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SOCIAL MOBILITY AS AN INCOME INEQUALITY DETERMINANT

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Abstract

The paper focuses on the social mobility as the key driver of the income inequality. The aim of the paper is to contribute to the assessment of the social mobility and explore its links to the level of inequality and the age structure of the country. Employing composite social mobility indicator featuring benefit-of-the-doubt weighting principle, scores, ranks and benchmarks for 55 countries worldwide are determined by slack-based data envelopment analysis (DEA) reduced model. The proposed measure is compared to a regular Global Social Mobility Index (GSMI). Score and rank correlations reveal some significant differences although Denmark is robustly confirmed as a leader in social mobility worldwide. The suggested DEA-based approach proved more flexible as to determining benchmarks for underperforming countries. Second stage regression analysis reveals higher levels of income inequality for the countries of lower social mobility and with higher share of young people.

Keywords

Income Inequality Determinants, Social Mobility, DEA-Based Index, Benefit-of-the-Doubt Weighting

I. Introduction

Income distribution issues and efficiency vs equity trade-off have attracted academic research as well as public debate for decades. Well documented for US by Piketty and Saez (2003) and for Western countries by Leigh (2007), Roine and Waldenström (2015) and Guvenen and Kaplan (2017), and Piketty et al. (2018), income inequality has been rising questions both regarding driving forces of the latter and policy implications.

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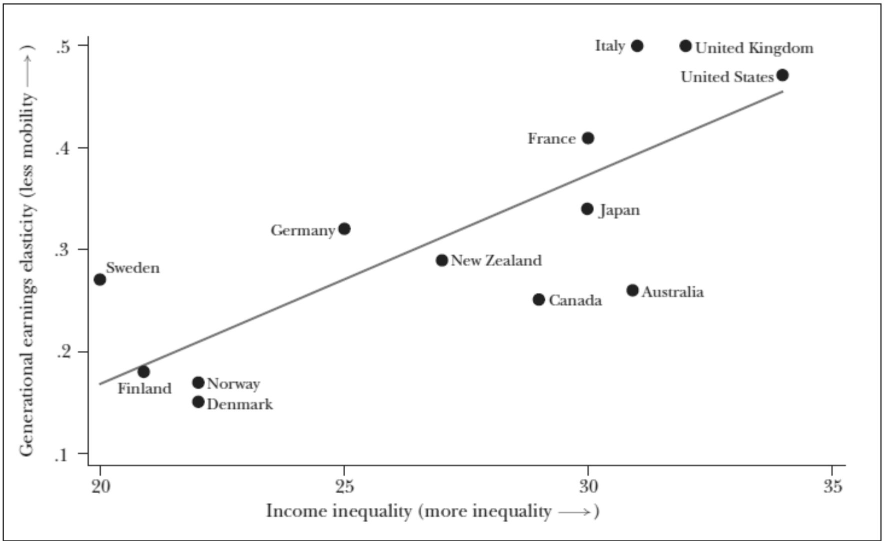
Call for more redistribution is countered by the argument of incentivizing role of inequality. In the fairness debate, standard measures of inequality seem inappropriate and equality of opportunity has been brought to the forefront. Concentrating on the sources and of inequality, *compensation* and *reward* principles (Fleurbaey, 2008) formally represent the idea that "unfair inequality shall be eliminated completely while fair inequalities ought to persist". According to opportunity egalitarians, inequality is ethically acceptable insomuch that they are consequence of individual responsibility and not the factors as biological sex, race, or the socioeconomic status of the family. In common perception, income inequality is associated with social immobility. Ideally, individuals would have the capabilities to prosper irregardless of their background or personal characteristics.

Empirically, the linkage between the social mobility and the general measure of income inequality within the country is represented by "The Great Gatsby Curve" (GGC). In Figure 1, an example of GGC for OECD countries is displayed. Income inequalities are measured by a standard Gini index while inequalities of opportunity are estimated by inter-generational income elasticity derived from paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid-1960s and measuring their adult outcomes in the mid to late 1990s (Corak, 2013). There is a clear tendency for less equitable societies to show less social mobility. Thus, United States or United Kingdom that exhibit low level of social mobility compared to Scandinavian countries have relatively unequal distribution of income.

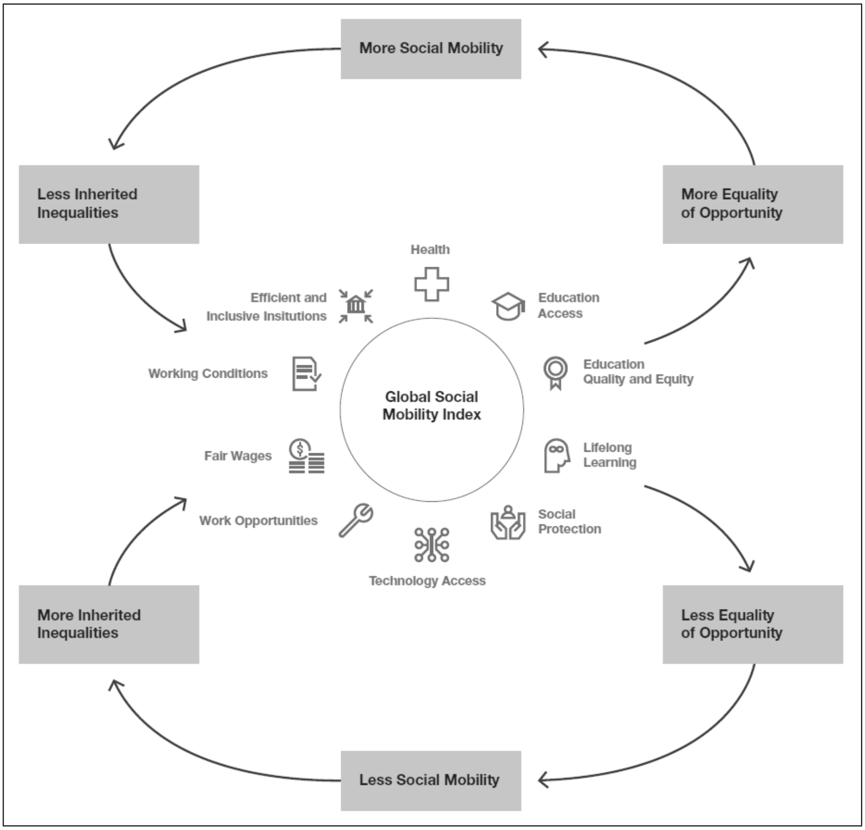
Figure 1: Great Gatsby Curve (OECD)



Source: Corak (2013)

Since data on intergenerational income mobility become available with significant time lags, the current generation's social mobility cannot be assessed in a timely manner. Along with that, simple correlation analysis based on GGC suffers from endogeneity issues and does not allow making causal claims. In the recent *Global Social Mobility Report* (WEF, 2020), a comprehensive conceptual framework of social mobility assessment is presented (Figure 2).

Figure 2: Global social mobility – conceptual framework



Source: WEF (2020)

There are two reinforcing cause-effect "circles". The "virtuous" one in the upper part of the scheme and the "vicious" in the lower part. Thus, the framework incorporates two-way causal linkages. In this perspective, GGC is viewed as the representation of the reduced-form of two simultaneous structural relashionships between income inequality and social mobility. As can be noticed from the central part, social mobility is considered a multi-dimensional phenomenon comprising ten dimensions: (1) health, (2) education access, (3) education quality and equity, (4) lifelong learning, (5) social protection, (6) technology access, (7) work opportunities, (8) fair wages, (9) working conditions, and (10) efficient and inclusive institutions. The proposed measure – Global Social Mobility Index (GSMI) focus on drivers of relative social mobility – "conversion factors" and enablers rather than intergenerational outcomes. Thus, GSMI presents "a forward-looking composite indicator which can serve as a basis for time-series analysis that allows economies to track progress and identify priority policy areas" (WEF, 2020). According to GSMI estimates, most equally shared opportunities for their populations are mostly provided by Nordic countries (Finland, Norway, Sweden, Denmark and Iceland), Denmark ranking the highest with the score of 85.2. Policy recommendations are based on benchmarks, which are suggested to be determined by the best performer in particular ten subdimensions. We challenge this approach by discussing the construction of composite indicators and propose an alternative, approach to generating benchmarks, more benevolent and realistic from the perspective of underperforming entities to our view.

Construction of composite indicators is widespread as a measurable feedback in control system in areas such as industrial competitiveness, sustainable development, globalization or innovation. Most commonly, additive aggregation is employed to integrate multidimensional measurement into a single indicator. In the course of the process, weights are ascribed to individual performance domains *ex ante* which, in a way, predetermines the total assessment score. In this study, we propose a benefit-of-the doubt approach where aggregating weights are determined endogenously given the output data of the countries under evaluation. This gives the discrimination that is less subject to criticism from the part of the determined underperformers.

The general aim of the paper is to assess the social mobility worldwide exploiting the new dataset from the Global Social Mobility Report. The multidimensional problem is proposed to be approached via performance frontier analysis. For underperforming entity, the approach allows determining a set of benchmarks that is argued to be more compatible with the actual mix of outputs. In a simple regression framework, we also explore the obtained index as a driving factor of the general income inequality.

II. Methodology and Data

DEA-based indices

The standard way of building composite indicators from s multiple output measures y_r, (r running from 1 to s) consists of constructing a weighted sum $\sum_{r=1}^{s} u_r y_r$; u_r denoting the respective aggregating weights. Applied to all entities, it imposes the same preferences for particular subdimension across the pool of evaluated units. *Benefit of the doubt* approach to weighting, pioneered by (Melyn and Moesen, 1991) and later elaborated on by Cherchye (2001) or Cherchye et al., (2004) to assess macroeconomic performance, individualizes the choice of weights.

$$\max I^{DEA} = \sum_{r=1}^{s} u_r y_{r0} \quad (r = 1, 2, \ldots, s) \tag{1}$$

$$\text{s.t.} \sum_{r=1}^{s} u_r y_{rj} \leq 1 \qquad (j = 1, 2, \ldots, n) \tag{2}$$

$$u_r \geq 0 \tag{3}$$

Each entity – decision making unit (DMU) in frontier analysis literature – is allowed to present itself in the most by choosing most favourable weights for its y_{r0}. Label "0" is used to indicate quantities of the unit under assessment. To avoid unboundedness, the magnitude of the performance score is constrained by one. Along with that, this constraint should be met by all the other competing DMUs who are forced to evaluate their set of outputs by the weights u_r proposed by DMU_0. Best performers are able to attain the highest possible score of 1 (100%) from the optimization, whereas DMUs with poor data are forced to choose weights resulting in lower values of the total performance indicator.

The optimization problem (1)–(3) is solved by each DMU to obtain its individual score determined by the optimal (highest possible) value of the objective (1). As shown in Lovell and Pastor (1999), (1)–(3) is equivalent to the reduced form of basic data envelopment analysis (DEA) model proposed by Charnes et al. (CCR, 1978). CCR model seeks to evaluate the efficiency of DMU given its outputs and inputs. In the evaluation problem (1)–(3), no inputs are involved and are formally replaced by a fixed constant ascribed to each DMU. CCR linear program allows for the dual representation:

$$\min \theta \tag{4}$$

$$\text{s.t.} \sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{r0} \quad (r = 1, 2, \ldots, s) \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j \leq 1 \qquad (j = 1, 2, \ldots, n) \tag{6}$$

$$\lambda_j \geq 0 \tag{7}$$

Given the same set of data y_{r0}, performance score θ from (4) is numerically identical to the latter from (1). Now θ represents an indirect measure of the distance between the datapoint DMU_0 and the best performance frontier constructed by (5)–(7) where λ_j stand for intensity variables according to which a DMU_j takes part in forming a "performance possibility frontier" (PPF) as a boundary of the multioutput possibility set. Clearly, only best performers can effectively contribute to the frontier generation, thus nonzero λ_j indicate *best practice* performers.

A number of computational and interpretational issues are linked to the nonnegativity constraint (3) for weights. Some inactive constraints of (5) represent the potential source of underperformance unaccounted for in the total score – a *slack*. SBM model by Tone (2001) solves the problem.

$$\max \rho = 1 + \frac{1}{s} \sum_{r=1}^{s} s_r^{+}/y_{r0} \tag{8}$$

$$\text{s.t.} \; \mathbf{y_0} = \mathbf{Y}\lambda - \mathbf{s}^{+} \tag{9}$$

$$\mathbf{e^T}\lambda \geq 1 \tag{10}$$

$$\mathbf{s}^{+}, \lambda \geq \mathbf{0} \tag{11}$$

Objective ρ from (8) directly includes all the (relative) slacks in the total penalty. The evaluation performance score could be determined as a reciprocal $1/\rho$. Much like (5)–(7)

and constraints (9)–(11) generate the empirical piece-wise *best practice* frontier by means of convex combinations of the best performers. Each point on the frontier represents the potential benchmark – the output mix that would be evaluated by the unit score. The actual benchmark for a particular DMU is determined as a *projection* onto the PPF using the optimal values of λ_j from the respective program. Along with that, a *peer group* of best performing DMUs related to DMU_0 is indicated. The latter helps in managerial decision making aimed at improving performance.

Second stage regression analysis

Determination of the scores, implied ranking, or projections (benchmarks) could be supplemented by the consequent second stage analysis. Since in DEA models the analogue to degrees of freedom constraint is active as well, the performance scores can be subject to further regression analysis allowing for a stochastics as well as statistical inference. As evaluation of factors, performance scores may enter regression analysis as exogenous variables. It is common practice to account for the fact that the score values are limited in magnitudes by opting for limited dependent variable models like Tobit (Hoff, 2007).

Data

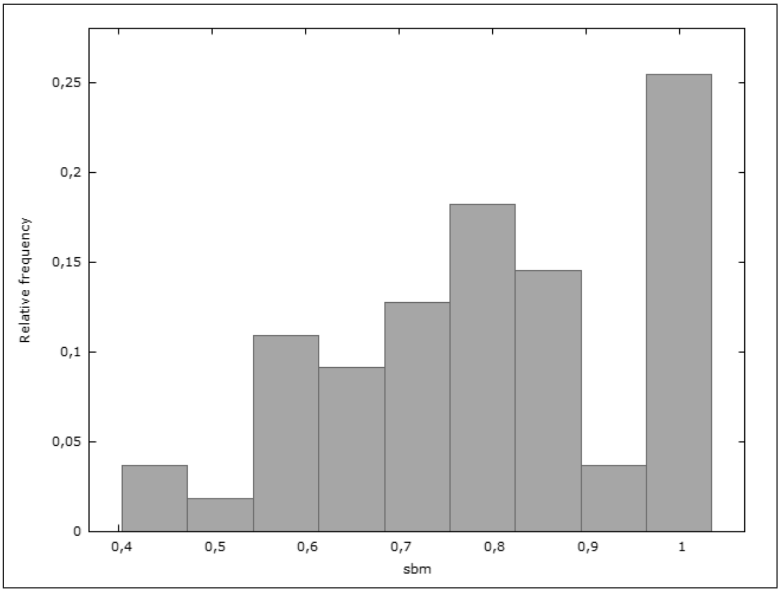
For DEA-based index of social mobility, we use data on ten pillars of GSMI as described in Section I. The data available in the year 2020 are collected from surveys conducted in previous years. Due to availability of all the other data, we choose to use the year 2017 for all variables. Gini index of disposable income comes from World Bank database. Income per capita *gdppc* is measured in thousands of USD and is sourced from UNCTADstat. In regression analysis acts as control variable accounting for the level of economic development of the country. Age structure available from the UNCTADstat comes in two alternative measures: *age_15* represents share of the population under 15 while and *age_65* denotes share of the population above 65. Both are supposed to reflect "older" societies by means of the higher values. Nevertheless, the two age related variables are not perfect substitutes and will be used in different variants of regression models. Number of countries given the data availability is 55. The dataset includes most of the highest GSMI ranking countries which should most probably form proposed PPF.

III. Results

In the first stage of the analysis, SBM measures of social mobility denoted *sbm* were calculated for each country solving problem of the type (8)–(11) for each of 55 countries (DMUs). Alongside, respective rank *rbsm* is determined. Twelve countries ranked number 1 – Belgium, Cyprus, Denmark, Finland, Germany, Iceland, Japan, Netherlands, New Zealand, Norway, Sweden, and Switzerland – attained the unit score (100%) and will therefore present the extreme points of the PPF boundary.

Excluding best practice performers, the distribution of *sbm* scores shows the probability mass concentration between the 0.6 and 0.9 as exhibited in Figure 3.

Figure 3: Distribution of *sbm* scores



Source: Authors' calculation

These quantities were compared to scores and ranking from the regular GSMI composite indicator labelled *gsmi* and *rgsmi* respectively. In GSMI ranking, Denmark is the only best performer with a score of 85.2 followed by Norway (83.6), Finland (83.6), Sweden (83.5) and Iceland (82.7). Thus, best practice countries are identified in a robust manner.

Table 1: Rank and score correlations

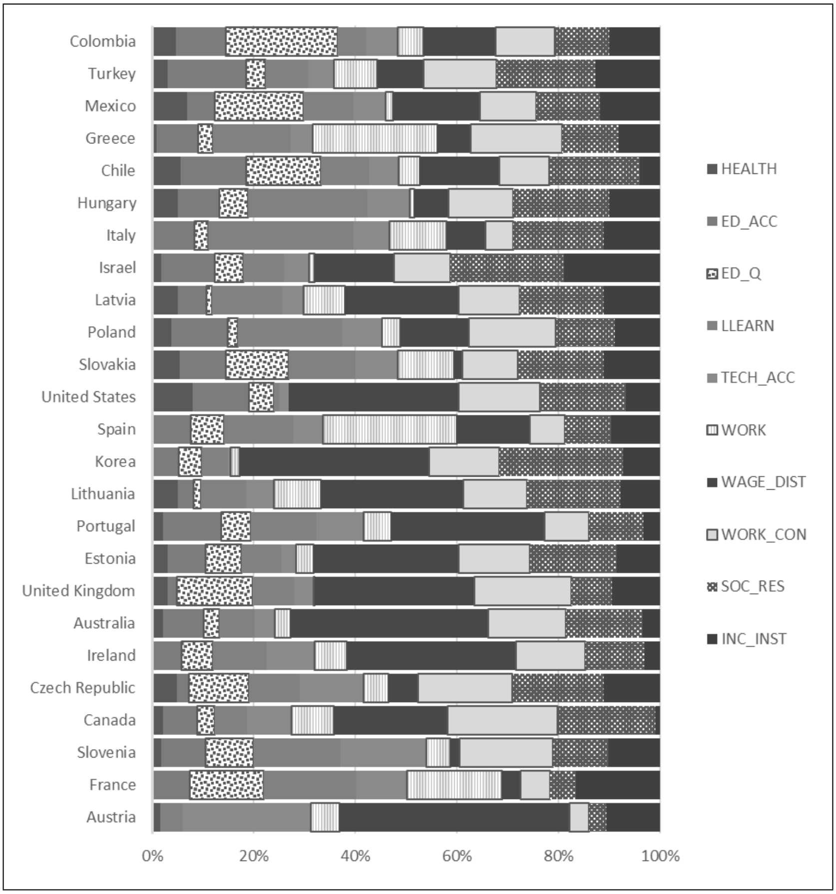
gsmi	*rgsmi*	*sbm*	*rsbm*	
1	−0.9785	0.9674	−0.9290	*gsmi*
	1	−0.9489	0.9439	*rgsmi*
		1	−0.9807	*sbm*
			1	*rsbm*

Source: Author's calculation

Table 1 displays cross-correlations between the aforementioned scores and ranks. Obviously, scores and ranks are negatively correlated. The correlation between the *sbm* and *gsmi* (0.9674) suggests only minor differences in evaluation, less so does rank correlation (0.9439). Some countries find their ranking unchanged – Argentina (ranked 45th), Brazil (49), Hungary (35) or Lithuania (25). There are nevertheless huge gaps in ranks for some countries – Cyprus (27 positions improvement of *rsbm* compared to *rgsmi*), Japan (+14), New Zealand (+20), Singapore (+18). This fully exposes the merit of benevolent and individually adjusted weighting. Countries that improved their appearance due to SBM

were allowed to present their strengths in a more favourable perspective. Full account of the ranks and scores is given in Appendix, Table A.
Nonzero solutions for slacks from optimizations (8)–(11) help determine performance gap in particular subdimension for underperforming countries, i.e. those with $sbm < 1$. The total penalty expressed by (8) is composed from individual relative performance slacks s_r^+/y_{r0} whose contribution to the total lack of output is visualized in Figure 4.

Figure 4: Decomposition of inefficiency for OECD countries



Source: Authors' calculation

Sources of underperformance depicted in Figure 4 are at considerable variance in selected (OECD) countries. For decision making it provides information as to potential for improvement. Thus, wage distribution (WAGE_DIST) could raise concerns in Korea, Baltic countries, United States, Australia, Austria or Ireland. On the other side, health issues (HEALTH) and access to technology (TECH_ACC) seem to be of no need to be prioritized in most countries of the group.

Benchmarking using DEA based frontier approach exploits the fact that *convex combinations* of best performing entities are considered feasible from the production theory perspective that underlies the construction of the production possibility set boundary in DEA models. For each DMU, an individual group of peers (best performers) is determined whose sub-outcomes from sub-dimensions are combined to calculate projection onto the frontier – acting as benchmark for the DMU under consideration. Therefore, benchmarks for particular countries need not to be identical. This statement is exemplified in Table 2 where projections for four underperforming countries are displayed.

Table 2: Projections (selected countries)

DMU	score		HEALTH	ED_ACC	ED_Q	LLEARN	TECH_ACC	WORK	WAGE_DIST	WORK_CON	SOC_RES	INC_INST
Denmark	1	data	90.2	85.0	86.1	75.1	94.1	82.1	80.7	82.7	89.8	85.8
		proj.	90.2	85.0	86.1	75.1	94.1	82.1	80.7	82.7	89.8	85.8
Switzerland	1	data	94.2	83.5	77.4	81.1	90.4	81.3	69.7	77.2	77.6	88.2
		proj.	94.2	83.5	77.4	81.1	90.4	81.3	69.7	77.2	77.6	88.2
Norway	1	data	90.9	86.5	85.5	73.6	89.8	84.5	76.7	79.5	81.5	87.4
		proj.	90.9	86.5	85.5	73.6	89.8	84.5	76.7	79.5	81.5	87.4
Slovakia	0.798	data	79.3	69.2	65.4	56.5	77.7	64.0	77.8	64.6	63.0	67.1
		proj.	90.2	85.0	86.1	75.1	94.1	82.1	80.7	82.7	89.8	85.8
Czech Republic	0.873	data	84.3	82.2	73.5	65.5	79.7	76.6	74.3	65.2	71.3	73.9
		proj.	90.2	85.0	86.1	75.1	94.1	82.1	80.7	82.7	89.8	85.8
France	0.905	data	91.3	78.5	72.6	64.4	84.3	68.4	74.9	76.6	82.2	73.7
		proj.	91.3	84.6	83.8	76.7	93.1	81.9	77.8	81.2	86.6	86.5
Austria	0.937	data	89.4	85.3	85.4	73.2	80.0	79.2	61.1	80.5	87.0	80.2
		proj.	90.4	85.3	85.4	75.3	93.7	82.1	79.8	82.5	89.1	85.8

Source: Authors' calculation

In Table 2, benchmarks for ten dimensions of social mobility are exhibited for Slovakia, Czechia, France and Austria (scoring $sbm < 1$). Alongside, data of three frontier countries – Denmark, Switzerland and Norway are given. Clearly, the best performers project onto himself. Thus, benchmarks for the three are identical to their data. In the course of calculation of the scores, peers for the selected countries were determined as follows. For Slovakia and Czechia the single peer is Denmark, two peers – Denmark and Switzerland – were determined for France, and the triplet Denmark, Netherlands and Norway for Austria. As regards the projections, one can see that for Slovakia and Czechia they correspond to the peer's data in each of ten dimensions. By way of contrast, France's benchmarks retain its best performance in HEALTH (91.3) which is balanced by a more relaxed benchmark values in that lie in between the sub-dimensional outcomes of the peers, e.g. ED_Q benchmark of 76.7 lies in between the ED_Q data of the two peers – Denmark (86.1) and Switzerland (77.4). Similarly, benchmarks for Austria are combined from three sets of outcomes – data of three peers. By large, Denmark acts as a peer for 41 countries excluding itself while Norway, Netherlands and Iceland for only single underperforming DMU. The rest of frontier countries do not have links to underperforming DMUs. It can be inferred that from frontier countries only Denmark has most commonly shared proportions of outputs whereas the other ones stand to a certain extent as extreme outlying datapoints. Denmark is thus confirmed as a robust leader in social mobility both by regular GSMI and SBM index.

After exploring the countries' performance in social mobility, the latter is exploited as factor driving the general income inequality represented by Gini coefficient (variable *gini*). In the regression framework, first take is made by running a simple regression of *gini* on *sbm* while controlling for the level of economic development proxied by *gdppc*. Model (1) in Table 3 is estimated via OLS. Since *gini* is ranged 0–100, in model (2) Tobit estimator is employed instead of OLS with the dependent variable in respective bounds.

Table 3: Determinants of income inequality (depvar: *gini*)

	OLS	Tobit			
	(1)	(2)	(3)	(4)	(5)
const	✓	✓	✓	✓	✓
sbm	−42.70 ***	−42.70 ***	−23.57 *	−32.07 ***	−21.97 *
	(12.03)	(11.70)	(13.38)	(11.59)	(13.36)
gdppc	0.08	0.08	0.04	0.08	0.02
	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)
age_15			17.84	43.35 ***	
			(19.27)	(15.83)	
age_65			−45.10		−63.36 **
			(36.83)		(27.15)
n	55	55	55	55	55
adj R2	0.43				
lnL	−178.8	−178.8	−174.3	−175.3	−174.6

Source: Authors' calculation

Age structure augments the model in three variants. Adding both age related variables results in insignificant individual coefficients. Joint test for *age_15* and *age_65* (Robust F(2, 50) = 3.70, p-value 0.03) render models (4) and (54) with individual inclusion of the latter meaningful. One can explore the particular contribution of alternative age structure proxies.

The results robustly show negative association of social mobility and income disparities. On average, countries with less social mobility are doomed to higher income inequality. Countries with "older" societies seem to have this relationship alleviated supposedly due to the fact that a larger portion of population receives wages.

IV. Conclusion

In the presented analysis, an alternative way of assessing social mobility was exemplified by employing frontier (data envelopment analysis) approach to the Global Social Mobility dataset. The benefit-of-the-doubt weighting approach strongly affected assessment scores and ranks of some countries. The results confirmed Denmark as a leader in social mobility worldwide. The proposed evaluation technique allows setting benchmarks that are theoretically rooted in production theory and are less demanding in comparison with the regular methods. Alongside, sources of underperformance are identified using solutions for slacks from DEA model. Empirical findings show wage distribution across industries to be the main concern for policy makers in OECD countries. Conversely, health and access to education proved relatively unproblematic domains. For Czechia and Slovakia social protection appears to be relatively the most challenging area for improvement. The second stage regression analysis aimed at exploring the obtained measure of social mobility as a determinant of general income inequality traditionally gauged by Gini index. Controlling for the economic development of the country as well as the age structure, the results suggest that higher levels of social mobility are associated with less income inequality in the society. At the same time, "younger" societies may suffer from higher inequality due to the lack of income in younger age groups. By and large, the DEA based index proved to be a useful tool to at least complement established measures and to theoretically corroborate decision making in practice.

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Appendix

Table A: Social mobility characteristics and inequality determinants

	gsmi	*rgsmi*	*sbm*	*rsbm*	*gdppc*	*gini*	*age_15*	*age_65*
Argentina	57.3	45	0.654	45	23597.1	41.1	0.329	0.110
Australia	75.1	16	0.866	21	49748.5	34.0	0.251	0.154
Austria	80.1	8	0.937	15	54390.6	29.7	0.194	0.190
Belgium	80.1	9	1	1	50726.6	27.4	0.225	0.186
Brazil	52.1	49	0.591	49	14596.9	53.3	0.298	0.086
Bulgaria	63.8	38	0.742	37	21533.7	40.4	0.186	0.208
Canada	76.1	14	0.887	18	48688.1	33.3	0.215	0.168
Colombia	50.3	52	0.567	52	14763.9	49.7	0.324	0.082
Croatia	66.7	34	0.768	33	26775.7	30.4	0.198	0.200
Cyprus	69.4	28	1	1	38277.4	31.4	0.320	0.184
Czechia	74.7	18	0.873	19	39031.1	24.9	0.196	0.190
Denmark	85.2	1	1	1	55673.5	28.7	0.226	0.197
Estonia	73.5	22	0.852	23	33903.1	30.4	0.206	0.193
Finland	83.6	3	1	1	47621.5	27.4	0.216	0.213
France	76.7	12	0.905	16	46369.7	31.6	0.243	0.194
Germany	78.8	11	1	1	53373.8	31.2	0.185	0.214
Greece	59.8	44	0.663	44	28558.3	34.4	0.193	0.214
Hungary	65.8	35	0.754	35	29801.5	30.6	0.194	0.186
Chile	60.3	43	0.692	41	23720.4	44.4	0.271	0.112
China	61.5	41	0.682	42	14151.8	39.1	0.239	0.103
Iceland	82.7	5	1	1	56944.8	26.1	0.264	0.144
India	42.7	54	0.441	54	6183.0	47.0	0.368	0.060
Indonesia	49.3	53	0.533	53	11073.5	38.1	0.357	0.057
Ireland	75.0	17	0.869	20	77779.9	31.4	0.277	0.135
Israel	68.1	32	0.782	32	39206.1	38.2	0.357	0.117
Italy	67.4	33	0.766	34	42111.5	35.9	0.182	0.225
Japan	76.1	15	1	1	41409.0	29.9	0.174	0.271
Kazakhstan	64.8	36	0.747	36	24699.3	27.5	0.337	0.071
Korea	71.4	24	0.810	26	41001.1	31.4	0.189	0.139
Latvia	69.0	30	0.795	31	28548.0	35.6	0.196	0.198

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	gsmi	*rgsmi*	*sbm*	*rsbm*	*gdppc*	*gini*	*age_15*	*age_65*
Lithuania	70.5	25	0.811	25	33826.6	37.3	0.197	0.193
Luxembourg	79.8	10	1	1	113905.6	34.5	0.219	0.141
Malaysia	62.0	40	0.679	43	25897.2	42.5	0.333	0.064
Mexico	52.6	48	0.592	48	19933.5	47.2	0.358	0.070
Netherlands	82.4	6	1	1	55509.3	28.5	0.223	0.188
New Zealand	74.3	21	1	1	40976.0	46.0	0.263	0.153
Norway	83.6	2	1	1	62782.1	27.0	0.238	0.168
Philippines	51.7	50	0.575	50	8199.1	44.3	0.413	0.049
Poland	69.1	29	0.797	30	30161.6	29.7	0.197	0.169
Portugal	72.0	23	0.832	24	33086.0	33.8	0.189	0.216
Romania	63.1	39	0.730	39	27220.0	36.0	0.207	0.179
Russia	64.7	37	0.736	38	25999.3	35.5	0.221	0.143
Saudi Arabia	57.1	46	0.624	46	48014.6	65.0	0.322	0.032
Singapore	74.6	19	1	1	95350.4	39.8	0.181	0.106
Slovakia	68.5	31	0.798	29	30917.6	23.2	0.203	0.151
Slovenia	76.4	13	0.893	17	36680.2	24.2	0.193	0.190
South Africa	41.4	55	0.439	55	13838.8	57.7	0.376	0.052
Spain	70.0	27	0.807	27	39626.5	34.7	0.194	0.191
Sweden	83.5	4	1	1	52413.1	28.8	0.226	0.200
Switzerland	82.1	7	1	1	69851.7	32.7	0.199	0.183
Thailand	55.4	47	0.612	47	17423.0	36.5	0.241	0.114
Turkey	51.3	51	0.572	51	28242.5	41.4	0.334	0.083
Ukraine	61.2	42	0.699	40	59885.7	26.0	0.201	0.162
United Kingdom	74.4	20	0.858	22	68504.5	35.1	0.232	0.183
USA	70.4	26	0.804	28	12321.9	41.2	0.254	0.154

Source: UNCTAD (2022), World Bank (2022), WEF (2020), authors' calculation