Supplementary Material

DIMINISHED EXPECTATIONS
Redistributive Preferences in Truncated Welfare States

By ALISHA HOLLAND

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Supplementary Material

The supplementary material contains the following additional results and summary statistics for "Diminished Expectations: Redistributive Preferences in Truncated Welfare States":

- Table A1 presents the OLS and logit regression results for individual-level benefit receipt.
- Table A2 uses disaggregated benefit receipt measures and self-reported income, rather than wealth as a proxy for income.
- Table A3 provides summary statistics for the individual-level variables.
- Table A4 presents the benefit redistribution results.
- Table A5 reports the results from cross-level interactions with coverage, absolute redistribution, and benefit redistribution measures.
- Table A6 includes major alternative explanations in the cross-level models.
- Table A7 tests the robustness of the results to the income tax and state capacity variables.
- Table A8 provides summary statistics for the national-level variables.
- Table A9 compares the demographic profile of the survey sample to Bogotá's population.
- Table A10 includes the regression results for benefit receipt, benefit expectations, and redistributive preferences from the 2014 Bogotá Survey.
- Table A11 includes summary statistics for the 2014 Bogotá Survey.

A. Benefit Receipt Models

Table A1 shows the results from OLS models used to estimate the relationship between individual benefit receipt and redistributive attitudes. Model 1 shows the baseline specification with year and country fixed effects.

Model 2 tests for whether benefits remain a significant predictor of attitudes once accounting for alternative political and economic explanations. Categorical independent variables are rescaled from 0 to 1 so that the coefficient represents the estimated change in redistributive attitudes moving from the lowest to highest level. First, individuals who identify as politically conservative may be less supportive of all forms of government welfare provision. The survey asks respondents to place themselves on a political scale that ranges from the left to the right (*Right*). Second, to examine the possible anti-redistribution effect of religiosity, I use a measure of attendance at religious meetings (*Religion*). I recode this measure from 0 for individuals who never attend religious meetings to 1 for individual who attend weekly religious meetings (monthly or yearly attendance are intermediate values). Third, economic insecurity has been hypothesized to increase redistributive demands so I include an indicator variable for whether an individual has lost a job in the past two years (*Unemployed*). Fourth, vote buying can provide basic goods and insurance to the poor, and therefore may decrease redistributive demands. I include an indicator variable that takes on a value of 1 if an individual reports being approached with a clientelistic offer (*Client*). I include a measure of crime fears, which takes on a value of 1 if the respondent names crime or violence as one of the country's main problems (*Crime*). Respondents who fear crime may be more supportive of inequality reduction as a way to improve security. Finally, I include an indicator of whether an individual paid a bribe to a bureaucrat (*Corruption*) to capture experiences of administrative corruption.

Model 3 considers the role of state reach. I run this model separately because the state reach variable on medical access (*State Reach*) only is available in 2016.

Models 4 through 6 repeat the specifications using logistic regressions and a binary dependent variable that takes on a value of 1 if individuals strongly support redistribution (6 or above on a 7-point scale). The binary specification is preferable due to the skewed distribution of responses.

However, logistic regression specifications with fixed effects can be biased. I therefore run the models both ways and concentrate on the robustness of the results.

Table A2 repeats the same OLS models using disaggregated measures of benefits. Models 1 through 4 show that each individual benefit measure is a significant predictor of redistributive support. Models 5-7 use self-reported income, rather than wealth measures, to capture socio-economic status. LAPOP has respondents report their household income range, divided into ten or sixteen categories depending on the survey wave. To standardize across waves, I take the logged mid-point of each income bracket (*Log Income*). Self-reported income predicts higher support for redistribution, contra dominant theories, but benefits remain significant predictors of attitudes.

Table A1: Benefit Receipt and Redistributive Preferences, LAPOP 2008-16

	OLS Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Benefits	0.094*	0.096*	0.120*	0.152*	0.146*	0.151*
	(0.012)	(0.016)	(0.029)	(0.016)	(0.023)	(0.034)
Income	-0.150*	-0.198*	-0.009	-0.203*	-0.279*	-0.065
	(0.019)	(0.027)	(0.042)	(0.024)	(0.036)	(0.049)
Education	0.179*	0.142*	0.537*	0.206*	0.178*	0.484*
	(0.026)	(0.037)	(0.059)	(0.033)	(0.049)	(0.067)
Female	-0.024*	-0.038*	-0.048*	-0.031*	-0.059*	-0.035
	(0.010)	(0.014)	(0.023)	(0.013)	(0.019)	(0.027)
Size	-0.108*	-0.083*	-0.034	-0.135*	-0.102*	-0.070
	(0.015)	(0.021)	(0.033)	(0.019)	(0.028)	(0.039)
Age	0.021	0.053	-0.200*	0.161*	0.175*	0.056
	(0.028)	(0.041)	(0.063)	(0.036)	(0.055)	(0.072)
Non-White	0.048*	0.034	0.023	0.066*	0.057*	0.014
	(0.015)	(0.022)	(0.033)	(0.019)	(0.029)	(0.038)
Right		-0.168*			-0.145*	
		(0.026)			(0.033)	
Religion		0.033			0.054*	
		(0.018)			(0.024)	
Unemployed		0.110*			0.152*	
		(0.027)			(0.039)	
Client		-0.034			-0.058	
		(0.022)			(0.030)	
Crime		0.050*			0.038	
		(0.016)			(0.022)	
Corruption		-0.108*			-0.055	
		(0.032)			(0.039)	
State Reach			0.354*			0.395*
			(0.063)			(0.069)
R^2	0.052	0.070	0.036			
N	106241	50672	23649	106241	50672	23649

Standard errors in parentheses, * $p < 0.05$, country and year fixed effects not shown.

Table A2: Disaggregated Benefits and Self-Reported Income, OLS Models, LAPOP 2008-16

	Disaggregated Benefits				Log Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pension	0.058*						
	(0.022)						
Health		0.050*					
		(0.020)					
Subsidy			0.145*				
			(0.025)				
CCT				0.090*			
				(0.014)			
Benefits					0.084*	0.083*	0.090*
					(0.012)	(0.017)	(0.029)
Income	-0.134*	-0.143*	-0.161*	-0.128*			
	(0.032)	(0.032)	(0.029)	(0.020)			
Log Income					0.021*	0.026*	0.020*
					(0.004)	(0.005)	(0.006)
Education	-0.006	-0.005	0.363*	0.195*	0.072*	-0.010	0.486*
	(0.045)	(0.044)	(0.041)	(0.028)	(0.025)	(0.036)	(0.059)
Female	-0.009	-0.015	-0.038*	-0.026*	-0.021*	-0.036*	-0.044
	(0.017)	(0.017)	(0.016)	(0.011)	(0.010)	(0.015)	(0.024)
Size	-0.019	-0.015	-0.132*	-0.121*	-0.135*	-0.132*	-0.050
	(0.025)	(0.025)	(0.023)	(0.016)	(0.015)	(0.021)	(0.033)
Age	0.024	0.035	-0.046	0.021	0.016	0.038	-0.201*
	(0.049)	(0.048)	(0.043)	(0.030)	(0.030)	(0.043)	(0.065)
Non-White	0.077*	0.083*	0.018	0.037*	0.061*	0.053*	0.030
	(0.027)	(0.027)	(0.023)	(0.016)	(0.015)	(0.022)	(0.033)
Right						-0.153*	
						(0.027)	
Religion						0.039*	
						(0.018)	
Unemployed						0.134*	
						(0.028)	
Client						-0.027	
						(0.023)	
Crime						0.054*	
						(0.017)	
Corruption						-0.132*	
						(0.033)	
State Reach							0.391*
							(0.063)
R^2	0.042	0.042	0.042	0.048	0.050	0.067	0.036
N	29755	29849	49358	89850	96247	46346	22513

Standard errors in parentheses, * $p < 0.05$, country and year fixed effects not shown.

Table A3 presents the summary statistics for the variables used in the individual-level benefit analyses.

Table A3: Summary Statistics, LAPOP 2008-16

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Redistribution	5.606	1.658	1	7	144554
Demand	0.620	0.485	0	1	144554
Benefits	0.309	0.462	0	1	118833
Pension	0.234	0.424	0	1	31427
Health	0.397	0.489	0	1	31538
Subsidy	0.114	0.318	0	1	57646
CCT	0.222	0.415	0	1	100938
Income	0.491	0.319	0	1	143903
Log Income	8.297	2.989	0	16.345	129002
Education	0.523	0.252	0	1	148799
Female	0.511	0.5	0	1	148797
Size	0.480	0.379	0	1	148799
Age	0.285	0.194	0	1	148389
Non-White	0.154	0.361	0	1	142135
Unemployed	0.067	0.251	0	1	148799
Client	0.119	0.324	0	1	68508
Crime	0.263	0.44	0	1	147778
Corruption	0.059	0.236	0	1	146791
State Reach	0.754	0.201	0	1	27978

B. Hierarchical Models

To operationalize welfare state truncation, I consider several measures. First, I use statistics from the World Bank's ASPIRE database on social assistance and social insurance coverage.[1] As described in the paper, I use the average coverage level in a country (*Coverage*).[2] ASPIRE does not report data on Venezuela, leaving 17 countries. Second, I also look at the size of the welfare state, measured as the percent of GDP dedicated to social expenditures (available from CEPAL) (*Social Exp.*). This captures the size of the welfare state, but does not capture who benefits from the expenditures. Third, I measure the combined inequality reduction from social assistance and social insurance spending (*benefit redistribution*), also using ASPIRE.[3] Last, as an additional source of progressivity data, I use a measure of absolute redistribution from SWIID v5.1. SWIID does not report progressivity data on Bolivia, Ecuador, and Nicaragua (leaving only 15 country groups).

Table A4 uses the estimated income coefficients from the multilevel model as the endogenous dependent variable. It shows that the hypothesized negative relationship exists between benefit redistribution and the polarization of preferences. It also disaggregates benefit redistribution into the inequality reduction achieved through social assistance (*social assistance redistribution*) and social insurance spending (*social insurance redistribution*). The results suggest that the effects are driven by social assistance expenditures, which tend to do more to help the poor.

[1] ASPIRE: The Atlas of Social Protection Indicators of Resilience and Equity, http://datatopics.worldbank.org/aspire/.

[2] This is the average of two variables named *cov_sa* and *cov_si* in the ASPIRE database.

[3] This is the sum of the variables named *gini_sa* and *gini_si*.

Table A4: Predicting Income Coefficients with Benefit Progressivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ben. Redis.	-0.002*	-0.002*	-0.002*						
	(0.001)	(0.001)	(0.001)						
Social Assis. Redis.				-0.004*	-0.004*	-0.004*			
				(0.002)	(0.002)	(0.002)			
Social Insur. Redis.							-0.001	-0.001	-0.001
							(0.001)	(0.001)	(0.001)
Inequality	-0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Social Exp	-0.005*	-0.005*	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*	-0.007*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Effectiveness		-0.008			-0.005			-0.011	
		(0.009)			(0.009)			(0.009)	
Ethnicity			-0.017			-0.003			-0.023
			(0.015)			(0.017)			(0.016)
Income Tax			- 0.000			-0.002			-0.001
			(0.002)			(0.002)			(0.002)
Left Rule			-0.014			-0.010			-0.022
			(0.023)			(0.024)			(0.023)
R^2	0.399	0.406	0.413	0.403	0.405	0.411	0.361	0.374	0.390
N	85	85	85	85	85	85	85	85	85

Standard errors in parentheses, * $p < 0.05$

Table A5 reports the results from the integrated hierarchical models, rather than the two-stage specification used in the paper. The advantage of the hierarchical specification is that it distinguishes between the effects on the level of support for redistribution (the coefficient of the national-level variable), and on the income coefficient (the interaction with income). Model 1 shows the basic model used to estimate the income coefficients for the two-stage regressions used in the paper. Models 2 and 3 show the interaction of income with coverage (measured by the percent of the population covered by welfare programs). Model 2 includes all years (where coverage is measured through the closest year estimate available), and Model 3 shows the results from 2010 (when the majority of coverage measurements are available). Model 4 considers a simpler view of coverage as the overall size of the welfare state (also measured in 2010 in most countries). The coverage results are less stable in the cross-level models than the progressivity ones. The level effect of coverage in increasing overall support for redistribution dwarfs the interaction effect in Model 2. However, coverage does have the expected relationship with attitudes in Models 3 and 4 (for the 2010 wave, which is closest to the year when the coverage measures were measured). Models 5 and 6 show the cross-level interactions between income and progressivity (measured by absolute redistribution and benefit redistribution), respectively. The interaction with income is negative and significant for all the progressivity measures. In other words, the coefficient on income is more negative in countries with more progressive expenditures, as expected. Models 7 through 10 show the results are similar when including the same national-level controls used in the paper.

Table A5: Cross-Level Interactions with Coverage and Progressivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Income	-0.153*	-0.235*	0.174	0.399*	0.023	0.031	0.173	0.398*	0.023	0.023
	(0.048)	(0.104)	(0.170)	(0.192)	(0.076)	(0.059)	(0.168)	(0.188)	(0.077)	(0.058)
Age	0.000	-0.011	0.078	0.042	0.012	-0.012	0.077	0.041	0.014	-0.014
	(0.024)	(0.024)	(0.047)	(0.047)	(0.027)	(0.024)	(0.047)	(0.047)	(0.027)	(0.024)
Size	-0.090*	-0.093*	-0.024	-0.012	-0.084*	-0.094*	-0.025	-0.011	-0.090*	-0.096*
	(0.013)	(0.013)	(0.025)	(0.025)	(0.015)	(0.013)	(0.025)	(0.025)	(0.015)	(0.013)
Female	-0.026*	-0.028*	-0.017	-0.016	-0.026*	-0.028*	-0.017	-0.016	-0.026*	-0.028*
	(0.009)	(0.009)	(0.017)	(0.017)	(0.010)	(0.009)	(0.017)	(0.017)	(0.010)	(0.009)
Education	0.161*	0.179*	0.050	0.010	0.184*	0.178*	0.050	0.010	0.180*	0.174*
	(0.022)	(0.022)	(0.043)	(0.042)	(0.025)	(0.022)	(0.043)	(0.042)	(0.025)	(0.022)
Coverage		0.434*	0.837				-0.110			
		(0.172)	(0.680)				(0.833)			
Cov.*Inc.		0.280	-0.962*				-0.960*			
		(0.272)	(0.477)				(0.473)			
Social Exp				0.051			0.010	0.012	-0.041*	-0.049*
				(0.030)			(0.031)	(0.028)	(0.007)	(0.006)
Social Exp.*Inc.				-0.054*				-0.054*		
				(0.019)				(0.018)		
Ab. Redis.					-0.172*				-0.200*	
					(0.019)				(0.023)	
Abs. Red*Inc.					-0.051*				-0.050*	
					(0.018)				(0.019)	
Ben. Redis.						-0.003				-0.014
						(0.009)				(0.009)
Ben. Red*Inc.						-0.048*				-0.045*
						(0.011)				(0.011)
Inequality							0.010	0.018	0.046*	0.009
							(0.026)	(0.020)	(0.008)	(0.005)
Ethnicity							-0.404	-0.429	-1.307	-0.892*
							(0.401)	(0.334)	(1.243)	(0.378)
Effectiveness							0.350	0.359	-0.399*	-0.263*
							(0.318)	(0.185)	(0.084)	(0.063)
GDP							0.012	0.011	0.020	0.111*
							(0.034)	(0.025)	(0.024)	(0.017)
Left Rule							-0.131	-0.287	-0.298	0.163
							(0.544)	(0.400)	(1.497)	(0.572)
var(Income)	0.037***	0.040***	0.035***	0.025***	0.028***	0.028***	0.034***	0.024***	0.029***	0.027***
	(0.014)	(0.016)	(0.016)	(0.013)	(0.012)	(0.012)	(0.016)	(0.013)	(0.012)	(0.011)
var(Constant)	0.103***	0.074***	0.091***	0.094***	0.377*	0.079***	0.050***	0.046***	0.682	0.085***
	(0.035)	(0.026)	(0.033)	(0.033)	(0.147)	(0.029)	(0.018)	(0.017)	(0.272)	(0.032)
var(Residual)	2.566***	2.495***	2.030***	2.088***	2.579***	2.495***	2.030***	2.088***	2.576***	2.493***
	(0.010)	(0.010)	(0.017)	(0.017)	(0.011)	(0.010)	(0.017)	(0.017)	(0.011)	(0.010)
N	139529	132483	29196	30650	109351	132483	29196	30650	109351	132483
Countries	18	17	17	18	15	17	17	17	15	17

Standard errors in parentheses, * $p < 0.05$

Table A6 presents the results from hierarchical models including several alternative explanations and different operationalizations of those variables. Models 1 and 2 examine the impact of revenue sources. I measure tax collection using the IMF's World Revenue Longitudinal Data (WorLD) from 2008-2014. I concentrate on two measures: (1) income tax revenue as % of GDP (individual and corporate) (*income tax*), and (2) the revenue residual (total revenue - tax, social spending, and grants), which captures nontax income (*nontax*). Nontax measures are missing for Guatemala and Costa Rica. Models 3 and 4 look at two indicators of state capacity, state effectiveness and corruption, using the World Bank's index of administrative quality. Models 5 and 6 then look at two proxies for ethnic heterogeneity. The first, used in the paper, considers the ethno-linguistic fractionalization index index. This index has been widely criticized, but continues to be used because no alternative exists cross-nationally. Another more recent alternative comes from Morgan and Kelly (2017), who measure inter-ethnic inequality (*BGI*).

Models 7, 8 and 9 turn to measures of left power. In addition to the years with the fraction of years that the executive has been from the left (*left rule*) used in the paper, I measure the programmatic nature of competition using the Democratic Accountability and Linkages Project's indicator of "general programmatic structuration," weighted by party size.[4] This measure comes from 2008 elite surveys and is time invariant. Higher values indicate more programmatic structuration. I also consider the impact of union density. Data on the proportion of the workforce organized in unions is limited and only available for the 1990s in Latin America. Huber et al. supplement data compiled by Roberts and Wibbels (1999) with U.S. State and Labor Department reports in their Latin America and the Caribbean Social Policy and Political Datasets. Given that unions are thought to have a long-run effect on socialization, I use this measure as additional test of power resource theories. Unfortunately, union data are missing for six countries, which severely reduces the ability to conclude anything about their effects in hierarchical models.

Turning to the results, greater income tax collection and more effective bureaucracies do have more polarized redistributive preferences. Many of the other variables are correctly signed, but fall short of statistical significance. Given the potential confounding role of taxation and state capacity, I analyze whether the coverage and progressivity variables are robust to their joint inclusion.

[4]In the original dataset, this is variable *cosalpo_4nwe*.

Table A6: Cross-Level Interactions with Alternative Explanations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income	0.062	-0.242*	-0.210*	-0.174*	-0.160	-0.148*	-0.045	-0.081	-0.056
	(0.119)	(0.061)	(0.058)	(0.050)	(0.121)	(0.048)	(0.070)	(0.087)	(0.149)
Age	0.001	0.007	-0.001	-0.000	-0.062*	0.000	-0.062*	-0.033	-0.062*
	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.030)	(0.024)
Size	-0.090*	-0.091*	-0.089*	-0.090*	-0.104*	-0.091*	-0.104*	-0.063*	-0.104*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)	(0.013)
Female	-0.026*	-0.024*	-0.026*	-0.026*	-0.026*	-0.027*	-0.026*	-0.035*	-0.026*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.009)
Education	0.160*	0.143*	0.160*	0.161*	0.067*	0.160*	0.067*	0.135*	0.067*
	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.026)	(0.022)
Income Tax	-0.040*								
	(0.015)								
Tax*Income	-0.043*								
	(0.022)								
Nontax		-0.018*							
		(0.003)							
Non-Tax*Income		0.011							
		(0.005)							
Effectiveness			-0.143*						
			(0.067)						
Effectiveness*Income			-0.245*						
			(0.081)						
Ethnicity					-0.680				
					(0.378)				
Ethnicity*Income					0.099				
					(0.259)				
BGI						1.724			
						(1.121)			
BGI*Income						0.619			
						(1.207)			
Left Rule							-0.858		
							(0.506)		
Left*Income							-0.457		
							(0.329)		
Unions								-0.614	
								(0.575)	
Unions*Income								-0.480	
								(0.377)	
Programmatic									0.069
									(0.960)
Programmatic*Income									-0.266
									(0.607)
var(Income)	0.037*	0.038*	0.049*	0.034*	0.039*	0.036*	0.034*	0.043*	0.038*
	(0.014)	(0.016)	(0.022)	(0.012)	(0.014)	(0.013)	(0.013)	(0.019)	(0.014)
var(Constant)	0.115*	0.077*	0.147*	0.094*	0.088*	0.122*	0.088*	0.105*	0.103*
	(0.039)	(0.028)	(0.056)	(0.035)	(0.030)	(0.044)	(0.030)	(0.043)	(0.035)
var(Residual)	2.566*	2.535*	2.566*	2.566*	2.612*	2.566*	2.612*	2.600*	2.612*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)
N	139529	125783	139529	139529	139529	139529	139529	94653	139529
Countries	18	16	18	18	18	18	18	12	18

Standard errors in parentheses, * $p < 0.05$

Table A7 tests whether coverage and progressivity are still robust predictors of preference structure once accounting for the tax structure and state strength. Models 1 through 4 jointly include state capacity, coverage, and progressivity. Models 5 through 8 jointly include income taxation, coverage, and progressivity. Coverage, as well as state capacity and taxation, lose significance when jointly included in the models, suggesting that they may be capturing similar concepts. Progressivity reassuringly remains a robust predictor of attitudinal polarization, even when accounting for tax and state capacity. Due to the clustering of these variables empirically,

Table A7: Cross-Level Interactions with State Capacity and Income Taxation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth	0.078	0.323	-0.023	-0.040	0.175	0.386	0.154	0.089
	(0.226)	(0.226)	(0.088)	(0.078)	(0.206)	(0.209)	(0.129)	(0.119)
Age	0.077	0.039	0.012	-0.013	0.078	0.041	0.014	-0.012
	(0.047)	(0.047)	(0.027)	(0.024)	(0.047)	(0.047)	(0.027)	(0.024)
Size	-0.026	-0.013	-0.082*	-0.093*	-0.024	-0.012	-0.084*	-0.094*
	(0.025)	(0.025)	(0.015)	(0.013)	(0.025)	(0.025)	(0.015)	(0.013)
Female	-0.017	-0.016	-0.026*	-0.028*	-0.017	-0.016	-0.026*	-0.028*
	(0.017)	(0.017)	(0.010)	(0.009)	(0.017)	(0.017)	(0.010)	(0.009)
Education	0.049	0.009	0.185*	0.177*	0.050	0.010	0.184*	0.177*
	(0.043)	(0.042)	(0.025)	(0.022)	(0.043)	(0.042)	(0.025)	(0.022)
Effectiveness	0.375*	0.335*	-0.367*	-0.075				
	(0.149)	(0.121)	(0.090)	(0.069)				
Effectiveness*Income	-0.074	-0.053	-0.080	-0.223*				
	(0.118)	(0.087)	(0.084)	(0.090)				
Coverage	-0.433				0.788			
	(0.770)				(0.767)			
Coverage*Income	-0.714				-0.961			
	(0.611)				(0.535)			
Social Exp		0.011				0.047		
		(0.029)				(0.033)		
Social Exp.*Income		-0.048*				-0.055*		
		(0.021)				(0.020)		
Ab. Redis.			-0.160*				-0.184*	
			(0.021)				(0.020)	
Abs. Red*Income			-0.041*				-0.045*	
			(0.021)				(0.019)	
Ben. Redis.				-0.003				-0.003
				(0.010)				(0.009)
Ben. Red*Income				-0.039*				-0.048*
				(0.014)				(0.011)
Income Tax					0.008	0.017	-0.044*	0.006
					(0.061)	(0.059)	(0.016)	(0.015)
Tax*Income					-0	0.006	-0.030	-0.012
					(0.043)	(0.037)	(0.023)	(0.022)
var(Income)	0.033*	0.024*	0.030*	0.043*	0.035*	0.025*	0.029*	0.029*
	(0.016)	(0.013)	(0.013)	(0.026)	(0.016)	(0.013)	(0.012)	(0.013)
var(Constant)	0.066*	0.065*	0.569	0.096*	0.091*	0.094*	0.441*	0.078*
	(0.024)	(0.023)	(0.222)	(0.040)	(0.033)	(0.032)	(0.171)	(0.029)
var(Residual)	2.030*	2.088*	2.578*	2.494*	2.030*	2.088*	2.578*	2.495*
	(0.017)	(0.017)	(0.011)	(0.010)	(0.017)	(0.017)	(0.011)	(0.010)
N	29196	30650	109351	132483	29196	30650	109351	132483
Countries	17	18	15	17	17	18	15	17

Table A8 reports the summary statistics for the higher level variables.

Table A8: Summary Statistics, National Variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**	**Source**
Coverage	0.33	0.099	0.12	0.596	85	Aspire
Absolute Redistribution	3.247	2.371	0.127	9.412	75	SWIID
Benefit Redistribution	3.593	3.579	-0.5	11.1	85	Aspire
Social Assistance Redistribution	1.909	1.538	0	6.9	85	Aspire
Social Insurance Redistribution	1.684	3.088	-1.2	9	85	Aspire
Social Expenditures	10.014	2.551	4.8	16	90	CEPAL
Inequality	48.328	3.946	37.907	54.896	90	SWIID
GDP per capita	7.944	3.372	2.305	13.14	90	WB
Ethnic fractionalization	0.427	0.187	0.169	0.74	90	ELF
BGI	-0.007	0.036	-0.048	0.066	90	Morgan & Kelly (2017)
Income Tax	5.009	1.397	1.9	8.4	90	WoRLD
Nontax	6.151	5.46	0.18	21.688	80	WoRLD
Effectiveness	-0.232	0.583	-1.23	1.26	90	WB
Corruption	-0.323	0.726	-1.38	1.57	90	WB
Left Rule	0.157	0.14	0	0.437	90	Huber & Stephens (2012)
Union Density	0.158	0.164	0.026	0.642	60	Huber & Stephens (2012)
Programmatic	0.232	0.08	0.087	0.332	90	DALP

C. Colombia Survey

I designed and implemented a face-to-face public opinion survey of 900 voters in Bogotá, Colombia. The Bogotá-based polling firm Cifras y Conceptos administered the survey between August 5 and 29, 2013. On average, the survey interview lasted 25 minutes. The survey was conducted on paper due to security concerns using tablets in poor areas of the city.

A clustered random sample was generated within the city. Thirty-six polling stations were selected as the primary sampling units (PSUs), with 25 interviews conducted in each PSU. To ensure sufficient power to compare preferences across class groups, 12 polling stations were selected from lower class groups (Strata 1 and 2), 12 polling stations from lower-middle class groups (Strata 3), and 12 polling stations from middle and upper class groups (Strata 4, 5, and 6). Survey weights must be used to adjust for the oversampling of upper-class groups to make population-representative statements; regression analyses use the equal division of class groups. Interviewers began from a randomly selected corner in the PSU and proceeded in a clockwise direction. Interviewers rotated between asking for a male and female respondent in the household.

Enumerators were part of the survey firm's trained professionals. On a separate sheet from the questionnaire, interviewers recorded the first name only and phone number of each respondent for the purposes of later supervision. Post-sampling verification was conducted on a randomly-selected 30 percent of the sample by telephone, after which this information was destroyed. The response rate for the survey was 15.6 percent; the cooperation rate was 23.7 percent, the refusal rate 23.3 percent, and the contact rate was 36.4 percent. Harvard University's Institutional Review Board approved the protocol for both the survey and accompanying qualitative research.

Table A9 reports demographic characteristics for the survey sample and the Bogotá population. Table A10 confirms the relationship between current benefits, expected benefits, and social policy preferences. Models 1 and 2 show that current benefits are associated with greater expected benefits. Models 3 through 8 then consider how benefit expectations relate to social policy preferences. The coefficients are positive and statistically significant in four of six models.

Table A9: Demographics of Survey Sample and Bogotá Population

	Survey Sample				Bogotá Population			
	Lower	Middle	Upper	Mean	Lower	Middle	Upper	Mean
Strata	33.3	33.3	33.3	3.1	48.8	35.7	13.8	2.6
CCT receipt	27.0	17.3	1.0	8.5	36.9	27.9	0.0	11.1
Subsidized health	47.0	25.6	3.0	25.2	33.6	14.3	1.7	23.9
Female				49.0				53.0
Age				39.0				29.5
Household size				3.9				3.7

Notes: Lower refers to Strata 1 and 2, middle is Strata 3, and upper refers to Strata 4, 5, and 6. CCT receipt refers to Familías en Acción. The higher average age reflects the fact that the survey was administered to adults over the age of 18.
Source: Strata, gender, age, and household statistics come from the District Planning Secretary (Secretaría Distrital de Planeación), 2010; health coverage and CCT access come from the DANE-SDP, Encuesta Multipropósito para Bogotá 2011.

I included a follow-up question on a second survey of Bogotá residents in which I asked about their concerns regarding social policy. The question used in the paper read, "Muchas personas quieren mejorar las vidas de los pobres, pero ven riesgos cuando el gobierno distrital tiene que incrementar el gasto social. Para usted cuál es el riesgo más grande que se ve al incrementar el gasto social?" Respondents then selected from the following responses (the order of appearance was randomized). "Other" responses, as well as the risks of migration (which was a minor preoccupation), were not shown in Figure 8 for simplicity's sake. The variable names in the data set are included in parentheses:

- Se acostumbra a las personas a vivir de los recursos del Estado (*dependence*).
- Los beneficiarios del gobierno pueden ser utilizados por los políticos para obtener votos (*buy votes*).
- Las ayudas del gobierno no llegan a las personas con necesidades (*reach poor*).
- El Estado tiene que cobrar más impuestos a la clase media (*middle tax*).
- Se atrae a personas de otras partes de país para que vivan en Bogotá y usen sus beneficios.
- Otro riesgo, cuál?

Table A11 reports the summary statistics for the Bogotá survey.

Table A10: Benefit Receipt, Expectations of Benefits, and Redistributive Preferences in Bogotá

	Expected Benefits		CCTs	Employment	Housing	Health	Inequality	Tax
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current Benefits	0.072*		0.065*	0.041	0.036	0.018	0.003	0.036
	(0.027)		(0.029)	(0.028)	(0.030)	(0.030)	(0.022)	(0.026)
Health Benefits		0.068*						
		(0.033)						
Pension Benefits		0.056*						
		(0.027)						
CCT Benefits		0.139*						
		(0.046)						
Expected Benefits			0.168*	0.123*	0.160*	0.154*	0.021	0.014
			(0.036)	(0.035)	(0.037)	(0.037)	(0.027)	(0.033)
Strata	-0.026	-0.008	-0.178*	-0.153*	-0.047	-0.086	0.038	-0.223*
	(0.053)	(0.054)	(0.056)	(0.055)	(0.058)	(0.058)	(0.042)	(0.052)
Female	-0.031	-0.029	0.038	0.050*	0.040	-0.041	0.008	-0.024
	(0.025)	(0.025)	(0.026)	(0.026)	(0.027)	(0.027)	(0.020)	(0.024)
Age	-0.059	-0.053	-0.019	0.015	-0.111*	-0.040	-0.032	-0.018
	(0.041)	(0.041)	(0.044)	(0.043)	(0.046)	(0.046)	(0.033)	(0.041)
Education	0.022	0.051	-0.081	-0.089	-0.095	-0.094	0.048	-0.027
	(0.055)	(0.057)	(0.059)	(0.058)	(0.061)	(0.061)	(0.045)	(0.054)
R^2	0.014	0.026	0.069	0.054	0.040	0.039	0.010	0.047
N	878	869	877	874	877	874	873	874

Standard errors in parentheses, * $p < 0.05$.

Table A11: Summary Statistics, Bogotá 2014 Survey

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
CCTs	0.497	0.398	0	1	899
Health	0.597	0.387	0	1	896
Employment	0.44	0.405	0	1	899
Housing	0.467	0.404	0	1	896
Inequality	0.822	0.291	0	1	895
Tax	0.701	0.361	0	1	896
Expected Benefits	0.319	0.361	0	1	893
Current Benefits	0.696	0.46	0	1	892
Health Benefits	0.254	0.436	0	1	893
Pension Benefits	0.471	0.499	0	1	892
CCT Benefits	0.085	0.278	0	1	898
Strata	0.433	0.307	0	1	900
Female	0.492	0.5	0	1	891
Age	0.538	0.314	0	1	900
Education	0.637	0.304	0	1	900