Why Are the Affluent Better Represented Around the World?[*]

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Abstract

Scholars have discovered remarkable inequalities in who gets represented in electoral democracies. Around the world, the preferences of the rich tend to be better represented than those of the less well-off. In this paper, we use the most comprehensive comparative dataset of unequal representation available to answer why the poor are underrepresented. By leveraging variation over time and across countries, we study which factors explain why representation is more unequal in some places than in others. We compile a number of covariates examined in previous studies and use machine learning to describe which mechanisms best explain the data. Globally, we find that economic conditions and good governance are most important in determining the extent of unequal representation, and we find little support for hypotheses related to political institutions, interest groups, or political behavior, such as turnout. These results provide the first broadly comparative explanations for unequal representation.

In recent years, scholars have discovered remarkable inequalities in who gets represented in electoral democracies around the world. In the US, a number of studies find that elected representatives appear to respond almost exclusively to the preferences of the very affluent when they pursue legislation (e.g., Bartels 2008; Flavin 2014; Gilens 2012; Jacobs and Page 2005). Other US studies raise questions about these findings and the extent of the inequality (e.g., Bhatti and Erikson 2001; Branham et al. 2017; Brunner et al. 2013; Enns 2015). Yet, outside the US, the growing number of studies all seem to find similarly unequal representation (e.g., Bernauer et al. 2015; Donnelly and Lefkofridi 2014; Giger et al. 2012; Lesschaeve 2017; Lupu and Warner 2017; Peters and Ensink 2015; Rosset 2016; Rosset and Stecker 2019; Rosset et al. 2013; Schakel and Hakhverdian 2018; Schakel et al. 2020).[1]

In the most comprehensive study to date, Lupu and Warner (Forthcoming) find that more affluent citizens are on average better represented by their elected officials than are poorer citizens. Digging deeper into specific cases, they find that this affluence bias exists on socioeconomic issues – and that a pro-poor bias exists on social or cultural issues (see also Bartels 2016; Gilens 2012; Lesschaeve 2017; Rosset and Stecker 2019). But their comparative dataset focuses on left-right positions that appear to capture socioeconomic policy preferences.

We use their dataset to study what might be driving unequal representation around the world. Why is representation more unequal in some countries and some years than others? To date, most scholarship on unequal representation has focused on documenting its existence and variation. Only a handful of studies examine the question of why representation tends to be unequal (Bartels 2008; Bernauer et al. 2015; Flavin 2014; Gilens 2012; Guntermann et al. 2020; Rosset 2016). And even these largely test just one or two potential explanations – such as campaign finance regulations or electoral disproportionality – in isolation.

Many plausible alternative explanations also exist, including income inequality, government partisanship, trade union strength, and corruption, to name a few. In this paper, we leverage variation across time and space to adjudicate among these plausible explanations for

[1] For a recent review, see Peters (2018).

what drives unequal representation. That is, in order to understand why representation is unequal on average, we ask why it is more unequal in some times and places than in others. We focus on five groups of possible explanations: those focusing on economic conditions, political institutions, governance, interest groups, and political behavior.

The list of plausible explanations is long, and unequal representation is undoubtedly multi-causal. There is also little in the way of theory about how to model these explanations or the interdependent relationships among the explanatory variables. Our aim is descriptive and not causal.[2] We want to know which of the many possible explanations for unequal representation seem to matter empirically so that scholars can begin to develop more parsimonious theories that can be tested. For this reason, we use machine learning rather than only vanilla linear regression analysis to evaluate which variables better explain the variation in the data (see Grimmer 2015; Molina and Garip 2019).

Using the global sample, we find that variables relating to economic conditions and governance are the most important for predicting affluence bias in representation. We find little support overall for hypotheses that affluence bias might be due to factors related to political institutions, interest groups, or political behavior, such as turnout or compulsory voting. Further, we find that these variables account not only for global patterns in unequal representation, but also largely differences among the wealthy democracies of Western Europe. Among this subset, the same basic groups of variables account for much of the variation in unequal representation, though the precise order of variable importance shifts somewhat: economic development becomes substantially less important, while campaign finance and party institutionalization become more important.

[2] On the merits of description for political science, see Gerring (2012).

Explaining Unequal Representation

Canonical theories typically divide the representative process into two stages: first, congruence or opinion representation—the process of generating a body of representatives that reflects the preferences of the electorate—and then, responsiveness—the process by which these representatives generate policies that reflect citizens' preferences (Achen 1978; Miller and Stokes 1963). Whereas recent empirical research on unequal representation in the US has focused on responsiveness (e.g., Bartels 2008; Gilens 2012), comparative work has tended to focus on congruence (e.g., Bernauer et al. 2015; Giger et al. 2012; Lupu and Warner Forthcoming; Schakel and Hakhverdian 2018). We build on this comparative work, asking why elected representative around the world seem to be more congruent with their more affluent constituents.

One group of explanations suggests that economic conditions may affect representation. Economic development may be associated with higher levels of education, greater opportunities for class-based mobilization, and declining opportunities for clientelism—all of which might increase the policy demands of the poor (Luna and Zechmeister 2005). Conversely, where economic resources are distributed unequally, the rich may be able to exert more disproportionate influence on policymakers (Erikson 2015; Rosset et al. 2013). Globalization – that is, a country's dependence on foreign trade or capital – may constrain the policy space such that elected representatives may be forced to take positions preferred by international economic elites (Andrews 1994; Cerny 1999; Kurzer 1991), which will presumably also be close to those of domestic elites.

A second approach suggests that domestic political institutions matter. Electoral systems with proportional representation are thought to promote more mass-elite congruence than majoritarian systems (e.g., Huber and Powell 1994; McDonald and Budge 2005; Powell 2009), although some studies challenge that finding (e.g., Blais and Bodet 2006; Ferland 2016; Golder and Lloyd 2014; Lupu et al. 2017). The logic is that proportional systems ensure that a larger swath of the electorate is represented in the legislature, which might also reduce biases toward the rich (see Bernauer et al. 2015). Representation may also be more equal in contexts where democratic governance and party systems are more consolidated. In these contexts, where party labels may be more informative (Lupu 2016), voters might be better able to select candidates who represent their preferences. Contexts with more robust political parties may also provide institutional vehicles for recruiting and supporting politicians who are less biased toward the preferences of the rich.

A third group of explanations focuses on different forms of governance. Where clientelism and corruption are rampant, representatives may have incentives to emphasize the preferences of the affluent because they fund their political machines or because poor voters are bought off (Stokes 2005). The ideological makeup of the legislature might also matter. Since leftist parties typically have less affluent core constituencies (Garrett 1998; Huber and Stephens 2001; Korpi and Palme 2003), having more leftists in office may produce less affluence bias.[3] Finally, some studies find that female representatives prioritize pro-poor policies more than their male counterparts (Clayton et al. 2019), suggesting that legislatures with more female representatives may be less biased in favor of the rich.

Interest groups often also play a substantial role in determining who runs for and wins public office (Grossman and Helpman 2001). Some interest groups favor the preferences of the rich while others emphasize the preferences of the poor, and the relative strength of these types of groups could help determine whether elected representatives better reflect one side over the other. For instance, since trade unions tend to represent the interests of the less affluent (Korpi 1983), contexts with stronger unions might demonstrate less affluence bias.

Scholars of US politics tend to focus on the role that interest groups and affluent citizens play through political donations (e.g., Bartels 2008; Flavin 2014; Gilens 2012). Since affluent voters and their allied interest groups are the source of most of the money involved in political campaigns, it seems plausible that they use their wealth to shift the selection of policymakers closer to their preferences. Although we know far less about the role of money in politics outside

[3] Along related lines, Rhodes and Schaffner (2017) find partisan differences in the US in affluence bias.

the US (Scarrow 2007), campaign contributions may similarly bias representation in other democracies (see Rosset 2016).

A final group of theories suggests that unequal representation might arise primarily through different patterns in political behavior. For instance, the affluence bias might just be a function of poor people being less likely to vote than the rich (e.g., Avery 2015; Leighley and Nagler 2013; Lijphart 1997; Schlozman et al. 2012). If elected representatives are reelection-oriented, they may discount the preferences of citizens who are unlikely to turn out to vote (Guntermann et al. 2020). Although disproportionate turnout among the rich is less common in developing countries (Gallego 2015; Kasara and Suryanarayan 2015), it is plausible that elected representative discount the preferences of the poor in contexts where they participate less. A related possibility is that political cleavages cross-cut, such that political dimensions beyond affluence – such as ethnicity or region – inform political selection (Lipset 1960). In these cases, we might see unequal representation on the affluence dimension but more equal representation along other salient cleavage dimensions.

Scholars are only beginning to evaluate which of these competing arguments might best explain the patterns of unequal representation around the world. Studies of the US generally conclude that the role of money in US politics is the most apt explanation for the inequalities they find (Bartels 2008; Flavin 2014; Gilens 2012). But their evidence is largely indirect, and they rule out only a small number of alternatives – most notably, disproportionately lower turnout by the less affluent. Comparative studies have only recently begun to study the topic, offering support for the importance of electoral institutions, turnout, and party public financing (Bernauer et al. 2015; Guntermann et al. 2020; Rosset 2016). But these too largely test a single explanation in isolation. We are still far from understanding why representation is unequal.

Empirical Strategy

To answer this question, we use a new dataset on mass-elite ideological congruence worldwide. Lupu and Warner (Forthcoming) collected every publicly available survey of national representatives or candidates in which respondents were asked to place themselves on a scale with "left" and "right" (or similar) anchors.[4] They then matched these elite surveys with data on mass preferences using publicly available surveys in which voting-age adults were similarly asked to place themselves on a left-right scale.[5]

The resulting dataset includes 92,000 unique legislator-year observations matched to 3.9 million citizen-year observations. It spans 565 country-years across 52 countries and 33 years, the largest collection of mass and elite ideological preferences of which we are aware.[6] Although the dataset represents all of the available information, note that it comes overwhelmingly from Europe and Latin America. To avoid problems arising from small samples, we restrict our analysis to the 285 country-years in which responses for at least 30 legislators and 30 citizens are available.

[4] In country-years with multiple legislator surveys, the authors select only one elite survey to minimize the risk of overlapping samples and exacerbated nonresponse bias. See the online appendix for further details about the construction of these data.

[5] For each elite respondent's legislative term, the authors matched him or her to citizen responses from any of the years during that term. For example, a member of parliament surveyed in 2011 for a 2010-2013 term was matched to mass survey respondents from 2010, 2011, 2012, or 2013.

[6] The countries are Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Chile, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, El Salvador, Estonia, Finland, France, Germany, Greece, Guatemala, Honduras, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Mexico, Netherlands, Nicaragua, Norway, Panama, Paraguay, Peru, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, Uruguay, and Venezuela. The years are 1967-2015, although most of the data begin in the 1990s.

Our dependent variable is a measure of congruence, the similarity between the preferences of citizens and those of their elected representatives. We compute congruence for each country-year using the Earth Mover's Distance (EMD), a measure of distributional similarity that has been shown to better capture mass-elite congruence than alternative approaches (Lupu et al. 2017). The EMD between two distributions solves a linear optimization problem, the optimal flow of mass from one distribution to the other until they are identical. In our case, the EMD captures the distance, or similarity, between the distribution of preferences of citizens and the distribution of preferences of elected representatives. We calculate the EMD for both the bottom and top quintile of citizens in terms of affluence. Since the EMD captures the distance between each distribution of citizen preferences and legislator positions, our dependent variable is the difference between these EMDs, computed as $\Delta\mathrm{EMD} = \mathrm{EMD}_{\mathrm{poor}} - \mathrm{EMD}_{\mathrm{rich}}$. Larger values indicate greater affluence bias, with legislators' preferences closer to those of the rich than of the poor. Figure 1 plots the distribution of our dependent variable by country, with each point indicating a country-year of data; crosses indicate country-years excluded from our statistical analyses due to small sample sizes. Variation in affluence bias does not appear to be predominantly within- or across-country, but rather a combination of both.

To measure affluence, we develop a rank-ordering of indicators, which privileges measuring wealth over household income and occupational status.[7] Where we have data on ownership of durable goods (e.g., a car or refrigerator), we use multiple correspondence analysis to generate a factored index of affluence (see Filmer and Pritchett 2001). Where these data are not available, we use household income or occupation, in that order. We then generate quintiles from

[7] We prefer measures of wealth because (1) nonresponse to questions about household income is typically high (these data are missing for 50% of respondents in our mass sample), and (2) occupational structures are difficult to compare across countries.

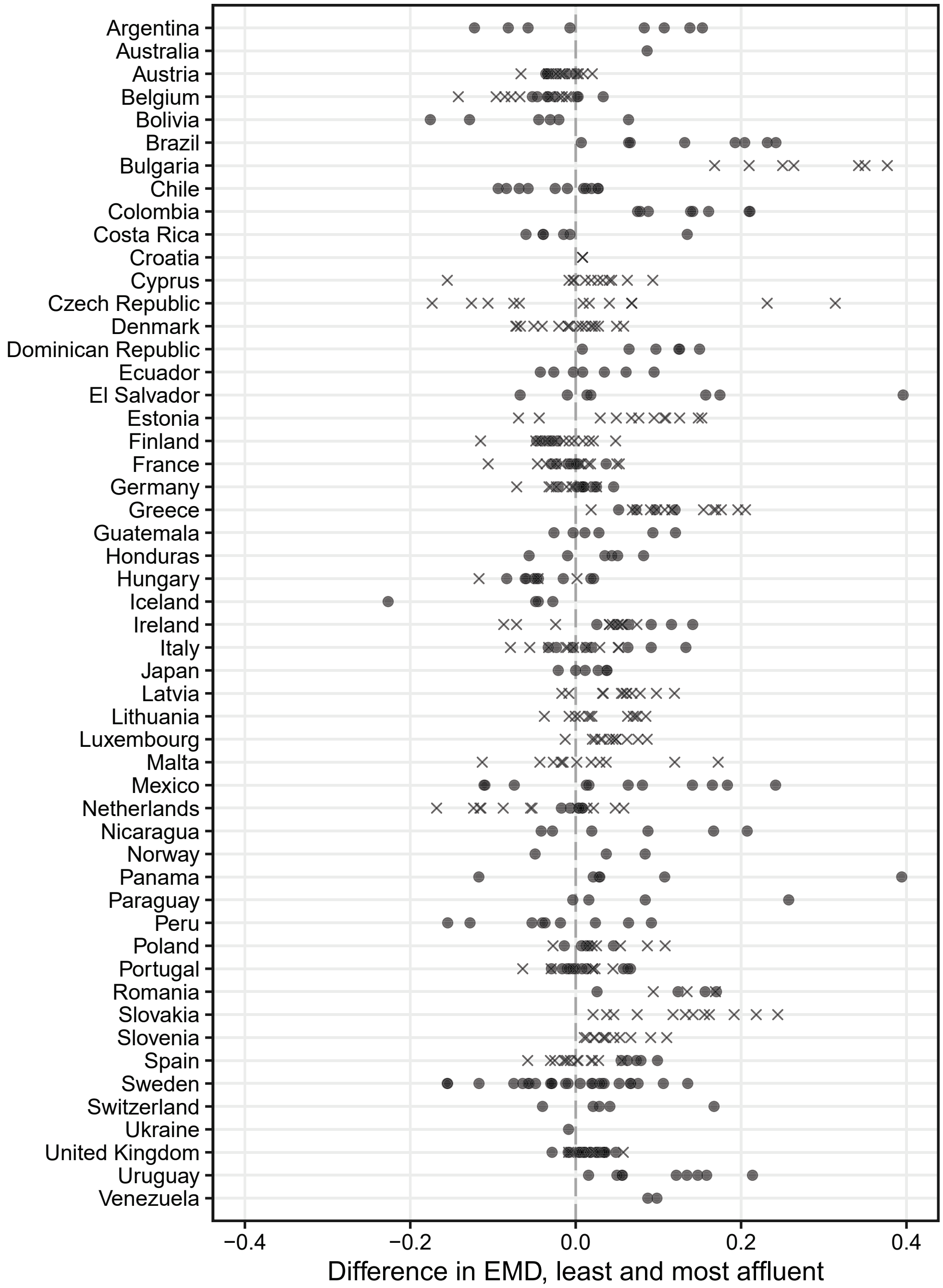

Figure 1: The distribution of affluence bias in the dataset. Each point represents the EMD between legislators and the least affluent quintile of voters, minus the EMD between legislators and the most affluent quintile of voters, for one country-year. Positive values indicate that the poor are underrepresented relative to the rich, while negative values indicate the opposite. Dots represent observations in the statistical analyses, while crosses indicate data that are excluded because there are too few respondents in the country-year.

Table 1: Summary statistics

Variable	Min.	Mean	Max.	% Miss.	Description
Δ EMD	-0.18	0.03	0.40	0	The EMD between the poorest voters and legislators minus the EMD between the richest voters and legislators. Larger values indicate a greater bias toward the affluent.
Economic conditions					
Foreign cap. depend.	17.37	22.71	27.32	3	Logged net FDI. Larger values indicate more dependence on foreign capital.
GDP (logged)	7.22	9.64	11.42	0	Logged GDP per capita. Larger values indicate more wealth.
HDI	0.57	0.80	0.94	1	Human Development Index. Larger values indicate more development.
Income inequality	25.30	39.47	58.10	10	Gini index. Larger values indicate more inequality.
Trade openness	16.59	76.03	191.54	0	Trade as a proportion of GDP. Larger values indicate more openness to trade.
Political institutions					
Age of democracy	1.00	53.88	176.00	0	Democracy age in years.
Disproportionality	0.81	6.36	17.80	37	Least Squares Index of electoral disproportionality. Larger values indicate greater disproportionality.
Party institutionalization	1.00	50.66	183.00	0	Mean party age in years. Larger values indicate greater party institutionalization.
Governance					
Clientelism	-1.33	0.68	3.29	0	Extent of main parties' programmatic linkages to citizens. Larger values indicate more clientelism.

Table 1: Summary statistics (continued)

Variable	Min.	Mean	Max.	% Miss.	Description
Corruption	0.01	0.28	0.88	0	Pervasiveness of political corruption. Larger values indicate more corruption.
Government ideology	1.00	5.66	9.25	2	Ideology of the governing party or parties. Larger values indicate more conservative/right-wing government.
% female legislators	0.02	0.23	0.47	0	Proportion of legislators who are women. Larger values indicate more female legislators.
Interest groups					
Civil society	0.40	0.86	0.98	0	Civil society participation in political process. Larger values indicate greater and more open civil society involvement.
Pol. donation restrictions	−1.97	1.25	4.04	0	Strength of disclosure requirements for donations to national election campaigns. Larger values indicate stricter requirements.
Trade union density	2.30	29.10	88.90	20	Proportion of employees who are union members. Larger values indicate greater trade union density.
Political behavior					
Compulsory voting	0.00	0.38	1.00	0	Compulsory voting (binary). 1 indicates any legal compulsion to vote, even if unenforced.
Cross-cuttingness	0.10	0.86	0.95	13	Cross-cuttingness of race and income. Larger values indicate greater cross-cuttingness.
Turnout	0.38	0.69	0.97	0	Voting turnout among voting-age population. Larger values indicate higher turnout.

See the text for variable sources. Note that each variable is centered and scaled prior to analysis.

the material wealth and income variables, and we recode occupational data into general categories (e.g., “white-collar professional”).[8]

To measure our independent variables of interest, we collected data on a range of covariates to test all of the potential explanations for the affluence effect discussed above. Summary statistics and descriptions are provided in Table 1, with data sources and coding rules summarized in the online appendix.

The first group of variables all relate to economic conditions. To measure levels of economic development, we use GDP per capita and the United Nations’ Human Development Index (HDI), a broad measure that encompasses health, education, and standard of living outcomes. Our measure of income inequality is the Gini index derived from economic household surveys and reported by the World Bank. To study the effects of globalization, we include both net foreign direct investment, as a measure of dependence on foreign capital, and trade openness.

Our second group of covariates relate to political institutions. To study the effects of electoral systems, we follow previous studies and focus on the translation of votes into seats using a Gallagher (1991) index of electoral disproportionality, as collated and updated by Gandrud (2019). For measures of how consolidated democratic governance and party systems are, we use the age of democracy calculated by Boix et al. (2013) and the mean party age provided in the Database of Political Institutions (DPI; Beck et al. 2001; Cruz et al. 2016).

The third set of covariates focuses on governance. We measure political clientelism using an index derived from expert surveys fielded by the Varieties of Democracy (V-Dem) project (recoded from a party linkages variable). We also use V-Dem’s index of political corruption, which captures six distinct types of corruption across legislative, judicial, and executive branches of government, as well as in the public sector (Coppedge et al. 2017). To examine government ideology, we build a measure of left-right ideology, weighted by party strength in government, for each country-year. Our data for this variable are drawn from the Chapel Hill Expert Survey Data

[8] Of the 565 observations in our data, 379 use asset wealth as a measure of affluence, 172 use household income, and 14 use occupation.

(CHES; Bakker et al. 2015; Polk et al. 2017), adding in data from the Manifesto Project (Volkens et al. 2018) and Baker and Greene (2011), rescaling these sources to the same 0-10 scale as in CHES. Finally, we study the proportion of legislators who are women, which we computed by scraping the website of the Inter-Parliamentary Union (2019), now downloadable from the Parline repository.

Our fourth group of potential explanations focuses on interest groups. Here we use a V-Dem index of civil society participation in policymaking to measure the overall strength of civil society and International Labor Organization data on trade union density to look specifically at the role of unions. To explore the effects of campaign finance, we include V-Dem's measure of the stringency of restrictions on political donations.

Our final group of covariates relate to political behavior. To examine the effects of cross-cutting cleavages, we use the measure of race-income cross-cuttingness developed by Selway (2011). We also want to examine the possible effect that disproportionately lower turnout by the poor may have on unequal representation. Prior studies suggest that these inequalities in participation are lower when turnout itself is higher and when voting is compulsory (Dassonneville et al. 2017; Gallego 2010; Persson et al. 2013). We derive both indicators from V-Dem, which measures electoral turnout among the voting-age population and a binary variable for whether citizens are required to vote, regardless of enforcement.

Modeling Affluence Bias

Which of these possible factors actually exert influence on the gap in representation between rich and poor? Answering this question poses methodological challenges. Representation is undoubtedly multi-causal, but we have little in the way of theory to guide us in modeling the relationships among all of these factors, let alone their independent relationships with representation. We could simply make strong assumptions and throw all of these variables into a kitchen-sink regression model, but this would unreasonably assert independence among the variables, assume linearity, and yield conditional results that are difficult to interpret (Achen 2005; Hindman 2015; Ray 2005). It would also undoubtedly lead us to overfitting, finding relationships among variables that fit noise in our particular dataset but are unlikely to generalize beyond our sample.[9] And, like many regression analyses, making such arbitrary modeling choices would lead us to underestimate (and understate) our modeling uncertainty (Bartels 1997; Montgomery et al. 2012).

One way to resolve these issues, particularly in descriptive studies like ours, is to turn to machine learning (Athey and Imbens 2019; Breiman 2001b; Molina and Garip 2019). Machine learning allows us to estimate models in which the parameters are algorithmically honed to provide better model fit while also incentivizing parsimony. The ensemble of machine learning algorithms we study allow for nonlinearities, interactions, nested functions, and a number of other complexities that are difficult to study in the framework of linear regression. By using split samples and cross-validation, machine learning also provides a more rigorous approach to measuring out-of-sample predictive power, thereby guarding against overfitting. At the same time, this approach subsumes standard linear regression, allowing us to also study the same models that could be estimated using ordinary least squares. These advantages have led more and more political scientists to use machine learning tools to study questions relating to topics as diverse as interest group politics, voting behavior, survey research methods, legislator ideology, genocide, and civil war onset (Becker et al. 2017; Bonica 2018; Cohen and Warner Forthcoming; Grimmer and Stewart 2013; Hainmueller and Hazlett 2014; Muchlinski et al. 2016).

We begin by imputing missing data among our independent variables.[10] Patterns of missingness in our variables vary from source to source, such that listwise deleting each

[9] Like most studies in political science, we have a relatively small sample – at least relative to most computer-science applications. As Hindman (2015) notes, small samples particularly stand to benefit from applying machine learning.

[10] Our results are substantively unchanged using listwise deletion; see the online appendix for details.

observation for which we do not have data on every variable would mean losing nearly half of our sample. Overall, 11% of our data are missing, so we use conditional multiple imputation to generate 11 imputation replicates, each with 10 iterations (Bodner 2008; Kropko et al. 2014). Each of these replicates is then partitioned into training and test samples containing 75% and 25% of the data, respectively, while preserving the marginal distributions of all variables. Training samples are used to find model parameters that produce the best predictions, while the test samples are used to measure how accurate those predictions are.

Next, we iterate through thirteen machine learning algorithms using the R package caret (Kuhn 2008). The models we study include the generalized linear model, linear discriminant, nearest-neighbor, neural network, and random forest implementations, including bagged and boosted variants.[11] Together, these models include all of the major flavors of machine learning prevalent in political science. For each replicate, each model's hyperparameters (e.g., the number of layers in a neural network) are "tuned" using five-fold cross-validation with five repeats, after which the hyperparameters that provide the lowest root mean-squared error (RMSE) are chosen (Bagnall and Cawley 2017). The model is then fit to the training replicate using these hyperparameters and the model parameters (e.g., coefficient estimates) that minimize RMSE. These $13 \times 11 = 143$ fitted models are then used to predict the gap in representation for observations in each of the 11 test samples.[12]

We care about two quantities of interest. First, we want to know which models provide the best fit, as evident in the smallest RMSE. Second, from the best-fitting models, we want to know

[11] Bagging refers to bootstrap aggregating, or sampling with replacement from the training data to create additional training observations (Breiman 1996). Boosting refers to reweighting observations, often according to the accuracy of the prediction from a previous iteration of the model, to focus on cases for which the model's prediction is worst (Freund and Schapire 1996). The full list of models we use is available in the online appendix.

[12] Since we are interested in examining the relative importance of our various explanatory variables, we do not model country indicators, autocorrelation, or other atheoretic variables.

which variables exert the greatest effect on the representation gap. A typical quantity in machine learning (e.g., Breiman 2001a; Hill and Jones 2014), "variable importance" metrics indicate the amount of information a covariate provides to the model for predicting the outcome. In essence, they tell us how much a model's predictive performance changes if each variable is removed. By default, caret rescales all variable importance measures (which differ across models) to a 0-100 scale, where zero indicates a variable provided no information to the model and 100 indicates a variable provided the most information among all covariates.[13]

Which Variables Matter Most?

All of the models we study perform reasonably well. The worst-fitting models are two neural network implementations, each of which produces a mean RMSE of 0.086 across the 11 imputed data replicates; the best-fitting model is a random forest with a mean RMSE of 0.074.[14] These slight differences shrink even further when we account for imputation uncertainty: all the models' standard deviation of RMSE across imputation replicates hover between 0.008 and 0.013, suggesting that most models perform as well as the others. Still, our tree-based models generally outperform our neural networks —an unsurprising result since neural networks are more prone to overfitting, which may be a problem for our small sample. Given these findings, we interpret results from the random forest.[15]

Figure 2 presents the variable importance results for the random forest. Dots indicate

[13] Many of our variables are multicollinear, which makes them more likely to have low (and unstable) variable importance scores, since they are providing less unique information to the model. High, stable variable importance scores in the presence of multicollinearity suggests a variable is still informative despite its correlation with other predictors.

[14] These RMSEs are in relation to the $[-1, 1]$ interval of the dependent variable. Full results are available in the online appendix.

[15] Note, however, that our substantive results are consistent across models.

median importance across the imputation replicates, with lines for interquartile ranges. We do not find much evidence suggesting political institutions are important for understanding variation in affluence bias. Disproportionality ranks dead last in variable importance, and in fact is not used in *any* of the random forests fit to the 11 imputation replicates, suggesting that it is never informative for understanding variation in affluence bias. While age of democracy is slightly above average in importance, the last institutional variable, party system institutionalization, is of below-average importance. Compulsory voting, foreign capital dependence, government ideology, and civil society strength round out the bottom five variables alongside disproportionality. Also somewhat striking is the below-average importance of restrictions on political donations. Taken as a whole, these results indicate that political institutions and campaign finance are far less important for determining the gap in representation between rich and poor than previously thought.

Which factors *are* important? Economic conditions and governance appear to be most important in providing information about unequal representation. Domestic economic factors like

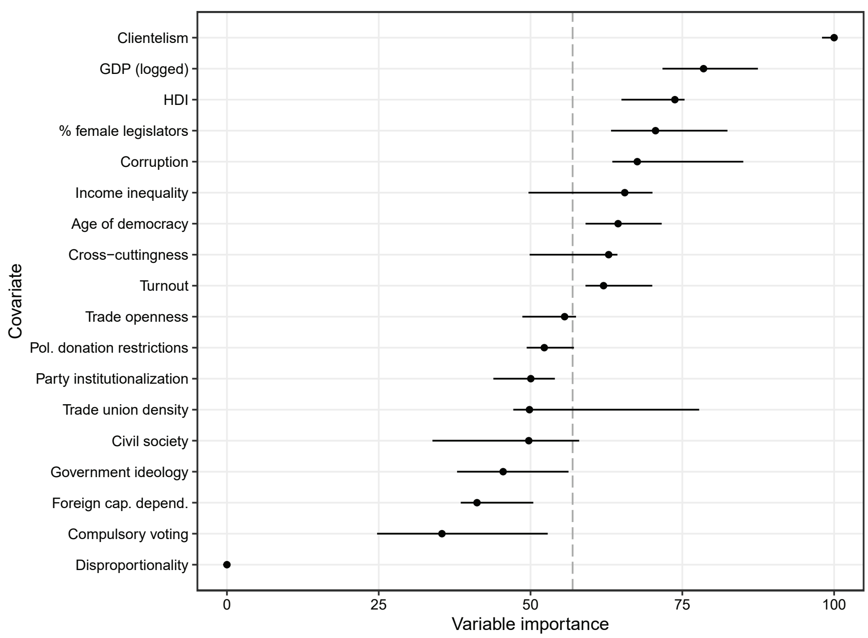

Figure 2: Variable importance. Each dot represents the mean variable importance, with lines for the interquartile range, across all imputation replications from the random forest model. Larger values indicate variables providing the model more information for predicting unequal representation. The dashed vertical line represents the mean variable importance score.

the levels of economic and social development and income inequality appear to be very important, representing three of the top six covariates. Among the governance variables, clientelism, corruption, and female representation demonstrate relatively high importance, rounding out the other half of the top six. The remaining variables – turnout, trade openness, and trade union density – all appear to have middling levels of importance.

These results suggest that unequal representation is not a product of globalization, the structure of domestic political institutions, or money in politics. Instead, we find the strongest support for arguments that economic development and good governance determine the extent of political inequality. Of course, these data are observational and our models correlational, so our analysis cannot shed light on whether these are underlying causal mechanisms or just broad associations. But these results provide the first cross-national evidence on the factors most strongly associated with unequal representation, suggesting directions for further theorizing and hypothesis-testing.

Direction of Effects

Beyond knowing which variables correlate most strongly with unequal representation, we also want to know whether these mechanisms work in the direction predicted by theory. To investigate this question, we vary each covariate along its interquartile range and predict affluence bias using each of the models fit to the imputed data replicates. The partial dependence plots in Figure 3 aggregate these predictions for the six most important variables,[16] providing the loess fit as a black line with 95% confidence intervals in gray.

The resulting relationships are largely consistent with theoretical expectations. Higher levels of clientelism, corruption, and income inequality are associated with higher levels of bias in representation in favor of the affluent. Conversely, as levels of economic and social development and female representation increase, unequal representation in favor of the rich appears to decline.

[16] Partial dependence plots for the other twelve variables are available in the online appendix.

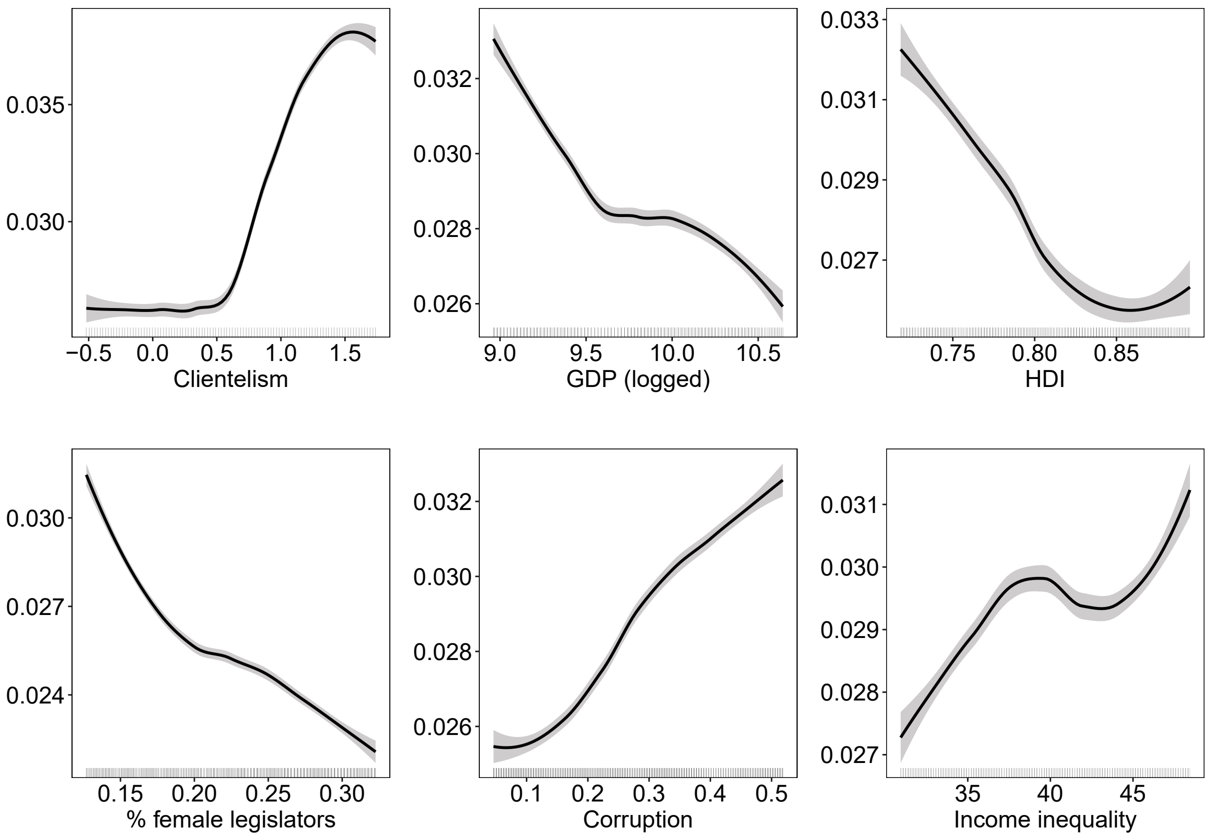

Figure 3: Partial dependence plots for the six most importance variables. Each panel provides the predicted change in unequal representation as a predictor is moved across its inter-quartile range. Lines represent loess fits, with 95% confidence intervals in gray, computed from random forest predictions across all imputation replicates. Rug plots are also provided along the x axis to indicate support in the underlying data for these predictions. Note the differing axes in each panel.

There are some nonlinearities in these relationships, but they nevertheless seem remarkably close to linear.

To quantify the magnitudes of these effects, Table 2 provides the change in the expected quantile of the dependent variable that results when each covariate is (separately) shifted from its 25th to its 75th quantile. For example, when clientelism is low, the gap in representation is predicted to be just above the empirical mean, in the 56th quantile. When clientelism is high, this gap is predicted to be in the 65th quantile, a shift of just over 8% of the observed representation gap (before rounding). For an example to build intuition, this shift corresponds to the difference

Table 2: Effect magnitudes from the random forest

Variable	Effect
Clientelism	0.08
GDP (logged)	−0.06
HDI	−0.05
% female legislators	−0.06
Corruption	0.06
Income inequality	0.03

Predictions indicate the difference in the quantile of the dependent variable that results when the covariate is shifted across its interquartile range, as generated by simulating out of the random forests fit to each of the imputed data replicates.

between Finland in 2014 (low clientelism) and Mexico in 1997 (high clientelism). On the other hand, when the human development index is shifted from its 25th to its 75th quantile, the EMD drops from the 62nd to the 56th quantile. Although this shift may seem small in the abstract, it corresponds to the difference between the Dominican Republic in 2014 (low HDI) and Ireland in 2011 (high HDI).

As expected, the largest effects are found among the most important variables. None of the variables by themselves account for massive portions of the representation gap. But together, these variables explain a substantial amount, consistent with our expectation that unequal representation is multi-causal.

Unequal Representation in Western Europe

By painting in such broad strokes, with a comprehensive cross-national dataset, our analysis may miss important variation among smaller subsets of cases. For instance, while factors such as clientelism, corruption, and levels of development are important for predicting unequal representation globally, these variables may prove less important among the more developed democracies in Western Europe – where much of the comparative research on unequal representation is focused. In these countries, levels of clientelism and corruption are comparatively low, and levels of development are comparatively high, particularly relative to Latin America.

To explore this possibility, we subset our data to include just Austria, Belgium, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. We then rerun all of the same models described above and compute the same variable importance measures. The results of this exercise are presented in Figure 4.

Subsetting to just these developed democracies does change the results, but not as much as one might expect. Economic development appears to be even more important for predicting the representation gap among Western European democracies than across our global sample. Corruption does drop off in importance but remains above average, while clientelism remains among the most important variables. Female representation also remains among the most

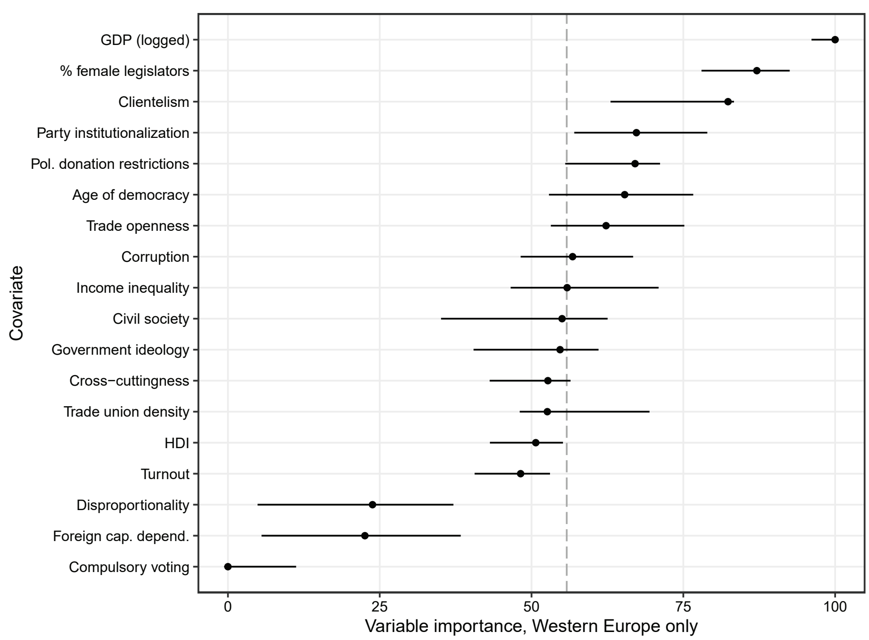

Figure 4: Variable importance in Western Europe. Each dot represents the mean variable importance, with lines for the interquartile range, across all imputation replications from the random forest model. Larger values indicate variables providing the model more information for predicting unequal representation.

important variables even within Western Europe. At the bottom end, disproportionality and compulsory voting remain among the least important variables, and other factors like globalization and government ideology continue to show middling or below-average importance.

Three notable differences do appear. Party institutionalization, which showed a middling level of importance in the global sample, is one of the most important variables in the Western European subset. Unsurprisingly, HDI appears to matter much less in Western Europe. Perhaps most notably, given its prominence in studies of the US, restrictions on political donations is vastly more important in Western Europe than globally.

On the whole, these results still suggest that economic conditions and governance are the most important areas for understanding unequal representation worldwide. While there are some differences between the more developed democracies in our dataset and the rest of the sample, most of the conclusions from the broader dataset hold also for this subset. Perhaps the most notable exception is that campaign finance and party institutionalization seem to matter more in Western Europe than they do elsewhere. Still, these results reassure us that the global patterns in the data are broadly worth pursuing for further theorizing and hypothesis-testing, regardless of whether one is ultimately interested in understanding unequal representation in but one region of the world.

Understanding Unequal Representation

Political scientists are coming to grips with the finding that around the world, elected representatives sometimes better reflect the preferences of rich citizens. While there are ongoing debates about the extent of this bias in the US, comparative research is remarkably uniform in uncovering such a bias, at least when it comes to economic issues. But we have few empirical studies that try to explain this bias. And those that do focus on a single explanatory factor in isolation and often a small number of countries.

Using a new dataset on mass-elite congruence around the world, matched to the relevant country-year covariates, we have sought to begin to fill this gap. Our descriptive efforts here reveal that variables relating to economic conditions and governance are the most important for predicting affluence bias in representation. We find little support overall for hypotheses that affluence bias might be due to factors relating to political institutions, interest groups, or political behavior, such as turnout.

This is but an initial exploration of the patterns in unequal representation around the world. Our study highlights factors that the data tell us appear to be most important in understanding differences in unequal representation over time and space. Our descriptive analysis relies on existing measures and on correlations in the data; we cannot draw conclusions from this about causal relationships among the variables. Still, this exercise should help guide future theorizing about this important research topic in democratic politics.

Broad studies of this kind are not without limitations. For one, we are limited by the kinds of measures that are available across time and space, though they surely do not exhaust the factors that might explain unequal representation. For instance, one possible explanation for affluence bias is that elected representatives misperceive the preferences of their constituents. Representatives' perceptions are an important link in the representational chain developed by Miller and Stokes (1963). There are reasons to think that with the spread of opinion polls, representatives' information about public preferences could be more accurate (Geer 1996), but there is also growing evidence of biases in how legislators and their staffs derive impressions of public opinion (Broockman and Skovron 2018; Butler 2014; Hertel-Fernandez et al. 2019). Another, related possibility is that elected representatives reflect better the preferences of the affluent because they themselves tend to be affluent, something that has recently received renewed attention (Carnes 2013; Carnes and Lupu 2015). Neither of these possibilities lend themselves to the kind of cross-national analysis we engage in here, but they surely merit further investigation.

There is also some comparative evidence that the poor and the rich may base their voting behavior on different issue domains (e.g., Calvo and Murillo 2019; De la O and Rodden 2008; Shayo 2009), which may explain why representation on the left-right dimension (our focus here) favors the affluent. If the rich care more about the economic issues captured by this dimension and the poor care more about other issues, then these inequalities may be a function of elected representatives simply reacting to issue publics. Again, while our empirical strategy is ill-equipped to study this possible explanation, we hope future research considers it further.

Our analysis also focuses on congruence and on collective representation, two among multiple other dimensions of the broad concept of democratic representation. As we note above, these choices are driven both by theoretical interest—theories of representation ascribe substantial normative significance to both congruence and collective representation—and empirical tractability, given the availability of a broad comparative dataset. This of course leaves open the possibility that the explanations for the type of unequal representation we study would not generalize to other dimensions. Indeed, the extent to which representation itself is unequal may vary depending on the policy domain and type of inequality one measures. But our efforts here still point to useful directions for understanding why the aspects of representation that we study are unequal.

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