIS database. The total number of observations is

[10] See Appendix A for a presentation of the Shorrocks–Wan 'ungrouping' algorithm. Recent applications of the algorithm include constructing individual-level wealth data for measuring the level and distribution of global wealth (Davies et al., 2011).

406.[11] We also include in our dataset estimates of the Gini index of inequality estimated from the LIS database and taken from the WIID database.

3.2. Control variables

Our choice of control variables follows that of Voitchovsky (2005). They include the log of GDP per capita in constant 2000 USD (y); the share of gross fixed capital formation in GDP (*Invest*), averaged over the previous five-year period; and the average years of schooling in the population aged 25 and over (*AvgYrsSch*). The first two variables come from the World Bank's *World Development Indicators 2012*;[12] the third is taken from Barro and Lee (2010). Table 1 presents the descriptive statistics of our dataset.

[Please insert Table 1 about here]

4. Empirical analysis

4.1. Model and estimation methods

We use a five-year panel data model similar to models used in the inequality-growth literature (see, e.g. Barro, 2000; Forbes, 2000; Voitchovsky, 2005). The estimated equation takes the following form:

$$y_{it} - y_{i,t-1} = (\alpha - 1)y_{i,t-1} + \beta X_{it} + u_{it}, \tag{4}$$

where $i = 1, ..., N$ denotes a country and $t = 1, ..., T$ is time with t and $t - 1$ five years apart. The variable y is the log of real GDP per capita. The approximate five-year growth rate of a country between $t - 1$ and t is therefore given by the left-hand side of equation (4). The $y_{i,t-1}$ on the right-hand side controls for convergence, while the vector X_{it} includes current or lagged values of a number of control variables. In our case, it includes inequality or polarization indices measured at $t - 1$, the average share of gross fixed capital formation in GDP (*Invest*) over the five-year period ending in t, and the average years of schooling in the adult population measured at $t - 1$ (*AvgYrsSch*). The term u_{it} includes a period-specific effect h_t

[11] Owing to the limited availability of data on control variables, only 379 observations are used in empirical models based on the LIS + WIID sample.

[12] Data for Taiwan are taken from the National Statistics of Taiwan.

that captures shocks common to all countries, a country-specific effect n_t that captures time-invariant country characteristics, and an error term v_t.

The specification of the empirical model in equation (4) is based on the neoclassical growth model that aims to explain the long-term steady level of per capita output (Barro, 2000). The model implies that the explanatory variables have a permanent effect on the level of per-capita output, but only a temporary effect on the growth rate during the transition to the new steady state. However, as noted by Barro (2000), since transition to the new steady state can take a long time, the growth effects of changes in explanatory variables (e.g. changes in polarization) can persist for a notable length of time.

For a number of reasons, standard estimation methods — such as OLS or fixed-effects (FE) or random-effects (RE) models for panel data — are not appropriate for estimating equation (4) (see, e.g. Baltagi, 2008). The standard estimation methods do not account for the dynamic structure of the estimated equation, which is evident after moving the term $y_{i,t-1}$ from the left-side to the right-side of equation (4). The presence of a lagged dependent variable means that the OLS estimator is biased and inconsistent; moreover, OLS suffers from omitted variable bias, as it does not account for country-specific effects n_t. The FE estimator is biased and inconsistent for a panel that features a small number of time periods. For these reasons, the main approach in estimating equation (4) is to use the first-difference generalized method of moments (GMM) estimator (Arellano and Bond, 1991) and system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998, 2000). The first-difference GMM estimator accounts for problems relating to omitted variable bias, the presence of a lagged dependent variable, and the measurement error, by taking the first-difference of (3) and instrumenting for first-differences with sufficiently lagged values of $y_{i,t}$ and X_{it}. In addition to instrumenting for differenced variables using lagged levels, the system GMM estimator uses lagged differences to instrument for levels variables. Since the system GMM estimator uses time-series information more efficiently, it is expected to provide more efficient estimates of parameters in equation (4) than the first-difference GMM estimator and to reduce the finite sample bias. In our study, we use a system GMM estimator as our primary estimator.

One particular econometric problem in using the GMM estimators for dynamic panel models is because the estimators create a large number of instrumental variables; this can overfit endogenous variables, bias the estimates, and weaken the standard tests of instrument validity (Roodman, 2009). To overcome such difficulties, several approaches for reducing the number of instruments have been proposed, including the use of only certain, but not all, lags of regressors as instruments, or ‘collapsing’ (i.e. horizontal squeezing of the instrument matrix) instruments (Roodman, 2009). These approaches are, however, somewhat arbitrary in reducing the instrument count and do not allow for a more statistically informed and data-driven choice of instruments. For this reason, we follow the recent approach of Bontempi and Mammi (2012) that uses principal component analysis (PCA) on the instrument matrix to select the optimal instrument set. In practice, we retain in our empirical model the *n* largest principal components that account for at least 90% of variance in the original data. While checking the robustness of our results, we also use other techniques for reducing the number of instruments, such as lag-depth truncation or instrument ‘collapsing’.

4.2. Results

4.2.1. Trends in cross-country income polarization

Both types of polarization indices presented in Section 2.1 — namely, the DER family and the W index — bear some conceptual resemblance to inequality measures. It is, therefore, important to determine whether polarization and inequality are empirically different within our dataset. The issue of whether polarization and inequality can be distinguished empirically has been a matter of some debate. Ravallion and Chen (1997) and Zhang and Kanbur (2001) each argue that measures of polarization generally do not generate very different results from those of standard measures of inequality. However, Esteban (2002), Duclos et al. (2004), and Lasso de la Vega and Urrutia (2006) provide evidence that the two types of indices differ empirically in a significant way.

Figures 1–2 compare trends in the Gini index of inequality taken from the LIS and the WIID databases, and the DER(1) polarization index estimated using methods described in Section 3.1.[13] Figure 1 shows a group of countries for which trends in income inequality as measured by the Gini index and trends in income polarization as measured by the DER(1) index behave in substantially different ways.

[Please insert Figures 1–2 about here]

[13] It is worth recalling here that among the DER family of polarization indices, the DER(1) index is the most dissimilar to the Gini index of inequality.

For each of the countries analysed in Figure 1, we can observe some periods during which inequality and polarization trends clearly diverge. On the other hand, Figure 2 shows a group of countries for which both types of distributional phenomena evolve in a broadly similar way, according to our data. The comparison presented in Figures 1–2 suggests that income polarization is empirically distinguishable from income inequality in our sample, and that the effect of polarization on economic growth may be different from that of inequality.

In our data, the empirical relationship between other polarization measures (i.e. DER indices with smaller values of α and the W index) and the Gini index is closer. The correlation between the W measure and the Gini is 0.97. It is also at least 0.92 for the DER indices with α in the range of 0.25–0.5. However, the correlation between the DER(1) index and the Gini index is notably lower: 0.64. For this reason, we use the DER(1) index as our main polarization measure in the empirical models presented in the following section.

4.2.2. Does income polarization affect economic growth?

Table 2 presents the results of estimating equation (4) with the system GMM estimator for the LIS sample, with and without the transition countries.[14] As pointed out in Section 4.1. (see also Voitchovsky, 2005), equation (4) explains the long-term steady state level of income; hence, it is not optimal for modelling the evolution of transition economies that were subject to dramatic systemic transformations starting mostly in the early 1990s. For this reason, we analyse our samples with and without the transition countries to control for the impact of inappropriate model specification.

[Please insert Table 2 about here]

The results within Table 2 suggest that the impact of income inequality as measured by the Gini index on growth in the LIS sample (both including and excluding the transition countries) is negative, while the impact of income polarization as measured by the DER(1) index is positive. However, these relationships are not statistically significant. The impact of other polarization indices — namely, DER(0.5) and W — on growth is negative, but again it is not statistically significant. Overall, results from Table 2 suggest that in the LIS sample

[14] In the group of transition countries, we included Bulgaria, China, the Czech Republic, Estonia, Georgia, Hungary, the Kyrgyz Republic, Latvia, Lithuania, Moldova, Poland, Romania, Russia, the Slovak Republic, Slovenia, Turkmenistan, Ukraine, and Uzbekistan.

there is no statistically significant impact of either inequality (as measured by the Gini index) or polarization on economic growth.

Table 3 extends our analysis for the LIS + WIID sample, which covers many more countries (73 vs. 28) and observations (379 vs. 132) than the LIS sample. The results for the full LIS + WIID sample suggest that the impact of the Gini index and each polarization index used on growth is negative and statistically significant at the 10% significance level at least. The size of the effect is similar for the Gini index and for the DER polarization indices. According to these results, a one standard deviation increase in the Gini index, which is about 0.12 in our data, reduces the rate of growth over the subsequent five-year period by approximately 5.1%, while for the DER indices the effect is in the 5.1–5.5% range. In the case of the W index, the effect is stronger and equals 7.2%.

[Please insert Table 3 about here]

However, if we were to exclude the group of transition countries from the sample, most of the results would lose their statistical significance. The only exception is for the DER(1) index, for which the conceptual difference between polarization and inequality is the strongest among the members of the DER family. The test for second-order serial correlation suggests that serial correlation is not a problem for this model. Similarly, the Hansen test of joint validity of instruments generates positive results. Overall, the results from Table 3 suggest that the negative impact of income polarization, as measured by the DER(1) index, on economic growth is robust to the exclusion of transition countries from the LIS + WIID sample, while the effects of income inequality (as measured by the Gini) and other polarization measures are not robust to this sample selection. Considering that the estimated equation cannot capture the evolution of transition countries, which were definitely far from their long-term steady-state paths, especially since the 1990s, we conclude that Table 3 offers some evidence in favour of the view that income polarization, as measured by the DER(1) index, has an adverse impact on economic growth, and that the impact of income inequality, as measured by the Gini index, is not statistically significant.

4.3. Robustness checks

The sensitivity of our results to the choice of polarization indices can be further investigated by examining the data in Table 4. The coefficient on the DER(0.75) index remains negative and statistically significant at the 10% level for both samples used; this confirms that the negative effect of income polarization on growth is captured by the DER measures, giving more weight to the identification of individuals with their social groups (i.e. the DER measures with α closer to its upper admissible bound equal to 1). The coefficient on DER(0.25) loses its significance in the sample that excludes transition countries, similar to the Gini index and the DER(0.5) index (see Table 3).

Table 5 tests the sensitivity of the results to the method of reducing the instrument count for the system GMM estimator. We test a specification with the DER(1) index as our preferred polarization measure, and use the LIS + WIID sample that excludes transition countries. The coefficient on the DER(1) retains its significance (at the 10% level) for various instrument-reducing techniques, even when the number of instruments is largely reduced. However, the size of the effect of income polarization on growth is smaller if other methods of dealing with instrument proliferation are applied.

[Please insert Tables 4–5 about here]

In another check on the results, equation (4) was re-estimated using other estimation methods. Table 6 compares the estimation of the impact of income polarization on growth, using our preferred system GMM technique and other methods such as OLS, FE estimation, and first-difference GMM. As mentioned, neither OLS nor FE accounts for the presence of the lagged dependent variable in equation (4) and, therefore, they provide biased parameter estimates. The first-difference GMM estimator accounts for this and for other sources of endogeneity, but it exploits cross-sectional variation in the data in a less efficient way.

[Please insert Table 6 about here]

Table 6 shows that the sign of the DER(1) coefficient is negative for all estimation methods used. However, while the coefficient estimated by the first-difference GMM is insignificant, this may be caused by the previously mentioned features of this estimator. It is worth noting here that the OLS estimate is negative and statistically significant; however, it is substantially lower than our preferred system GMM estimate. The FE estimate is also negative, but statistically insignificant.

In another robustness check, we tested whether the results differ among various subsets of the LIS + WIID sample. In particular, we used the 2012 World Bank classification to divide the LIS + WIID sample into 1) high-income countries; 2) upper-middle-income countries; and 3) low and lower-middle-income countries. We then separately estimated equation (4) for each subset of countries, using the system GMM estimator. The estimated impact of polarization on growth was found to be insignificant in every case (results not reported).

We also estimated another popular specification of equation (4) with control variables taken from Forbes (2000).[15] The coefficient on the DER(1) index remained negative, but became insignificant. This result is consistent with the replication of Forbes' (2000) results by Roodman (2009), who showed that the significance of the Gini index in Forbes' specification depends on a high instrument count: when the number of instruments is reduced, the first-difference GMM estimator that she used generates insignificant results.

Overall, the results of robustness checks as presented in this section suggest that in our data, income polarization as measured by the DER(1) index has a short-term negative and fairly robust effect on economic growth.

5. Conclusions

The current study examined the empirical impact of income polarization on economic growth. We constructed an unbalanced panel of more than 70 countries, with observations from the 1960–2005 period. The most popular polarization indices — namely, the DER family of Duclos et al. (2003) and the W index of Wolfson (1994) — were calculated from the original micro-level datasets taken from the LIS database and from constructed synthetic micro-level datasets produced from grouped distributional data available in the WIID. In constructing synthetic datasets, we used the 'ungrouping' algorithm of Shorrocks and Wan (2009), which we found in our simulation study to be able, with satisfactory precision, to recover the values of polarization indices from grouped data.

The analysis of trends in polarization indices over time revealed some interesting patterns. In particular, we found that for a number of countries, the trend in income inequality as measured by the Gini index and the trend in the DER(1) polarization index move in opposite directions over long periods of time. This result suggests that in our data, income polarization is empirically distinguishable from income inequality.

[15] The specification used by Forbes (2000) replaces $Invest_t$ by the price level of investment (taken from the Penn World Tables) and $AvgYrsSch_{t-1}$ by male and female average years of secondary schooling (taken from the Barro–Lee dataset).

We found no statistically significant relationship between either income inequality or income polarization and economic growth in our smaller sample, which had come from the advanced economies represented in the LIS database. However, in our preferred larger sample consisting of data from the LIS and the WIID databases and excluding transition countries, we found a negative and statistically significant short-term effect of income polarization, as measured by the DER(1) index, on economic growth. In this sample, there is no statistically significant effect of inequality as measured by the Gini index on growth. These results seem to be fairly robust to various model specifications and estimation techniques.

Our conclusion calls for more empirical research on income polarization and, in particular, on various socioeconomic consequences of polarization. Such research could establish the specific channels or mechanisms through which income polarization may affect growth. Specifically, studies devoted to estimating the impact of income polarization on political instability, social conflicts, or similar socioeconomic phenomena already addressed in the existing theoretical literature seem worth undertaking.

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Tables and figures

Table 1. Descriptive statistics

	LIS sample				LIS + WIID sample			
Variables	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
y	9.7131	0.6053	8.1343	10.859	8.5726	1.4368	4.8064	10.8649
Invest	9.5937	1.8792	4.8195	13.19	7.9576	2.7733	1.1359	13.2701
AvgYrsSch	21.692	3.2490	16.528	31.958	22.356	5.6141	11.433	70.4741
Gini	0.2905	0.0552	0.196	0.502	0.3795	0.1167	0.196	0.714
DER(0.25)	0.2495	0.0362	0.186	0.382	0.2899	0.0619	0.1803	0.4739
DER(0.5)	0.2317	0.0276	0.179	0.341	0.2504	0.044	0.1639	0.4708
DER(0.75)	0.2249	0.0233	0.1655	0.329	0.2318	0.0441	0.1535	0.4962
DER(1)	0.2241	0.0223	0.1574	0.331	0.2251	0.0545	0.1454	0.5464
W	0.1219	0.0281	0.08	0.234	0.1709	0.0688	0.08	0.4773

Note: Income is observed between 1965 and 2010, while education, inequality, and polarization measures are between 1960 and 2005. Investment is observed between 1965 and 2010, and measures the average investment in the last five years. The sample size for the LIS sample is 132 observations, while that for the LIS + WIID sample is 379 observations.

Table 2. System GMM estimates, full LIS sample (columns 1–4), and excluding transition countries (columns 5–8)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$y_{t\text{-}1}$	-0.0235	-0.0303	-0.0106	-0.0201	-0.0762	-0.0538	-0.0617	-0.0384
	(0.0388)	(0.0464)	(0.0516)	(0.0363)	(0.1586)	(0.0905)	(0.1039)	(0.1042)
Invest_t	0.0138**	0.0123*	0.0135**	0.0142**	0.0085	0.0118**	0.0116**	0.0124*
	(0.0054)	(0.0060)	(0.0063)	(0.0060)	(0.0095)	(0.0050)	(0.0055)	(0.0063)
$\text{AvgYrsSch}_{t\text{-}1}$	-0.0015	-0.0113	-0.0083	-0.0082	-0.0109	-0.0031	0.0056	-0.0032
	(0.0140)	(0.0192)	(0.0183)	(0.0153)	(0.0215)	(0.0174)	(0.0143)	(0.0170)
$\text{Gini}_{t\text{-}1}$	-0.2304				-0.1523			
	(0.5294)				(0.6330)			
$\text{DER}(0.5)_{t\text{-}1}$		-0.0119				-0.5309		
		(1.1464)				(1.1894)		
$\text{DER}(1)_{t\text{-}1}$			1.1154				0.7096	
			(0.7578)				(0.8209)	
$\text{W}_{t\text{-}1}$				-0.1848				-0.3156
				(0.8439)				(0.9160)
N	132	132	132	132	116	116	116	116
Countries	28	28	28	28	22	22	22	22
Instruments	40	40	41	40	39	39	39	39
AR(1)	0.127	0.115	0.0855	0.133	0.206	0.0775	0.121	0.0884
AR(2)	0.248	0.234	0.270	0.247	0.269	0.309	0.328	0.299
Hansen	0.970	0.917	0.966	0.968	1.000	1.000	1.000	0.999

Note: The dependent variable is Δy_t, where $t - (t - 1)$ is a five-year period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by country are in parentheses. Two-step system GMM estimates with the Windmeijer (2005) correction. Period dummies are included but not reported. AR(1) and AR(2) denote *p*-values for tests of, respectively, first-order and second-order serial correlation. The number of instruments was chosen using PCA (see the main text). Hansen denotes the *p*-value of the Hansen test of the joint validity of instruments.

Table 3. System GMM estimates, full LIS + WIID sample (columns 1–4), and excluding transition countries (columns 5–8)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
y_{t-1}	-0.0195	-0.0134	-0.0041	-0.0243**	-0.0104	-0.0164	-0.0073	-0.0102
	(0.0151)	(0.0167)	(0.0193)	(0.0105)	(0.0122)	(0.0200)	(0.0086)	(0.0079)
Invest_t	0.0149***	0.0142***	0.0137***	0.0138***	0.0049	0.0064**	0.0063**	0.0069**
	(0.0045)	(0.0039)	(0.0040)	(0.0040)	(0.0036)	(0.0028)	(0.0026)	(0.0034)
AvgYrsSch_{t-1}	-0.0083	-0.0163	-0.0142	-0.0182*	0.0083	-0.0103	-0.0028	-0.0028
	(0.0100)	(0.0103)	(0.0109)	(0.0108)	(0.0102)	(0.0124)	(0.0074)	(0.0070)
Gini_{t-1}	-0.4313***				-0.0941			
	(0.1619)				(0.2933)			
$\text{DER}(0.5)_{t-1}$		-1.1528**				-1.2120		
		(0.5500)				(0.7326)		
$\text{DER}(1)_{t-1}$			-0.8366*				-0.8363**	
			(0.4635)				(0.3975)	
W_{t-1}				-1.0153**				-0.4324
				(0.4756)				(0.3836)
N	379	379	379	379	320	320	320	320
Countries	73	73	73	73	58	58	58	58
Instruments	57	58	59	58	54	54	56	55
AR(1)	0.261	0.236	0.183	0.226	0.000446	0.000308	0.000619	0.000361
AR(2)	0.0258	0.0333	0.0349	0.0357	0.0200	0.0485	0.0607	0.0369
Hansen	0.427	0.381	0.337	0.399	0.467	0.339	0.291	0.508

Note: See note to Table 2.

Table 4. System GMM estimates, full LIS + WIID sample (columns 1–2), and excluding transition countries (columns 3–4): other DER indices

	(1)	(2)	(3)	(4)
$y_{t\text{-}1}$	-0.0186	-0.0086	-0.0149	-0.0114
	(0.0159)	(0.0168)	(0.0135)	(0.0123)
$Invest_t$	0.0150^{***}	0.0150^{***}	0.0059	0.0069^{**}
	(0.0041)	(0.0035)	(0.0037)	(0.0029)
$AvgYrsSch_{t\text{-}1}$	-0.0128	-0.0118	0.0025	-0.0033
	(0.0090)	(0.0109)	(0.0094)	(0.0101)
$DER(0.25)_{t\text{-}1}$	-0.8406^{**}		-0.5283	
	(0.3290)		(0.4718)	
$DER(0.75)_{t\text{-}1}$		-1.1039^{*}		-1.1450^{*}
		(0.6582)		(0.6443)
N	379	379	320	320
Countries	73	73	58	58
Instruments	57	58	54	55
AR(1)	0.255	0.222	0.000452	0.000626
AR(2)	0.0275	0.0419	0.0284	0.0661
Hansen	0.341	0.504	0.424	0.224

Note: See note to Table 2.

Table 5. System GMM estimates, and LIS + WIID sample excluding transition countries: robustness to choice of instruments

	PCA (Table 3)	Collapsed Instruments	Collapsed third-lag instruments	Collapsed fourth-lag instruments
$y_{t\text{-}1}$	-0.0073	-0.0142	-0.0075	0.0063
	(0.0086)	(0.0312)	(0.0250)	(0.0214)
$Invest_t$	0.0063^{**}	0.0130^{***}	0.0135^{***}	0.0128^{***}
	(0.0026)	(0.0043)	(0.0033)	(0.0037)
$AvgYrsSch_{t\text{-}1}$	-0.0028	0.0149	-0.0050	-0.0056
	(0.0074)	(0.0191)	(0.0235)	(0.0172)
$DER(1)_{t\text{-}1}$	-0.8363^{**}	-0.5468^{*}	-0.4859^{*}	-0.4592^{*}
	(0.3975)	(0.3041)	(0.2638)	(0.2589)
N	320	320	320	320
Countries	58	58	58	58
Instruments	56	51	26	30
AR(1)	0.000619	0.000804	0.000529	0.000549
AR(2)	0.0607	0.0529	0.0554	0.0503
Hansen	0.291	0.235	0.104	0.156

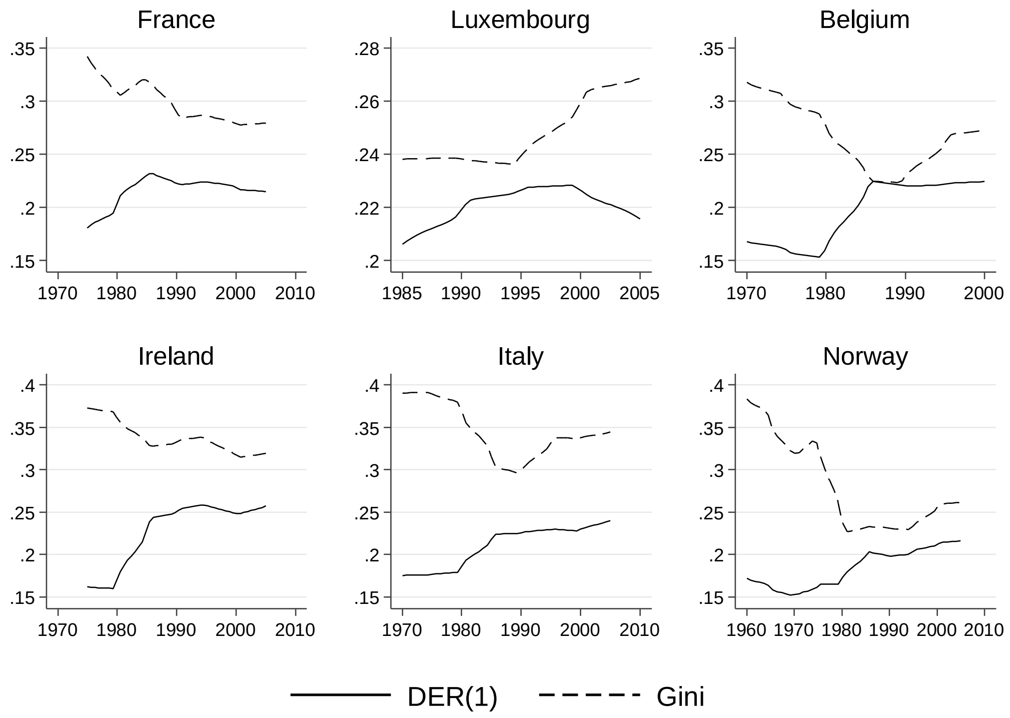
Note: See note to Table 2.

Table 6. System GMM estimates, and LIS + WIID sample excluding transition countries: robustness to estimation methods

	(1) System GMM	(2) OLS	(3) FE	(4) RE	(5) First-difference GMM
y_{t-1}	-0.0073	-0.0032	-0.2955***	-0.0088	-0.4615***
	(0.0086)	(0.0050)	(0.0461)	(0.0057)	(0.0920)
$Invest_t$	0.0063**	0.0047***	0.0076***	0.0042***	0.0067**
	(0.0026)	(0.0014)	(0.0023)	(0.0016)	(0.0031)
$AvgYrsSch_{t-1}$	-0.0028	-0.0022	-0.0096	0.0008	0.0220
	(0.0074)	(0.0028)	(0.0079)	(0.0029)	(0.0250)
$DER(1)_{t-1}$	-0.8363**	-0.2629**	-0.1467	-0.2750**	-0.5996
	(0.3975)	(0.1065)	(0.1757)	(0.1125)	(0.3970)
N	320	320	320	320	260
Countries	58		58	58	58
Instruments	56				56
AR(1)	0.000619				0.0146
AR(2)	0.0607				0.0990
Hansen	0.291				0.253

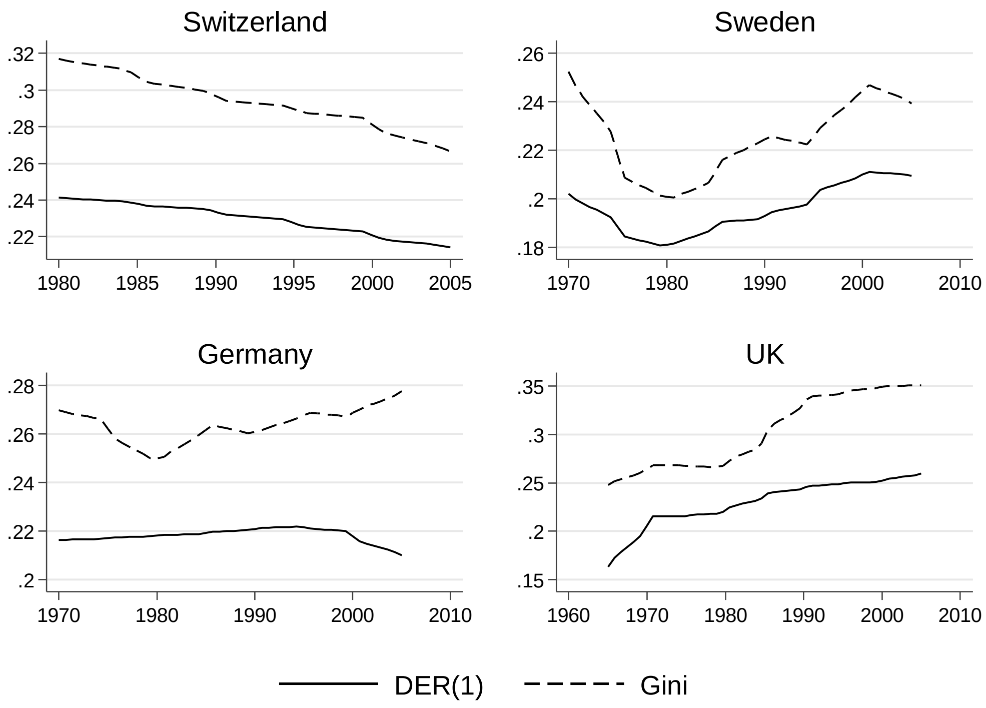
Note: See note to Table 2.

Figure 1. Empirical differences between the Gini index of inequality and the DER(1) index of polarization



Note: Curves are smoothed using kernel-weighted local polynomial smoothing.

Figure 2. Similarities between the Gini index of inequality and the DER(1) index of polarization



Note: See note to Figure 1.

Appendix A. Shorrocks–Wan data ungrouping algorithm (for eventual publication as electronic supplementary material online)

Shorrocks and Wan's (2009) algorithm for constructing individual-level income data from grouped data on income distribution consists of two stages. We assume that the grouped data come in a form of quantile or decile income shares, although they may also consist of Lorenz curve coordinates or frequencies with the associated bounds on income classes. Let the grouped data be given in m income classes with the corresponding mean income of class k given by μ_k^* and the proportion of the population in class k given by p_k^*. In the first stage of the algorithm, a chosen theoretical parametric model (e.g. lognormal [LN]) is fitted to the grouped data using, for example, maximum likelihood estimation. The parameter estimates for the model are next used, to generate a random initial micro-level data sample of a given size n. The resulting observations are grouped into m non-overlapping and ordered classes, with class k containing $m_k = n(p_k^* - p_{k-1}^*)$ observations. The ith synthetic observation in class k is denoted by x_{ki} ($k = 1, ..., m$; $i = 1, ..., m_k$), while the mean of class k in the generated sample is denoted by μ_k.

Stage two of the algorithm adjusts the initial sample so that the sample values match the original values of the grouped data. In this stage are two steps. The first step adjusts the generated observations so that for each income group, the original μ_k^* lies within the range of the generated sample values for that group. This is achieved by adjusting each $x_j \in (\mu_k, \mu_{k+1})$, $k = 1, ..., m - 1$ in the following way:

$$\hat{x}_j = \mu_k^* + \frac{\mu_{k+1}^* - \mu_k^*}{\mu_{k+1} - \mu_k}(x_j - \mu_k).$$

Appropriate adjustments are also made to observations smaller than μ_1 and larger than μ_{m-1}. In the second step of the second stage, the algorithm keeps the group cut-offs fixed and compresses the gaps between the sample values of the cut-offs (for details, see Shorrocks and Wan, 2009). The result of this procedure is a synthetic sample with means for each income class, μ_k, matching the original values μ_k^* taken from the grouped data.

For the choice of the parametric model to be used in the first stage of the algorithm, Shorrocks and Wan (2009) considered the LN, the Singh–Maddala (SM), and the Generalized Beta of the Second Kind (GB2) models.[16] Their simulations suggest that the LN model performs best, as it allows for reconstructing the Gini index of inequality from grouped data with a mean absolute percentage error (MAPE) lower than 0.2%. The results of using the LN

[16] See Kleiber and Kotz (2003) for a detailed presentation of these distributions.

model were less satisfactory for other inequality indices: MAPE for the Theil index was about 1%, while those for the mean logarithmic deviation (MLD) and the coefficient of variation squared were about 4% and 2.5%, respectively. The best results for the MLD index were achieved by performing only the first stage of the algorithm using the SM model. This suggests that the use of the algorithm in reconstructing polarization indices from grouped data should be preceded by an appropriate simulation study (see Appendix B).

Appendix B. Calculating polarization indices from grouped data: Monte Carlo simulation results (for eventual publication as electronic supplementary material online)

Tables B.1 and B.2 present the results of a simulation study devoted to measuring the accuracy of the Shorrocks–Wan ungrouping algorithm in reconstructing polarization indices from grouped data. The set-up of the simulation is as follows. From a representative sample of US incomes collected in the Current Population Survey (CPS) for the year 2010, 500 samples of sizes 1,000 and 2,000 were drawn. For each sample, quintile and decile shares were computed, as well as the 'true' values of the DER indices and the W index. The ungrouping algorithm was then applied to calculated income shares, and synthetic samples of sizes 1,000 and 2,000 were generated. Finally, the values of the polarization indices for the synthetic samples were computed, and then compared to the 'true' values. The performance of the algorithm was assessed using the mean absolute percentage error (MAPE) between the 'true' values of polarization indices and the values computed for 500 synthetic samples.

Table B.1. Mean absolute percentage error: DER(1) index

Grouping type	First stage only			Both stages		
	LN	SM	GB2	LN	SM	GB2
	1,000 observations, 500 replications					
Quintiles	6.40	11.72	17.50	0.74	3.19	23.71
Deciles	6.62	3.42	17.95	1.27	1.61	9.92
	2,000 observations, 500 replications					
Quintiles	6.90	11.95	16.08	0.89	2.88	29.71
Deciles	7.43	3.06	16.47	0.96	1.42	12.35

The simulation results for the DER(1) index are shown in Table B.1. The results suggest that the two-stage version of the algorithm with the lognormal (LN) model used in the first stage to generate a 'raw' sample performs best. In this setting, the MAPE for DER(1) was lower than 1% for both quintiles and deciles and samples of size 2,000. For other DER indices with $\alpha \in <0.25;1)$, the MAPE in this simulation set-up was always smaller than that for DER(1), and it ranged from 0.25% to 0.70%.

The results for the W polarization measures are presented in Table B.2. In this case, using both stages of the ungrouping algorithm with the LN model in the first stage was again, in general, the best scenario. The SM model seemed to give somewhat better results than the

LN model in the case of deciles, but it was much worse in the case of quintiles. The MAPE for the LN model and the samples of size 2,000 was less than 1.2%.

Table B.2. Mean absolute percentage error: W index

Grouping type	First stage only			Both stages		
	LN	SM	GB2	LN	SM	GB2
	1,000 observations, 500 replications					
Quintiles	3.81	2.83	66.81	1.47	3.35	11.72
Deciles	4.26	2.65	62.89	1.38	1.45	3.22
	2,000 observations, 500 replications					
Quintiles	3.51	4.74	66.93	1.16	3.43	11.71
Deciles	4.03	2.26	62.71	1.15	1.08	3.07

Overall, the results of the simulation suggest that the Shorrocks–Wan procedure is able to recover the values of polarization indices from grouped data with satisfactory accuracy. We have therefore used the algorithm with the LN model in the first stage to generate synthetic samples of size 2,000 in our construction of polarization indices (Section 3).

Appendix C. Inequality and polarization indices (for eventual publication as electronic supplementary material online)

Table C.1. The Gini coefficient

Country	1960	1965	1970	1975	1980	1985	1990	1995	2000	2005
Argentina	*0.463*	*0.360*	*0.364*	*0.368*	*0.425*	*0.435*	*0.444*	*0.474*	*0.479*	*0.501*
Australia					0.281	0.292	0.302	0.304	0.314	0.310
Austria						0.227	0.252	0.277	0.256	0.268
Bangladesh		*0.386*	*0.378*	*0.369*	*0.351*	*0.356*	*0.336*			
Belgium			*0.321*	*0.301*	*0.282*	0.226	0.222	0.266	0.275	
Bolivia							*0.525*	*0.579*	*0.633*	
Brazil	*0.572*	*0.589*	*0.606*	*0.625*	*0.597*	*0.589*	*0.605*	*0.603*	*0.586*	0.564
Bulgaria		*0.223*	*0.212*	*0.178*	*0.234*	*0.235*	*0.237*	*0.390*	*0.422*	
Canada	*0.321*	*0.315*	0.315	0.288	0.283	0.282	0.281	0.284	0.316	0.319
Chile							*0.540*	*0.545*	*0.595*	
China		*0.328*	*0.299*	*0.286*	*0.295*	*0.331*	*0.357*	*0.452*	*0.403*	*0.454*
Colombia			*0.504*	*0.475*	*0.585*	*0.560*	*0.534*	*0.566*	*0.574*	0.562
Costa Rica				*0.464*	*0.510*	*0.464*	*0.441*	*0.475*	*0.458*	*0.472*
Czech Rep.							0.206	0.256	0.262	0.267
Denmark						0.252	0.237	0.219	0.225	0.228
Dominican Rep.						*0.434*	*0.502*	*0.516*	*0.520*	*0.506*
Ecuador								*0.501*	*0.560*	*0.535*
El Salvador							*0.526*	*0.506*	*0.538*	*0.484*
Estonia								*0.353*	0.360	0.347
Finland			*0.308*	*0.267*	*0.214*	0.207	0.209	0.217	0.253	0.266
France				*0.352*	0.295	0.332	0.282	0.289	0.277	0.280
Georgia									*0.503*	*0.466*
Germany			0.271	0.264	0.244	0.266	0.258	0.270	0.266	0.280
Ghana							*0.518*	*0.509*		
Greece								0.348	0.332	0.325
Guatemala							*0.594*	*0.596*	*0.598*	0.504
Honduras									*0.511*	*0.566*
Hong Kong	*0.479*	*0.501*	*0.509*	*0.420*	*0.394*	*0.446*	*0.422*	*0.434*	*0.514*	
Hungary		*0.259*	*0.229*	*0.238*	*0.215*	*0.209*	0.283	0.321	0.292	0.291
India	*0.475*	*0.460*	*0.475*							
Indonesia			*0.439*	*0.436*	*0.433*	*0.404*	*0.387*	*0.416*	*0.396*	
Ireland				*0.374*	*0.366*	0.325	0.333	0.341	0.312	0.321
Israel					0.304	0.310	0.305	0.337	0.349	0.375
Italy			*0.390*	*0.392*	*0.375*	0.309	0.291	0.339	0.336	0.346
Jamaica							*0.582*	*0.613*	*0.540*	
Japan	*0.360*	*0.380*	*0.414*	*0.369*	*0.334*	*0.357*				
Korea, Rep.								*0.334*	*0.369*	0.310
Kyrgyz Rep.									*0.375*	*0.352*
Latvia								*0.309*	*0.350*	*0.359*
Lesotho							*0.630*	*0.690*		
Lithuania							*0.224*	*0.373*	*0.347*	*0.324*
Luxembourg						0.238	0.239	0.235	0.262	0.270
Malaysia			*0.512*	*0.531*	*0.506*	*0.478*	*0.491*	*0.500*		
Mauritania							*0.734*	*0.714*		

Mexico	*0.555*	*0.524*	*0.536*	*0.574*	*0.504*	0.433	0.467	0.502	0.499	0.468
Moldova							*0.242*	*0.365*	*0.405*	
Netherlands					*0.252*	0.228	0.263	0.256	0.230	0.264
New Zealand					*0.347*	*0.358*	*0.401*	*0.380*	*0.402*	
Nicaragua								*0.565*	*0.541*	*0.523*
Nigeria					*0.512*	*0.479*	*0.572*	*0.522*		
Norway	*0.388*	*0.360*	*0.305*	*0.350*	0.223	0.234	0.231	0.229	0.259	0.262
Pakistan		*0.365*	*0.329*	*0.349*	*0.369*					
Panama							*0.565*	*0.568*	*0.578*	*0.548*
Paraguay						*0.451*	*0.398*	*0.568*	*0.555*	*0.539*
Peru								*0.547*	*0.496*	0.477
Philippines		*0.499*	*0.474*	*0.466*	*0.460*	*0.455*	*0.436*	*0.533*	*0.494*	*0.479*
Poland						0.271	0.262	0.311	0.284	0.316
Portugal					*0.341*	*0.335*	*0.329*	*0.374*	*0.347*	
Romania							*0.229*	*0.311*	*0.303*	
Russian Fed.								*0.472*	0.453	
Slovak Rep.							0.189	0.250	*0.243*	*0.255*
Slovenia								0.229	0.232	0.231
Spain		*0.393*	*0.377*	*0.361*	0.320	0.312	0.304	0.351	0.336	0.316
Sri Lanka		*0.466*	*0.353*	*0.351*	*0.445*	*0.449*				
Sweden			0.260	0.214	0.196	0.211	0.228	0.220	0.251	0.237
Switzerland					0.319	0.308	0.296	0.289	0.283	0.263
Taiwan					0.267	0.271	0.271	0.284	0.289	0.305
Thailand			*0.438*	*0.428*	*0.440*	*0.452*	*0.498*	*0.440*	*0.448*	*0.427*
Turkey		*0.505*	*0.554*	*0.515*			*0.438*	*0.484*		
Turkmenistan							*0.262*	*0.358*		
Uganda								*0.522*	*0.546*	
Ukraine					*0.334*	*0.325*	*0.246*			
United Kingdom		*0.244*	0.268	0.268	0.265	0.296	0.338	0.343	0.350	0.351
United States				0.312	0.297	0.329	0.334	0.353	0.367	0.373
Uzbekistan							*0.280*	*0.333*		
Venezuela								*0.474*	*0.458*	*0.476*
Zambia							*0.776*	*0.647*	*0.666*	

Note: Values taken from the WIID database are marked in italics. The remaining values are calculated from the LIS database.

Table C.2. DER(1) polarization index

Country	1960	1965	1970	1975	1980	1985	1990	1995	2000	2005
Argentina	*0.300*	*0.168*	*0.198*	*0.167*	*0.196*	*0.211*	*0.226*	*0.218*	*0.215*	*0.214*
Australia					0.215	0.221	0.220	0.241	0.241	0.237
Austria						0.237	0.229	0.222	0.216	0.223
Bangladesh		*0.373*	*0.286*	*0.199*	*0.178*	*0.179*	*0.180*			
Belgium			*0.169*	*0.160*	*0.150*	0.227	0.219	0.222	0.225	
Bolivia							*0.234*	*0.322*	*0.409*	
Brazil	*0.307*	*0.331*	*0.354*	*0.433*	*0.327*	*0.307*	*0.352*	*0.358*	*0.302*	0.266
Bulgaria		*0.149*	*0.156*	*0.144*	*0.161*	*0.147*	*0.184*	*0.198*	*0.203*	
Canada	*0.156*	*0.156*	0.212	0.206	0.206	0.216	0.215	0.214	0.228	0.226
Chile							*0.253*	*0.272*	*0.361*	
China		*0.169*	*0.162*	*0.161*	*0.164*	*0.174*	*0.172*	*0.212*	*0.192*	*0.209*
Colombia			*0.533*	*0.218*	*0.311*	*0.276*	*0.241*	*0.280*	*0.278*	0.263
Costa Rica				*0.207*	*0.237*	*0.204*	*0.187*	*0.202*	*0.197*	*0.207*
Czech Rep.							0.216	0.232	0.236	0.240
Denmark						0.213	0.209	0.208	0.210	0.210
Dominican Rep.						*0.298*	*0.237*	*0.240*	*0.234*	*0.227*
Ecuador								*0.237*	*0.264*	*0.238*
El Salvador							*0.232*	*0.214*	*0.227*	*0.201*
Estonia								*0.161*	0.261	0.253
Finland			*0.160*	*0.152*	*0.145*	0.189	0.190	0.200	0.202	0.207
France				*0.176*	0.202	0.238	0.219	0.226	0.218	0.214
Georgia									*0.214*	*0.192*
Germany			0.216	0.217	0.218	0.219	0.221	0.222	0.219	0.208
Ghana							*0.225*	*0.216*		
Greece								0.234	0.237	0.236
Guatemala							*0.327*	*0.340*	*0.353*	0.317
Honduras									*0.222*	*0.258*
Hong Kong	*0.306*	*0.248*	*0.271*	*0.187*	*0.187*	*0.197*	*0.223*	*0.195*	*0.228*	
Hungary		*0.159*	*0.151*	*0.147*	*0.147*	*0.149*	0.232	0.237	0.251	0.240
India	*0.230*	*0.220*	*0.228*							
Indonesia			*0.262*	*0.306*	*0.349*	*0.204*	*0.203*	*0.214*	*0.199*	
Ireland				*0.162*	*0.159*	0.240	0.251	0.262	0.244	0.260
Israel					0.216	0.221	0.222	0.226	0.233	0.236
Italy			*0.175*	*0.176*	*0.180*	0.224	0.225	0.231	0.227	0.243
Jamaica							*0.290*	*0.397*	*0.231*	
Japan	*0.178*	*0.170*	*0.180*	*0.169*	*0.160*	*0.164*				
Korea, Rep.								*0.158*	*0.160*	0.207
Kyrgyz Rep.									*0.185*	*0.184*
Latvia								*0.163*	*0.185*	*0.188*
Lesotho							*0.409*	*0.546*		
Lithuania							*0.149*	*0.173*	*0.164*	*0.163*
Luxembourg						0.203	0.221	0.227	0.229	0.213
Malaysia			*0.272*	*0.264*	*0.228*	*0.213*	*0.231*	*0.232*		
Mauritania							*0.539*	*0.527*		
Mexico	*0.334*	*0.239*	*0.246*	*0.290*	*0.216*	0.259	0.277	0.331	0.316	0.264
Moldova							*0.150*	*0.174*	*0.182*	
Netherlands					*0.232*	0.232	0.220	0.210	0.208	0.221

New Zealand					*0.161*	*0.162*	*0.173*	*0.170*	*0.181*	
Nicaragua								*0.254*	*0.239*	*0.238*
Nigeria					*0.241*	*0.228*	*0.278*	*0.246*		
Norway	*0.174*	*0.161*	*0.149*	*0.165*	0.166	0.206	0.196	0.203	0.213	0.217
Pakistan		*0.179*	*0.178*	*0.187*	*0.200*					
Panama							*0.257*	*0.260*	*0.277*	*0.242*
Paraguay						*0.205*	*0.185*	*0.306*	*0.243*	*0.235*
Peru								*0.256*	*0.211*	0.215
Philippines		*0.232*	*0.231*	*0.236*	<u>*0.272*</u>	*0.307*	*0.230*	*0.271*	*0.237*	*0.227*
Poland						0.217	0.224	0.228	0.221	0.227
Portugal					*0.172*	<u>*0.173*</u>	*0.174*	*0.187*	*0.192*	
Romania							*0.151*	*0.163*	*0.159*	
Russian Fed.								*0.200*	0.195	
Slovak Rep.							0.208	0.216	*0.157*	*0.159*
Slovenia								0.211	0.206	0.206
Spain		*0.182*	<u>*0.172*</u>	*0.163*	0.225	<u>0.225</u>	0.225	0.241	0.240	0.223
Sri Lanka		*0.206*	*0.183*	*0.177*	*0.224*	*0.233*				
Sweden			0.205	0.187	0.178	0.190	0.192	0.200	0.212	0.209
Switzerland					0.242	<u>0.238</u>	0.234	<u>0.228</u>	0.221	0.213
Taiwan					0.222	0.226	0.219	0.211	0.215	0.221
Thailand			*0.202*	*0.188*	<u>*0.192*</u>	*0.196*	*0.225*	*0.218*	*0.227*	*0.211*
Turkey		*0.259*	*0.285*	*0.227*			*0.201*	*0.237*		
Turkmenistan							*0.203*	*0.173*		
Uganda								*0.229*	*0.262*	
Ukraine					*0.196*	*0.257*	*0.160*			
United Kingdom		*0.153*	0.215	0.215	0.220	0.238	0.245	0.250	0.251	0.261
United States				0.208	0.205	0.215	0.215	0.222	0.236	0.234
Uzbekistan							*0.159*	*0.167*		
Venezuela								*0.204*	*0.196*	*0.198*
Zambia							*0.595*	*0.443*	*0.461*	

Note: Values calculated using the Shorrocks–Wan ungrouping algorithm from the grouped WIID data are marked in italics; interpolated values are underscored. The remaining values are directly calculated from LIS micro-level data.

Table C.3. The W polarization index

Country	1960	1965	1970	1975	1980	1985	1990	1995	2000	2005
Argentina	*0.163*	*0.157*	*0.158*	*0.166*	*0.204*	*0.199*	*0.194*	*0.207*	*0.211*	*0.240*
Australia					0.127	0.129	0.136	0.141	0.142	0.142
Austria						0.098	0.109	0.119	0.104	0.106
Bangladesh		*0.268*	*0.219*	*0.169*	*0.152*	*0.148*	*0.140*			
Belgium			*0.132*	*0.126*	*0.119*	0.097	0.097	0.108	0.111	
Bolivia							*0.245*	*0.302*	*0.358*	
Brazil	*0.243*	*0.284*	*0.324*	*0.335*	*0.334*	*0.313*	*0.330*	*0.314*	*0.298*	0.273
Bulgaria		*0.085*	*0.083*	*0.080*	*0.114*	*0.098*	*0.100*	*0.148*	*0.158*	
Canada	*0.135*	*0.140*	0.132	0.121	0.121	0.119	0.120	0.122	0.131	0.134
Chile							*0.252*	*0.243*	*0.275*	
China		*0.136*	*0.126*	*0.118*	*0.140*	*0.157*	*0.177*	*0.228*	*0.185*	*0.248*
Colombia			*0.227*	*0.203*	*0.287*	*0.271*	*0.255*	*0.254*	*0.285*	0.263
Costa Rica				*0.213*	*0.234*	*0.197*	*0.202*	*0.220*	*0.215*	*0.219*
Czech Rep.							0.078	0.105	0.107	0.109
Denmark						0.098	0.095	0.089	0.091	0.093
Dominican Rep.						*0.298*	*0.232*	*0.246*	*0.249*	*0.238*
Ecuador								*0.222*	*0.250*	*0.249*
El Salvador							*0.244*	*0.236*	*0.268*	*0.228*
Estonia								*0.150*	0.155	0.151
Finland			*0.135*	*0.111*	*0.090*	0.083	0.084	0.085	0.101	0.103
France				*0.162*	0.117	0.119	0.114	0.118	0.115	0.112
Georgia									*0.241*	*0.215*
Germany			0.109	0.105	0.103	0.105	0.103	0.111	0.105	0.110
Ghana							*0.257*	*0.246*		
Greece								0.150	0.149	0.140
Guatemala							*0.306*	*0.299*	*0.292*	0.243
Honduras									*0.239*	*0.277*
Hong Kong	*0.194*	*0.211*	*0.199*	*0.171*	*0.169*	*0.193*	*0.198*	*0.191*	*0.215*	
Hungary		*0.109*	*0.098*	*0.098*	*0.088*	*0.087*	0.113	0.130	0.119	0.115
India	*0.231*	*0.198*	*0.230*							
Indonesia			*0.139*	*0.206*	*0.273*	*0.168*	*0.158*	*0.174*	*0.168*	
Ireland				*0.165*	*0.161*	0.154	0.151	0.148	0.133	0.137
Israel					0.139	0.141	0.140	0.152	0.159	0.171
Italy			*0.168*	*0.165*	*0.155*	0.138	0.126	0.145	0.143	0.142
Jamaica							*0.283*	*0.285*	*0.268*	
Japan	*0.152*	*0.163*	*0.192*	*0.155*	*0.153*	*0.152*				
Korea, Rep.								*0.134*	*0.161*	0.131
Kyrgyz Rep.									*0.173*	*0.168*
Latvia								*0.120*	*0.121*	*0.140*
Lesotho							*0.355*	*0.477*		
Lithuania							*0.096*	*0.159*	*0.140*	*0.127*
Luxembourg						0.102	0.104	0.101	0.114	0.110
Malaysia			*0.237*	*0.260*	*0.237*	*0.222*	*0.231*	*0.237*		
Mauritania							*0.484*	*0.452*		
Mexico	*0.282*	*0.275*	*0.264*	*0.290*	*0.248*	0.198	0.202	0.227	0.234	0.209
Moldova							*0.102*	*0.170*	*0.183*	
Netherlands					*0.102*	0.097	0.106	0.108	0.095	0.103

New Zealand					*0.157*	*0.162*	*0.183*	*0.169*	*0.185*	
Nicaragua								*0.281*	*0.245*	*0.234*
Nigeria					*0.279*	*0.228*	*0.285*	*0.243*		
Norway	*0.165*	*0.148*	*0.124*	*0.142*	0.089	0.094	0.090	0.085	0.091	0.091
Pakistan		*0.156*	*0.135*	*0.139*	*0.145*					
Panama							*0.293*	*0.297*	*0.303*	*0.280*
Paraguay						*0.210*	*0.187*	*0.277*	*0.272*	*0.258*
Peru								*0.244*	*0.238*	0.228
Philippines		*0.263*	*0.202*	*0.197*	*0.200*	*0.203*	*0.200*	*0.238*	*0.244*	*0.234*
Poland						0.116	0.108	0.120	0.112	0.126
Portugal					*0.146*	*0.143*	*0.141*	*0.149*	*0.135*	
Romania							*0.094*	*0.124*	*0.125*	
Russian Fed.								*0.209*	0.189	
Slovak Rep.							0.075	0.097	*0.099*	*0.103*
Slovenia								0.093	0.092	0.094
Spain		*0.180*	*0.167*	*0.154*	0.137	0.134	0.130	0.157	0.146	0.140
Sri Lanka		*0.197*	*0.152*	*0.142*	*0.176*	*0.177*				
Sweden			0.100	0.090	0.081	0.084	0.090	0.080	0.097	0.094
Switzerland					0.114	0.113	0.112	0.112	0.112	0.108
Taiwan					0.112	0.111	0.115	0.117	0.121	0.128
Thailand			*0.178*	*0.188*	*0.196*	*0.203*	*0.237*	*0.214*	*0.228*	*0.218*
Turkey		*0.238*	*0.327*	*0.236*			*0.200*	*0.218*		
Turkmenistan							*0.126*	*0.160*		
Uganda								*0.256*	*0.242*	
Ukraine					*0.119*	*0.107*	*0.109*			
United Kingdom		*0.095*	0.113	0.110	0.116	0.133	0.150	0.151	0.152	0.145
United States				0.130	0.129	0.150	0.151	0.159	0.153	0.157
Uzbekistan							*0.120*	*0.149*		
Venezuela								*0.215*	*0.218*	*0.215*
Zambia							*0.437*	*0.327*	*0.340*	

Note: See note to Table C.2.