Appendix C

Underlying Micro-Level Results from Chapter 3

In the main text I focused on presenting only the essential results of the analysis using visual techniques to make the results more clear. Here I present the detailed results of the underlying micro-level models referenced in Chapter 3. I begin in Table C.1 with models of general redistributive attitudes. These results are based on a multi-level regression model with support for government redistribution to equalize incomes as the dependent variable. Data are from the General Social Survey. Individuals are nested within years, which produces a two-level data structure where the key context-level variable is top income shares.

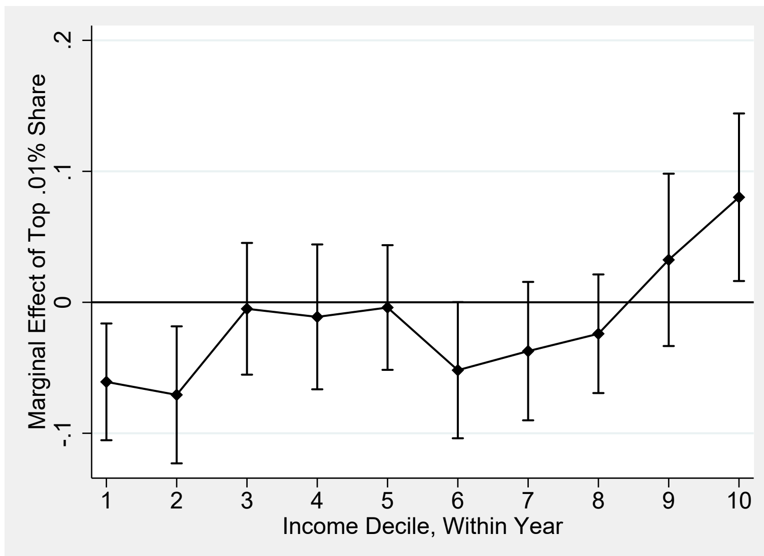
Model 1 is a baseline model including only top income shares along with basic controls for sex, ethnicity, race, age, and education. The control variables produce the expected results, but there is no effect of inequality in this model. In Model 2, however, I add individual-level family income as well as an interaction term between family income and context-level inequality to the model. In that model we see that higher levels of inequality reduce support for redistribution, but that this effect is primarily present among those with low incomes. This was shown in the charts from the main text, and is generated by the fact that the interaction term between family income and inequality is positive. What we can say here is that the coefficient reported for top income shares in this model captures the effect of top income shares for the poorest respondents. But as income increases, the effect of top income

Table C.1: Multi-Level Models of Support for Redistribution

	(1)	(2)	(3)	(4)
Top .01% Share	-0.018	-0.064^{**}	-0.041	0.032
	(0.020)	(0.022)	(0.022)	(0.039)
Female	0.284^{***}	0.249^{***}	0.201^{***}	0.231^{***}
	(0.024)	(0.029)	(0.026)	(0.044)
White, Non-Hispanic	-0.729^{***}	-0.621^{***}	-0.302^{***}	-0.500^{***}
	(0.044)	(0.048)	(0.043)	(0.038)
Age	-0.006^{***}	-0.006^{***}	-0.008^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Education	-0.237^{***}	-0.134^{***}	-0.134^{***}	-0.157^{***}
	(0.021)	(0.025)	(0.020)	(0.024)
Income Decile		-0.137^{***}	-0.120^{***}	-0.116^{***}
		(0.013)	(0.013)	(0.024)
Income Decile × Top Share		0.008^{**}	0.008^{**}	0.003
		(0.003)	(0.003)	(0.005)
Party Identification			-0.251^{***}	
			(0.015)	
Racial Bias				-0.369^{*}
				(0.167)
Top .01% Share × Racial Bias				-0.133^{**}
				(0.043)
Constant	4.348^{***}	4.923^{***}	5.287^{***}	4.933^{***}
	(0.079)	(0.092)	(0.086)	(0.114)
Level 1 N	29796	26877	26401	11380
Level 2 N	22	22	17	22

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



Source: Author's calculations from GSS data.

Note: Charts plot the predicted marginal effect of an increase in inequality on support for redistribution for those with differing levels of family income. Calculations based on a multi-level logit model including national-level top .01% income share at time of survey, race/ethnicity, sex, age, education, and categorical income along with income interacted with inequality.

Figure C.1: Effect of Top .01% Share on Attitudes Toward Redistribution as Income Increases shares becomes more positive. The interaction is strong enough that the negative effect of inequality is only present among those at the bottom end of the income distribution, as was discussed in the main text. Model 3 simply shows that this effect is maintained when a control for party identification is added. And Model 4 presents the results with a measure of racial bias and its interaction with inequality added. We see that the income effect from Model 2 is completely driven by racial attitudes and that inequality only reduces support for redistribution among those evidencing more racial bias.

Figure C.1 demonstrates that the basic conclusions remain unchanged if we allow the conditioning effect of income on the impact of inequality to be non-linear. This chart is the result of a re-estimation of the core model with income measured categorically rather than continuously. The interaction between income and inequality then, is actually a series of interactions between the income category of a respondent and the level of inequality present. We see that even if we relax the assumption that the conditioning effect of inequality is linear (which is what is assumed in the results presented in the main text), we still see evidence that those at the low end of the income distribution are less supportive of redistribution as inequality rises and those at the top end of the distribution respond to higher inequality differently.

Table C.2 presents three models of support for a minimum wage increase. These models are estimated with data from the 2006 Cooperative Congressional Election Study. The dependent variable is a dichotomous choice between support for a minimum wage increase and opposition. Given the dichotomous dependent variable and the hierarchical structure of the data (individuals nested in states), these models are estimated with a multi-level logit model.

The first model is the one that charts in the main text are based on. There, we see that attitudes toward a specific redistributive policy measured in a cross section follow the same pattern as general attitudes toward redistribution captured over multiple time periods. Those

Table C.2: Multi-Level Models of Support for Minimum Wage

	(1)	(2)	(3)
State Top 1% Share	-0.031^{**}	-0.034^{***}	-0.022^{**}
	(0.010)	(0.010)	(0.008)
Age	-0.001	-0.001	-0.005^{***}
	(0.001)	(0.001)	(0.001)
White, non-Hispanic	-0.242^{***}	-0.241^{***}	-0.647^{***}
	(0.070)	(0.070)	(0.094)
Female	0.773^{***}	0.774^{***}	0.799^{***}
	(0.046)	(0.046)	(0.040)
Education	-0.075^{***}	-0.075^{***}	0.001
	(0.019)	(0.019)	(0.020)
Income	-0.143^{***}	-0.145^{***}	-0.163^{***}
	(0.022)	(0.022)	(0.024)
Party Identification	-0.633^{***}	-0.632^{***}	
	(0.012)	(0.012)	
State Top 1% Share × Income	0.004^{***}	0.004^{***}	0.003^{**}
	(0.001)	(0.001)	(0.001)
State Median Income		0.000	
		(0.000)	
Constant	5.562^{***}	5.395^{***}	2.905^{***}
	(0.210)	(0.250)	(0.198)
Level 1 N	29334	29334	29747
Level 2 N	50	50	50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

living in states with more inequality tend to be less supportive of a minimum wage increase, but this effect is concentrated among those at the bottom end of the income distribution, which is shown by the positive interaction between family income and state inequality. Model 2 shows that this pattern is robust to the inclusion of state median income at the context level. Model 3 shows that the results are consistent whether or not one controls for party identification.

Table C.3: Multi-Level Models of Support for Capital Gains Tax

	(1)	(2)	(3)
State Top 1% Share	-0.027^{***}	-0.022^{***}	-0.020^{***}
	(0.006)	(0.007)	(0.006)
Age	-0.017^{***}	-0.017^{***}	-0.015^{***}
	(0.001)	(0.001)	(0.001)
White, non-Hispanic	0.021	0.020	-0.436^{***}
	(0.043)	(0.043)	(0.053)
Female	0.660^{***}	0.659^{***}	0.695^{***}
	(0.037)	(0.037)	(0.031)
Education	-0.036^{**}	-0.035^{**}	0.023
	(0.013)	(0.013)	(0.014)
Income	-0.152^{***}	-0.149^{***}	-0.166^{***}
	(0.019)	(0.018)	(0.022)
State Top 1% Share × Income	0.003^{***}	0.002^{***}	0.002^{*}
	(0.001)	(0.001)	(0.001)
Party Identification	-0.567^{***}	-0.568^{***}	
	(0.011)	(0.011)	
State Median Income		-0.000^{**}	
		(0.000)	
Constant	4.611^{***}	4.914^{***}	2.347^{***}
	(0.162)	(0.184)	(0.157)
Level 1 N	30727	30727	31192
Level 2 N	50	50	50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.3 presents models similar to those in the previous table, but here the dependent variable is opposition to a capital gains tax cut. Since capital gains taxes are progressive, opposing a cut is pro-redistribution. Again, multi-level logit models are used due the nested structure of the data and the dichotomous dependent variable. The results from Model 1 are charted in the main text, where I argue that people living in states with more income concentration are less supportive of redistribution, with that effect being exclusively present for those with low levels of income. Model 2 shows this result is robust to inclusion of state-level median income. And Model 3 shows the result remains even when the control for partisanship is excluded.

Table C.4 simply re-estimates the prior models of support for the capital gains tax and minimum wage but examines the context of inequality at the congressional district level. In these models, the data are modeled as individuals nested within congressional districts. Comparing the estimates from these models to comparable models reported earlier shows that there are similar patterns present. That is, the interaction term between district level inequality and family income is positive. And the estimate for district level inequality in general is negative. But these estimates are much more noisy and do not reach statistical significance.

Table C.4: Multi-Level Models of Support for Redistributive Policy, Inequality Varying at District Level

	Capital Gains	Minimum Wage
District-Level Gini	-2.085	-1.587
	(1.794)	(1.894)
Age	-0.017^{***}	-0.001
	(0.001)	(0.001)
White, non-Hispanic	0.033	-0.214^{***}
	(0.046)	(0.055)
Female	0.663^{***}	0.776^{***}
	(0.034)	(0.039)
Education	-0.036^{**}	-0.075^{***}
	(0.013)	(0.017)
Income	-0.196^{*}	-0.199^{*}
	(0.080)	(0.083)
Party Identification	-0.571^{***}	-0.640^{***}
	(0.010)	(0.012)
District-Level Gini $\times$ Income	0.223	0.317
	(0.181)	(0.186)
Constant	4.970^{***}	5.640^{***}
	(0.800)	(0.849)
Level 1 N	30727	29334
Level 2 N	435	435

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$