UNEQUAL DEMOCRACIES

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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. Why? We use the most comprehensive comparative dataset of unequal representation available to answer this question. By leveraging variation over time and across countries, we study what factors explain why representation is more unequal is some times and places? We compiled a number of covariates posited by previous studies and use machine learning to see which best explain the data. We find that economic conditions, government partisanship, and clean government determine the extent of unequal representation, and we find no support for hypotheses related to turnout or electoral institutions. These results provide the first broadly comparative explanations for unequal representation.

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In recent years, scholars have discovered remarkable inequalities in who gets represented in electoral democracies around the world. In the U.S., elected representatives appear to respond almost exclusively to the preferences of the very affluent when they pursue legislation (Bartels 2008; Ellis 2013; Flavin 2014; Gilens 2005, 2012; Gilens and Page 2014; Jacobs and Page 2005; Rhodes and Schaffner 2017; Rigby and Wright 2013).[1] In other contexts, too, representatives seem to represent more closely the preferences of the rich than those of the less-affluent (Bernauer et al. 2015; Giger et al. 2012; Lupu and Warner 2017; Rosset 2013; Rosset et al. 2013; Schakel and Hakhverdian 2018).[2]

In the most comprehensive study to date, **?** 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. But their comparative dataset focuses on left-right positions that appear to capture socioeconomic policy preferences.

We use this 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. But most of these studies offer little evidence to explain why representation tends to be unequal. When they do, studies in the U.S. typically conclude that it is campaign finance and lobbying that make representation unequal: the outsize influence of money in U.S. politics means that elected representatives respond most to the preferences of the people financing their campaigns and lobbying them (Bartels 2008; Flavin 2014; Gilens 2012). But plausible alternatives also exist: economic conditions, government partisanship, election turnout, electoral rules, globalization, civil society, and democratic quality, to name a few.

[1] There is some debate among scholars of U.S. politics about the extent of this bias (e.g., Branham et al. 2017; Enns 2015; Soroka and Wlezien 2008, 2010; Wlezien and Soroka 2011), although it is widely acknowledged to exist.

[2] More citations to be added.

In this paper, we leverage variation across time and space to adjudicate among these plausible explanations for why representation is more unequal is some times and places than in others. Since the list of plausible explanations is long and we have little theoretical reason to find some more plausible than others, we use machine learning to evaluate which variables better explain the variation in the data. We find that economic conditions, government partisanship, and clean government are the most important variables predicting affluence bias in representation. We find little support for hypotheses that affluence bias might be due to factors like turnout, electoral institutions, or globalization.

Explaining Unequal Representation

Why might elected representatives unequally represent the preferences of the more affluent? Scholars of U.S. politics tend to blame the outsize influence of campaign contributions (Bartels 2008; Flavin 2014; Gilens 2012). Affluent voters are the source of most of the money involved in political campaigns (Brady et al. 1995; Gilens 2012), so it seems highly plausible that they use their wealth to influence the selection of policymakers. Although we know far less about the role of money in politics outside the U.S. (Scarrow 2007), campaign contributions may similarly bias representation in other democracies.

Another explanation for unequal representation may be that poor people are less likely to vote than the rich (e.g., Erikson 2015; Lijphart 1997; Schlozman et al. 2012). If elected representatives care about reelection, they may discount the preferences of citizens who are unlikely to turn out to vote. U.S. studies find little evidence that disproportionate turnout accounts for the affluence bias in representation (Bartels 2008; Gilens 2012), although that evidence is mostly indirect. Although disproportionate turnout among the rich is less common in developing countries (Gallego 2015; Kasara and Suryanarayan 2015), it seems at least plausible that elected representative discount the preferences of the poor in contexts where they participate less.

Looking across countries, institutions may also matter. Electoral systems with proportional representation are thought to promote more mass-elite congruence than majoritarian systems (Budge and McDonald 2007; Ezrow 2007; Huber and Powell 1994; McDonald and Budge 2005; Powell 2006, 2009; Powell and Vanberg 2000), although some studies challenge that finding (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).

Other structural features may also be important. Civil society organizations like trade unions may be able to mobilize support for politicians who better represent the preferences of the less-affluent, or may be able to lobby for political positions closer to them. 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. And systems with cross-cutting cleavages may also be those with lower levels of affluence bias since dimensions other than the socioeconomic one are more politically salient.

Representation may also be more equal in contexts where democratic governance is more robust. Older democracies and those with lower levels of clientelism and corruption may be less captured by economic elites and therefore exhibit lower affluence bias.

Finally, 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). On the other hand, where economic resources are distributed unequally, the rich may be able to exert more disproportionate influence on policymakers (Rosset et al. 2013). Globalization may constrain the policy space such that elected representatives may be forced to take positions preferred by international economic elites, which will be closer to those of domestic elites.

In this paper, we leverage cross-national variation on these potential explanations for inequality to adjudicate among them. If these explanations are right, we should find that affluence bias in representation is highest in times and places where, for instance, campaign finance is less regulated, where legislative seats are allocated more disproportionately, where economies are less developed and more unequal, and where clientelism and corruption are more widespread. Even if we do find support for the direction of these relationships, which of these factors best explain unequal representation?

Empirical Strategy

To answer this question, we collected data on mass-elite ideological congruence worldwide. As outlined in detail in **?**, we first gathered all publicly available surveys of national representatives or candidates in which respondents were asked to place themselves on a scale with "left" and "right" (or similar) anchors. In country-years with multiple legislator surveys, we selected only one elite survey, to minimize the risk of overlapping samples and exacerbated nonresponse bias. Our final sample comprise 92,000 unique legislator-year observations.

We then gathered data on mass preferences using publicly available surveys in which voting-age adults were similarly asked to place themselves on a left-right scale. We identified each elite respondent's legislative term and 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. In gathering mass data, we privileged samples in which: data were generated alongside a matching legislator survey; question wordings were coordinated with a legislator survey; the response scale was most similar to that of the legislator survey; and data were collected as part of a large, cross-national project, to increase comparability across space and time. The resulting data include 3.9 million citizen-year observations.

Together, these samples span 565 country-years across 52 countries and 33 years, the largest collection of mass and elite ideological preferences of which we are aware.[3] We restrict

[3] The countries are Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Chile, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic,

attention to the 276 country-years in which responses for at least 30 legislators and 30 citizens are available, to avoid any problems arising from small samples. For each country-year, we compute the Earth Mover's Distance between the least and most affluent mass quintiles (EMD; Lupu et al. 2017). We computed affluence quintiles using a factored index of material wealth from respondents' ownership of durable goods such as cars or refrigerators.[4] Since the EMD captures the distance between each distribution of citizen preferences and legislator preferences, our dependent variable is the difference between these EMDs, computed as $\Delta\text{EMD} = \text{EMD}_{\text{poor}} - \text{EMD}_{\text{rich}}$. Larger values indicate greater affluence bias, with legislators' preferences closer to those of the rich than of the poor.

We then collected data on a range of covariates to test all of the potential mechanisms behind the affluence effect, discussed above. Summary statistics and descriptions are provided in Table 1, with data sources and coding rules summarized in the Appendix. The first group of variables all relate to the contours of the domestic economy. To measure national wealth, we use the World Bank (2019) measure of gross domestic product (GDP) per capita. We also study net foreign direct investment (FDI) as a measure of dependence on foreign capital. We log both variables to ease computation and interpretation. We examine trade as a proportion of GDP and the Gini Index, to measure openness to trade and income inequality (respectively), both also from the World Bank. To examine the strength of workers' interests, we use the International Labor Organization (ILO; 2019) data on trade union density. From the United Nations Development Program (2018) we study the Human Development Index, a broad measure that encompasses

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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.

[4] Where such data are not available, we use household income or occupation to compute affluence quintiles (see **?**).

health, education, and standard of living outcomes, as coded in the Quality of Government dataset (Teorell et al. 2019). Our last economic variable is the Varieties of Democracy (V-Dem) Political Corruption Index, 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).

Our second group of covariates relate to political institutions. We borrow the age of democracy measure from Boix et al. (2013), updated through 2018. We also examine party institutionalization via the mean party age variable provided in the Database of Political Institutions (DPI; Beck et al. 2001; Cruz et al. 2016). To explore the limits on campaign finance, we study V-Dem's measure of the stringency of restrictions on political donations. We also use V-Dem's measure of compulsory voting, which we recode into a binary variable for whether citizens are required to vote, regardless of enforcement. Last, we examine the translation of votes into seats using a Gallagher (1991) index of electoral disproportionality, collated and updated by Gandrud (2019).

Our final group of covariates relate to political behavior. To measure the cross-cuttingness of social cleavages, we study the measure of race-income cross-cuttingness developed by Selway (2011). We investigate civil society participation in policymaking, as well as the pervasiveness of political clientelism, both from V-Dem (the latter recoded from a party linkages variable). We also study turnout using V-Dem's electoral turnout among voting-age population variable. 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 (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 the latter sources to be on 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.

Table 1: Summary statistics

Variable	Min.	Mean	Max.	% Miss.	Description
Δ EMD	-0.15	0.03	0.36	0.00	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.
Age of democracy	1.00	54.80	176.00	0.00	Democracy age in years.
Civil society	0.40	0.86	0.98	0.00	Civil society participation in political process. Larger values indicate greater and more open civil society involvement.
Clientelism	-1.34	0.65	3.29	0.00	Extent of main parties' programmatic linkages to citizens. Larger values indicate more clientelism.
Compulsory voting	0.00	0.37	1.00	0.00	Compulsory voting (binary). 1 indicates any legal compulsion to vote, even if unenforced.
Corruption	0.01	0.28	0.88	0.00	Pervasiveness of political corruption. Larger values indicate more corruption.
Cross-cuttingness	0.10	0.86	0.95	0.26	Cross-cuttingness of race and income. Larger values indicate greater cross-cuttingness.
Disproportionality	0.81	6.36	17.80	0.72	Least Squares Index of electoral disproportionality. Larger values indicate greater disproportionality.
Foreign cap. depend.	14.51	22.64	27.32	0.15	Logged net FDI. Larger values indicate more dependence on foreign capital.

Table 1: Summary statistics (continued)

Variable	Min.	Mean	Max.	% Miss.	Description
GDP (logged)	7.22	9.67	11.43	0.00	Logged GDP per capita. Larger values indicate more wealth.
HDI	0.57	0.80	0.94	0.03	Human Development Index. Larger values indicate more development.
Income inequality	25.30	39.34	58.10	0.22	Gini index. Larger values indicate more inequality.
Government ideology	1.00	5.66	9.25	0.00	Ideology of the governing party or parties. Larger values indicate more conservative/right-wing government.
Party institutionalization	1.50	51.86	183.00	0.01	Mean party age in years. Larger values indicate greater party institutionalization.
% female legislators	0.02	0.23	0.47	0.00	Proportion of legislators who are women. Larger values indicate more female legislators.
Pol. donation restrictions	−1.97	1.25	4.04	0.00	Strength of disclosure requirements for donations to national election campaigns. Larger values indicate stricter requirements.
Trade openness	16.59	76.48	191.54	0.01	Trade as a proportion of GDP. Larger values indicate more openness to trade.
Trade union density	2.30	29.26	88.90	0.39	Proportion of employees who are union members. Larger values indicate greater trade union density.
Turnout	0.38	0.69	0.97	0.00	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.

Predicting Affluence Bias

We are interested in learning which potential mechanisms exert the most influence on the gap in representation between rich and poor. Our goal is therefore to build models that best predict the affluence effect worldwide using the covariates described above. The challenge is one of model choice: with 18 covariates of interest, there are 2^{18} possible models that could be studied to see which variables exert a significant effect on this representation gap. Further, these only include additive linear models; once interactions and nonlinearities are introduced, the model space becomes intractably large. Without knowing which model is the best one—which model provides the best fit to the data—it is impossible to draw inferences about which variables are most informative for predicting the affluence effect.

We turn to machine learning (ML), the science of learning patterns in data, to help solve this problem. ML allows us to iteratively estimate models, honing the parameters to provide better model fit. The ML algorithms we study allow for nonlinearities, interactions, nested functions, and a number of other complexities that are difficult to study in the framework of an additive linear model. And by using cross-validation and split samples, ML provides a more rigorous approach to measuring out-of-sample predictive power, better measures of model fit, and more robust inferences.

More specifically, we begin by imputing missing data. We use conditional multiple imputation to generate 11 imputation replicates (Kropko et al. 2014), as our overall proportion of data missingness is 11% (Bodner 2008). We ensure each imputation converges after 10 iterations. Each of these 11 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 sixteen machine learning algorithms using the R package caret (Kuhn 2008). The models we study include neural network, random forest, vector machine, nearest-neighbor, and generalized linear model implementations, including bagged and boosted variants. 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 $16 \times 11 = 176$ fitted models are then used to predict the gap in representation for observations in each of the 11 test samples.

We care about three quantities of interest. First, we want to know which models provide the best predictions, as evident in the smallest RMSE. Second, from the best-fitting models, we want to know which variables exert the greatest effect on the representation gap. A bread-and-butter quantity in machine learning (e.g., Breiman 2001; Hill and Jones 2014), "variable importance" metrics indicate the amount of information a covariate provides to the model for predicting the outcome. By default, caret rescales all variable importance measures (which differ across models) to a 0-100 scale, where larger values indicate more important. Finally, once we have identified the most important variables for predicting the affluence effect, we want to know the substantive impact of each variable, or the direction each relationship runs.

Which Variables Matter?

All of the models we study predict the affluence effect with reasonable accuracy. The worst-fitting model is a deep neural network, which produces a mean RMSE of 0.08 across the 11 imputed data replicates; the best-fitting model is a random forest with a mean RMSE of 0.07. These slight differences grow even smaller when we account for imputation uncertainty: all models' standard deviation of RMSE across imputation replicates hover between 0.008 and 0.011, suggesting that most models predict approximately as accurately as one another. Nonetheless, all three of the best-performing models are random forest variants, while two of the bottom three are neural networks—an intuitive result given that neural networks are more prone to over-fitting, which may be a problem given our small sample size. Given these findings, we choose to interpret results from the vanilla random forest.[5]

Variable importance results for the random forest are presented in Figure 1. Dots indicate median importance across imputation replicates, with lines for inter-quartile ranges, and a dashed vertical line at the mean across all variables. The starkest result is the poor performance of covariates relating to political institutions. Restrictions on political donations, party

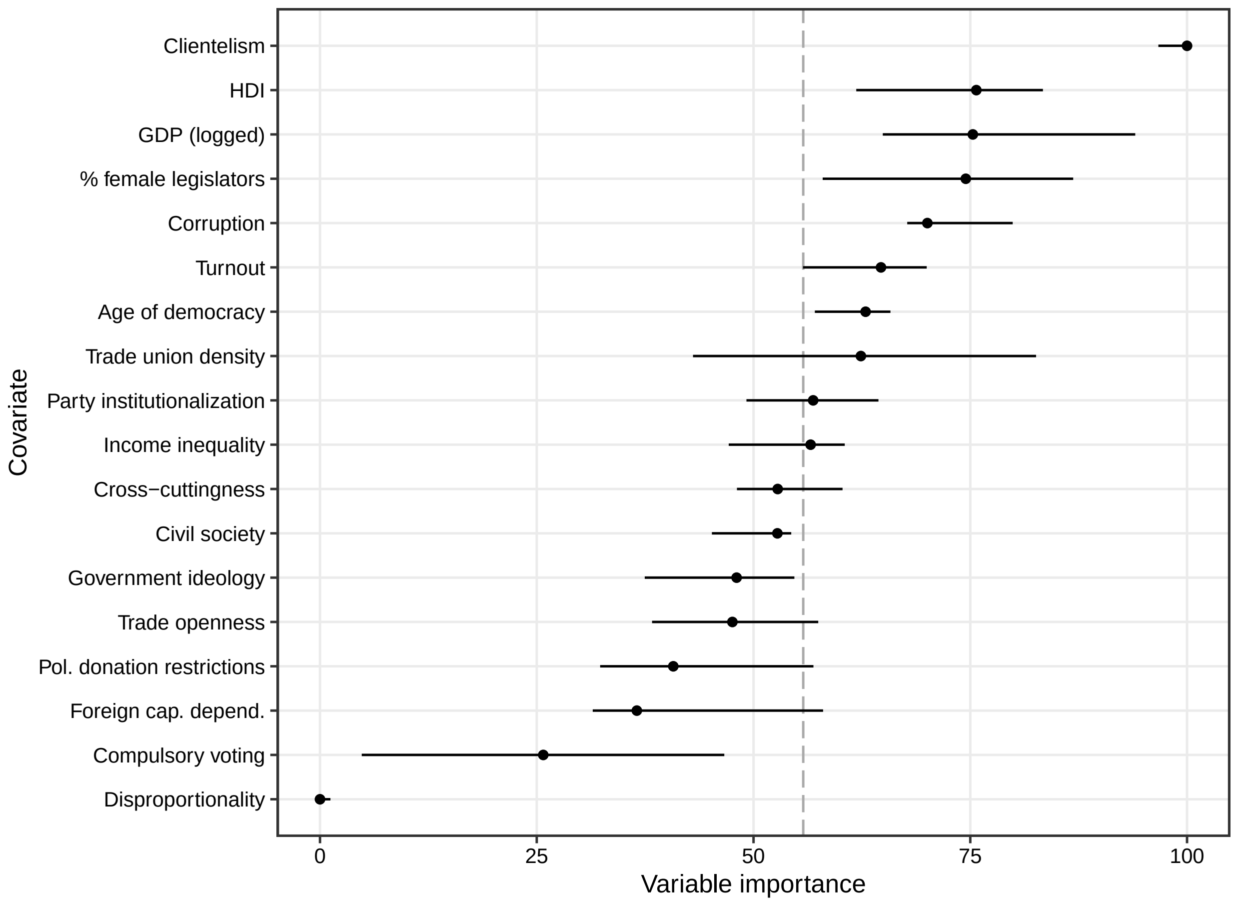

Figure 1: Variable importance. Each dot represents the mean variable importance, with lines for the interquartile range, across all imputation replications from the random forest model. Larger values indicate variables providing the model more information for predicting unequal representation.

[5] Note, however, that our results are broadly consistent across all models.

institutionalization, compulsory voting, and disproportionality make up the four least-important variables, with only age of democracy providing above-average information to the models. Taken as a whole, these results indicate that political institutions are far less important for determining the gap in representation between rich and poor than has been previously theorized.

Further, while variables relating to political behavior and the economy perform much better, we find significant divergence within these groups. Behavioral covariates relating to who is represented and how—the extent of clientelism, the ideology of the government, and the proportion of legislators who are women—all perform strongly. Yet broad measures of who participates and how, including the cross-cuttingness, civil society, and turnout variables, are all of middling importance. Similarly, variables relating to the organization of the domestic economy are very important, including per capita income, inequality, human development, and corruption. Yet economic variables that focus on international economics—such as dependence on foreign capital and trade openness—are much less important.

Together, these results suggest that the affluence bias is produced not by countries' balance of payments or trade structure, nor by their citizens' patterns of participation, nor by the structure of domestic political institutions. Instead, we find the strongest support for arguments that the structure of the domestic economy and the nature of political representation determine the extent of unequal representation. Our data are observational, and our models are correlational, so our analysis does not shed light on whether these mechanisms are causal. Nevertheless, these results provide the first broad cross-national evidence that the affluence bias is most strongly related to the domestic economy and the nature of representation, and not other factors theorized in the literature.

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

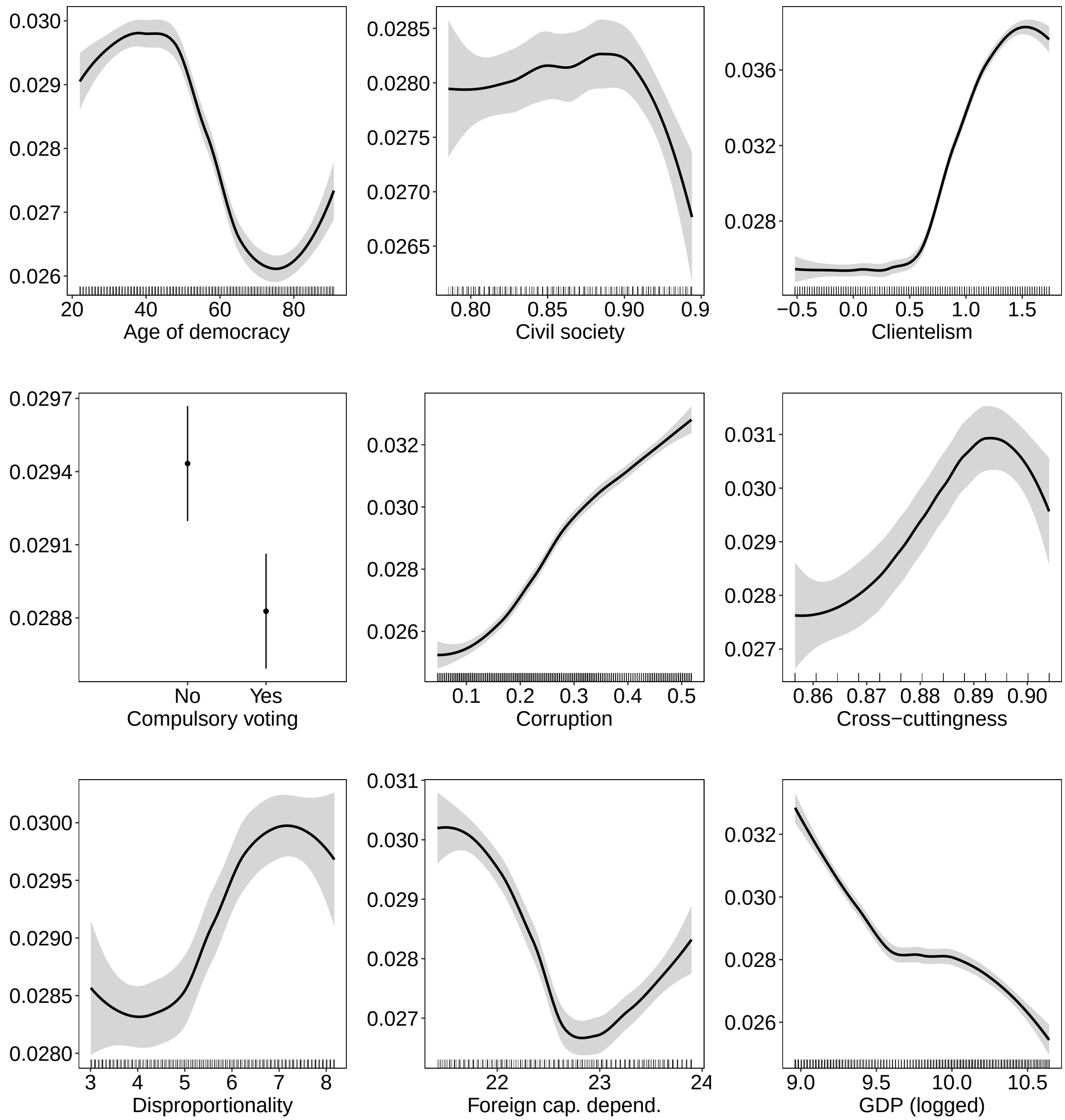

Figure 2: Partial dependence plots. Each panel provides the predicted change in unequal representation as a predictor is moved across its inter-quartile range. Lines represent loess fits, with 95% confidence intervals in gray, computed from random forest predictions across all imputation replicates. 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.

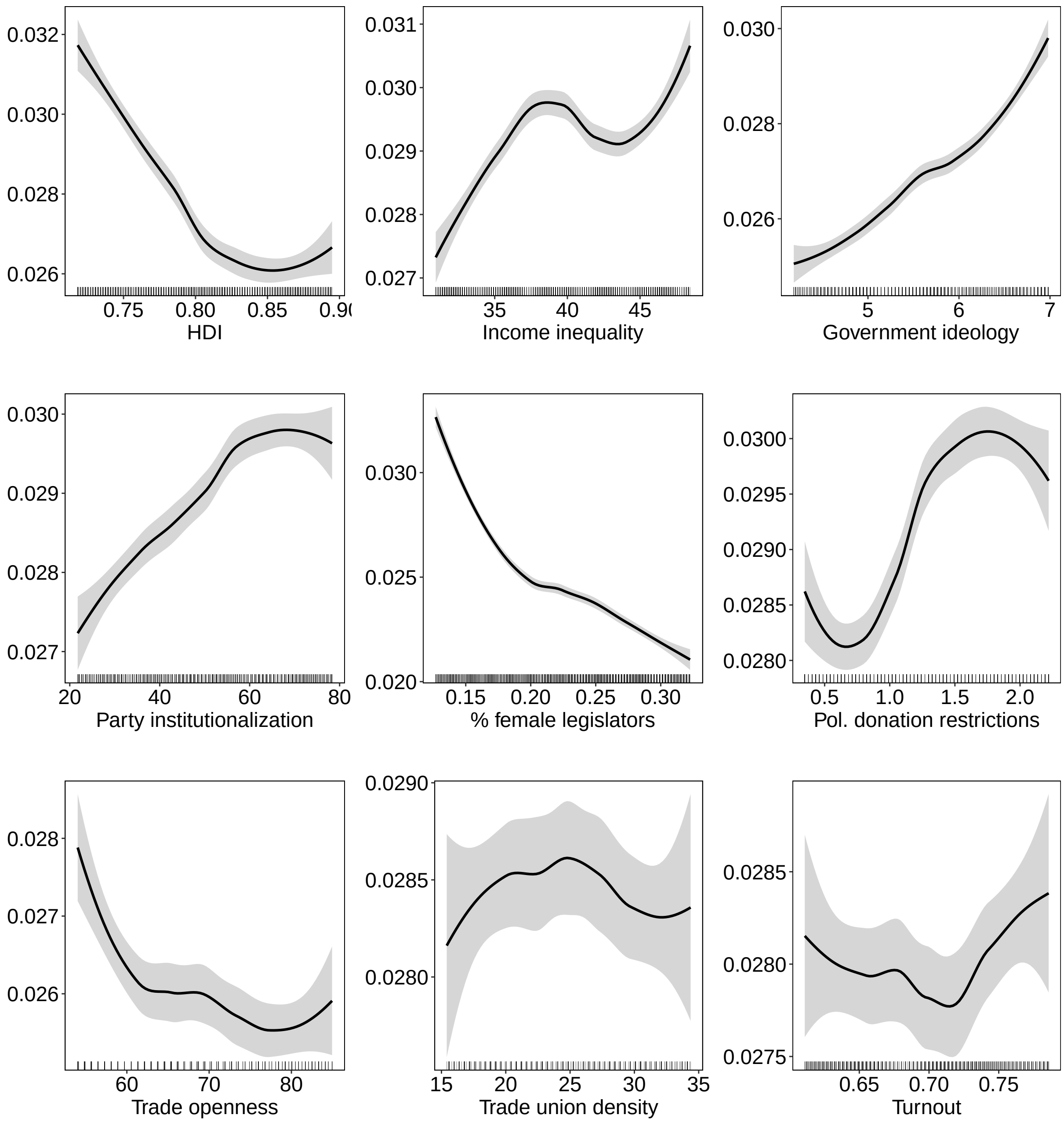

Figure 2 (continued): Partial dependence plots. Each panel provides the predicted change in unequal representation as a predictor is moved across its inter-quartile range. Lines represent loess fits, with 95% confidence intervals in gray, computed from random forest predictions across all imputation 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.

Table 2: Effect magnitudes from the random forest

Variable	Effect	Variable	Effect
Clientelism	0.08	Civil society	−0.01
Income inequality	0.03	Turnout	0.00
Government ideology	0.04	Trade union density	0.00
HDI	−0.05	Trade openness	−0.01
GDP (logged)	−0.06	Cross-cuttingness	0.02
Corruption	0.06	Pol. donation restrictions	0.01
Age of democracy	−0.01	Party institutionalization	0.02
% female legislators	−0.07	Compulsory voting	−0.01
Foreign cap. depend.	−0.02	Disproportionality	0.01

Predictions indicate the difference in the quantile of the dependent variable that results when the covariate is moved from its 25th to 75th quantile, as generated by simulating out of the random forests fit to each of the 11 imputed data replicates.

investigate this question, we vary each covariate along its inter-quartile range and predict the affluence gap using each of the models fit to the 11 imputed data replicates. The partial dependence plots in Figure 2 aggregate these predictions, providing the loess fit as a black line with 95% confidence intervals in gray.

As expected, increased clientelism, corruption, and income inequality and more conservative government all correlate with greater bias toward the affluent. Also as expected, increased GDP, human development, and the proportion of female legislators all correlate with less bias toward the affluent. Less important variables see effects that are much less pronounced, as with party institutionalization, or have nonlinear effects which might indicate that they simply mediate other covariates (e.g., civil society participation).

To quantify the magnitude 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 0.03, which is just above the empirical mean, in the 57th quantile. When clientelism is high, this gap is predicted to be 0.04, the 64thth quantile, resulting in a shift of 7% of the observed representation gap. As expected, the largest effects are found among the most important variables. Substantively, this effect size of 7% is quite large: the shift in clientelism from its 25th to its 75th quantile corresponds to a shift in the representation gap that most closely resembles a shift from Norway in 2005 to Mexico in 2004.

Taken as a whole, these findings suggest that changes in the structure of the domestic economy and the nature of political representation are most important for understanding the affluence effect worldwide. While most variables behave the way theory predicts, the correlations are inconclusive or nonlinear for many of the hypotheses studied in the literature. Yet those variables relating to clientelism, inequality, human development, corruption, government ideology, and proportion of female legislators all show strong and substantively important correlations to the affluence bias. Understanding when and where the poor are underrepresented relative to the rich depends on understanding these mechanisms.

Why Is Representation Unequal?

Our analysis suggests that unequal representation, at least on a socioeconomic left-right dimension, is produced not by countries' balance of payments or trade structure, nor by their citizens' patterns of participation, nor by the structure of domestic political institutions. Instead, we find the strongest support for arguments that the structure of the domestic economy and the nature of political representation determine the extent of unequal representation. We find that economic conditions, government partisanship, and clean government are the most important variables predicting affluence bias in representation. We find little support for hypotheses that affluence bias might be due to factors like turnout, electoral institutions, or globalization.

Of course, these data are observational, and our models are correlational, so our analysis does not shed light on whether these mechanisms are causal. Nevertheless, these results provide the first broad cross-national evidence that the affluence bias is most strongly related to the domestic economy and the nature of representation, and not other factors theorized in the literature.

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