European Bank
for Reconstruction and Development

Inequality of Opportunity and Support for Democracy: Evidence from Transition Countries

Fabian Reutzel

Summary

The linkage between income inequality and citizens' support for democracy has widely been discussed in the literature (e.g. Acemoglu and Robinson, 2001; Andersen, 2012). However, drawing inequality can further be decomposed into two components drawing on the theory of inequality of opportunity (IOp) proposed by Roemer (1998). Inequality arising due to differences in effort is perceived as ”fair”, while inequality due to differences in circumstances (e.g. unequal starting conditions) is regarded as ”unfair”. Using multiple state-of-the-art estimation methods, comparable IOp measures for 27 former communist countries (”transition countries”) and 3 Western democracies are calculated. Incorporating these IOp measures into the individual-level attitude formation process reveals that higher levels of IOp correspond to higher levels of support for the concept of democracy while overall income inequality has no statistically significant effect. This observation can be rationalized by citizens regarding democracy as a means to achieve equality of opportunity rather than simply as a vehicle for redistribution.

Keywords: Inequality of opportunity; Public opinion; Democracy.

JEL Classification Number: D63, P16

Contact details: Fabian Reutzel, Paris School of Economics, 48 Boulevard Jourdan, 75014 Paris
Phone: +49 157 7188912; email: reutzel.fabian@psestudent.eu.

Fabian Reutzel is a M2 Public Policy and Development student at the Paris School of Economics.

This work has benefited immensely from discussions with Paolo Brunori and Vito Peragine. Furthermore, I am grateful to Marc Lipfert for his enduring support throughout the writing process. I thankfully acknowledge funding from the ”Serlenga01295719Rpu” project for my stay at the University of Bari and from the DAAD's Carlo-Schmid-Program for my research assistantship at the Office of the Chief Economist of the EBRD and thank Michelle Brock for the opportunity to pursue this research project during the latter stay.

Working Paper No. 248 **Prepared in November 2020**

1 Introduction

"There is a clear need for systematic empirical analyses of the impact of social mobility (and perceptions thereof) on political attitudes and the resulting political behavior." Acemoglu et al. (2018)

Research on the linkage between inequality and democracy has so far mostly neglected fairness concerns in the evaluation of inequality and evolved around two contrasting approaches. On the one hand, the survey-based political science literature on democratic support focuses, besides individual-level traits (political beliefs and education), on political and economical evaluation of regime performance (satisfaction with representation of interests; own economic and national situation; e.g. Andersen (2012); Muller (1988); Evans and Whitefield (1995)). On the other hand, the theory-focused political economy literature regards democracy mainly as a mechanism for redistribution from wealthy elites to poor citizens and, hence, emphasizes potential future gains rather than past experience (e.g Acemoglu and Robinson, 2001; Boix et al., 2003).

Meanwhile, the literature on inequality and preferences for redistribution (see Alesina and Giuliano, 2011, for an extensive review) stresses the importance of social mobility, values and beliefs about distributive justice and the importance of an individual's relative income. Further, Acemoglu et al. (2018) formally investigate the impact of social mobility and the arising time-conflicting political preferences of a median voter expecting to be upward mobile on the consolidation of democracy.[1] Given their multiple equilibria results, they call for an empirical investigation of the linkage between social mobility and regime support.

The Inequality of Opportunity (IOp) framework operationalizes distributional justice by regarding inequalities due to difference in efforts and personal responsibility as "fair" (reward principle) and deeming inequalities due to factors beyond the individual's responsibility as "unfair" (compensation principle; see Ferreira and Peragine, 2016, for an extensive review). IOp is conceptually and empirically closely related to intergenerational mobility and, hence, can be regarded as the missing link between the concepts of income inequality and social mobility (Brunori et al., 2013). [2]

Merging survey-based and political-economy literature, Krieckhaus et al. (2013) derives a binary distinction across two dimensions of support motives. The individual either relates to her evaluation of past/current economic conditions or to her future expectations of economic conditions that will arise from the type of political regime it supports (retrospective vs. prospective evaluation). Further, the individual either evaluates her personal benefit from economic conditions or the overall societal (national) performance of her supported regime type (egocentirc vs.

[1] If the median voter expects to move up (respectively down), he would prefer to give less voice to poorer (respectively richer) social groups because he anticipates having different preferences than future agents who will occupy the same social station as herself.

[2] If higher inequality decreases intergenerational mobility, this is likely due to opportunities for economic advancement being more unequally distributed among children. Conversely, lower mobility may contribute to the persistence of income inequality through making opportunity sets very different among the children of different income classes.

sociotropic evaluation).

Educational and economic mobility and their subjective perception can be important explanations of support for democracy in democratic post-socialist (”transition”) countries such as Poland, Hungary, and Czech Republic (Brock et al., 2016; Gugushvili, 2020). Studying democratic support in transition countries is of particular interest, as exposure to the early socialization might impact the evaluation and conceptual support for the current democratic regime (Mishler and Rose, 2002).

This thesis combines insights from the preference-for-redistribution literature, i.e. the importance of process fairness and social mobility, with the support-for-democracy framework employed by Krieckhaus et al. (2013) through incorporating IOp measures into the attitude formation process. Determining the effect of IOp, which can be regarded as the ”unfair” part of overall economic inequality, on the support for democracy provides a proxy for the relative importance of fairness concerns compared to the effect of overall inequality. Using individual-level survey data from 27 former transition countries and 3 Western European comparator countries in 2010 and 2016, this thesis applies the developed framework and assesses its explanatory value.

The results of the analysis suggest that disentangling the sources of economic inequality is of major importance. While overall economic inequality does not affect support for democracy when controlling for the level of democratization, IOp does have significant impact. Yet, the effect is heterogeneous across time: In 2010 higher levels of IOp are associated with higher levels of support for democracy independent of the current democracy level, whereas in 2016 this positive effect declines with the level of democracy. In line with the presented attitude formation framework by Krieckhaus et al. (2013), this corresponds to a sizable prospective evaluation of IOp and an increase in the retrospective component of the evaluation of the regime output. A possible explanation is that citizens regard democracy as a means to achieve equality of opportunity but the associated faith in the democratic regime to deliver such transformation has declined. In turn, the main contribution of the thesis is to provide evidence that fairness concerns are crucial when assessing the impact of economic inequality on support for democracy. Hence, the IOp framework can be an important tool to understand democratic backsliding in post-socialist societies and the associated rise of populism.

Further, in line with egocentric evaluation premise, the individual's position in the national income distribution is found to be an important determinant of attitudes towards democracy, i.e. the support for democracy is increasing in the individual's income position. Based on the IOp framework, a new reference group with similar starting conditions for determining an individual's relative economic standing is derived, which yields similar results. Though, this effect is decreasing between 2010 and 2016, hinting at a decline of the importance of the individual's economic circumstances for the support of democracy.

The remainder of this thesis is organized as follows. First, section 2 reviews the literature regarding the support for democracy (2.1), the linkage between inequality, IOp and democracy (2.2) and the transition to democracy in former communist countries (2.3). In section 3 the IOp framework is formally introduced (3.1) and the attitude formation process is described in detail (3.2). Section 4 presents measurement approaches of IOp (4.1) and the empirical framework of the thesis (4.2). After introducing the data sources in section 5, section 6 presents results and sensitivity analyses for the IOp estimation as well as for the attitude formation. Lastly, section 7 discusses the limitations of the thesis and concludes with suggestions for further research.

2 Literature

2.1 Democratic Support

In political science, the conception that democracy is entrenched in the attitudes and orientations of the public is well established. Lipset (1959) postulates that political legitimacy, i.e the belief that existing political institutions are the most appropriate ones, is one of the principal requisites of stable democracy. Easton (1975) extends this theory of legitimacy by distinguishing between three political objects that citizens might support: (1) the government and other political actors, i.e. the most concrete objects; (2) the nation or political community, i.e. the most abstract object; and (3) the regime, or the basic rules and principles by which authority is wielded in a state, i.e. the intermediate object of support and the focus of the following analysis. He further differentiates between specific and diffuse support for these objects.

In the case of public support for the regime, i.e. democracy, specific support focuses on regime outputs, while diffuse support focuses on the principles of the regime. Whereas the former exhibits an instrumental character and, hence, might be rather volatile across time and government performance, the later is normative and, therefore, more durable helping to bolster regimes during political or economic crises (Easton, 1975). Thus, normative (diffuse) public support for democracy helps to ensure its survival, i.e with such support, a democracy is legitimate and stable but in the absence of it, democracy is unstable and susceptible to fail. Claassen (2020) empirically evaluates this link between the mass public opinion and the dynamics of political regimes and finds a positive effect of such normative support for democracy on subsequent democratic change. He further presents evidence that normative support is more robustly linked with the endurance of democracy than with its emergence.

In the political economy literature, however, democracy is mainly regarded as a mechanism for redistribution which implies the accordance of preferences for democracy with preferences for redistribution. Democracy as a regime is conceptualized by weights assigned to individuals within each social group which determine the distribution of political power and therewith the pivotal voter who ”chooses” the current redistribution policy as well as the future political regime (e.g. Acemoglu and Robinson, 2006; Acemoglu et al., 2018).

2.2 Inequality, IOp & Democracy

The linkage between inequality, social mobility and democracy has drawn attention in political science and political economics alike.

Political scientist mainly present evidence of a negative association between economic inequality and democracy. Examining 22 democratic, mainly European countries, Solt (2008) finds that higher levels of income inequality depress political interest and participation in elections among all but the most affluent citizens. His results suggest that greater economic inequality yields greater political inequality as conjectured by the relative power theory (Goodin and Dryzek, 1980), i.e. if money can be used to influence others, a higher concentration of income and wealth will be associated with concentrated political power. In turn, citizens' regime support is expected to decrease if economic inequality rises as they become disillusioned by the ability of democracy to balance policies between the poor and the rich.[3] Analyzing 20 European democracies, Anderson and Singer (2008) present evidence that greater inequality is associated with lower levels of support for the political system. Such negative effects of inequality on attitudes towards democracy are more pronounced among individuals on the political left while being much less corrosive among individuals on the political right.[4] Further individual characteristic like socio-economic resources (e.g. education and income) are found to positively affect satisfaction with democracy/regime output and citizens satisfied with a regime's output tend to exhibit more favorable attitudes towards democracy (e.g. Schäfer, 2012; Waldron-Moore, 1999). Using multiple waves of the World Values Survey, Krieckhaus et al. (2013) confirms such results, i.e. higher levels of economic inequality reduce support for democracy among all social classes. The effects of inter-generational mobility on regime support have mostly been studied through the lens of sociology on the individual-level and confirm the claim that individuals' regime support increases in experienced mobility, i.e. downward mobile individuals blame the regime whereas upward mobile praise it in light of their experience (Daenekindt et al., 2018).

In contrast, the political-economy literature mainly draws on the Meltzer and Richard (1981) framework to link inequality and social mobility to attitudes towards democracy. Higher inequality corresponds to the poor being less affluent compared to their fellow citizens, so redistributive policies and democracy as a means to it should become more attractive to them. In turn, redistribution becomes more costly to the well-off as inequality increases, so wealthy individuals should become more hostile towards redistribution and democracy. Acemoglu and Robinson (2001) provide a simple model explaining transformation to democracy by the poor being able to contest power by threatening revolution, which may force the rich elite to democratize. In such a setting, democracy may not consolidate due to its redistributive nature by incentivizing the elite to mount a coup. In turn, highly unequal societies are less likely to consolidate democracy. Acemoglu et al. (2015) reviews the literature on macro-outcomes of democracy and discusses mechanisms why inequality may not decline as countries become more democratic.[5]

Augmenting the two-class model of Acemoglu and Robinson (2001) with social mobility, Leventoğlu (2005, 2014) formally confirms the claim of de Tocqueville (1835) that greater social mobility softens the distributional conflict in society and makes the transition to democracy and

[3]In terms of the Easton (1975) categorization, this would be regarded as a spillover from the specific to the diffuse support for democracy and would be in line with the finding by Klingemann (1999) which implies that satisfaction with democratic practice goes along with higher levels of support for democracy as an ideal.

[4]Such effect heterogeneity might cause the effect on the whole population to be smaller and non-significant depending on the political views held by the majority of the citizens if one cannot control for the individual's political orientation as in the dataset employed in this thesis.

[5]Potential mechanisms for the absence of declining inequality under democracy are (1) political capture by the rich, (2) inequality-increasing market opportunities and (3) middle class bias of redistributive policies.

democratic consolidation more likely, i.e. if members of a social group expect to transition to some other social group in the near future, they should have less reason to exclude these other social groups from the political process. Acemoglu et al. (2018) enhance such framework by allowing for varying speed of social mobility generating endogenously time-conflicting preferences of the median voter.[1] They find the impact of social mobility to depend on the distance between the mean and the median of preferences over policy, i.e. if they are close, democracy is stable (meaning that the median voter would not wish to undermine democracy) and stability increases with social mobility. Conversely, when the mean and median are not close, greater social mobility reduces the stability of democracy.

In line with the Meltzer and Richard (1981) interpretation of democracy, a review of the literature on inequality and preferences for redistribution is beneficial. Multiple impact factors for the preference formation process are invoked (see Alesina and Giuliano, 2011, for an overview). As formally derived by Piketty (1995), Alesina et al. (2018) identify beliefs about intergenerational mobility as a key driver of policy preferences, i.e. individuals being optimistic about mobility tend to favor less generous redistributive policies and lower levels of government involvement (i.e. "prospect of upward mobility" (POUM) hypothesis Benabou and Ok (2001)).[6] Alesina and Ferrara (2005) and Alesina and Angeletos (2005) provide evidence of the importance of beliefs about distributive fairness as formalized by Benabou and Tirole (2006), i.e. individuals prefer more redistribution to the poor if they believe that poverty is caused by circumstances beyond an individual's control rather than individual effort. Also, socio-economic individual-level characteristics such as absolute and relative income are important determinants of preferences for redistribution Corneo and Grüner (2002), i.e. individuals care about how much income they receive but also about how much they receive compared to others. Yet, documenting the impact of values and beliefs about distributive justice, Fong (2001) finds that economic self-interest cannot solely explain the effect of these beliefs on redistributive preferences. Even though individual perception on social mobility is prone to errors[7] and the perception's impact in the attitude formation process being correlated with political orientation (Alesina et al., 2018)[6], IOp as objective measure of social mobility might still be important for the preferences for redistribution and, thus, for attitudes towards democracy.

Equality of opportunity is an important ideal of distributive justice and fairness is deeply rooted in the concept of democracy (Verba, 2006). On these grounds, citizens' evaluation of regime performance does not only rely on economic outcomes but can be substantially shaped by the perception of procedural fairness of the outcome generating process (Magalhães, 2016), i.e. the importance of economic evaluations varies by macroeconomic context and individual factors in combination with procedural fairness are relevant moderators of performance-driven regime attitudes. Inequality of opportunity can be regarded as the measure linking social mobility and intergenerational income mobility and thus as an objective metric of fairness (Brunori et al., 2013).

[6] As for the more pronounced negative effect of inequality on attitudes towards democracy among individuals on the political left in Andersen and Fetner (2008), Alesina et al. (2018) also confirm such an effect heterogeneity based on political orientation, i.e. left-wing respondents' preferences for redistribution are correlated with their mobility perceptions while no such connection is found for right-wing respondents.

[7] Brunori (2017) documents that IOp measures are only weakly correlated with the actual perception of it. Instead, personal experiences of intergenerational social mobility and other contextual factors are important determinants of perceived IOp.

2.3 Transition Countries & Democracy

Support for democracy in former soviet countries has to be studied by taking into account both transitions that have occurred, i.e from communism to democracy and from central-planing to market economy. Increases in skill-premia and an associated rise in income inequality have lead to changes in the perception of inequality (Kelley and Zagorski, 2004). Nevertheless, views on the acceptable level of economic inequality remain more egalitarian than in Western comparator countries (Suhrcke, 2001). Kitschelt (1992) indicates that support for democracy during the transition to democracy was closely tied to market success and, hence, to the individual's income. Evans and Whitefield (1995) document the importance of contextual political factors and experience, e.g. democracy effectiveness of the institutions and participation in the electoral processes, for the evaluations of regime and market output, i.e. controlling for support for marketization, the influences of economic factors on democratic support diminishes. Citizens in transition countries tend to exhibit substantially lower levels of democratic support compared to citizens in more established democracies (Andersen, 2012), which is in line with a learning process for supporting the new regime conjectured by Mishler and Rose 1999; 2002. While subjective mobility perceptions are found to be important explanations of democratic support (Gugushvili, 2020), an objective cross-country assessment of IOp across transition countries and their impact on support for democracy remains without precedent.

3 Theoretical Framework

First, to determine the influence of overall economic inequality and IOp as well as the associated context of relative socio-economic position on individual attitudes towards democracy, the concept and analytical framework of IOp is introduced. Second, the categorization of Krieckhaus et al. (2013) is revisited and implications for the effects of overall inequality and IOp are derived. Additionally, theoretical considerations regarding the effect of an individual's relative socio-economic position are discussed.

3.1 Inequality of Opportunity

Inequality of opportunity, in its conception used by economists today, is grounded on a debate by political philosophers and theoretical economists about the ideal of egalitarianism. Following Rawls (1971), multiple authors propose alternative dimensions upon which equity should be implemented. Dworkin (1981a,b) argues for equalization of individual resource endowments rather than achievements. Explicitly recognizing the role of individual responsibility as a source of ethically inoffensive inequality (e.g. Cohen, 1989), society should remove inequality arising from factors influencing individual outcomes for which she cannot be held responsible (see Ferreira and Peragine, 2016, for a summary).

The workhorse model, proposed by Roemer (1998), regards individual outcomes such as income or consumption to be determined by individual characteristics. It subsumes these individual characteristics using a binary classification into circumstances C_i, i.e. characteristics which lie beyond individual control, and effort E_i, i.e. characteristics which, contrariwise, are at least partially controlled by individuals. Inequality due to circumstances beyond individual responsibility are regarded as ethically unjustified, so one requires society to compensate individuals for differences in outcomes which are due to factors beyond their control (compensation principle). Outcome inequalities due to differences in efforts are regarded as ethically legitimate, so one requires societies to respect rewards to individual effort (reward principle).

Compensation for circumstances C_i can be formulated in two ways: ex-ante and ex-post.[8] The conceptual distinction revolves around whether compensation is to be accorded to individuals prior to the determination of their effort levels, or after their efforts are revealed (see Ferreira and Peragine, 2016, for an overview). Since measuring effort is rather difficult empirically, most of the applied literature (Brunori et al., 2013; Ferreira and Gignoux, 2011), as well as this thesis, opt for conceptualizing compensation prior (i.e. ex-ante) to the realization of efforts. The compensation principle requires equalization of some valuation of the opportunity sets available to everyone, regardless of their circumstances (see Ramos and Van de Gaer, 2016, for a review of different empirical approaches).

Consider a finite population indexed by $i = 1, \dots, N$ and each individual being characterized by the tuple $\{y_i, C_i, E_i\}$. Regarding outcome differences due to a correlation between circumstances and effort as a violation of equality of opportunity (Roemer, 1998), circumstances have a direct and an indirect effect on the outcome of interest. For example, certain groups may be banned from offices/positions due to outright discrimination (direct effect), which may provoke adjustments in individual effort because the imposed circumstance constraints alter the individual's optimization problem (indirect effect). Based on this assumption, the outcome generating process can be written as $y_i = g(C_i, E_i(C_i))$. The information on C_i is used to construct a partition of disjunct types $\Omega = T_1, \dots, T_P$ such that all members of a type are homogeneous in their circumstances C_i. The average outcome of type k is denoted by μ^k and considered as the value v_k of the corresponding opportunity set.[9] Equality of opportunity is achieved if type-means are equalized across types, i.e. if $\mu^k = \mu^l \, \forall l, k | T_k, T_l \in \Omega$.

Following the ex-ante approach, computing inequality in a counterfactual distribution $M = (\mu_1^1, \dots, \mu_i^k, \dots, \mu_N^P)$ in which each individual i of type k is assigned her corresponding type outcome μ^k yields a scalar measure of IOp I.[10] In turn, the IOp measure quantifies the extent to which individual outcomes are determined by circumstance characteristics, i.e. the more inequality in predicted outcomes, the more circumstances beyond individual control influence outcomes, and the more inequality of opportunity there is.

[8] Fleurbaey and Peragine (2013) show that conflicts between compensation and reward are an aspect of the broader conflict between ex ante and ex post perspectives and that the two are not compatible.

[9] The employed ex-ante approach proposed by Bourguignon et al. (2007) and Checchi and Peragine (2010) interprets the type-specific outcome distribution as the opportunity set of individuals belonging to each type. Hence, a value v_k of the opportunity set of each type k has to be selected for the comparison of opportunity sets across types (see section 4.1 for its empirical application and Ferreira and Peragine (2016) for further discussion).

[10] I decreases with Pigou-Dalton transfers between circumstance types but is invariant to such transfers within circumstance types. Hence, inequality in the counterfactual distribution of type-means can be considered unfair as it only depends on disparities due to unalterable circumstance characteristics.

3.2 Attitude Formation

In line with Krieckhaus et al. (2013), an individual's attitude formation based on the aggregated measure I of individual outcomes, $I = f(y_1, \ldots, y_N)$ (e.g. a country's Gini of consumption expenditure), can be divided in egocentric vs. sociotropic and retrospective vs. prospective. *Sociotropic* means an individual's level of support for democracy s_i is independent of her own outcome y_i, e.g. level of consumption or rank in national consumption distribution $r(y_i)$, so $s_i \perp\!\!\!\perp y_i$. *Egocentric*, in contrast, corresponds to an individual's support level s_i depending on her own outcome y_i, hence $s_i(y_i)$. *Retrospective* means that an individual's support level s_i depends on the past performance of the current level of democracy d, e.g. good governance (absence of corruption), income inequality (Gini) - thus, how the past practice of democracy has shaped the aggregated/individual outcome, $s_i(I(d))$; $s_i(y_i(d))$. *Prospective* on the other hand implies that an individual's support for democracy s_i is independent of the past performance of the current level of democracy, so the individual does not regard the current level of inequality as an outcome of the current level of democracy but rather as a proxy for future gains from redistribution through democracy ($\frac{\partial s_i}{\partial I} > 0$).

Based on this 4 case distinction (see table 1), the effect of economic inequality on attitudes towards democracy can be hypothesized as follows:

(1) If an individual is prospective sociotropic, her level of support would be independent of her own level/rank of consumption ($s_i \perp\!\!\!\perp y_i$) and economic outcomes would not be assessed as past performance of the implemented level of democracy. Based on the classic political economy literature (e.g Acemoglu and Robinson, 2006), higher levels of inequality entail larger potential societal gains from redistribution through democracy such that the citizen's support for democracy is expected to rise ($\frac{\partial s_i}{\partial I} > 0$).

(2) If an individual is retrospective sociotropic, her level of support would be independent of her own level/rank of consumption ($s_i \perp\!\!\!\perp y_i$) but economic outcomes would be assessed as past performance of the implemented level of democracy. Based on the survey literature (e.g Anderson and Tverdova, 2003), high levels of inequality will be attributed to a non-satisfactory performance of the current system of government and, hence, the presence of high levels of inequality are expected to lead to disillusion/frustration about democracy and lower levels of democratic support ($\frac{\partial s_i}{\partial I(d)} < 0$).

(3) If an individual is prospective egocentric, her level of support would dependent on her own level/rank of consumption ($s_i(y_i)$) but economic outcomes would not be assessed as past performance of the implemented level of democracy. Based the political economy literature with self-interested individuals (e.g Boix et al., 2003), future gains from redistribution through democracy depend on the individual's current level of consumption and, hence, support for democracy should be lower for individuals with high income than for low-income individuals ($\frac{\partial s_i}{\partial y_i} < 0$). Further, such a negative relationship between an individual's current level of consumption and support for democracy should be stronger in countries with higher levels of inequality ($\frac{\partial^2 s_i}{\partial y_i \partial I} > 0$).

(4) If an individual is retrospective egocentric, her level of support would dependent on her own level/rank of consumption ($s_i(y_i)$) and economic outcomes would be assessed as past perfor-

	prospective	retrospective
sociotropic	prospective sociotropic	retrospective sociotropic
egocentric	prospective egocentric	retrospective egocentric

Table 1: Attitude Formation Processes proposed by Krieckhaus et al. (2013)

mance of the implemented level of democracy. Following (2) and allowing heterogeneous effects based on levels/rank of consumption, support for democracy should be higher for high-income individuals if inequality is high since democracy has performed well by preserving their privileged economic status, whereas low-income individuals shall exhibit lower support levels due disillusion/frustration ($\frac{\partial s_i}{\partial y_i} < 0$). Conversely, in a low inequality setting high-income individuals might be less supportive of democracy since they favor lower levels of redistribution through a different form of government while low-income individuals want to keep the current level of redistribution, thus they are supporting democracy ($\frac{\partial^2 s_i}{\partial y_i \, \partial I} < 0$).

For the effect of IOp on attitudes towards democracy, hypotheses can be derived along similar lines when regarding democracy is a vehicle for fair process. *Prospective* corresponds to higher levels of IOp being associated with larger gains from advancements in process fairness facilitated by democracy. *Retrospective* resembles individuals regarding the current level of IOp as output of the regime and, hence, high levels of IOp imply bad regime performance which causes the individual to lose faith in the regime's ability to generate equal opportunities. Given the IOp framework, ranking an individual's outcome y_i conditional on her circumstance type T, $r(y_i|T)$, corresponds to determining an individual's level of effort since, by assumption, differences in outcomes within the same circumstance type T only arise due to differences in effort.[11] Based on such a conditional ranking, an effort distribution or rather a relative ranking of how well the individual has performed given her initial conditions can be generated which, in a stylized case, divides individuals in low/high effort. As discussed by Clark and d'Ambrosio (2015), individual attitudes towards inequality depend critically on the reference group that the individual has in mind when evaluating her relative standing. In the presence of unequal opportunities, the individual's type (given a reasonable level of parsimony) might be such a relevant reference group. As high effort individuals generate higher outcomes in the current societal setting compared to their low-effort peers, they tend to praise the current regime for their success while low-effort individuals blame it for their outcome (Daenekindt et al., 2018). Thus, if individuals are *egocentric*, the individual's support for democracy should be lower for low-effort (i.e. low outcome conditional on circumstances) individuals.

[11] Within the group of individuals of the same type no "unfair" factors, which could affect the individual's outcome, prevail.

4 Empirical Framework

4.1 Empirical IOp Measurement (First Stage)

Measuring ex-ante IOp corresponds to computing inequality in an estimated counterfactual distribution $\tilde{M}$. This counterfactual distribution can be estimated by either a non-parametric or a parametric approach.

The non-parametric estimation as proposed by Checchi and Peragine (2010) follows a two-stage methodology. First, one partitions the sample into types based on all observable circumstances C and then one chooses the arithmetic mean of the outcome of type k, denoted by μ_k, as the value v_k of the opportunity set of type k. Second, the counterfactual $\tilde{\mu}_i$ for each individual i belonging to type k is defined as $\tilde{\mu}_i = \hat{\mu}_k$, where $\hat{\mu}_k$ is the sample estimate for μ_k, and the inequality in $\tilde{M}$ is measured.

The *Standard* parametric ex-ante approach suggested by Bourguignon et al. (2007) and Ferreira and Gignoux (2011) alters the two-step procedure by estimating $\tilde{M}$ based on the predictions of a reduced form regression. Operationally, this corresponds to first estimating:

$$\ln y_i = \alpha + \beta C_i + \epsilon_i \,.^{12} \tag{1}$$

Second, one uses the estimated parameters $\hat{\beta}$ to parametrically construct an estimate for the distribution of type means $\tilde{M} = (\tilde{\mu}_1, \ldots, \tilde{\mu}_i, \ldots, \tilde{\mu}_N)$:

$$\tilde{\mu}_i = \exp(\hat{\alpha} + \hat{\beta} C_i) \,. \tag{2}$$

Such a specification accounts for both the direct and the indirect effect of circumstances since the correlation between C_i and E_i is implicitly captured by β.[13]

The parametric approach does not directly identify types to predict a counterfactual distribution but linearly approximates the types' average outcomes by the predictions of a regression of circumstances on outcomes. Such estimation procedure is more parsimonious than the non-parametric approach which makes it the methodology of choice for estimation when few observations are available (see discussion in Ferreira and Gignoux, 2011). Yet, parsimony comes at the cost of imposing the assumption that the effect of the circumstances on outcome is supposedly fixed and additive.[14,15] By construction, the linear parametric approach explains less inequality

[12] The presented log-linear specification is due to the analogy to the Mincer equation and the standard choice in empirical studies, see Brunori et al. (2019c); Ferreira and Gignoux (2011).

[13] The reduced-form outcome generating process is $y_i = \alpha + \gamma C_i + \delta E_i + u_i$. Circumstances may also influence the individual's outcome indirectly through effort, $e_i = \zeta C_i + \nu_i$. Substituting back into the outcome generating process yields $y_i = \beta C_i + \epsilon_i$ where $\beta = \gamma + \delta\zeta$ and $\epsilon_i = \delta\nu_i + u_i$.

[14] Hufe and Peichl (2015) present evidence for the importance of considering interaction terms as they acknowledge substantial divergence between IOp estimates obtained via a linear model specification, as in equation (1), and a non-linear model which corresponds to circumstances being fully interacted.

[15] The parametric and the non-parametric methods coincide when all explanatory variables are categorical, and the parametric counterfactual distribution is obtained by the prediction of a regression model where y is regressed

than the non-parametric one as the latter draws on the full set of interactions to explain the variability in outcomes. The resulting trade-off between the two approaches has to be balanced given the data availability, i.e. a linear specification might be too restrictive, whereas including the full set of circumstances' interactions might cause very large sampling variance of the estimated counterfactual distribution when the number of observations per type is limited (see Brunori et al., 2019c, for an extensive discussion).

Inequality of opportunity estimates have traditionally been proposed as lower bounds due to the downward bias resulting from the partial observability of circumstances that affect the individual outcome (e.g. Ferreira and Gignoux, 2011).[16] Brunori et al. (2019c) point out that such IOp estimates may suffer from upward bias as a consequence of sampling variance and associated over-fitting. However, when the sample size is small relative to the number of types/regressors, upward bias might prevail. Sample size is a major concern with respect to the IOp estimates of this thesis as most cross-country studies use larger samples, e.g. the ones drawing on the EU-SILC data (i.e Marrero and Rodríguez, 2012; Brunori et al., 2019c) use more than 5000 observations per country while the sample size of the data employed in this thesis varies between 800 and 1400 per country (see section 5). Therefore, the empirical framework tries to address the data limitation by using different methods to construct the counterfactual distribution.

Balancing the two sources of bias and easing the assumption of circumstances' effects being fixed and additive, Brunori et al. (2019c) propose a model selection based on k-fold *cross-validation (CV)*[17] via MSE (see appendix for the error decomposition and the resulting motivation for the MSE criteria usage). As adjusted by EqualChances.org (2018) Project, one first estimates linear models with different levels of circumstance granularity (e.g. parental education coded as high/low or primary/secondary/tertiary education) and selects the appropriate level of granularity by means of CV. Second, using the chosen level of circumstance granularity, all alternatives models with subsets of circumstance interactions between (and including) the linear and the fully interacted specifications are estimated and the best specification is chosen via CV. Such a model selection eases the linearity assumptions and accounts for sampling variance.

Alternatively, Hufe et al. (2019) propose a lower bound estimate based on cross-validated *Lasso* estimations (Tibshirani, 2011) that select the relevant circumstance parameters $C_j^r \subseteq C_j$ in a way that maximizes the prediction accuracy of the estimated model out-of-sample to correct for the

on all possible combinations of circumstance values. Following Brunori et al. (2019c), the reduced-form estimation can be written as $y_i = \sum_{j=1}^{J} \sum_{k=1}^{K_j} \chi_{j_k} c_{ij_k} + u_i$, where c_{ij_k} identifies each category of the observable characteristics by means of a dichotomous variable, and χ_{j_k} is the corresponding coefficient. Further, for all $j \in \{1, \ldots, J\}$, K_j denotes the possible values taken by circumstance C_j and $|K_j|$ describes the cardinality of K_j of C_j. The population can be partitioned into P types, where a type is a selection of values, one for each circumstance, that is, $P = \prod_{i=j}^{J} = |K_j|$. Hence, interacting all values of all regressors with each other yields a model with P dummies which corresponds to estimating the arithmetic mean of y for each type k.

[16] This result follows from the assumption of orthogonality between circumstances and effort (see Roemer, 1998), i.e. enlarging the set of observed circumstances can only increase IOp as it accounts for a further potential source of it.

[17] The k-fold cross-validation procedure divides the sample into k-folds. Under each model specification, the model parameters are estimated on $k-1$ folds and the ensuing predictions are benchmarked against the data points in the k^{th} fold. Repeating this procedure k times, one chooses the model that delivers the lowest average mean-squared prediction error across the k iterations.

upward bias due to sampling variance in the distribution of type means,

$$\underset{\beta}{\text{argmin}} \underbrace{\sum_i (\ln y_i - \alpha - \sum_j \beta_j C_{ij})^2}_{(1)} + \underbrace{\sum_j \lambda |\beta_j|}_{(2)} \ .^{18} \tag{3}$$

Part (1) of equation (3) is a perfect mirror of the OLS algorithm used for estimating equation (2) while part (2) introduces a penalization term that varies with the absolute value of the estimated coeffcient $\hat{\beta}_j$, i.e the larger the penalization parameter λ, the more parsimonious the model and the lower the variance (bias) in the predictions based on the parameter vector $\hat{\beta}^{Lasso}$. The optimal parameterization of λ is chosen via a 10-fold CV. In turn, circumstance characteristics on which coefficients are not shrunk to zero, C_j^r, are retained to estimate the counterfactual distribution via OLS. Such a model selection provides the most parsimonious parametric specification and, hence, yields a rather conservative estimate of IOp which serves as benchmark for the results presented in section 6.

The usage of k-fold CV for model selection might imply using an alternative model specification for each country in a given data source and for the same country for different time periods as each time the country's sample differs. Comparing IOp measures across countries, one might compare measures obtained with different specifications which is in contrast with the common practice to use the same model specification for all countries of a unified data source Brunori et al. (2019c). Yet, given the varying data quality across countries and survey waves of the used dataset, the increased reliability (lower bias) of the estimated IOp measures yields a valid sensitivity check/benchmark for the standard estimation.

As an alternative to the discussed parametric approaches, Brunori et al. (2019a) present a more data driven estimation method by using conditional inference regression forests, i.e. creating many trees and average over all of these to make predictions. Trees divide the population into non-overlapping groups, $G = \{g_1, \ldots, g_m, \ldots g_M\}$ where each group g_m is homogeneous in the expression of some input variables $x = (x^1, \ldots, x^J)$. Partitioning is based on recursive binary splitting, i.e. starting by dividing the full sample into two distinct groups according to the value they take in one input variable $x_j \in X$.[19] The process is continued such that one of the two groups is divided into more subgroups (potentially based on another $x_k \in x$), and iterated further. Brunori et al. (2019a) follow the conditional inference methodology (Hothorn et al., 2006) to conduct the splits, i.e. trees are grown by a series of permutation tests.[20,21]

[18] Such a procedure is called post-Lasso estimation (Hastie et al., 2009) and differs from a standard Lasso estimation by estimating the relevant parameters after shrinkage by means of OLS instead of directly using the penalized Lasso parameters.

[19] If x_j is a continuous or ordered variable (e.g. parental education), then $i \in t_l$ if $x_i^k < \tilde{x}^k$ and $i \in t_m$ if $x_i^k \geq \tilde{x}^k$, where $\tilde{x}^k$ is a splitting value chosen by the algorithm. If x_k is a categorical variable (e.g. urbanity status) then the categories can be split into any two arbitrary groups.

[20] First, based on univariate tests between each $x^k \in x$ and outcome y, the most related x^k to y is chosen as potential splitting variable x^*. Second, if the dependence between y and x^* is sufficiently strong then a split is made. Whenever x^* can be split in several ways, the sample is split into two subsamples such that the dependence with y is maximized. Such procedure is repeated in each of the two subsamples until no circumstance in any subsample is sufficiently related to y.

[21] Structure and depth of the tree hinge crucially on the permutation tests' critical value to reject the null hypothesis α, i.e the less stringent the α-requirement, the more splits are detected as significant and the deeper the

Given all input variables being circumstances only ($x = C$), each resulting group $g_m \in G_M$ can be interpreted as a circumstance type $t_m \in T$. The conditional expectation for observation i is estimated from the mean outcome $\hat{\mu_m}$ of the group g_m of size N_m to which the i^{th} observation is assigned and, in turn, yield the predicted value

$$\hat{f}(x_i) = \hat{\mu}_{m(i)} = \frac{1}{N_m} \sum_{j \in g_m} y_j \ . \tag{4}$$

The vector of predicted values $\hat{y}^C = (\hat{f}(x_1), \ldots, \hat{f}(x_i), \ldots, \hat{f}(x_N))$ corresponds to the counterfactual distribution $\tilde{M}$. Random forests are a collection of such trees, where each tree is estimated on a random subsample of the population and $B*$ of such trees are estimated in total. Further, only a random subset of circumstances $\{x^p \in x : p \in \hat{P} \subset \{1, \ldots, P\}\}$ of size $\bar{P}^*$ is allowed to be used at each splitting point. Yet, they inherit some advantages over the usage of a single tree for IOp estimation: (1) averaging over B^* predictions cushions the variance in the estimates of y^C and smoothes the non-linear impact of circumstance characteristics; and (2) drawing only on subsets of all circumstance variables increases the likelihood that all observed circumstances with informational content will be identified as the splitting variable x^* at some point which helps to leverage information contained in the set of observed circumstances. Predictions for M are formed by

$$\hat{f}(x; \alpha^*, \bar{P}^, B^*) = \frac{1}{B^*} \sum_{b=1}^{B^*} \hat{f}^b(x; \alpha^*, \bar{P}^*). \tag{5}$$

The thesis follows Brunori et al. (2019a) in fixing $B^* = 200$,[22] $\alpha^* = 1$,[23] and determining $\bar{P}^*$ by minimizing the out-of-bag error.[24] Such a supervised learning method solves the problem of circumstance selection and specification of a functional form according to which circumstances co-produce the outcome of interest. Further, unlike the parametric approaches, it does not rely on the full set of circumstance to generate individual-level predictions increasing the number of observations in the counterfactual distribution. Hence, the random forest approach provides a valuable sensitivity check to the previously presented parametric approaches in terms of the impact of model selection and missing circumstance variables.

To summarize the information in the estimated counterfactual distributions ($\tilde{M}$) the literature proposes the usage of the Gini coefficient or the mean log deviation (MLD). Following Brunori

tree is grown.

[22]The choice of fixing $B^* = 200$ is motivated by the reduction of computational costs as at level of 200 the marginal gain of drawing an additional subsample in terms of out-of sample prediction accuracy becomes negligible. Given the smaller number of circumstance variables available compared to Brunori et al. (2019a), a smaller B would also be sufficient but for comparability their choice is adopted.

[23]Simultaneously determining both α^* and $\bar{P}^*$ via out-of-bag procedure , the optimal level of α is often very high, i.e. trees are grown very deep. At the limit, $\alpha = 1$, splits are made as long as each terminal node has at least a minimum number of observations. Single trees within the forest surely overfit the data and perform poorly out-of-sample but averaging over many overfitted trees remedies such drawbacks. Hence, setting $\alpha = 1$ a priori is a sensible strategy to reduce computational costs.

[24]The out-of-bag procedure follows a similar logic as k-fold CV, i.e. instead of leaving out the kth fraction of the sample to make out-of-sample predictions, one leverages the fact that each tree of a forest is grown on a subsample (bag) that excludes some observations and, hence, uses the out-of-bag data points to evaluate the predictive accuracy. Given the smaller number of observations available, the fraction of the sample used is increased to 0.75 compared to 0.5 by Brunori et al. (2019a).

et al. (2019b) and Aaberge et al. (2011), the Gini coefficient is employed throughout the analysis, though main results and graphical representation of the MLD IOp results are provided as sensitivity checks (see table A8 and figures A8 and A9).[25] The second stage estimations employ a relative measure of IOp that relates the Gini coefficient of the estimated counterfactual distributions $\tilde{M}$ to the Gini coefficient of the actual outcome distribution Y, $IOp^{rel} = \frac{Gini(\tilde{M})}{Gini(Y)}$. The relative IOp measure can be interpreted as the share of total inequality being explained by circumstances and, hence, violating the ideal of equal opportunities.

4.2 Individual-level Support for Democracy (Second Stage)

In order to test the hypotheses on the attitude formation derived in section 3.2, country-wide consumption inequality or IOp measures are incorporated in individual-level attitude formation regression:[26]

$$attitude_{tci} = \alpha + \beta_1 I_{tc} + \beta_2 I_{tc} \times demo_{tc} + \Phi X_{tci} + \Lambda Z_{tc} + \gamma_t + \epsilon_{tci} \tag{6}$$

where i, c and, t index individuals, countries and years (2010 or 2016). I_{tc} is a scalar country-level inequality measure (overall Gini or IOp) and $demo$ is the Polity2 score (i.e. political regime measure, proxy for the implemented level of democracy, see Plümper and Neumayer (2010)). The specification controls for a vector of individual-level (X_{tci}) and country-level (Z_{tc}) characteristics as well as year-fixed effects (γ_t). More specifically, X_{tci} includes: gender, age and age squared, educational attainment and the circumstance variables of the first stage.[27] Time-varying country characteristics Z_{tc} include PPP-adjusted GDP per capita, 5 year average GDP per capita growth and 5 year average unemployment rate and dummy variables for countries without communist past as well as for new EU member states.[28]

[25]Brunori et al. (2019b) discuss the merits of using the Gini coefficient, i.e. (1) MLD is very sensitive to extreme values (see figure A1 for further explanation), (2) MLD is perfectly decomposable in between- and within-types inequality (main argument for its usage) but the desirability of such property remains questionable as e.g. the Lorenz partial ordering does not decompose exactly in a between and within component, and (3) the Gini coefficient values belong to a well-defined interval [0,1] while the MLD is not bounded above which limits a straightforward interpretation of the results. For those reasons, the presented results use the Gini coefficient although it is not perfectly decomposable in between- and within-types inequality whenever the type income distributions overlap, i.e. $Gini(Y) = Gini(Y_{within}) + Gini(M) + K$, where K is a residual greater than zero when there is overlapping between the types' distributions. K measures the part of inequality that is jointly determined by effort and circumstances, but that cannot be disentangled into the effect of effort and the effect of circumstances.

[26]Ideally, one might want to incorporate both parts of inequality, the fair and the unfair one, into the attitude formation process. Yet, acknowledging the shortcomings in data quality, generating a measure of fair inequality as residual part of the overall consumption inequality of the sample used in the IOp estimation is likely to understate the salient level of economic inequality as for most countries the estimation sample's consumption inequality understates the inequality in disposable income that is documented by other public sources. Also, such a procedure would be questionable given that the Gini itself is not perfectly decomposable. Further, due to the aforementioned limited matching of the estimation sample's consumption inequality and the inequality in disposable income from other sources, combining the relative IOp of the former with the level of the later in the attitude formation also appears to be questionable.

[27]The inclusion of dummy variables for marital status and labor market status, coded as employed, unemployed, student, retired and others, (e.g. Solt, 2008; Gugushvili, 2020) has been tested but did not alter results.

[28]Excluding Western democracies is presented as a sensitivity check in section 6.3.

Besides the mentioned standard personal controls, one has to consider additional confounders of the effect of overall inequality/IOp on the attitude towards democracy formation process: (1) governance as mitigating factor of fairness concerns (Brock, 2020); (2) communist party membership of parents as a proxy for intergenerational transmission of regime attitudes (Alesina and Fuchs-Schündeln, 2007); (3) perceived mobility experience as determinant of beliefs in IOp (Gugushvili, 2020); (4) communist experience, i.e. if individuals have lived/been socialized under communism, they have to re-learn political support in relation to the new regime and have the experience of a different regime form as a benchmark (Mishler and Rose, 2002); and (5) life satisfaction, i.e. individuals in former communist countries have been found to link life satisfaction and perceived regime performance (Djankov et al., 2016).

The presented specification allows to test retro- vs. prospective hypotheses or rather their relative weight by assessing the sign and significance of the β coefficients, i.e. due to the included interaction between IOp and the current level of democracy, both evaluation types might be at play. Further, including an individual's overall rank of consumption $r(y_i)$ in the set of independent variables allows to check the egocentric vs. sociotropic hypothesis for consumption inequality in the binary classification of Krieckhaus et al. (2013) through testing its coefficient's significance. Yet, one might rather want to compare the effect sizes of the inequality measure and an individual's rank in order to determine the relative importance of the two support motives as individuals are likely to care about both - their personal outcome as well as the societal outcome. Instead of an individual's rank in the consumption expenditure distribution one can generate such rank conditional on her circumstance-type T, $r(y_i|T)$, which corresponds to her level of effort or rather a relative ranking of how well the individual has performed given her initial conditions (see section 3.2). Such conditional ranking serves to check the egocentric hypothesis in the dimension of IOp. Given the aforementioned sample size concerns, the population is divided into 4 types (corresponding to the most parsimonious type definition of Brunori et al. (2019c)) based on the individual's place of birth (urban/rural) and parental education (less/upper secondary or more). Within these types individuals are divided into 3 effort groups each (low, median, high). Yet, in the case of larger samples a finer partition in terms of types and effort is likely to be beneficial as opportunity sets might vary substantially along additional/more granular circumstances and differences in attitudes are likely to be found in the tails of the effort distribution.[29]

As the dependent variable is measured binary (i.e. the individual either supports democracy as regime form or not), the regression is a probit estimated via maximum likelihood. The main results follow the common practice to use robust standard errors (SE) clustered at the country level to account for the potential correlation existing in the errors within countries (e.g. Brock, 2020; Andersen, 2012).[30] Also, more conservative SE estimates based on bootstrap methods

[29]Donni et al. (2015) present a latent variable approach to define types for IOp measurement. Using such types is beyond the scope of this thesis but would yield an interesting cross-check. However, since the theoretical framework aims at employing a type-definition salient to the individual, the chosen ad-hoc type definitions better suit the purpose of the analysis.

[30]Cluster-robust standard errors (SE) remain consistent given any kind of between- and within-cluster heteroscedasticity and autocorrelation under the key assumption that lower-level units belonging to different clusters are independent (Wooldridge, 2003). This assumptions is arguably satisfied in the setting at hand as individuals in country i are independent from individuals in country j $\forall i, j \in C$. The main limitation of inference with cluster-robust standard errors is that the asymptotic justification assumes that the number of clusters goes to infinity which is apparently violated in the application at hand and results in downward biased standard errors

are presented in section 6.3. Note that the estimation does not provide strict identification and coefficients are correlations only.

As an alternative to the previously described individual-level specification, a multi-level model is specified as a sensitivity check (see section AVII for model specification and section 6.3. Multi-level modelling is a common practice in the political science literature in order to accounted for the nested data structure to avoid underestimating the standard errors of the contextual variables (e.g. Ritter and Solt (2019); Brunori (2017)).

5 Data & Variable Definitions

The primary data sources are the most recent waves (2010, 2016) of the Life in Transition Survey (LiTS), a cross-sectional household survey administered by the European Bank for Reconstruction and Development (EBRD) and the World Bank. The data are largely comparable across 28 former communist countries (”transition countries”) and 3 Western democracies as comparator countries (Germany, Italy and Greece), over two waves.[31] The number of households interviewed per country is ca. 800 in 2010 and ca. 1,400 in 2016, generating a nationally representative sample of households. The LiTS provides extensive individual-level information on circumstances and attitudes, and covers countries with heterogeneous levels of democratization and economic development.

5.1 IOp Estimation

For calculating IOp measures, equalized monthly household consumption expenditure based on 7 different consumption categories (food, utilities, transportation, education, health, clothing, durable goods) is employed. As income is measured with greater error than consumption expenditure and consumption being closer to permanent income than current income (given access to consumption-smoothing mechanisms), Deaton (1997) argues for preferring consumption over income data in assessing the distribution of welfare in developing countries. Additionally, consumption inequality in almost all countries is lower than income inequality (Deaton and Grosh, 2000), so consumption inequality can be interpreted as a lower bound for income inequality. Following Hufe et al. (2018), the countries' year-specific consumption distribution is winsorized at the 1st and the 99.5th-percentile to curb the influence of outliers.[32] The analysis focuses on the

(Bertrand et al., 2004).

[31] Following Gugushvili (2020), Bosnia and Herzegovina is excluded from the group of former communist countries because of complicated socio-political arrangements. Further, Turkey and Cyprus are excluded from the group of comparator countries as they have featured their own democratic transitions, though each of a different kind. As the democratic transformation of Eastern Germany has been more rapid than for the other former Communist countries in the sample and given the limited sample, Germany is regarded as a Western comparator country while parental communist party membership is excluded from the set of circumstances.

[32] Further, the countries' year-specific consumption distribution is an aggregation of 7 different consumption items within which values are winsorized 0.5th and the 99.5th-percentile on a country-year basis.

working age population, i.e. restricting the sample to respondents aged between 26 and 64. To ensure the representativeness of the country samples all results are calculated by using appropriate individual cross-sectional weights.

Circumstance variables across both waves include mother's and father's education, parental membership in communist party, place of birth and ethnicity.[33] The question types for parental education differ across waves, i.e. in 2010 respondents are asked to state the years of education their parent has completed, whereas in 2016 the highest degree obtained is recorded. As the length of educational careers varies across country, drawing on UNESCO (2020) data to map years of education into degrees in line with International Standard Classification of Education (ISCED) is a reasonable first step to enhance the matching accuracy compared to a uniform coding rule.[34] However, such coding still yields implausible imbalances between parental educational attainment across waves. As one of the motivations for the usage of the LiTS is to compare countries across time, a more data driven approach is implemented by matching years of education into degrees based on observed bunching (see figure A2 for comparison of composition of parental education across coding approaches and waves). Further, in line with Brunori et al. (2019c) and Hufe et al. (2019), a meaningful pre-aggregation of educational degrees into 4 categories is performed in order to reduce sampling variance of the estimated counterfactual distribution and to ease the computation for CV procedures.[35] In line with the literature (e.g. Brunori et al., 2019c; Ferreira and Gignoux, 2011; Hufe et al., 2018) and a type-based interpretation of parental education, father's and mother's education are employed as categorical variables.

Parental political affiliation (i.e. whether a parent was a communist party member) captures network effects as party membership was often required for admission into specific schools and professions during Communism (Heyns, 2005). In turn, following Brock (2020), a dummy variable for parental communist party membership is included in the set of circumstances. Respondent's place of birth affects the development opportunities during childhood as well as the residence later in life with the associated economic opportunities (Brunori et al., 2019b; Brock, 2020). In line with Álvarez and Menéndez (2018) and Brock (2020), the place of birth variable distinguishes between urban and rural areas with respect to the place of birth. Belonging to an ethnic minority can severely limit development and employment opportunities through outright discrimination or language barriers (Ferreira and Gignoux, 2011). Based on self-reported ethnicity or by utilizing the ability to speak the country's predominant language, respondents' minority status is included as a binary variable.[36] Table A1 presents summary statistics of the circumstance variables and documents an considerably increase in sample size and data quality in terms of item non-response from 2010 to 2016. In turn, IOp estimates for 2016 can be regarded as more reliable then the 2010 ones.

[33]Following Ferreira and Gignoux (2011), gender is excluded from the set of circumstances because the outcome (i.e. consumption expenditure) is defined at the household level.

[34]Brock (2020) adapts a uniform coding resulting in large compositional changes in parental education across waves, which can be regarded as a threat to the comparability of her estimates over time.

[35]The pre-aggregation is performed on the country-level in order to maximize the IOp estimates' comparability across time. This procedure does not automatically impede comparability across countries as the relevant circumstance granularity and aggregations are likely to vary across countries (Brunori et al., 2019c).

[36]Parental communist party membership and ethnic minority status have been excluded for the IOp estimation in countries with less than 5% or less than 50 respondents exhibiting those characteristics in order to facilitate reliable inference.

The alignment of the LiTS sample with public data is key to the validity of the IOp estimates. For its assessment, the analysis draws on the Standardized World Income Inequality Database (SWIID) which aims to maximize the comparability of income inequality data across time and countries by drawing on a large range of data sources and also, confidence intervals are provided to capture the underlying data quality (Solt, 2020). As the SWIID reports Gini coefficients for disposable income, its estimates are viewed as upper bound for the generated consumption expenditure based measures based on the LiTS. In order to assess the data quality of LiTS, confidence intervals of the country samples' Gini coefficients are derived based on 200 bootstrapped re-samples using the normal approximation method.[37] Figures A3 and A4 present graphical representations of this comparison (see also table A3). Given the upper bound character of the SWIID estimates, IOp estimates which are based on consumption distributions with inequality well above the upper end of the SWIID's confidence interval are excluded from the analysis.[38]

5.2 Attitude Formation

5.2.1 Dependent Variable

Corresponding to the discussion in section 2.1, the focus of the thesis is the normative (diffuse) support for democracy, i.e. do individuals belief that democracy is the best regime type. In line with previous studies (Gugushvili, 2020; Claassen, 2020), this attitude towards the political regime is measured dichotomously based on the question ”With which one of the following statements do you agree most?”, which exhibits 3 possible answers (1) ”Democracy is preferable to any other form of political system”, (2) ”Under some circumstances, an authoritarian government may be preferable to a democratic one”, and (3) ”For people like me, it does not matter whether a government is democratic or authoritarian”; where only (1) is counted as support for democracy, while (2) and (3) are regraded as non-support.

5.2.2 Country-level Variables

The employed measure of the level of democratization is the Polity2 index based on the Polity IV Project database (Center for Systemic Peace, 2018). The Polity2 index with a range of [-10,10]

[37] Confidence interval of the mean of a measurement variable being estimated on the assumption that the statistic follows a normal distribution, and that the variance is therefore independent of the mean.

[38] Azerbaijan and Uzbekistan are not covered in SWIID and no reliable data sources is available to verify the Gini coefficient of the IOp estimation sample. Uzbekistan's Gini (point) estimates are reasonable in size and do not vary remarkably (0.284 in 2010 and 0.329 in 2016). Azerbaijan exhibits the largest change in the Gini (point) estimates in the estimation sample (point estimates of .322 in 2010 and .235 in 2016, which amounts to a change of -.087) but the estimates do not seem to be exceptionally high compared to the other transition economies. Nevertheless, results are robust to the exclusion of Azerbaijan. Tajikistan exhibits the second largest change (point estimates of .407 in 2010 and .341 in 2016, which amounts to a change of -.066) and it is also the country with the highest SWIID Gini coefficient in the sample. As such a large change probably corresponds to differences in the data's ability to capture inequality, resulting IOp measures are likely to be non-comparable across waves and likely to over/understate prevailing IOp. For these reasons, Tajikistan is excluded from the second stage analysis.

corresponds to distinct regime categories, i.e. ”autocracies” (-10 to -6), ”anocracies” (-5 to +5), and ”democracies” (+6 to +10).[39]

For measuring the quality of institutions, the governance measure from the Worldwide Governance Indicator (WGI) project Kaufmann and Kraay (2019) is used. The database provides country-level assessments of formal institutions that are not directly attributed to the form of government/regime itself: government effectiveness, regulatory quality, rule of law and control of corruption. Scores [-2.5, 2.5] are relative, i.e individual index scores for each year are normalized to have a mean of zero across all countries of the database, and the scale has no inherent value. Following Easterly and Levine (2016) and Brock (2020), the employed governance indicator is the average of the scores across the 4 mentioned dimensions.[40]

All macroeconomic indicators, i.e. GDP per capita, average GDP per capita growth rate and average unemployment rate across the last 5 years[41], are obtained from the IMF World Economic Outlook database 2020. Additionally, dummy variables for countries without communist past as well as for new EU member states are included.

5.2.3 Individual-level Variables

The standard controls are a gender dummy, age and age squared and educational attainment (no education, primary, secondary, tertiary education). Also included is binary indicator for life-satisfaction.[42] Further, the circumstance variables from the first stage with parental education as aggregate for father’s and mother’s education (i.e. the highest educational degree obtained by either parent) are included in the set of individual controls.[43] Additionally, as employed in the analysis of Gugushvili (2020), the individual’s perceived mobility experience as expressed by agreeing or disagreeing with the statement ”I have done better in life than my parents” serves

[39] An alternative data source is the Varieties of Democracy (V-Dem) project. Yet, its regime measure is less granular (i.e. closed/electoral autocracy, electoral/liberal democracy) and the its liberal democracy measure (for instance utilized by Claassen, 2020) is highly correlated with governance (correlation coefficient of 0.879). For the given sample of countries, separately accounting for both dimensions, formal regime transition and institutional quality (governance), appears to be beneficial for the assessment at hand as Brock (2020) finds a mediating effect of governance on the impact of IOp on fairness beliefs which can be a channel trough which IOp influences support for democracy.

[40] The database comprises two additional dimensions, ”Voice and Accountability” and ”Political Stability and Absence of Violence”. As these dimensions are to a certain degree related to the governmental regime in place and, hence, would be highly correlated to measures of political regime, the constructed governance indicator excludes these dimensions.

[41] GDP per capita is a proxy for a country’s economic development/affluence. Average GDP per capita growth rate and average unemployment rate across the last 5 years are proxies for long-run regime performance. Decreasing the time span to 3 years or using contemporary growth/unemployment, i.e. accounting for different levels of inertia, does not alter results.

[42] The binary indicator is based on the question ”All things considered, I am satisfied with my life now” with answer choice ranging from ”strongly disagree” (1) to ”strongly agree” (5) and (3) being ”Neither disagree nor agree”, where affirmative responses (”agree” (4), ”strongly agree” (5)) are coded as satisfied with life and (1)-(3) being regarded as non-satisfaction.

[43] Following Brock (2020), the respondent’s education and parental educational attainment are employed as continuous variables in the second stage to facilitate the interpretation of its effect.

as an explanatory variable.[44] Lastly, regressions include a dummy variable for experience of communism, i.e. participation in the labor market under communism and being socialized under such regime as indicated by being aged 16 or older at the fall of the iron curtain in 1990.

6 Results

6.1 IOp Estimation (First Stage)

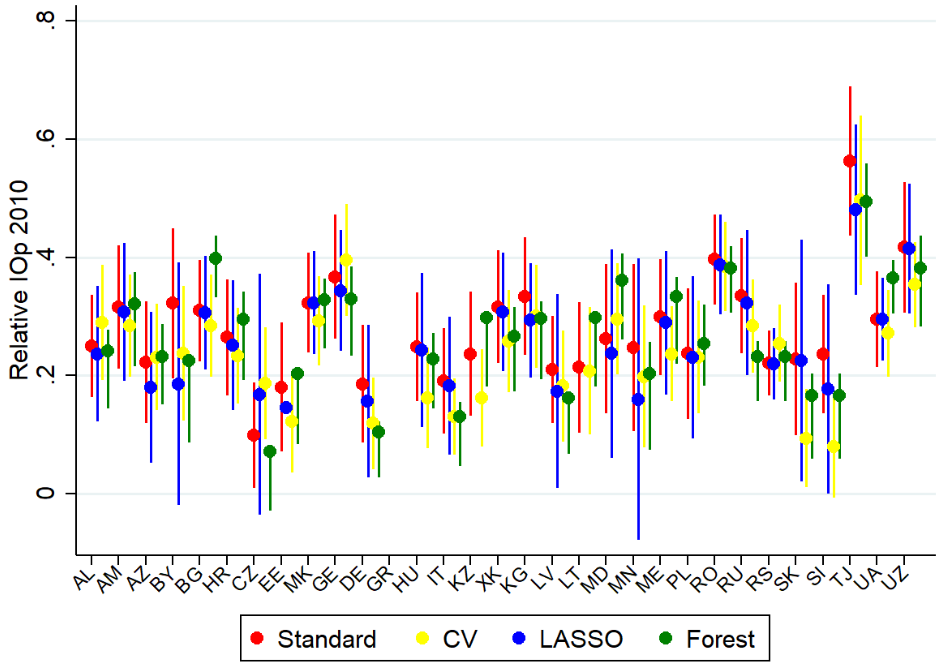
In order to meaningfully compare IOp across countries, figures A3 and A4 display the relative IOp estimates, i.e. the percentage of overall inequality that can be explained by exogenous circumstances, across the different estimation methodologies. Tables A4 and A5 present an overview of the point estimates and confidence intervals for relative and absolute IOp estimates. Data points for the *Standard* estimate indicate IOp based on all observable circumstances available assuming linearity and additivity of circumstance effects (Ferreira and Gignoux, 2011). *CV* corresponds to model selection based on cross-validation with multiple-circumstance granularity and interaction terms relaxing the linearity assumption (Brunori et al., 2019c; EqualChances.org, 2018). Like in the standard approach, estimates based on the *Lasso* procedure also use the full set of observable circumstances but account for potential upward biases by shrinking irrelevant circumstance parameters to zero. Estimates produced by the conditional inference regression *Forest* methodology do not impose assumptions on the functional form according to which circumstances co-produce an individual's outcome and are based on a larger sample as they do not require full circumstance information.

Figures 1 and 2 graphically present the first stage estimation results across the different methodologies for the relative IOp measure. The *Standard* IOp estimate ranges from 16.4% (Italy) to 57.3% (Tajikistan) in 2010 and from 9.6% (Azerbaijan) to 51.6% (North Macedonia) in 2016. Allowing for interactions between circumstances and trading-off up- and downward bias via *CV* does for most countries lead to small changes of the IOp estimates, such that estimates range from 11.9% (Germany) to 50.6% (Tajikistan) in 2010 and from 4.35% (Azerbaijan) to 50% (North Macedonia) in 2016. Limiting the sampling variation and the ensuing potential for upward biases in the standard estimates, the *Lasso* estimation provides for the majority of the countries only minor reductions in the coefficients of IOp. According to these Lasso-based estimates, between 14.6% (Italy) and 52.8% (Tajikistan) in 2010 and between 9.4% (Azerbaijan) and 58% (North Macedonia) in 2016 of outcome inequality must be considered "unfair".[45] The difference between standard estimates and the results of the non-parametric, data-driven *Forest* methodology varies on a country basis. Forest-based estimates range from 10.5% (Germany) to 49.5% (Tajikistan) in 2010 and from 19% (Italy) to 50% (North Macedonia) in 2016.

[44] Coding corresponds to the one of the question on life-satisfaction (see footnote 42).

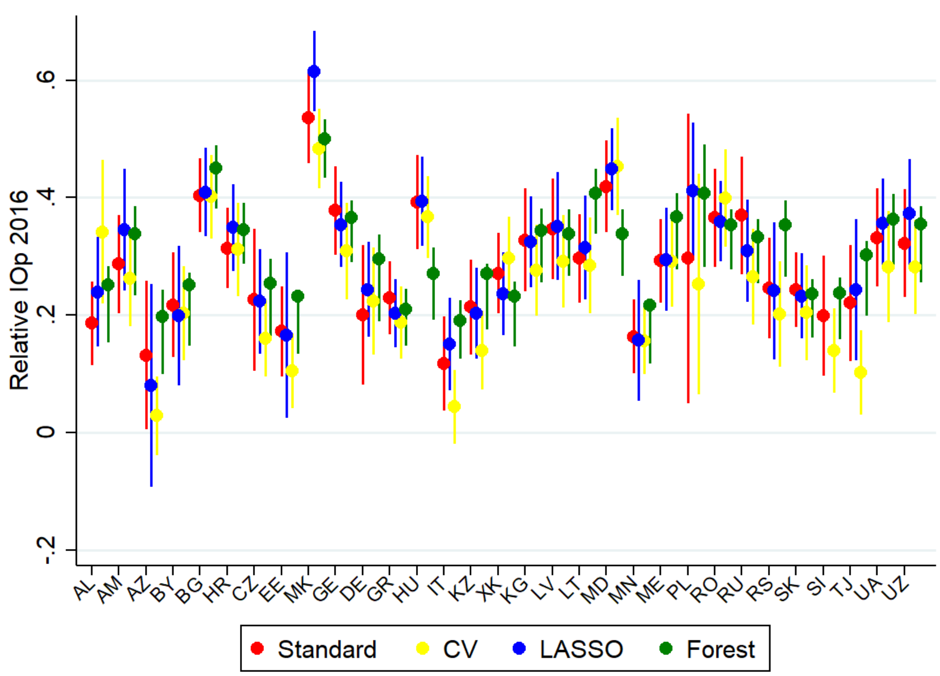
[45] For Estonia and Lithuania the Lasso algorithm shrank all coefficients to zero and, in turn, no IOp estimates are reported.

Figure 1: Comparison of IOp Estimates by Methodology (2010)



Notes: The figure depicts point estimates (dots) and 95% confidence intervals (spikes) for the countries' relative IOp in 2010 based on the different methodologies presented: (1) Standard, (2) CV-based interacted model, (3) Lasso, and (4) conditional inference Forest (see table A4 and section 4.1; Sources: LiTS; SWIID).

Figure 2: Comparison of IOp Estimates by Methodology (2016)



Notes: The figure depicts point estimates (dots) and 95% confidence intervals (spikes) for the countries' relative IOp in 2016 based on the different methodologies presented: (1) Standard, (2) CV-based interacted model, (3) Lasso, and (4) conditional inference Forest (see table A4 and section 4.1; Sources: LiTS; SWIID).

Considering the sample median, in 2010 the IOp share of overall inequality varies from 23.9% (Lasso) to 26% (Forest) while in 2016 it ranges from 26.4% (CV) to 33.3% (Forest). The median difference between Standard and Lasso estimates amounts to 1 percentage point in 2010 and 0.4 percentage points in 2016, which, in line with the results of Hufe et al. (2018) for developing countries, suggests that the standard estimation approach is largely uncompromised by overfitting circumstance parameters - at least when employing the LiTS data.[46] Relaxing the assumptions on the functional form of the circumstance effects might be beneficial to obtain more accurate IOp estimates (i.e. better capturing the influence of circumstances) as the median increase of 4 percentage points in 2010 and 3.2 percentage points in 2016 between the Standard and the presented CV-based methodology suggests. The differences between standard and forest estimates vary widely between countries ([-8,13.5] percentage points in 2010 and [-21,25] percentage points in 2016) yielding significant downward/upward corrections of IOp for certain countries. These large differences suggest that missing circumstance data for parts of the sample population might severely undermine results for such outlier countries (table A2 shows the country sample sizes by estimation method). In turn, these findings supports the claim of Brunori et al. (2019a) that their proposed forest methodology can yield substantial improvements in terms of curtailing sampling variance by trading off upward and downward bias. Further, while their empirical application is based on high-quality EU-SILC data, the presented results show an additional advantage of the approach, i.e. allowing to detect issues in data quality. Given the varying data quality across survey waves and countries, the forest approach appears to produce the most reliable IOp estimates and, hence, is used in the main results presented later on.

Along side with assessing the robustness of IOp estimates to different methodological approaches based on point estimates, one would like to check their reliability by deriving 95% confidence intervals based on 200 bootstrapped re-samples of the data using the normal approximation method (Brunori et al., 2019a). Therefore, besides point estimates, figures A3 and A4 display such confidence intervals and reveal the major limitation of the analysis presented below, i.e. the sizeable noise in the IOp estimates. The median size of the confidence intervals ranges from 11.2 percentage points (Forest in 2016) to 20.2 percentage points (CV in 2010) with the one for the standard method being 17.3 (15.2) percentage points in 2010 (2016). These confidence intervals are well beyond the ones presented by Brunori et al. (2019a) for IOp estimates based on EU-SILC data.[47] Further, these results hinder the usage of changes for identification (as it is done, for instance, in the analysis of Brock (2020)) and limit the reliability of the second stage results. Figure A5 depicts the IOp estimates in 2010 and 2016, and supports this assessment as changes are sensitive to the estimation method.

Overall, the IOp estimates reproduce the finding of Brunori et al. (2013), i.e. overall income inequality is positively related to relative IOp (correlation coefficient 0.557 (0.289) with p-value 0.003 (0.136) in 2010 (2016)). Figures A6 and A7 visualize this association.

[46] This finding stands in contrast to recent results on European countries which suggests that the standard approach overestimates lower bound IOp (Brunori et al., 2019c). One explanation might be the quality of the underlying data sources, which in the case of the presented analysis is a major concern.

[47] As an implication, this would also call into question the reliability of estimates presented in related empirical studies that use the same data source (e.g. Brock, 2020).

Table 2: Main Results

	pooled				2010		2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-1.350	-0.334			-2.565		-1.908	
	(1.204)	(2.346)			(2.327)		(3.839)	
IOp			0.762	2.977***		2.605***		4.831***
			(0.520)	(0.834)		(0.928)		(1.664)
Gini × Polity2		-0.144			0.036		-0.114	
		(0.266)			(0.294)		(0.478)	
IOp × Polity2				-0.271***		-0.161**		-0.608***
				(0.081)		(0.071)		(0.181)
Polity2	0.020	0.059	-0.005	0.075***	-0.002	0.032	0.075	0.182***
	(0.015)	(0.067)	(0.015)	(0.025)	(0.083)	(0.028)	(0.119)	(0.053)
actual Position	0.079***	0.079***	0.078***	0.080***	0.108***	0.107***	0.054***	0.059***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)	(0.016)	(0.016)	(0.016)
Mobility Experience	0.050***	0.051***	0.055***	0.055***	0.036**	0.045***	0.063***	0.064***
	(0.015)	(0.014)	(0.014)	(0.014)	(0.018)	(0.017)	(0.019)	(0.018)
Communist Experience	0.044	0.044	0.035	0.039	0.022	0.018	0.002	0.010
	(0.046)	(0.047)	(0.042)	(0.043)	(0.067)	(0.065)	(0.047)	(0.045)
Number of individuals	32935	32935	34605	34605	11701	12510	21234	22095
Number of countries	28	28	30	30	24	26	24	26
pseudo R^2	0.048	0.049	0.046	0.049	0.061	0.063	0.058	0.056

Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations using relative IOp estimates calculated via the Forest methodology (see section 4.1). Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects while for columns 5-8 the year of the survey wave is indicated above. Columns 1 and 3 report model specifications without an interaction between overall inequality/IOp and the level of democracy (Polity2 score). Columns 2, 4 and 5-8 include such an interaction which corresponds to the model specification of equation (6). All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors clustered at the country level are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

6.2 Attitudes towards Democracy (Second Stage)

Bearing in mind the discussed limitations applying to the IOp estimates, table 2 presents the results from the main regression of this thesis. Columns 1, 2, 5 and 7 determine the effect of overall inequality on support for democracy, whereas columns 3, 4, 6 and 8 investigate the effect of IOp on such attitudes. All regressions include controls for individual characteristics and macroeconomic controls as outlined in section 5. Further, following Gugushvili (2020), the estimation sample is limited to individuals aged 25 or older but the presented results are robust to including 18-24 year olds. Given the broached issues of sample size and data quality, the forest IOp estimates are used as conjectured above.

Assessing the effect of overall inequality/IOp by solely including the respective measure into a regression of democratic support on individual-level factors and country-level controls (column 1 and 3) assumes the effect of the respective inequality measure to be constant across all levels of overall inequality/IOp. Instead, including an interaction between the level of democracy and the respective inequality measure allows such effect to differ based on the level of democracy that currently prevails in the individual's country of residence. In such an enhanced framework (corresponding to eq. 6), the interaction term captures the idea of *retrospective* regime assessment while the coefficient of the respective inequality measure can be interpreted as the *prospective* component of regime support. Evaluating the importance of such a distinction, i.e. allowing both dimensions of regime evaluation (prospective and retrospective), by including an interaction term in the pooled analysis of the two survey waves with a year fixed effect (column 2 and 4), one notes considerable change in size and significance of the coefficients compared the non-interacted models (column 1 and 3). In turn, the analysis of the single survey waves follows the interacted model specification.

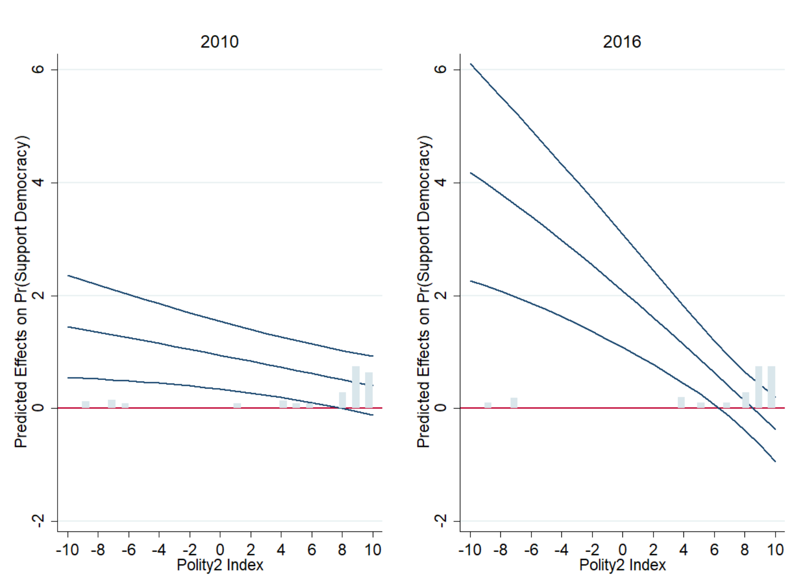
The first finding is that overall inequality in disposable income (columns 1,2,5 and 7), when controlling for mobility experience and actual position in the consumption expenditure distribution, might not matter as significantly for individual democratic support as suggested by previous research (e.g. Andersen, 2012; Krieckhaus et al., 2013). Neither in the pooled analysis (columns 1 and 2) nor in the separate analyses for 2010 and 2016 (columns 5 and 7) the negative effect of overall inequality and likewise the interaction term are significant.

The second finding, and the main contribution of this thesis, is the importance of the source of inequality for normative regime support, i.e. while the overall inequality does not seem to significantly affect such attitudes, IOp appears to be an important determinant of it. The coefficient of IOp, which in the presence of the interaction term corresponds to the prospective component of regime support, is positive and significant across both years and the pooled analysis. The interaction term, i.e. the retrospective dimension, is also significant and, yet, negative in the pooled and year-based analysis. While the interaction term, seems to be rather small in 2010 (column 6), its importance increases noticeably in 2016 (column 8).

Figure 3 undergirds the outlined interpretation by illustrating the overall effect of IOp for an average respondent for different levels of democracy as indicated by the Polity2 index, i.e. it depicts the marginal effect of IOp at each level of democracy, holding all other covariates constant at their sample means. The effect of IOp on the probability of supporting democracy is on the vertical axis while the horizontal axis presents the level of democracy. The vertical bars show the density of countries at each level of democracy. While the effect for 2010 (left) does only slightly change with the level of democracy, the influence of the level of democracy becomes more pronounced in 2016. Further, one can recognize that the effect of IOp in 2016 for democracies (Polity2 index > 5) differs from the countries with non/less democratic regimes, i.e. as the attitude formation becomes retrospective individuals living in a full democracy tend to lose faith in democracy to generate equal opportunities. Yet, this thesis explicitly aims to examine transition countries with their differing levels of regime types. Figure 4 displays the same calculations, but with respect to overall inequality. In line with the regression results (column 5 and 7), the figure shows a slightly negative but non-significant effect of overall inequality across all levels of democracy for 2010 (left) while in 2016 (right) the negative effect is found to be significant for full democracies only.[48]

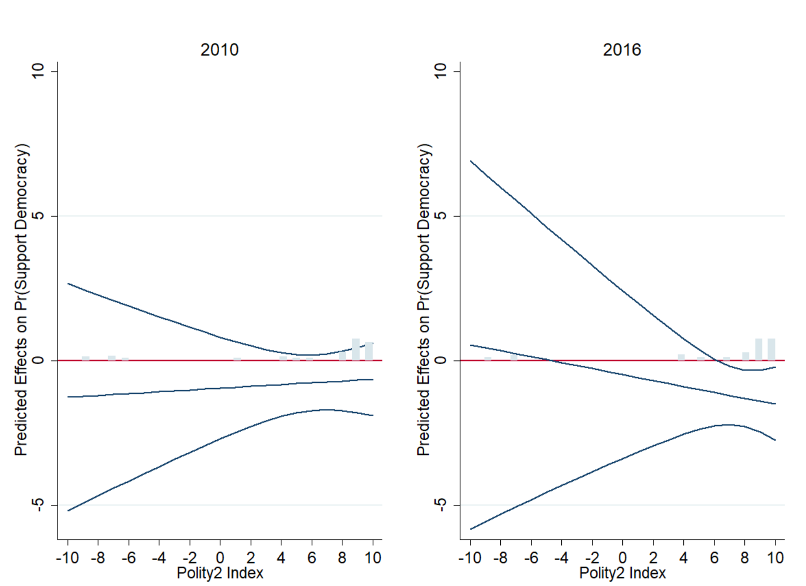
[48]The effect of IOp/overall inequality on full democracies may differ from the effects found in this thesis, as a more granular democracy measure (e.g. the liberal democracy index of the Varieties of Democracy Project as employed by Claassen (2020)) would be beneficial to capture differences between the democratic systems, but further research is needed to address this issue adequately.

Figure 3: Marginal Effects of IOp Conditional on Polity2



Notes: The figures depict the marginal effects of IOp on the probability of supporting democracy conditional on the level of democracy (Polity2) in 2010 and 2016, corresponding to columns 4 and 6 of table 2. Further displayed are the 95% confidence bands of such marginal effects and a histogram of the Polity2 index in the estimation sample (Source: LiTS).

Figure 4: Marginal Effects of Overall Inequality Conditional on Polity2



Notes: The figures depict the marginal effects of overall inequality on the probability of supporting democracy conditional on the level of democracy (Polity2) in 2010 and 2016, corresponding to columns 4 and 6 of table 2. Further displayed are 95% confidence bands of such marginal effects and a histogram of the Polity2 index in the estimation sample (Source: LiTS).

Investigating the *egocentric* vs. *sociotropic* hypothesis, a significant positive effect is obtained for the rank in the consumption expenditure distribution (actual position) on the probability to support democracy independent of the respective inequality measure used. In line with previous research (e.g. Andersen, 2012; Krieckhaus et al., 2013), these results suggest that individuals consider their economic well-being when forming regime attitudes and, hence, their attitudes exhibit a sizeable egocentric component. Further, the importance of economic affluence declines between 2010 and 2016, hinting at declining explanatory power of egocentric economic motives for regime support. Employing the type-based ranking derived in section 4.2 produces similar findings. The similarity of the results can be attributed to the high correlation between the two kinds of ranking (correlation coefficient 0.895 with p-value 0.000, see table A6 for results). As the type ranking divides individuals only in 3 effort categories (low, median, high) within 4 types (rural/urban $\times$ parents with/without upper secondary education) due to the limited sample size, such a low-granularity distinction in terms of types and effort appears to be insufficient to generate meaningful differences between ranking individuals in the overall consumption distribution and ranking individuals conditional on their circumstance type.[49] Further, confirming the findings of Gugushvili (2020), experienced personal mobility has a significantly positive effect on the attitude towards democracy across all specifications.

6.3 Sensitivity Analysis

Given the varying data quality across survey waves and countries, several sensitivity checks are performed to assess the robustness of the findings to alternative specification choices. While the presented results for IOp are considerably robust to the different checks presented below, the findings with respect to overall inequality do not reproduce across all checks performed.

First, given the different estimation methods for IOp employed in the first stage, one would like to check the robustness of the results regarding the IOp measure of choice that is incorporated into the second stage. Table A7 presents the results of such a comparison. The previously discussed findings appear to be robust across the different IOp estimation methodologies. Yet, one has to note that the limited data quality of the 2010 LiTS (i.e. considerable item non-response share of observations and smaller sample size; see table A2) seems to restrict the reliability of the standard and CV approach for the attitude formation regression as the results across all 4 estimation methodologies closely align for the high quality 2016 data.

Another valuable sensitivity check is the usage of the MLD as an alternative choice of inequality measure. Figures A8 and A9 display the results of the IOp estimation across methodologies using the MLD and illustrate that the MLD IOp estimates are less dispersed compared to the Gini ones due to the MLD's lower sensitivity with respect to low levels of inequality (see figure A1 for details). Table A8 presents the results of the second stage based on these MLD IOp estimates which confirm all of the findings presented in section 6.2.

Given that Andersen (2012) obtained the findings of a similar sized impact of overall inequality on support for democracy between former Communist and Western countries and a larger influence of the respondent's economic affluence on democratic support, the exclusion of the Western

[49] For reasons of comparability, table 2 displays coefficients of the absolute position based on 3 consumption expenditure categories (low, median, high). Using deciles does not alter the coefficients' significance.

comparator countries (Italy, Germany, Greece) constitutes a valuable sensitivity check. Table A9 presents the results of this subgroup analysis. Again, the main findings are robust to this sample restriction. Further, no substantial difference is found for the effect of an individual's rank in the consumption expenditure distribution between former Communist and Western countries. Yet, an interesting side-note is the significantly positive effect of communist experience on support for democracy in the pooled analysis which suggests that, having been socialized under communism, people might rather value the liberties of the new regime than being nostalgic about the past regime. The significant negative effect of new EU membership status in 2010 constitutes a further interesting side-note as it allows the interpretation that the elite-driven EU accession process initially might have undermined the individual's democratic support.

A worthwhile addition is to investigate whether the effect of overall inequality and IOp also varies by individual economic affluence (see Andersen, 2012, for an investigation of the effect of the former). Including an interaction term between overall inequality/IOp and an individual's rank in the consumption expenditure allows to test this hypothesis. Table A10 presents the associated results with no significant effect of the interaction term for overall inequality across all specifications. For IOp, the interaction term with an individual's rank in the consumption expenditure remains insignificant in 2010 and in the pooled analysis, but is positive and significant for 2016. This result suggests that while the impact of IOp has been prospective (i.e. democracy as mean to generate equal opportunities) in 2010 independent of the respondent's economic affluence, this positive effect on the regime attitude is limited only to the more affluent respondents in 2016, which supports the idea of regime disillusion by the poor (see figure A10 for a graphical representation of the results).

Further, following Gugushvili (2020), the importance of the respondent's labor market status (employed, unemployed, students, retired, and other) has been tested by the inclusion of corresponding dummy variables. This exercise yields no significant effect for unemployment but confirms the age driven difference in attitudes as students exhibit higher levels of support and retirees' support is significantly lower. Hence, in the main specification for this effect is partially accounted for by the age variable as general results are not altered. Also, results are found to be robust to the inclusion of region fixed effects.[50]

As conjectured in section 4.2, clustering standard errors (SE) at the country level might be too lenient given the small number of clusters present, i.e. 30 in the most comprehensive sample.[30] Table A11 reports more conservative SEs as they are based on pairs cluster bootstrap, i.e. yielding larger SE compared to simple cluster-robust SE and help to better account for the small number of clusters.[51] Yet, acknowledging that such adjustment might be insufficient (see Cameron et al., 2008, for an extensive discussion), Wald-type hypothesis tests for the IOp and Gini coefficient regressors based on the concept of wild cluster bootstrapping, as recommend by Cameron and Miller (2015) and adjusted in the score-based approach for Maximum-Likelihood estimations by Kline and Santos (2012), are also reported. Given the genuinely conservative adjustment the IOp coefficients become insignificant but the Wald-type test for the exclusion of the coefficients still

[50]For readability, regression outputs are omitted from the appendix but are available on request.

[51]The resampling is performed over entire clusters, rather than over individual observations. Each bootstrap resample will have exactly J clusters, with some of the original clusters not appearing at all while others of the original clusters may be repeated in the resample two or more times. The term "pairs" is used as (y_j, X_j) are sampled as a pair.

suggests their inclusion might be valuable to the model and more valuable than the inclusion of overall inequality.

To investigate the robustness of the results to the usage of the alternative multilevel modeling approach, such a model is specified (see section AVII for details) and table A12 presents the corresponding results. The multilevel specification supports the findings on IOp discussed in section 6.2. However, it calls into question the non-importance of overall inequality, as a significantly negative effect of overall inequality can be found for 2010 and in the pooled analysis. Given the model's assumption of a random intercept, these divergent results suggest the non-importance of overall inequality in the main analysis might be driven by countries with really low/high overall inequality.[52]

7 Conclusion

When individuals form their attitudes towards democracy they do not only consider their economic well-being under the current regime but also take into account a variety of other personal and individual factors. Yet, existing research has focused on overall inequality when assessing the linkage between economic inequality and democracy. Considering only the impact of overall inequality on attitudes towards democracy might thus be misleading as fairness concerns matter when individuals evaluate economic inequality. The IOp framework reflects widely-held principles of distributive justice. This thesis adopts the IOp framework in an empirical analysis yielding the following insights.

The main contribution of this thesis is to provide evidence emphasizing that fairness concerns are crucial when assessing the impact of economic inequality on support for democracy. While overall economic inequality does not seem to have a significant impact on an individual's attitude towards democracy, IOp estimates are significantly correlated with such attitudes. Adjusting the attitude formation framework by Krieckhaus et al. (2013), the obtained positive correlation between support for democracy and IOp can be rationalized by a prospective evaluation of democracy as a means to generate equal opportunities. Yet, this prospective assessment appears to have declined over time as the positive effect of IOp diminishes with a country's current level of democracy as measured by the Polity2 index. In consequence, an individual's assessment seems to have become more retrospective which suggests that prevailing high levels of IOp in fully democratic countries triggers regime dissatisfaction. Also, the influence of economic affluence for the individual democratic support is found to be slightly diminishing between 2010 and 2016. However, it is detected that the prospective assessment of IOp becomes tied to the individual's relative economic well-being in 2016.

Further, this thesis reviews the benefits of different IOp estimation methodologies in a setting where availability of circumstance data and sample size are limited. First, upward bias due to sampling variance in the counterfactual distribution appears to be no major concern in the given

[52] While the main results are robust to the exclusion of single "outlier" countries, excluding all countries with relatively low/high overall inequality would undermine the samples repressiveness for the group of post-communist "transition" countries.

context as Lasso and Standard estimates do widely align. Also, utilizing the Lasso approach for variable selection of the CV-based model selection for interaction between circumstances appears to be an interesting addition to increase the reliability of the latter approach. Second, conditional inference forests may prove a valuable addition to parametric estimation procedures as they help to assess the impact of item non-response on the IOp estimates and provide more sample estimates due the usage of all observations available including the ones with missing items.

Given the limitations in terms of sample size and data quality as well as the focus on transition countries, the presented results may not reproduce for Western Democracies. Yet, investigating economic inequality trough the lens of the IOp methodology can be an important tool to understand democratic backsliding in post-socialist societies. Further, the presented framework could be adjusted to study the rise of populism in Western Europe as one could, for instance, draw on high-quality EU-SILC data for IOp estimation and link these estimates with Euro-barometer attitudes data.

References

R. Aaberge, M. Mogstad, and V. Peragine (2011), “Measuring long-term inequality of opportunity”, *Journal of Public Economics*, *95*(3-4), 193–204.

D. Acemoglu, G. Egorov, and K. Sonin (2018), “Social mobility and stability of democracy: Reevaluating de tocqueville”, *The Quarterly Journal of Economics*, *133*(2), 1041–1105.

D. Acemoglu, S. Naidu, P. Restrepo, and J. A. Robinson (2015), “Democracy, redistribution, and inequality”, in *Handbook of Income Distribution*, vol. 2, 1885–1966, Elsevier.

D. Acemoglu and J. A. Robinson (2001), “A theory of political transitions”, *American Economic Review*, *91*(4), 938–963.

D. Acemoglu and J. A. Robinson (2006), *Economic origins of dictatorship and democracy*, Cambridge University Press.

N. Ajzenman, C. G. Aksoy, and S. Guriev (2020), “Exposure to transit migration, public attitudes and entrepreneurship”, *IZA Discussion Papers*, *No. 13130*.

A. Alesina and G.-M. Angeletos (2005), “Fairness and redistribution”, *American Economic Review*, *95*(4), 960–980.

A. Alesina and E. L. Ferrara (2005), “Preferences for redistribution in the land of opportunities”, *Journal of Public Economics*, *89*(5–6), 897–931.

A. Alesina and N. Fuchs-Schündeln (2007), “Good-bye Lenin (or not?): The effect of communism on people’s preferences”, *American Economic Review*, *97*(4), 1507–1528.

A. Alesina and P. Giuliano (2011), “Preferences for redistribution”, in *Handbook of Social Economics*, vol. 1, 93–131, Elsevier.

A. Alesina, S. Stantcheva, and E. Teso (2018), “Intergenerational mobility and preferences for redistribution”, *American Economic Review*, *108*(2), 521–54.

A. S. Álvarez and A. J. L. Menéndez (2018), “Income inequality and inequality of opportunity in europe: Are they on the rise?”, in *Inequality, taxation and intergenerational transmission*, vol. 26, Emerald Publishing Limited.

R. Andersen (2012), “Support for democracy in cross-national perspective: The detrimental effect of economic inequality”, *Research in Social Stratification and Mobility*, *30*(4), 389–402.

R. Andersen and T. Fetner (2008), “Economic inequality and intolerance: Attitudes toward homosexuality in 35 democracies”, *American Journal of Political Science*, *52*(4), 942–958.

C. J. Anderson and M. M. Singer (2008), “The sensitive left and the impervious right: multilevel models and the politics of inequality, ideology, and legitimacy in europe”, *Comparative Political Studies*, *41*(4-5), 564–599.

C. J. Anderson and Y. V. Tverdova (2003), “Corruption, political allegiances, and attitudes toward government in contemporary democracies”, *American Journal of Political Science*, *47*(1), 91–109.

R. Benabou and E. A. Ok (2001), “Social mobility and the demand for redistribution: the poum hypothesis”, *The Quarterly Journal of Economics*, *116*(2), 447–487.

R. Benabou and J. Tirole (2006), “Belief in a just world and redistributive politics”, *The Quarterly Journal of Economics*, *121*(2), 699–746.

M. Bertrand, E. Duflo, and S. Mullainathan (2004), “How much should we trust differences-in-differences estimates?”, *The Quarterly journal of economics*, *119*(1), 249–275.

C. Boix et al. (2003), *Democracy and redistribution*, Cambridge University Press.

F. Bourguignon, F. H. G. Ferreira, and M. Menéndez (2007), “Inequality of Opportunity in Brazil”, *Review of Income and Wealth*, *53*(4), 585–618.

J. M. Brock (2020), “Unfair inequality, governance and individual beliefs”, *Journal of Comparative Economics*, *forthcoming*.

J. M. Brock, V. Peragine, and S. Tonini (2016), “Inequality of opportunity”, in *Transition Report 2016-17. Transition for all: Equal opportunities in an unequal world*, chap. 3, 81–98, London: European Bank for Reconstruction and Development.

P. Brunori (2017), “The perception of inequality of opportunity in Europe”, *Review of Income and Wealth*, *63*(3), 464–491.

P. Brunori, F. H. Ferreira, and V. Peragine (2013), “Inequality of opportunity, income inequality, and economic mobility: Some international comparisons”, in E. Paus (Ed.), *Getting development right: structural transformation, inclusion and sustainability in the post-crisis era*, 85–115, Palgrave Macmillan.

P. Brunori, P. Hufe, and D. G. Mahler (2019a), “The roots of inequality: Estimating inequality of opportunity from regression trees and forests”.

P. Brunori, F. Palmisano, and V. Peragine (2019b), “Inequality of opportunity in sub-saharan africa”, *Applied Economics*, *51*(60), 6428–6458.

P. Brunori, V. Peragine, and L. Serlenga (2019c), “Upward and downward bias when measuring inequality of opportunity”, *Social Choice and Welfare*, *52*(4), 635–661.

A. C. Cameron, J. B. Gelbach, and D. L. Miller (2008), “Bootstrap-based improvements for inference with clustered errors”, *The Review of Economics and Statistics*, *90*(3), 414–427.

A. C. Cameron and D. L. Miller (2015), “A practitioner’s guide to cluster-robust inference”, *Journal of Human Resources*, *50*(2), 317–372.

Center for Systemic Peace (2018), “Polity5 project, political regime characteristics and transitions, 1800-2018”, Data retrieved in April 2020. `http://www.systemicpeace.org/inscr/p5v2018.xls`.

D. Checchi and V. Peragine (2010), "Inequality of opportunity in italy", *The Journal of Economic Inequality*, *8*(4), 429–450.

C. Claassen (2020), "Does public support help democracy survive?", *American Journal of Political Science*, *64*(1), 118–134.

A. E. Clark and C. d'Ambrosio (2015), "Attitudes to income inequality: Experimental and survey evidence", in *Handbook of Income Distribution*, vol. 2, 1147–1208, Elsevier.

G. A. Cohen (1989), "On the currency of egalitarian justice", *Ethics*, *99*(4), 906–944.

G. Corneo and H. P. Grüner (2002), "Individual preferences for political redistribution", *Journal of Public Economics*, *83*(1), 83–107.

S. Daenekindt, J. van der Waal, and W. de Koster (2018), "Social mobility and political distrust: cults of gratitude and resentment?", *Acta Politica*, *53*(2), 269–282.

A. De Toqueville (1835), *Democracy in America*.

A. Deaton (1997), *The analysis of household surveys: a microeconometric approach to development policy*, World Bank.

A. Deaton and M. Grosh (2000), "Consumption, in designing household survey questionnaires for developing countries: lessons from 15 years of living standards measurement study", *World Bank*.

S. Djankov, E. Nikolova, and J. Zilinsky (2016), "The happiness gap in Eastern Europe", *Journal of Comparative Economics*, *44*(1), 108–124.

P. L. Donni, J. G. Rodríguez, and P. R. Dias (2015), "Empirical definition of social types in the analysis of inequality of opportunity: a latent classes approach", *Social Choice and Welfare*, *44*(3), 673–701.

R. Dworkin (1981a), "What is equality? part 1: Equality of welfare", *Philosophy & public affairs*, 185–246.

R. Dworkin (1981b), "What is equality? part 2: Equality of resources", *Philosophy & public affairs*, 283–345.

W. Easterly and R. Levine (2016), "The european origins of economic development", *Journal of Economic Growth*, *21*(3), 225–257.

D. Easton (1975), "A re-assessment of the concept of political support", *British Journal of Political Science*, *5*(4), 435–457.

EqualChances.org (2018), "Methodological note for the equalchances.org database on equality of opportunity and social mobility", `http://www.equalchances.org/`.

G. Evans and S. Whitefield (1995), "The politics and economics of democratic commitment: Support for democracy in transition societies", *British Journal of Political Science*, 485–514.

F. H. Ferreira and J. Gignoux (2011), "The measurement of inequality of opportunity: Theory and an application to latin america", *Review of Income and Wealth*, *57*(4), 651–657.

F. H. Ferreira and V. Peragine (2016), "Equality of opportunity: Theory and evidence", in M. D. Adler, and M. Fleurbaey (Eds.), *The Oxford handbook of well-being and public policy*, Oxford University Press.

M. Fleurbaey and V. Peragine (2013), "Ex ante versus ex post equality of opportunity", *Economica*, *80*(317), 118–130.

C. Fong (2001), "Social preferences, self-interest, and the demand for redistribution", *Journal of Public Economics*, *82*(2), 225–246.

R. Goodin and J. Dryzek (1980), "Rational participation: The politics of relative power", *British Journal of Political Science*, *10*(3), 273–292.

A. Gugushvili (2020), "Social origins of support for democracy: a study of intergenerational mobility", *International Review of Sociology*, 1–21.

T. Hastie, R. Tibshirani, and J. Friedman (2009), *The elements of statistical learning: data mining, inference, and prediction*, Heidelberg: Springer.

B. Heyns (2005), "Emerging inequalities in Central and Eastern Europe", *Annual Review of Sociology*, *31*, 163–197.

T. Hothorn, K. Hornik, and A. Zeileis (2006), "Unbiased recursive partitioning: A conditional inference framework", *Journal of Computational and Graphical Statistics*, *15*(3), 651–674.

P. Hufe, R. Kanbur, and A. Peichl (2018), "Measuring unfair inequality: Reconciling equality of opportunity and freedom from poverty", *CESifo Working Paper Series*, *No. 323*.

P. Hufe and A. Peichl (2015), "Lower bounds and the linearity assumption in parametric estimations of inequality of opportunity", *IZA Discussion Papers*, *No. 9605*.

P. Hufe, A. Peichl, and D. Weishaar (2019), "Lower and upper bounds of inequality of opportunity in emerging economies", *Ifo Working Paper*, *NR301*.

International Monetary Fund (2020), "World Economic Outlook Database", Data retrieved in April 2020. `https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/index.aspx`.

D. Kaufmann and A. Kraay (2019), "Worldwide Governance Indicators (WGI) project", Data retrieved in April 2020. `https://info.worldbank.org/governance/wgi/Home/downLoadFile?fileName=wgidataset.xlsx`.

J. Kelley and K. Zagorski (2004), "Economic change and the legitimation of inequality: The transition from socialism to the free market in central-east europe", *Research in Social Stratification and Mobility*, *22*, 319–364.

H. Kitschelt (1992), "The formation of party systems in east central europe", *Politics & Society*, *20*(1), 7–50.

P. Kline and A. Santos (2012), "A score based approach to wild bootstrap inference", *Journal of Econometric Methods*, *1*(1), 23–41.

H.-D. Klingemann (1999), "Mapping political support in the 1990s: A global analysis", in P. Norris (Ed.), *Critical citizens: Global support for democratic government*, 31–56, Oxford University Press Oxford.

J. Krieckhaus, B. Son, N. M. Bellinger, and J. M. Wells (2013), "Economic inequality and democratic support", *The Journal of Politics*, *76*(1), 139–151.

B. Leventoğlu (2005), "Social mobility and political transitions", *Journal of Theoretical Politics*, *17*(4), 465–496.

B. Leventoğlu (2014), "Social mobility, middle class, and political transitions", *Journal of Conflict Resolution*, *58*(5), 825–864.

S. M. Lipset (1959), "Some social requisites of democracy: Economic development and political legitimacy", *American Political Science Review*, *53*(1), 69–105.

P. C. Magalhães (2016), "Economic evaluations, procedural fairness, and satisfaction with democracy", *Political Research Quarterly*, *69*(3), 522–534.

G. A. Marrero and J. G. Rodríguez (2012), "Inequality of opportunity in europe", *Review of Income and Wealth*, *58*(4), 597–621.

A. H. Meltzer and S. F. Richard (1981), "A rational theory of the size of government", *Journal of Political Economy*, *89*(5), 914–927.

W. Mishler and R. Rose (1999), "Five years after the fall: Trajectories of support for democracy in post-communist europe", in *Critical Citizens: Global Support for Democratic Governance*, Oxford University Press.

W. Mishler and R. Rose (2002), "Learning and re-learning regime support: The dynamics of post-communist regimes", *European Journal of Political Research*, *41*(1), 5–36.

E. N. Muller (1988), "Democracy, economic development, and income inequality", *American Sociological Review*, 50–68.

T. Piketty (1995), "Social mobility and redistributive politics", *The Quarterly Journal of Economics*, *110*(3), 551–584.

T. Plümper and E. Neumayer (2010), "The level of democracy during interregnum periods: Recoding the polity2 score", *Political analysis*, 206–226.

X. Ramos and D. Van de Gaer (2016), "Approaches to inequality of opportunity: Principles, measures and evidence", *Journal of Economic Surveys*, *30*(5), 855–883.

J. Rawls (1971), *A theory of justice*, Harvard University Press.

M. Ritter and F. Solt (2019), "Economic inequality and campaign participation", *Social Science Quarterly*, *100*(3), 678–688.

J. E. Roemer (1998), *Theories of Distributive Justice*, Boston, MA: Harvard University Press.

A. Schäfer (2012), "Consequences of social inequality for democracy in western europe", *Zeitschrift für vergleichende Politikwissenschaft*, *6*(2), 23–45.

F. Solt (2008), "Economic inequality and democratic political engagement", *American Journal of Political Science*, *52*(1), 48–60.

F. Solt (2020), "Measuring income inequality across countries and over time: The standardized world income inequality database", *Social Science Quarterly*, *101*(3), 1183–1199, sWIID Version 8.3, May 2020.

M. R. Steenbergen and B. S. Jones (2002), "Modeling multilevel data structures", *American Journal of Political Science*, 218–237.

M. Suhrcke (2001), "Preferences for inequality: East vs. west", *HWWA Discussion Paper*.

R. Tibshirani (2011), "Regression shrinkage and selection via the lasso: a retrospective", *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *73*(3), 273–282.

UNESCO (2020), "Uis.stat, duration by level of education", Data retrieved in April 2020. `http://data.uis.unesco.org/`.

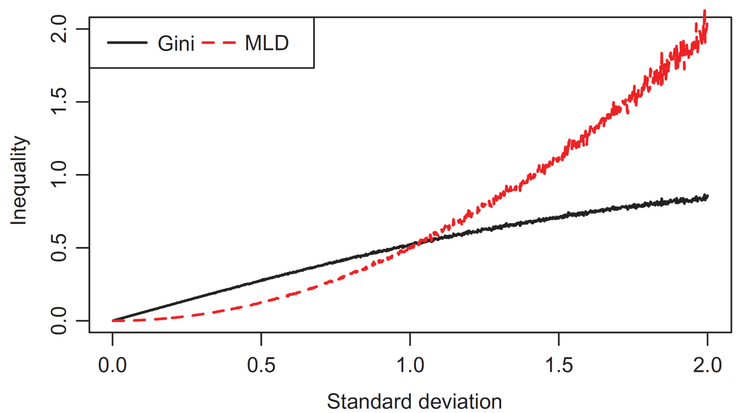
S. Verba (2006), "Fairness, equality, and democracy: three big words", *Social Research*, 499–540.

P. Waldron-Moore (1999), "Eastern europe at the crossroads of democratic transition: Evaluating support for democratic institutions, satisfaction with democratic government, and consolidation of democratic regimes", *Comparative Political Studies*, *32*(1), 32–62.

J. M. Wooldridge (2003), "Cluster-sample methods in applied econometrics", *American Economic Review*, *93*(2), 133–138.

AI Gini vs. MLD

Figure A1: Comparison of the Inequality Sensitivity of Gini and MLD

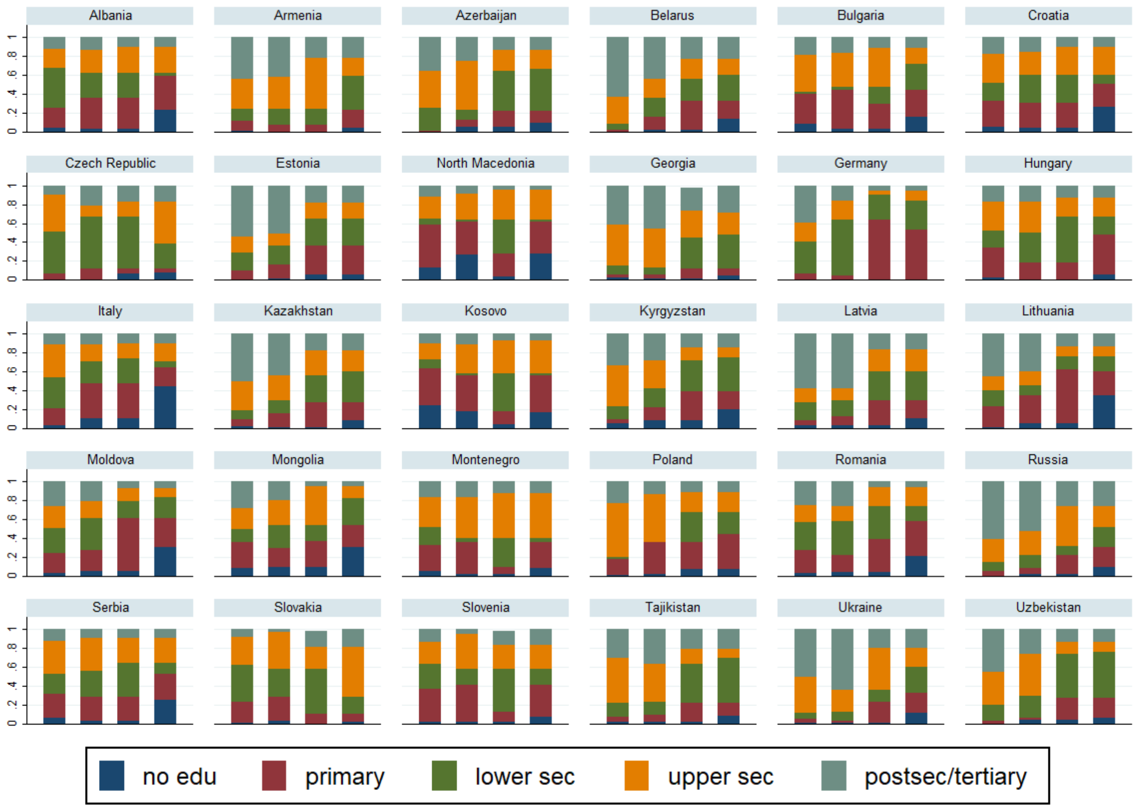


Source: Brunori et al. (2019b)

Notes: The Figure plots the Gini coefficient (black solid line) and the MLD (red-dashed line) for 1000 log normal distributions with mean zero and different levels of inequality. The Gini coefficient increases linearly with the increase in the standard deviation, whereas the convexity of the MLD curve reveals a low sensitivity of this index with respect to low levels of inequality and high sensitivity with respect to extreme values. The figure also helps to understand why empirical estimates systematically find higher IOp in terms of Gini coefficient than in terms of MLD: if the standard deviation is above 1, the Gini coefficient is smaller than the MLD. Yet, a value of the standard deviation above 1 for a log-normal distribution indicates a level of inequality that corresponds to a Gini coefficient above 0.5. Such a level of inequality is higher than what is found for most empirical distributions of consumption, which are by construction at least weakly higher than IOp. Since the maximum level of inequality in the estimation sample is well below 0.5 (Georgia 2010: 0.404), the presented IOp estimates using Gini are larger then the ones using MLD (compare figures 1 and 2 and figures A8 and A9).

AII Mapping & Comparability of Parental Education

Figure A2: Comparison of Parental Education across Waves & Coding



Notes: Parental education is asked in terms of years of education in 2010 and in terms of educational degree in 2016. To generate comparable IOp measures, years of education are mapped into educational degrees. The segments of the bars correspond to the share of each degree category in the sample with full consumption data. The first bar depicts parents' highest educational degrees in 2016. The bars 2 to 4 correspond on parents' highest educational degrees in 2010 according to different forms of matching: (2) based on observed bunching of the years of education; (3) based on UNESCO conversion tables; and (4) based on a uniform matching rule. As the overlap between the respondents' definitions of their parents' educational degrees and the UNESCO's ISCED standards is limited across countries, a manual adjustment (2) is beneficial to create comparabiltiy across survey waves for the IOp estimation (Source: LiTS).

AIII Summary Statistics

Table A1: Summary Statistics - Circumstances

Country	2010					2016				
	Urbanity at Birth	Minority	Communist Party	Father's education	Mother's education	Urbanity at Birth	Minority	Communist Party	Father's education	Mother's education
AL	0.524	0.00	0.144	0.323	0.243	0.511	0.000	0.178	0.253	0.209
AM	0.658	0.000	0.106	0.696	0.699	0.489	0.000	0.184	0.640	0.639
AZ	0.527	0.000	0.121	0.730	0.640	0.635	0.000	0.134	0.721	0.661
BY	0.639	0.424	0.158	0.579	0.573	0.658	0.124	0.276	0.869	0.848
BG	0.547	0.138	0.174	0.413	0.382	0.575	0.172	0.155	0.428	0.397
HR	0.590	0.000	0.088	0.327	0.260	0.695	0.000	0.101	0.367	0.305
EE	0.546	0.296	0.106	0.457	0.453	0.583	0.298	0.128	0.500	0.476
MK	0.614	0.345	0.116	0.315	0.210	0.518	0.258	0.135	0.286	0.197
GE	0.508	0.000	0.169	0.760	0.773	0.526	0.077	0.200	0.775	0.766
DE	0.485	0.000	0.000	0.286	0.245	0.524	0.000	0.000	0.465	0.419
GR	.	.	.	.	.	0.580	0.066	0.000	0.258	0.191
HU	0.709	0.000	0.062	0.377	0.308	0.666	0.000	0.078	0.346	0.286
IT	0.761	0.000	0.000	0.241	0.188	0.810	0.000	0.000	0.369	0.325
KZ	0.475	0.640	0.156	0.616	0.556	0.411	0.460	0.224	0.728	0.715
XK	0.504	0.146	0.000	0.401	0.145	0.426	0.243	0.000	0.224	0.116
KG	0.264	0.293	0.175	0.522	0.463	0.298	0.280	0.168	0.716	0.703
LV	0.622	0.486	0.090	0.495	0.523	0.609	0.343	0.108	0.549	0.514
LT	0.506	0.148	0.077	0.391	0.379	0.416	0.117	0.057	0.385	0.375
MD	0.401	0.433	0.000	0.278	0.295	0.320	0.112	0.075	0.356	0.330
MN	0.371	0.000	0.146	0.424	0.418	0.193	0.221	0.331	0.433	0.391
ME	0.555	0.615	0.240	0.551	0.425	0.586	0.502	0.218	0.385	0.314
PL	0.372	0.000	0.000	0.572	0.562	0.571	0.000	0.000	0.671	0.646
RO	0.412	0.000	0.189	0.305	0.255	0.463	0.091	0.138	0.312	0.249
RU	0.654	0.140	0.232	0.660	0.669	0.656	0.088	0.218	0.744	0.733
RS	0.659	0.093	0.190	0.362	0.252	0.509	0.078	0.200	0.348	0.287
SK	0.843	0.097	0.129	0.338	0.320	0.638	0.096	0.107	0.245	0.209
SI	0.705	0.118	0.000	0.336	0.270	0.601	0.082	0.079	0.243	0.200
TJ	0.137	0.271	0.000	0.761	0.521	0.153	0.231	0.125	0.715	0.509
UA	0.389	0.381	0.165	0.737	0.751	0.526	0.089	0.201	0.776	0.774
UZ	0.353	0.153	0.000	0.643	0.564	0.309	0.150	0.090	0.757	0.654

Notes: Displayed igures are portions of the sample with full consumption data. For instance, with respect to parental education, the portion of the sample whose mother/father completed at least upper secondary education is reported (Source: LiTS).

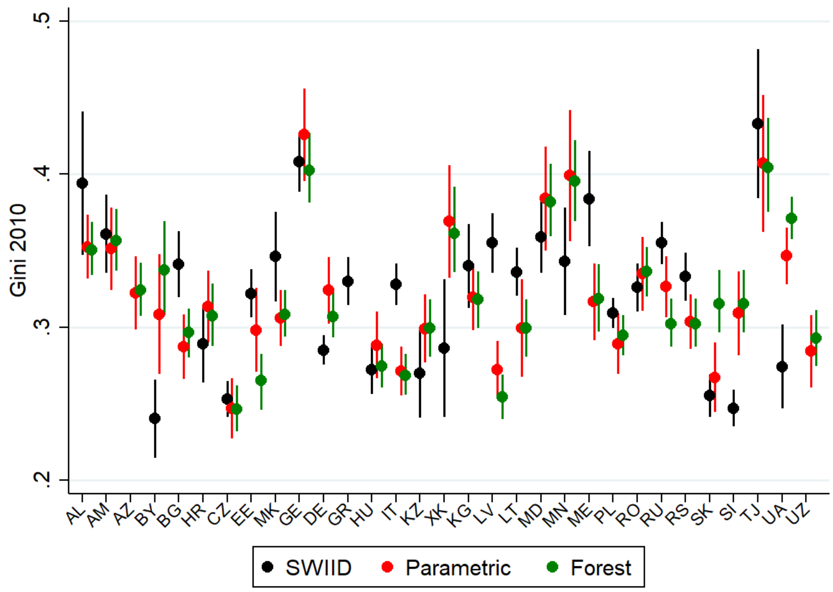
Table A2: Summary - Sample Size by Estimation Procedure

		2010			2016		
Country	ISO-Code	N	Parametric	Forest	N	Parametric	Forest
Albania	AL	873	492	548	1370	705	708
Armenia	AM	868	417	511	1404	978	1048
Azerbaijan	AZ	815	462	611	1251	478	529
Belarus	BY	813	250	366	1405	721	744
Bulgaria	BG	952	504	697	1417	1026	1041
Croatia	HR	940	561	592	1383	952	980
Czech Republic	CZ	924	396	627	1444	1215	1237
Estonia	EE	884	415	601	1436	1002	1155
North Macedonia	MK	937	732	808	1350	812	825
Georgia	GE	887	470	581	1422	1168	1216
Germany	DE	981	656	776	1389	768	781
Greece	GR				1395	1232	1244
Hungary	HU	978	607	776	1416	1094	1121
Italy	IT	970	742	866	1424	1145	1155
Kazakhstan	KZ	860	423	585	1387	1049	1101
Kosovo	XK	820	507	569	1288	821	868
Kyrgyzstan	KG	829	622	692	1316	1061	1076
Latvia	LV	906	516	768	1414	965	1204
Lithuania	LT	915	299	778	1391	1002	1096
Moldova	MD	953	435	685	1402	941	1071
Mongolia	MN	746	272	404	1360	1296	1328
Montenegro	ME	849	477	575	1327	757	802
Poland	PL	1488	446	728	1430	471	475
Romania	RO	988	640	803	1423	947	985
Russia	RU	1403	599	823	1367	811	854
Serbia	RS	1400	1013	1124	1412	693	704
Slovakia	SK	908	378	580	1443	1109	1124
Slovenia	SI	870	404	543	1422	1028	1079
Tajikistan	TJ	811	227	319	1266	633	650
Ukraine	UA	1392	945	1392	1436	853	884
Uzbekistan	UZ	1263	508	646	1369	665	731

Notes: N denotes the overall number of respondents in the survey. The Forest sample size corresponds to all respondents with complete consumption data. The parametric approaches (Standard, CV, Lasso) employ smaller sample sizes as they rely on list-wise deletion of observations in case of item non-response (Source: LiTS).

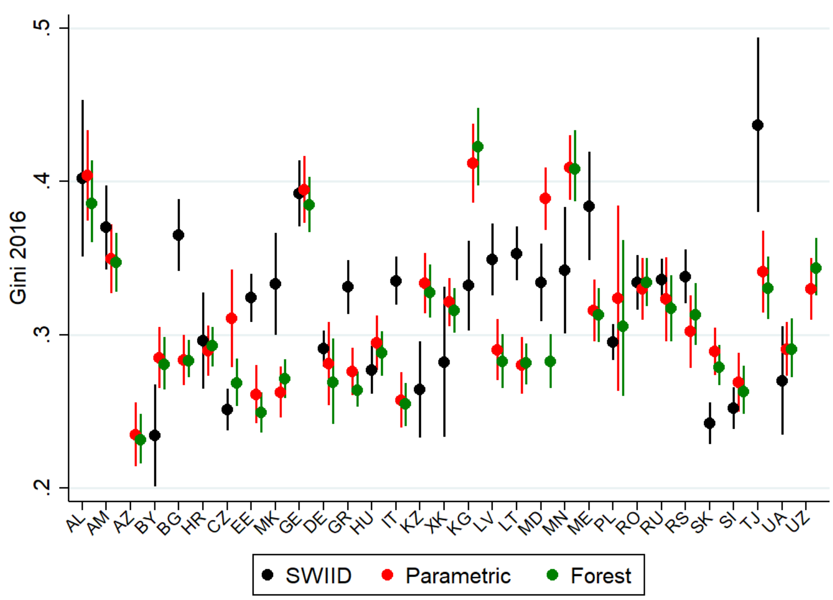
AIV Comparison - Overall Inequality LiTS and SWIID

Figure A3: Comparison - Gini IOp Estimates and SWIID (2010)



Notes: The figure depicts point estimates (dots) and 95% confidence intervals (spikes) for the countries' Gini coefficients of (1) the SWIID database, (2) the estimation sample of the parametric IOp methods (Standard, CV, Lasso), and (3) the Forest IOp estimation (see table A3; Sources: LiTS; SWIID).

Figure A4: Comparison - Gini IOp Estimates and SWIID (2016)



Notes: The figure depicts point estimates (dots) and 95% confidence intervals (spikes) for the countries' Gini coefficients of (1) the SWIID database, (2) the estimation sample of the parametric IOp methods (Standard, CV, Lasso), and (3) the Forest IOp estimation (see table A3; Sources: LiTS; SWIID).

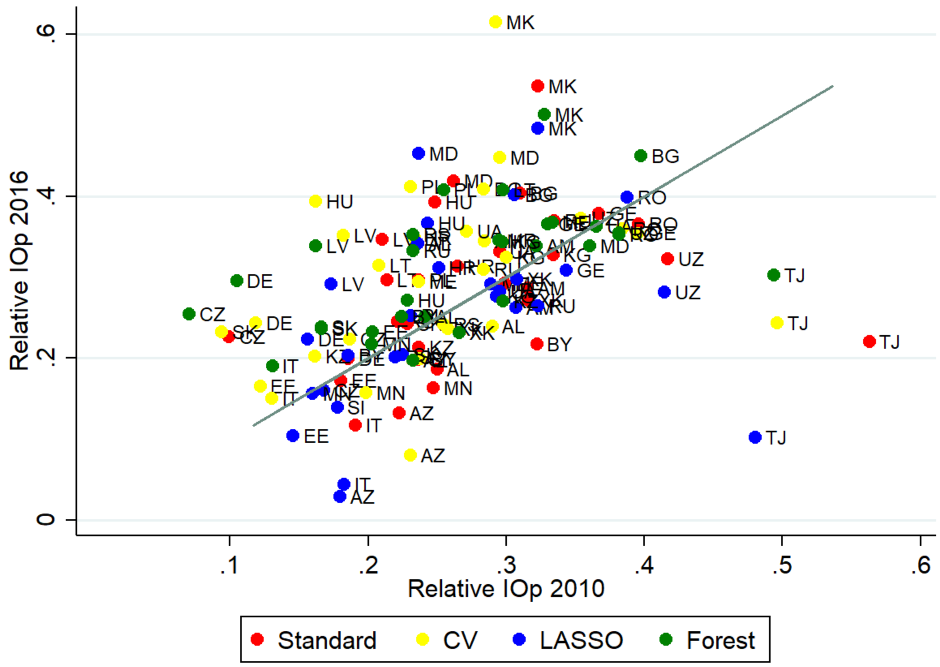
Table A3: Point Estimates & CI - Overall Inequality Estimates

	2010			2016		
Country	SWIID	Parametric	Forest	SWIID	Parametric	Forest
AL	0.393	0.353	0.350	0.402	0.404	0.386
	[0.346;0.440]	[0.332;0.373]	[0.334;0.369]	[0.351;0.453]	[0.375;0.433]	[0.360;0.414]
AM	0.363	0.351	0.357	0.370	0.350	0.347
	[0.339;0.387]	[0.324;0.378]	[0.337;0.377]	[0.343;0.397]	[0.327;0.372]	[0.328;0.366]
AZ	.	0.322	0.324	.	0.235	0.231
	[.;.]	[0.298;0.346]	[0.307;0.342]	[.;.]	[0.214;0.256]	[0.216;0.248]
BY	0.240	0.308	0.337	0.234	0.285	0.281
	[0.213;0.267]	[0.269;0.348]	[0.308;0.369]	[0.201;0.267]	[0.265;0.305]	[0.264;0.298]
BG	0.337	0.287	0.297	0.365	0.283	0.283
	[0.315;0.359]	[0.266;0.308]	[0.280;0.312]	[0.341;0.389]	[0.267;0.300]	[0.272;0.296]
HR	0.285	0.313	0.307	0.296	0.290	0.293
	[0.260;0.310]	[0.290;0.337]	[0.288;0.328]	[0.265;0.327]	[0.273;0.306]	[0.279;0.305]
CZ	0.252	0.247	0.246	0.251	0.311	0.268
	[0.240;0.264]	[0.227;0.266]	[0.232;0.262]	[0.237;0.265]	[0.279;0.343]	[0.253;0.284]
EE	0.319	0.298	0.265	0.324	0.261	0.249
	[0.303;0.335]	[0.271;0.325]	[0.246;0.282]	[0.308;0.340]	[0.242;0.280]	[0.236;0.262]
MK	0.348	0.306	0.308	0.333	0.262	0.271
	[0.319;0.377]	[0.288;0.324]	[0.294;0.324]	[0.300;0.366]	[0.246;0.279]	[0.258;0.284]
GE	0.404	0.426	0.403	0.392	0.395	0.385
	[0.382;0.426]	[0.396;0.456]	[0.381;0.427]	[0.370;0.414]	[0.373;0.417]	[0.367;0.403]
DE	0.284	0.324	0.307	0.291	0.281	0.269
	[0.272;0.296]	[0.302;0.346]	[0.293;0.323]	[0.279;0.303]	[0.254;0.308]	[0.241;0.297]
GR	0.327	.	.	0.331	0.276	0.264
	[0.313;0.341]	[.;.]	[.;.]	[0.313;0.349]	[0.260;0.291]	[0.253;0.276]
HU	0.269	0.288	0.274	0.277	0.295	0.288
	[0.253;0.285]	[0.266;0.310]	[0.261;0.289]	[0.261;0.293]	[0.277;0.313]	[0.273;0.302]
IT	0.326	0.271	0.268	0.335	0.257	0.255
	[0.312;0.340]	[0.255;0.287]	[0.256;0.283]	[0.319;0.351]	[0.239;0.275]	[0.240;0.269]
KZ	0.273	0.299	0.299	0.264	0.333	0.328
	[0.244;0.302]	[0.277;0.321]	[0.281;0.318]	[0.233;0.295]	[0.314;0.353]	[0.311;0.346]
XK	0.287	0.369	0.361	0.282	0.321	0.316
	[0.238;0.336]	[0.332;0.406]	[0.336;0.392]	[0.233;0.331]	[0.306;0.337]	[0.301;0.331]
KG	0.343	0.319	0.318	0.332	0.412	0.423
	[0.316;0.370]	[0.298;0.341]	[0.299;0.337]	[0.303;0.361]	[0.386;0.438]	[0.397;0.448]
LV	0.355	0.272	0.254	0.349	0.290	0.282
	[0.335;0.375]	[0.253;0.291]	[0.240;0.269]	[0.325;0.373]	[0.270;0.310]	[0.265;0.300]
LT	0.340	0.299	0.299	0.353	0.280	0.282
	[0.324;0.356]	[0.267;0.331]	[0.281;0.318]	[0.335;0.371]	[0.261;0.299]	[0.268;0.294]
MD	0.364	0.384	0.382	0.334	0.389	0.282
	[0.340;0.388]	[0.350;0.418]	[0.359;0.407]	[0.309;0.359]	[0.368;0.409]	[0.265;0.300]
MN	0.343	0.399	0.395	0.342	0.409	0.408
	[0.308;0.378]	[0.356;0.442]	[0.369;0.422]	[0.301;0.383]	[0.388;0.430]	[0.387;0.433]
ME	0.385	0.316	0.319	0.384	0.316	0.313
	[0.354;0.416]	[0.291;0.342]	[0.297;0.341]	[0.349;0.419]	[0.296;0.336]	[0.295;0.330]
PL	0.307	0.289	0.295	0.295	0.324	0.305
	[0.295;0.319]	[0.269;0.309]	[0.282;0.308]	[0.283;0.307]	[0.263;0.384]	[0.260;0.362]
RO	0.326	0.335	0.336	0.334	0.330	0.334
	[0.310;0.342]	[0.311;0.359]	[0.320;0.352]	[0.316;0.352]	[0.310;0.350]	[0.318;0.350]
RU	0.361	0.326	0.302	0.336	0.323	0.317
	[0.345;0.377]	[0.306;0.346]	[0.287;0.318]	[0.322;0.350]	[0.296;0.351]	[0.295;0.339]
RS	0.334	0.304	0.302	0.338	0.302	0.313
	[0.316;0.352]	[0.286;0.321]	[0.287;0.318]	[0.320;0.356]	[0.278;0.326]	[0.293;0.334]
SK	0.255	0.267	0.315	0.242	0.289	0.279
	[0.243;0.267]	[0.244;0.290]	[0.296;0.337]	[0.228;0.256]	[0.274;0.304]	[0.267;0.293]
SI	0.243	0.309	0.315	0.252	0.269	0.263
	[0.231;0.255]	[0.282;0.336]	[0.296;0.337]	[0.238;0.266]	[0.249;0.288]	[0.248;0.280]
TJ	0.433	0.407	0.404	0.437	0.341	0.330
	[0.386;0.480]	[0.362;0.452]	[0.375;0.437]	[0.380;0.494]	[0.314;0.368]	[0.310;0.351]
UA	0.276	0.346	0.371	0.270	0.291	0.290
	[0.249;0.303]	[0.328;0.365]	[0.357;0.385]	[0.235;0.305]	[0.273;0.308]	[0.272;0.310]
UZ	.	0.284	0.293	.	0.330	0.343
	[.;.]	[0.260;0.308]	[0.274;0.311]	[.;.]	[0.309;0.350]	[0.326;0.363]

Notes: Overall inequality is measured by the Gini coefficient in the estimation sample of the respective approach indicated in the table header. 95% confidence intervals are derived based on 200 bootstrapped re-samples using the normal approximation method. Estimates of the SWIID database are presented as a benchmark (Sources: LiTS; SWIID).

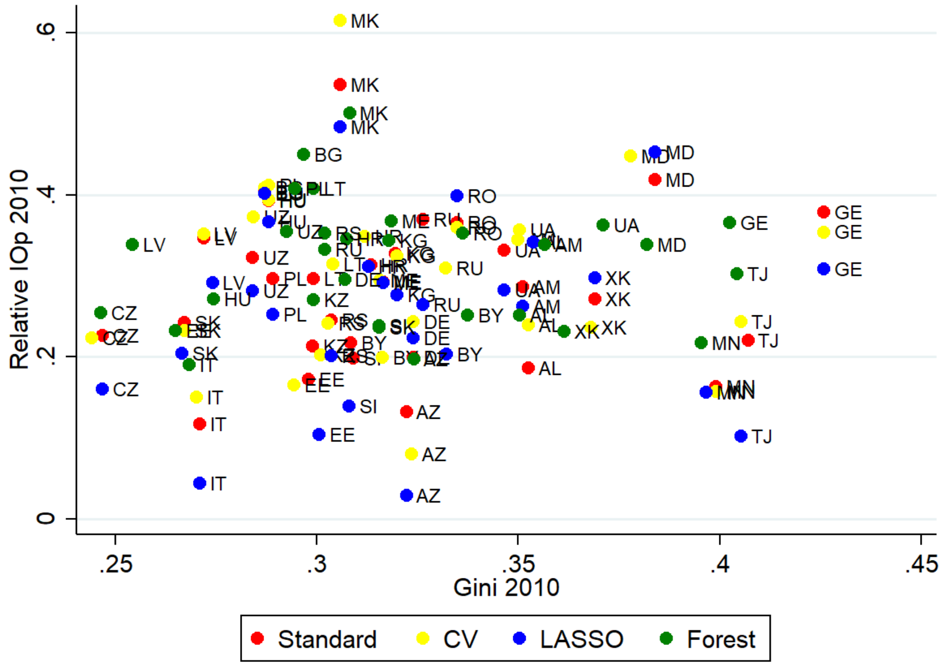
AV Comparison of IOp Estimates across Methodologies & Time

Figure A5: Comparison of IOp 2010 and 2016



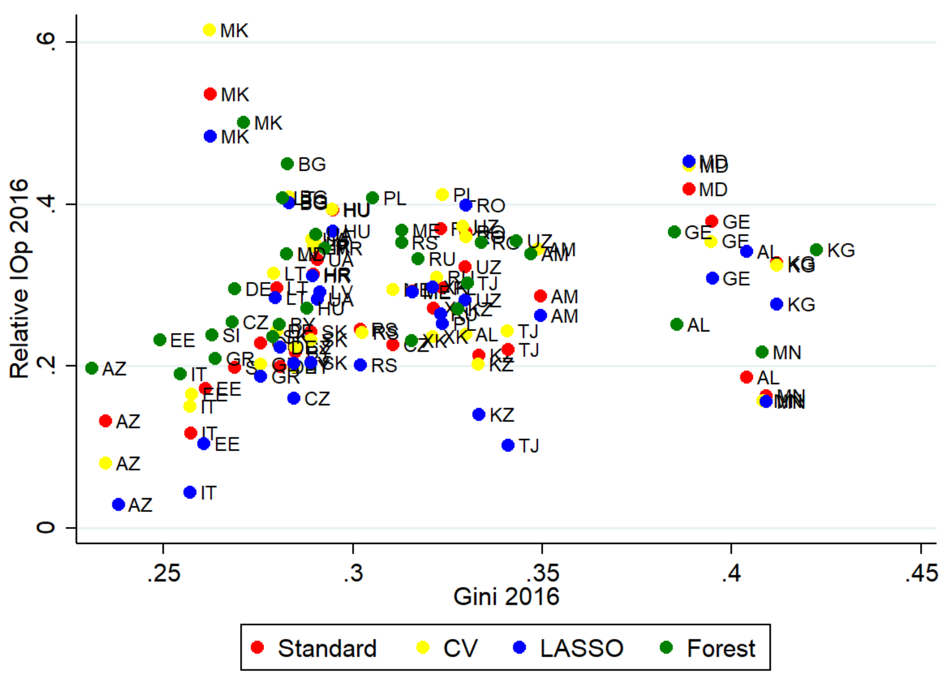
Notes: The figure plots relative IOp estimates for 2010 (x-axis) and 2016 (y-axis) for the different IOp estimation methodologies (Standard, CV, Lasso, Forest). The 45° line highlights increases and decreases across survey waves (Source: LiTS).

Figure A6: Comparison of IOp Estimates and Overall Inequality (2010)



Notes: The figure plots estimates for total inequality Gini (x-axis) and relative IOP (y-axis) in 2010 for the different IOp estimation methodologies (Standard, CV, Lasso, Forest; Source: LiTS).

Figure A7: Comparison of IOp Estimates and Overall Inequality (2016)



Notes: The figure plots estimates for total inequality Gini (x-axis) and relative IOP (y-axis) in 2016 for the different IOp estimation methodologies (Standard, CV, Lasso, Forest; Source: LiTS).

Table A4: Point Estimates & CI - Relative IOp Estimates

	2010				2016			
Country	Standard	CV	Lasso	Forest	Standard	CV	Lasso	Forest
AL	0.289	0.290	0.268	0.241	0.502	0.299	0.494	0.251
	[0.195;0.382]	[0.192;0.388]	[0.152;0.383]	[0.144;0.277]	[0.334;0.669]	[0.184;0.413]	[0.347;0.641]	[0.153;0.283]
AM	0.350	0.284	0.342	0.322	0.297	0.291	0.332	0.338
	[0.263;0.437]	[0.198;0.370]	[0.240;0.443]	[0.215;0.375]	[0.216;0.377]	[0.216;0.365]	[0.240;0.423]	[0.233;0.385]
AZ	0.213	0.231	0.191	0.233	0.096	0.044	0.094	0.197
	[0.127;0.300]	[0.141;0.321]	[0.078;0.303]	[0.152;0.287]	[0.006;0.186]	[-0.033;0.121]	[-0.034;0.223]	[0.099;0.243]
BY	0.360	0.238	0.346	0.224	0.206	0.173	0.194	0.251
	[0.244;0.475]	[0.124;0.352]	[0.226;0.466]	[0.087;0.236]	[0.130;0.281]	[0.096;0.250]	[0.109;0.279]	[0.147;0.272]
BG	0.328	0.284	0.325	0.398	0.434	0.404	0.448	0.450
	[0.252;0.405]	[0.197;0.370]	[0.250;0.400]	[0.333;0.436]	[0.368;0.499]	[0.336;0.471]	[0.381;0.516]	[0.381;0.489]
HR	0.273	0.234	0.259	0.295	0.341	0.338	0.367	0.346
	[0.189;0.357]	[0.152;0.315]	[0.178;0.341]	[0.192;0.341]	[0.275;0.407]	[0.258;0.418]	[0.296;0.438]	[0.287;0.390]
CZ	0.095	0.187	0.164	0.071	0.210	0.157	0.200	0.255
	[0.008;0.181]	[0.093;0.281]	[-0.011;0.339]	[-0.029;0.065]	[0.107;0.313]	[0.093;0.220]	[0.042;0.357]	[0.164;0.295]
EE	0.180	0.122	.	0.203	0.183	0.084	0.176	0.232
	[0.076;0.284]	[0.036;0.208]	[.;.]	[0.084;0.214]	[0.112;0.255]	[0.027;0.140]	[0.054;0.298]	[0.134;0.238]
MK	0.303	0.292	0.302	0.328	0.516	0.500	0.581	0.501
	[0.225;0.381]	[0.217;0.368]	[0.228;0.376]	[0.245;0.363]	[0.445;0.587]	[0.427;0.574]	[0.516;0.645]	[0.434;0.534]
GE	0.421	0.395	0.387	0.330	0.373	0.349	0.361	0.366
	[0.322;0.521]	[0.300;0.490]	[0.282;0.491]	[0.234;0.384]	[0.288;0.458]	[0.263;0.434]	[0.286;0.436]	[0.290;0.394]
DE	0.174	0.119	0.153	0.105	0.197	0.178	0.274	0.296
	[0.094;0.253]	[0.041;0.196]	[0.052;0.254]	[0.028;0.122]	[0.103;0.292]	[0.088;0.269]	[0.195;0.354]	[0.189;0.337]
GR	.	.	.	.	0.229	0.192	0.200	0.210
	[.;.]	[.;.]	[.;.]	[.;.]	[0.170;0.287]	[0.130;0.254]	[0.143;0.258]	[0.148;0.244]
HU	0.226	0.162	0.222	0.228	0.393	0.374	0.393	0.271
	[0.142;0.310]	[0.077;0.247]	[0.118;0.327]	[0.144;0.272]	[0.322;0.464]	[0.303;0.445]	[0.324;0.463]	[0.192;0.315]
IT	0.164	0.131	0.146	0.131	0.099	0.066	0.120	0.190
	[0.089;0.238]	[0.066;0.196]	[0.044;0.247]	[0.046;0.156]	[0.024;0.175]	[-0.013;0.146]	[0.050;0.190]	[0.126;0.225]
KZ	0.233	0.161	0.228	0.298	0.212	0.167	0.197	0.271
	[0.141;0.324]	[0.079;0.244]	[0.108;0.349]	[0.181;0.309]	[0.145;0.279]	[0.105;0.230]	[0.135;0.259]	[0.176;0.288]
XK	0.287	0.277	0.283	0.266	0.300	0.301	0.283	0.231
	[0.214;0.359]	[0.196;0.358]	[0.193;0.374]	[0.173;0.316]	[0.231;0.368]	[0.227;0.374]	[0.221;0.345]	[0.147;0.257]
KG	0.313	0.300	0.257	0.297	0.298	0.287	0.299	0.344
	[0.234;0.391]	[0.213;0.387]	[0.168;0.346]	[0.194;0.325]	[0.233;0.364]	[0.221;0.353]	[0.234;0.365]	[0.256;0.382]
LV	0.230	0.182	0.171	0.162	0.324	0.310	0.341	0.338
	[0.131;0.329]	[0.088;0.276]	[0.012;0.331]	[0.068;0.172]	[0.247;0.400]	[0.234;0.385]	[0.257;0.425]	[0.267;0.380]
LT	0.244	0.208	.	0.298	0.312	0.287	0.337	0.408
	[0.130;0.359]	[0.100;0.316]	[.;.]	[0.181;0.309]	[0.226;0.398]	[0.213;0.360]	[0.263;0.411]	[0.339;0.449]
MD	0.281	0.295	0.266	0.360	0.464	0.443	0.475	0.338
	[0.184;0.378]	[0.201;0.390]	[0.146;0.386]	[0.260;0.406]	[0.385;0.544]	[0.366;0.519]	[0.405;0.546]	[0.267;0.380]
MN	0.251	0.248	0.194	0.203	0.158	0.152	0.140	0.217
	[0.138;0.364]	[0.137;0.360]	[0.034;0.353]	[0.075;0.256]	[0.103;0.214]	[0.099;0.205]	[0.074;0.205]	[0.117;0.223]
ME	0.300	0.237	0.296	0.333	0.326	0.257	0.320	0.368
	[0.209;0.392]	[0.156;0.317]	[0.203;0.389]	[0.220;0.367]	[0.255;0.396]	[0.187;0.326]	[0.253;0.386]	[0.277;0.408]
PL	0.226	0.231	0.224	0.255	0.198	0.136	0.352	0.408
	[0.123;0.330]	[0.129;0.333]	[0.114;0.333]	[0.183;0.320]	[0.006;0.389]	[-0.075;0.347]	[0.242;0.461]	[0.282;0.491]
RO	0.377	0.330	0.370	0.382	0.428	0.433	0.409	0.353
	[0.308;0.445]	[0.251;0.408]	[0.290;0.449]	[0.306;0.419]	[0.359;0.498]	[0.346;0.520]	[0.335;0.483]	[0.277;0.380]
RU	0.304	0.268	0.295	0.233	0.336	0.274	0.284	0.333
	[0.215;0.394]	[0.178;0.359]	[0.210;0.380]	[0.156;0.259]	[0.240;0.433]	[0.167;0.381]	[0.207;0.361]	[0.254;0.363]
RS	0.209	0.270	0.207	0.233	0.302	0.176	0.277	0.353
	[0.147;0.270]	[0.207;0.332]	[0.149;0.265]	[0.156;0.259]	[0.224;0.379]	[0.102;0.250]	[0.189;0.364]	[0.265;0.396]
SK	0.190	0.146	0.185	0.166	0.264	0.191	0.243	0.237
	[0.094;0.286]	[0.059;0.232]	[0.028;0.342]	[0.059;0.203]	[0.186;0.342]	[0.110;0.271]	[0.162;0.325]	[0.161;0.261]
SI	0.194	0.183	0.160	0.166	0.182	0.141	0.098	0.238
	[0.108;0.280]	[0.090;0.275]	[0.013;0.307]	[0.059;0.203]	[0.112;0.252]	[0.057;0.225]	[-0.032;0.228]	[0.159;0.264]
TJ	0.573	0.507	0.528	0.494	0.203	0.101	0.178	0.303
	[0.454;0.692]	[0.372;0.641]	[0.387;0.669]	[0.400;0.559]	[0.111;0.294]	[0.028;0.173]	[0.070;0.287]	[0.199;0.326]
UA	0.302	0.252	0.302	0.365	0.340	0.284	0.363	0.363
	[0.218;0.385]	[0.177;0.326]	[0.217;0.387]	[0.305;0.395]	[0.258;0.422]	[0.190;0.377]	[0.287;0.440]	[0.286;0.406]
UZ	0.395	0.334	0.387	0.382	0.323	0.300	0.374	0.355
	[0.315;0.474]	[0.250;0.417]	[0.302;0.471]	[0.283;0.437]	[0.243;0.403]	[0.212;0.388]	[0.298;0.450]	[0.256;0.386]

Notes: IOp is measured by the Gini coefficient in the estimated counterfactual distribution $\tilde{M}$ divided by overall inequality. $\tilde{M}$ is constructed by the respective estimation approach indicated in the table header. 95% confidence intervals are derived based on 200 bootstrapped re-samples using the normal approximation method (Source: LiTS).

Table A5: Point Estimates & CI - Absolute IOp Estimates

	2010				2016			
Country	Standard	CV	Lasso	Forest	Standard	CV	Lasso	Forest
AL	0.102	0.102	0.095	0.085	0.165	0.099	0.162	0.097
	[0.066;0.137]	[0.067;0.138]	[0.052;0.137]	[0.050;0.098]	[0.105;0.225]	[0.059;0.138]	[0.109;0.215]	[0.060;0.109]
AM	0.123	0.099	0.120	0.115	0.104	0.101	0.116	0.117
	[0.090;0.156]	[0.068;0.131]	[0.082;0.158]	[0.074;0.136]	[0.074;0.134]	[0.075;0.128]	[0.083;0.149]	[0.079;0.135]
AZ	0.069	0.075	0.061	0.075	0.023	0.010	0.022	0.046
	[0.040;0.097]	[0.044;0.105]	[0.025;0.098]	[0.048;0.094]	[0.000;0.045]	[-0.007;0.028]	[-0.008;0.052]	[0.023;0.057]
BY	0.111	0.075	0.107	0.076	0.059	0.049	0.055	0.070
	[0.073;0.149]	[0.041;0.109]	[0.068;0.145]	[0.026;0.083]	[0.037;0.080]	[0.026;0.073]	[0.031;0.079]	[0.040;0.078]
BG	0.094	0.081	0.093	0.118	0.123	0.114	0.127	0.127
	[0.071;0.118]	[0.056;0.107]	[0.070;0.117]	[0.096;0.131]	[0.103;0.143]	[0.095;0.134]	[0.107;0.147]	[0.107;0.140]
HR	0.086	0.073	0.081	0.091	0.099	0.098	0.106	0.101
	[0.059;0.112]	[0.047;0.099]	[0.055;0.107]	[0.059;0.105]	[0.078;0.119]	[0.074;0.122]	[0.084;0.129]	[0.083;0.115]
CZ	0.023	0.046	0.040	0.017	0.065	0.045	0.062	0.068
	[0.002;0.045]	[0.022;0.069]	[-0.003;0.084]	[-0.007;0.016]	[0.033;0.098]	[0.026;0.063]	[0.013;0.111]	[0.043;0.081]
EE	0.054	0.036	.	0.054	0.048	0.022	0.046	0.058
	[0.022;0.085]	[0.011;0.061]	[.;.]	[0.021;0.058]	[0.029;0.066]	[0.007;0.036]	[0.014;0.078]	[0.033;0.060]
MK	0.093	0.089	0.092	0.101	0.135	0.131	0.152	0.136
	[0.067;0.118]	[0.064;0.115]	[0.068;0.117]	[0.074;0.114]	[0.113;0.158]	[0.108;0.154]	[0.132;0.173]	[0.115;0.147]
GE	0.180	0.168	0.165	0.133	0.147	0.138	0.143	0.141
	[0.133;0.226]	[0.126;0.210]	[0.116;0.213]	[0.092;0.157]	[0.111;0.183]	[0.101;0.174]	[0.111;0.174]	[0.110;0.153]
DE	0.056	0.038	0.050	0.032	0.055	0.050	0.077	0.079
	[0.029;0.083]	[0.013;0.064]	[0.016;0.083]	[0.008;0.038]	[0.026;0.085]	[0.025;0.075]	[0.055;0.099]	[0.050;0.092]
GR	.	.	.	.	0.063	0.053	0.055	0.055
	[.;.]	[.;.]	[.;.]	[.;.]	[0.046;0.080]	[0.035;0.071]	[0.039;0.071]	[0.039;0.065]
HU	0.065	0.047	0.064	0.063	0.116	0.110	0.116	0.078
	[0.040;0.090]	[0.021;0.072]	[0.033;0.095]	[0.039;0.075]	[0.092;0.140]	[0.087;0.134]	[0.092;0.140]	[0.054;0.092]
IT	0.044	0.035	0.040	0.035	0.026	0.017	0.031	0.048
	[0.024;0.065]	[0.018;0.053]	[0.012;0.067]	[0.012;0.042]	[0.006;0.045]	[-0.003;0.037]	[0.013;0.049]	[0.032;0.057]
KZ	0.070	0.049	0.068	0.089	0.071	0.056	0.066	0.089
	[0.041;0.098]	[0.024;0.074]	[0.031;0.106]	[0.050;0.096]	[0.047;0.094]	[0.034;0.077]	[0.044;0.087]	[0.057;0.095]
XK	0.106	0.102	0.105	0.096	0.096	0.097	0.091	0.073
	[0.077;0.135]	[0.069;0.135]	[0.069;0.140]	[0.060;0.118]	[0.074;0.119]	[0.072;0.122]	[0.070;0.111]	[0.046;0.082]
KG	0.100	0.096	0.082	0.094	0.123	0.118	0.123	0.145
	[0.073;0.127]	[0.066;0.126]	[0.052;0.113]	[0.058;0.107]	[0.094;0.152]	[0.089;0.148]	[0.094;0.152]	[0.104;0.165]
LV	0.062	0.049	0.047	0.041	0.094	0.090	0.099	0.096
	[0.034;0.091]	[0.023;0.076]	[0.003;0.091]	[0.016;0.044]	[0.068;0.120]	[0.064;0.116]	[0.072;0.127]	[0.074;0.109]
LT	0.073	0.063	.	0.089	0.087	0.080	0.094	0.115
	[0.038;0.108]	[0.028;0.098]	[.;.]	[0.050;0.096]	[0.062;0.113]	[0.058;0.102]	[0.072;0.116]	[0.092;0.129]
MD	0.108	0.112	0.101	0.138	0.180	0.172	0.185	0.096
	[0.068;0.147]	[0.074;0.149]	[0.053;0.149]	[0.097;0.158]	[0.146;0.215]	[0.140;0.205]	[0.155;0.214]	[0.074;0.109]
MN	0.100	0.099	0.077	0.080	0.065	0.062	0.057	0.089
	[0.053;0.148]	[0.053;0.145]	[0.014;0.140]	[0.027;0.104]	[0.042;0.088]	[0.040;0.084]	[0.030;0.084]	[0.046;0.094]
ME	0.095	0.075	0.094	0.106	0.103	0.080	0.101	0.115
	[0.065;0.125]	[0.049;0.101]	[0.062;0.125]	[0.068;0.119]	[0.079;0.127]	[0.057;0.102]	[0.079;0.123]	[0.085;0.129]
PL	0.065	0.066	0.065	0.075	0.064	0.044	0.114	0.124
	[0.034;0.097]	[0.036;0.097]	[0.033;0.097]	[0.053;0.095]	[-0.011;0.139]	[-0.036;0.124]	[0.072;0.156]	[0.085;0.156]
RO	0.126	0.110	0.124	0.128	0.141	0.143	0.135	0.118
	[0.100;0.152]	[0.081;0.139]	[0.095;0.152]	[0.101;0.143]	[0.114;0.168]	[0.110;0.176]	[0.106;0.164]	[0.091;0.128]
RU	0.099	0.087	0.096	0.070	0.109	0.088	0.092	0.106
	[0.069;0.130]	[0.057;0.118]	[0.067;0.125]	[0.046;0.080]	[0.076;0.142]	[0.051;0.126]	[0.066;0.118]	[0.078;0.118]
RS	0.063	0.081	0.063	0.070	0.091	0.053	0.084	0.110
	[0.044;0.083]	[0.061;0.101]	[0.044;0.081]	[0.046;0.080]	[0.067;0.115]	[0.031;0.076]	[0.056;0.111]	[0.079;0.127]
SK	0.051	0.039	0.049	0.052	0.076	0.055	0.070	0.066
	[0.024;0.077]	[0.015;0.064]	[0.006;0.093]	[0.017;0.066]	[0.052;0.101]	[0.031;0.079]	[0.046;0.095]	[0.045;0.074]
SI	0.060	0.056	0.049	0.052	0.049	0.038	0.026	0.063
	[0.032;0.088]	[0.027;0.086]	[0.003;0.095]	[0.017;0.066]	[0.029;0.069]	[0.015;0.061]	[-0.009;0.062]	[0.041;0.071]
TJ	0.233	0.206	0.215	0.200	0.069	0.034	0.061	0.100
	[0.173;0.293]	[0.143;0.270]	[0.147;0.283]	[0.154;0.235]	[0.038;0.101]	[0.010;0.059]	[0.025;0.097]	[0.064;0.109]
UA	0.104	0.087	0.105	0.136	0.099	0.082	0.106	0.105
	[0.075;0.134]	[0.061;0.113]	[0.075;0.134]	[0.112;0.148]	[0.073;0.125]	[0.054;0.110]	[0.083;0.129]	[0.082;0.119]
UZ	0.112	0.095	0.110	0.112	0.106	0.099	0.123	0.122
	[0.087;0.137]	[0.071;0.119]	[0.085;0.135]	[0.081;0.130]	[0.079;0.134]	[0.069;0.128]	[0.095;0.151]	[0.087;0.134]

Notes: IOp is measured by the Gini coefficient in the estimated counterfactual distribution $\tilde{M}$ which is constructed by the respective estimation approach indicated in the table header. 95% confidence intervals are derived based on 200 bootstrapped re-samples using the normal approximation method (Source: LiTS).

AVI Sensitivity Analysis

Table A6: Main Results - Type-based Position

	pooled				2010		2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-1.403	-0.417			-2.629		-2.000	
	(1.207)	(2.345)			(2.335)		(3.856)	
IOp Forest			0.760	2.957***		2.612***		4.832***
			(0.521)	(0.846)		(0.932)		(1.688)
Gini × Polity2		-0.140			0.043		-0.107	
		(0.266)			(0.295)		(0.480)	
IOp Forest × Polity2				-0.269***		-0.160**		-0.610***
				(0.083)		(0.072)		(0.183)
Polity2	0.021	0.059	-0.004	0.075***	-0.004	0.032	0.074	0.183***
	(0.015)	(0.067)	(0.015)	(0.025)	(0.084)	(0.028)	(0.120)	(0.054)
type-based Position	0.070***	0.070***	0.070***	0.071***	0.097***	0.097***	0.049***	0.053***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.015)	(0.014)	(0.016)	(0.015)
Mobility Experience	0.051***	0.052***	0.056***	0.055***	0.036**	0.045***	0.064***	0.064***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.017)	(0.019)	(0.019)
Communist Experience	0.045	0.045	0.036	0.040	0.020	0.017	0.005	0.013
	(0.047)	(0.047)	(0.043)	(0.043)	(0.068)	(0.065)	(0.048)	(0.046)
Number of individuals	32829	32829	34496	34496	11701	12510	21128	21986
Number of countries	28	28	30	30	24	26	24	26
pseudo R^2	0.048	0.048	0.046	0.049	0.061	0.062	0.058	0.055

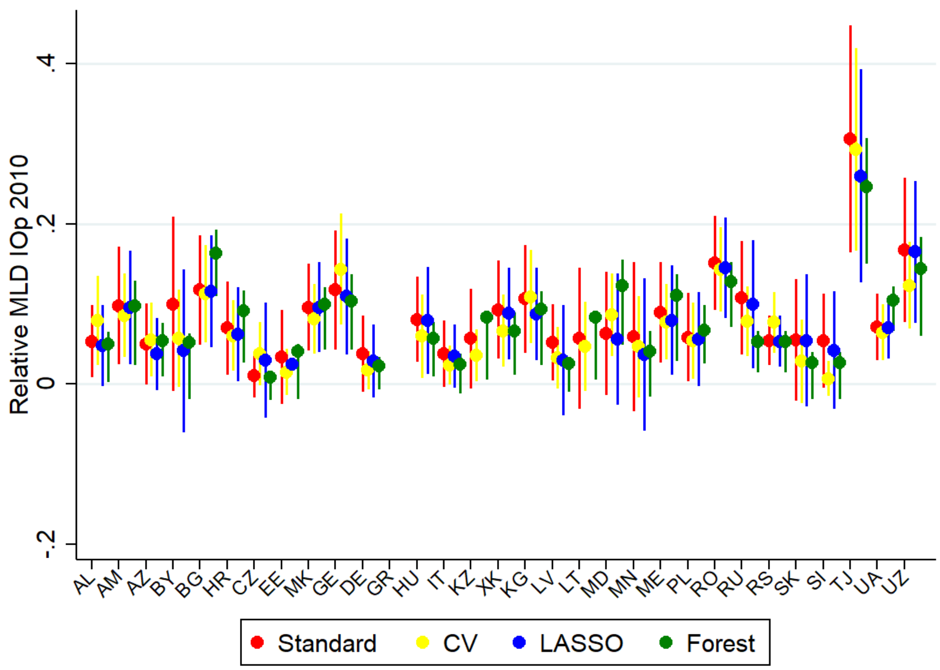
Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations. Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects while for columns 5-8 the year of analysis is indicated above. Columns 1 and 3 report model specifications without interaction between overall inequality/IOp and the level of democracy (Polity2 score). Columns 2, 4 and 5-8 include such an interaction which corresponds to the model specification of equation (6). All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors clustered at the country level are in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

Table A7: Main Results - Comparison of IOp Estimation Methodologies

	pooled				2010				2016			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IOp Standard	1.944***				0.797				2.893*			
	(0.616)				(0.897)				(1.551)			
IOp Standard × Polity2	-0.141**				0.032				-0.280			
	(0.070)				(0.089)				(0.174)			
IOp CV		2.361***				0.820				3.161**		
		(0.758)				(1.257)				(1.299)		
IOp CV × Polity2		-0.182**				0.033				-0.297**		
		(0.083)				(0.114)				(0.142)		
IOp Lasso			2.167***				1.340				3.274***	
			(0.539)				(0.861)				(0.914)	
IOp Lasso × Polity2			-0.165***				0.040				-0.314***	
			(0.062)				(0.086)				(0.102)	
IOp Forest				2.977***				2.605***				4.831***
				(0.834)				(0.928)				(1.664)
IOp Forest × Polity2				-0.271***				-0.161**				-0.608***
				(0.081)				(0.071)				(0.181)
Polity2	0.030*	0.034*	0.037**	0.075***	-0.026	-0.028	-0.030	0.032	0.068	0.065**	0.085***	0.182***
	(0.017)	(0.019)	(0.018)	(0.025)	(0.026)	(0.029)	(0.026)	(0.028)	(0.043)	(0.033)	(0.031)	(0.053)
actual Position	0.081***	0.081***	0.082***	0.080***	0.108***	0.107***	0.111***	0.107***	0.060***	0.060***	0.060***	0.059***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Mobility Experience	0.052***	0.052***	0.052***	0.055***	0.045***	0.043***	0.046**	0.045***	0.061***	0.062***	0.061***	0.064***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.017)	(0.017)	(0.019)	(0.017)	(0.019)	(0.019)	(0.019)	(0.018)
Communist Experience	0.039	0.041	0.041	0.039	0.018	0.019	0.032	0.018	0.006	0.006	0.003	0.010
	(0.043)	(0.043)	(0.043)	(0.043)	(0.064)	(0.064)	(0.068)	(0.065)	(0.045)	(0.046)	(0.045)	(0.045)
Number of individuals	34605	34605	33866	34605	12510	12510	11771	12510	22095	22095	22095	22095
Number of countries	30	30	30	30	26	26	24	26	26	26	26	26
pseudo R^2	0.048	0.049	0.050	0.049	0.061	0.060	0.063	0.063	0.053	0.055	0.057	0.056

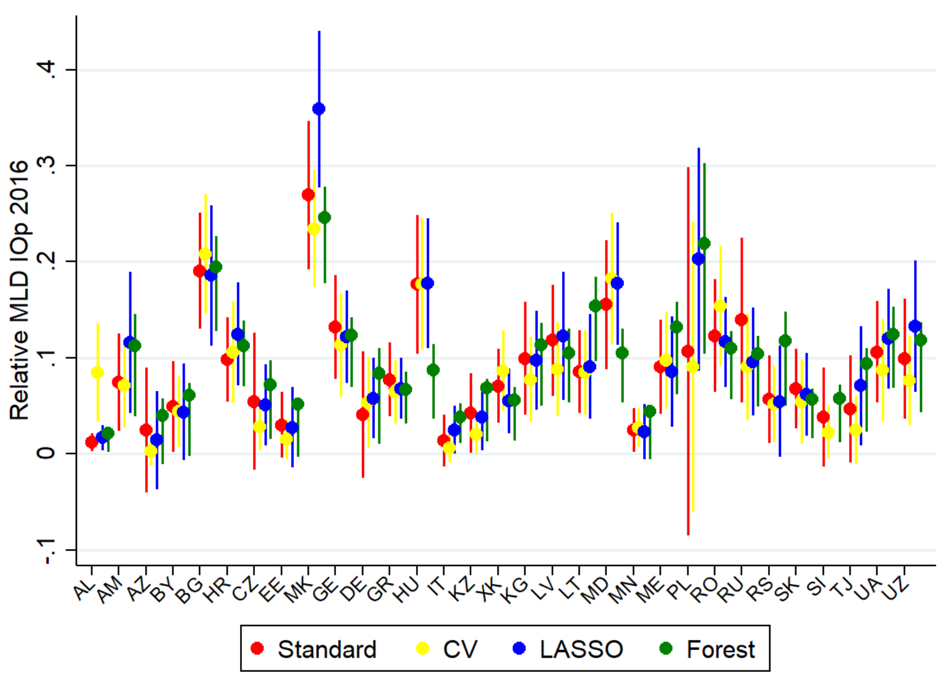
Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations of equation (6). Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects, while for columns 5-12 the year of analysis is indicated above. All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors clustered at the country level are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

Figure A8: Comparison of MLD IOp Estimates by Methodology (2010)



Notes: The figure depicts point estimates (dots) and 95% confidence intervals (spikes) for the countries' relative MLD IOp in 2010 based on the different methodologies presented: (1) Standard, (2) CV-based interacted model, (3) Lasso, and (4) conditional inference Forest (see table A4 and section 4.1; Sources: LiTS; SWIID).

Figure A9: Comparison of MLD IOp Estimates by Methodology (2016)



Notes: The figure depicts point estimates (dots) and 95% confidence intervals (spikes) for the countries' relative MLD IOp in 2016 based on the different methodologies presented: (1) Standard, (2) CV-based interacted model, (3) Lasso, and (4) conditional inference Forest (see table A4 and section 4.1; Sources: LiTS; SWIID).

Table A8: Main Results - MLD IOp Estimates

	pooled		2010	2016
	(1)	(2)	(3)	(4)
IOp MLD	1.248	5.233***	4.352**	9.113***
	(0.843)	(1.399)	(1.734)	(3.306)
IOp MLD × Polity2		-0.474***	-0.203*	-1.073***
		(0.131)	(0.119)	(0.358)
Polity2	-0.005	0.037***	0.003	0.095***
	(0.015)	(0.014)	(0.018)	(0.033)
actual Position	0.078***	0.079***	0.107***	0.060***
	(0.012)	(0.012)	(0.016)	(0.016)
Mobility Experience	0.056***	0.056***	0.044**	0.063***
	(0.014)	(0.014)	(0.017)	(0.019)
Communist Experience	0.038	0.040	0.019	0.005
	(0.042)	(0.043)	(0.065)	(0.046)
Number of individuals	34605	34605	12510	22095
Number of countries	30	30	26	26
pseudo R^2	0.046	0.049	0.063	0.055

Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations of equation (6) using relative MLD IOp estimates calculated via the Forest methodology (see section 4.1). Columns 1 and 2 show estimates for the pooled analysis of both survey waves with year fixed effects, while for columns 3 and 4 the year of analysis is indicated above. All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors clustered at the country level are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

Table A9: Main Results - Former Communist Countries only

	pooled				2010		2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-0.966	-0.439			-2.704		-2.015	
	(1.245)	(2.494)			(2.323)		(3.865)	
IOp Forest			0.542	2.967***		2.641***		3.871**
			(0.556)	(0.892)		(0.974)		(1.596)
Gini × Polity2		-0.076			0.052		0.066	
		(0.276)			(0.297)		(0.468)	
IOp Forest × Polity2				-0.295***		-0.159**		-0.571***
				(0.082)		(0.070)		(0.172)
Polity2	0.023	0.044	-0.001	0.086***	-0.005	0.031	0.020	0.170***
	(0.014)	(0.070)	(0.015)	(0.026)	(0.084)	(0.028)	(0.116)	(0.052)
actual Position	0.087***	0.087***	0.085***	0.087***	0.106***	0.105***	0.065***	0.067***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.019)	(0.018)	(0.016)	(0.016)
Mobility Experience	0.043***	0.043***	0.049***	0.047***	0.042**	0.051***	0.049***	0.052***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.018)	(0.018)	(0.017)	(0.017)
Communist Experience	0.090***	0.090***	0.081**	0.084**	0.066	0.063	0.042	0.044
	(0.035)	(0.035)	(0.033)	(0.033)	(0.067)	(0.065)	(0.039)	(0.036)
new EU member	-0.222	-0.219	-0.115	-0.181	-0.332*	-0.439***	-0.099	0.203
	(0.159)	(0.162)	(0.186)	(0.186)	(0.172)	(0.169)	(0.190)	(0.220)
Number of individuals	28427	28427	30097	30097	10294	11103	18133	18994
Number of countries	25	25	27	27	22	24	21	23
pseudo R^2	0.028	0.028	0.027	0.031	0.049	0.053	0.033	0.037

Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations using relative IOp estimates calculated via the Forest methodology (see section 4.1). Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects, while for columns 5-8 the year of analysis is indicated above. Columns 1 and 3 report model specifications without an interaction between overall inequality/IOp and the level of democracy (Polity2 score). Columns 2, 4 and 5-8 include such an interaction term which corresponds to the model specification of equation (6). All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors clustered at the country level are in parentheses.

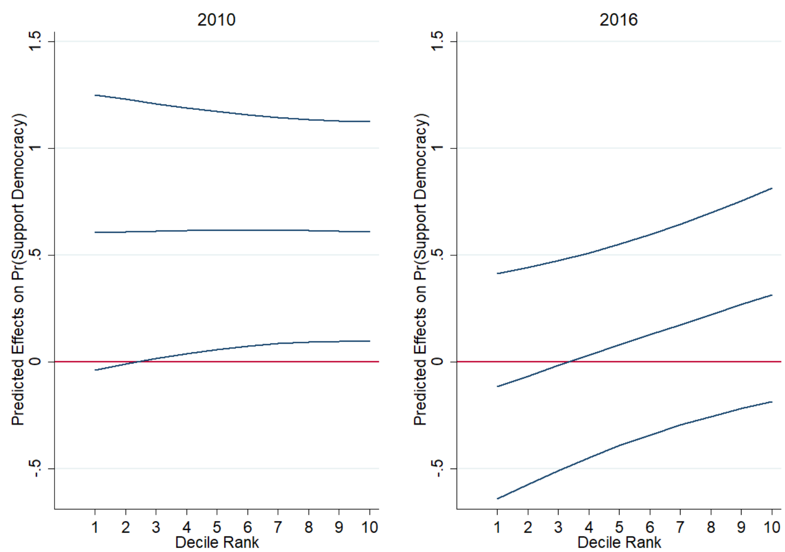
* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

Table A10: Interaction with Consumption Decile Rank

	pooled				2010		2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-0.320		-0.522		-2.163		-2.368	
	(2.340)		(2.558)		(2.649)		(3.946)	
IOp Forest		2.981***		2.728***		2.557**		4.146**
		(0.832)		(0.974)		(1.062)		(1.689)
Gini × Polity2	-0.145		-0.145		0.037		-0.114	
	(0.265)		(0.265)		(0.294)		(0.478)	
IOp Forest × Polity2		-0.272***		-0.271***		-0.161**		-0.608***
		(0.081)		(0.081)		(0.071)		(0.180)
Gini × actual Position			0.037		-0.068		0.085	
			(0.118)		(0.144)		(0.146)	
IOp Forest × actual Position				0.045		0.009		0.123**
				(0.051)		(0.061)		(0.061)
Polity2	0.059	0.075***	0.059	0.075***	-0.002	0.032	0.075	0.182***
	(0.067)	(0.025)	(0.067)	(0.025)	(0.083)	(0.028)	(0.119)	(0.052)
actual Position	0.024***	0.025***	0.012	0.012	0.056	0.031**	-0.012	-0.020
	(0.004)	(0.004)	(0.040)	(0.016)	(0.046)	(0.016)	(0.050)	(0.020)
Mobility Experience	0.051***	0.054***	0.051***	0.054***	0.035**	0.044**	0.063***	0.063***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.017)	(0.019)	(0.018)
Number of individuals	32935	34605	32935	34605	11701	12510	21234	22095
Number of countries	28	30	28	30	24	26	24	26
pseudo R^2	0.049	0.049	0.049	0.049	0.062	0.064	0.058	0.056

Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations using relative IOp estimates calculated via the Forest methodology (see section 4.1). Additional to the main analysis, an interaction term between the respective inequality measure and the individual's decile rank in the consumption expenditure distribution is included in all models. Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects, while for columns 5-8 the year of analysis is indicated above. Columns 1 and 3 report model specifications without interaction between overall inequality/IOp and the level of democracy (Polity2 score). Columns 2, 4 and 5-8 include such interaction which corresponds to the model specification of equation (6). All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors clustered at the country level are in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

Figure A10: Marginal Effects of IOp conditional on Decile Rank



Notes: The figures depict the marginal effects of IOp on the probability of supporting democracy conditional on the individual's consumption decile rank in 2010 and 2016, corresponding to columns 4 and 6 of table A10. Further displayed are the 95% confidence bands of such marginal effects and a histogram of the Polity2 index in the estimation sample (Source: LiTS).

Table A11: Main Results - Bootstrapped Standard Errors

	pooled				2010		2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-1.350	-0.334			-2.565		-1.908	
	(1.489)	(5.941)			(11.005)		(12.712)	
IOp			0.762	2.977		2.605		4.831
			(0.689)	(2.526)		(6.805)		(10.066)
Gini × Polity2		-0.144			0.036		-0.114	
		(0.668)			(1.291)		(1.362)	
IOp × Polity2				-0.271		-0.161		-0.608
				(0.259)		(0.737)		(1.165)
Polity2	0.020	0.059	-0.005	0.075	-0.002	0.032	0.075	0.182
	(0.026)	(0.197)	(0.019)	(0.080)	(0.445)	(0.209)	(0.420)	(0.376)
actual Position	0.079***	0.079***	0.078***	0.080***	0.108***	0.107***	0.054***	0.059***
	(0.014)	(0.012)	(0.011)	(0.010)	(0.020)	(0.016)	(0.016)	(0.016)
Mobility Experience	0.050***	0.051***	0.055***	0.055***	0.036**	0.045**	0.063***	0.064***
	(0.015)	(0.012)	(0.016)	(0.013)	(0.016)	(0.017)	(0.015)	(0.018)
Communist Experience	0.044	0.044	0.035	0.039	0.022	0.018	0.002	0.010
	(0.045)	(0.045)	(0.034)	(0.038)	(0.057)	(0.071)	(0.037)	(0.041)
Number of individuals	32935	32935	34605	34605	11701	12510	21234	22095
Number of countries	28	28	30	30	24	26	24	26
pseudo R^2	0.048	0.049	0.046	0.049	0.061	0.063	0.058	0.056
p-value Wald test β Gini/IOp	0.298	0.901	0.186	0.082	0.270	0.069	0.688	0.062

Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations using relative IOp estimates calculated via the Forest methodology (see section 4.1). Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects, while for columns 5-8 the year of analysis is indicated above. Columns 1 and 3 report model specifications without an interaction between overall inequality/IOp and the level of democracy (Polity2 score). Columns 2, 4 and 5-8 include such an interaction which corresponds to the model specification of equation (6). All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors following score-based cluster bootstrapping (Kline and Santos, 2012) are in parentheses. Further, p-values for Wald-type tests for the exclusion of the coefficient of Gini/IOp based on such bootstrapping are reported. * $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)

AVII Multilevel Model

Following the notation of Steenbergen and Jones (2002), level 1 is the individual and level 2 is the country. Multilevel modeling accounts for observations being nested by explicitly modeling the proportion of variance that is attributable to within-cluster and between-cluster variation. The associated assumption of normally distributed random effects, though, imposes a structure on the data generating process unlike the model-free clustered standard errors. However, such an assumption may not be met in practice and the model structure also does not addresses the uncertainty of level 1 measures. Yet, multi-level modeling helps to address the country sample selection problem, i.e. outliers in country-level measures are captured by the random effect intercept.

Considering the most simple case with a varying intercept due to a country-level random effect ν_c and no cross-level interaction between levels (i.e. individual-level effects do not depend on country-level variables, e.g. the effect of an individual's education on his/her support for democracy is independent of the country's level of IOp), as employed by Ritter and Solt (2019), a multi-level model to determine the effect of country-level IOp on individual-level support for democracy consists of level 1 equation[53]

$$attitude_{ilct} = \alpha_{0c} + \alpha_{1c} X_{ilct} + \epsilon_{ilct} \tag{7}$$

and level 2 equation

$$\alpha_{0c} = \beta_{00} + \beta_{01} I_{ct} + \beta_{02} Z_{ct} + \gamma_t + \nu_{c0} \, . \tag{8}$$

Assuming that the effect of individual-level predictors is fixed ($\alpha_{1c} = \beta_{10}$, i.e. no interaction between level 2 and level 1 predictors), substituting equation (8) in equation (7) yields

$$attitude_{ilct} = \beta_{00} + \beta_{01} I_{ct} + \beta_{02} Z_{ct} + \beta_{10} X_{ilct} + \gamma_t + \nu_{c0} + \epsilon_{ilct} \, . \tag{9}$$

[53] Alternatively, the specification would also take into account variance at the primary sampling unit (PSU) level l, resulting in a three level hierarchical model: the individual level intercept is α_{0lc}, equation (8) becomes $\alpha_{0lc} = \beta_{00c} + \beta_{01c} P_{lct} + \delta_{0lct}$ with P_{lct} being an PSU level predictor like perceived average income decentile (e.g. Brock, 2020), and level 3 is the country level c such that $\beta_{00c} = \gamma_{000} + \gamma_{001} I_{ct} + \gamma_{002} Z_{ct} + \gamma_t + \nu_{00c}$. Yet, such hierarchical model specification rather adheres to settings in which PSU-level effects are the focus of the analysis (e.g. Ajzenman et al., 2020) and, hence, constitutes a unnecessary complication for the research question at hand and would also be too demanding for the presented data (1,639 PSU-clusters nested in 34 countries).

Table A12: Main Results - Multilevel Model

	pooled				2010		2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-2.652***	9.831***			-2.376		-5.963*	
	(0.321)	(2.285)			(2.170)		(3.405)	
IOp			0.605***	1.560**		2.202*		5.351**
			(0.118)	(0.662)		(1.128)		(2.588)
Gini × Polity2		-1.439***			-0.050		0.193	
		(0.256)			(0.261)		(0.443)	
IOp × Polity2				-0.107		-0.180		-0.683**
				(0.073)		(0.113)		(0.303)
Polity2	0.014**	0.522***	0.029***	0.061***	0.031	0.043	0.014	0.221**
	(0.006)	(0.092)	(0.006)	(0.023)	(0.075)	(0.037)	(0.126)	(0.093)
actual Position	0.077***	0.077***	0.076***	0.076***	0.105***	0.100***	0.050***	0.049***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.015)	(0.015)	(0.012)	(0.011)
Mobility Experience	0.050***	0.053***	0.049***	0.050***	0.043***	0.047***	0.071***	0.067***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.009)	(0.008)
Communist Experience	0.037	0.039	0.031	0.033	0.033	0.030	-0.010	0.001
	(0.030)	(0.030)	(0.029)	(0.029)	(0.053)	(0.051)	(0.037)	(0.037)
Number of individuals	32935	32935	34605	34605	11701	12510	21234	22095
Number of countries	28	28	30	30	24	26	24	26

Notes: The dependent variable is a binary variable indicating support for democracy and reported coefficients are based on probit estimations using relative IOp estimates calculated via the Forest methodology (see section 4.1). Columns 1 to 4 show estimates for the pooled analysis of both survey waves with year fixed effects, while for columns 5-8 the year of analysis is indicated above. Columns 1 and 3 report model specifications without an interaction between overall inequality/IOp and the level of democracy (Polity2 score). Columns 2, 4 and 5-8 include such an interaction which corresponds to the model specification of equation (6). All regressions include individual-level controls (gender, age and age squared, educational attainment, life satisfaction and circumstances) and country-level controls (Governance, GDP per capita, 5 year average GDP per capita growth and unemployment rate, dummy variables for non-former Communist countries and for new EU member countries). Standard errors are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$ (Sources: LiTS; SWIID; WEO; WGI; Polity IV)