The Externalities of Inequality: Replication Analyses and Extensions

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Introduction

A vast literature in political economy addresses the empirical observation that preferences over redistribution vary substantially both within and between countries. To explain this heterogeneity, the canonical theoretical model of redistribution emphasizes materialist considerations, claiming that monetary incentives dictate preferences. According to this logic, preferences for redistribution vary as a function of one's distance from the mean of the national income distribution, with the rich therefore being relatively unsupportive of redistribution (Meltzer and Richard 1981).

In a recent paper, Rueda and Stegmeuller (2016) present evidence to substantiate this core claim. But they also highlight the existence of substantial geographic variation in support for redistribution among the wealthy – a relationship that does not follow directly from this earlier model of redistribution. They find that the rich are *more* favorable towards redistribution in regions with higher income inequality than the rich in more equal regions. Rueda and Stegmueller argue that, though material interests dominate preferences for redistribution among the poor, the rich can "afford" to account for the negative externalities that are associated with high levels of inequality. Specifically,

the rich may consider increased crime from inequality when formulating preferences over redistribution. Fear of crime, then, incentivizes the rich to support redistribution as a means of preventing crime in the future; this incentive is especially strong in regions with higher inequality.

In this paper, we attempt to replicate and extend Rueda and Stegmeuller's analysis. We first try to corroborate the existence of the correlations implied by the original paper. We then test whether it is appropriate to make a causal argument like that advanced in the original paper. We do so by applying causal mediation analysis (Imai et al. 2011) to Rueda and Stegmueller's theory. We find, consistent with Rueda and Stegmueller, that the rich in more unequal regions are significantly more supportive of redistribution than the rich in more equal regions. However, despite finding some correlational evidence that regional inequality is associated with fear of crime, which in turn is associated with increased probability of supporting redistribution, our results imply that the effect of regional inequality on preferences for redistribution is *not* significantly mediated by fear of crime. That is, regional variation in fear of crime can explain very little of the overall positive relationship between income inequality and support for redistribution preferences. Before concluding, we briefly probe alternative mechanisms that may explain this relationship.

Replication: Data and models

Rueda and Stegmueller (2016) test their argument − that regional inequality affects preferences for redistribution among the rich through increased fear of crime − using European Social Survey (ESS) data from 2002-2008. Their dependent variable of interest is support for redistribution, which is captured by measuring agreement (on a five-point scale) with the statement, "the government should take measures to reduce differences in income levels." The key independent variables are income distance, which captures the distance from the mean of the national income distribution of the respondent, and

regional inequality. Note that in the ESS, respondents are asked to indicate a range into which their income falls, so income distance for each respondent in the analysis is represented by the midpoint of the chosen range minus the national mean in that year. Income is also transformed into 2005 PPP dollars to enable comparison across regions. To capture regional inequality, Rueda and Stegmueller decompose the Gini Index into regional sub-parts, accounting for measurment error using small-sample correction (Deltas 2003), as well as a jackknifing variance estimator that is then incorporated into multiple imputation (Blackwell, Honaker, and King 2017). The final independent variable of interest in estimating support for redistribution is an endogenous measure of fear of crime.

Rueda and Stegmueller employ a bivariate ordered probit model in which they first model fear of crime and then feed the modeled treatment, recursively, into a model of redistribution preferences. The model of crime and redistribution is represented as follows:

$$C_i^* = \alpha_1(v_i - \bar{v}) + \beta_1 w_j + \delta_1' \mathbf{x}_{1ij} + \epsilon_{iC}$$
$$R_i^* = \lambda_1 C_i + \lambda_2 C_i(v_i - \bar{v}) + \alpha_2(v_i - \bar{v}) + \beta_2 w_j + \gamma w_j(v_i - \bar{v}) + \delta_2' \mathbf{x}_{2ij} + \epsilon_{iR},$$

where v_i represents income, w_j represents regional inequality, and $\mathbf{x}_{ij}$ is a vector of controls. The bivariate ordered probit model is a maximization of the joint bivariate normal distribution where crime (C_i) influences preferences for redistribution (R_i) but not vice versa. In their results, Rueda and Stegmueller focus primarily on the interaction between fear of crime and income and its effect on redistribution preferences. They find that the marginal effect of fear of crime on preferences for redistribution is significant and positive, and that inclusion of the externality decreases the direct effect of regional inequality on support for redistribution.

In replicating their results, we follow Rueda and Stegmueller in using multiple imputation to generate five multiply-imputed datasets (Honaker, King, and Blackwell

2009).[1] We use Rueda and Stegmueller's measures of income distance and regional inequality. However, following Rueda (2018), we dichotomize both fear of crime and support for redistribution. As levels of support for redistribution are quite high across almost all regions in Europe, we might think that neutrality indicates implicit disagreement. The results are substantively equal whether or not we dichotomize, so to ease computation and interpretation, we use binary variables in all subsequent analyses.

We first model redistribution without fear of crime, as in the original paper, and corroborate the main empirical observation. However, replicating Rueda and Stegmueller's model with endogenous crime is more complicated. They use a Stata package called cmp to estimate their bivariate probit model.[2] Unfortunately, there is very little documentation indicating, first, what assumptions must hold for the bivariate ordered probit model to be an unbiased estimator,[3] and second, how to estimate a bivariate ordered probit model outside of cmp. Our best understanding, particularly given that cmp is a generalized package for estimating seemingly-unrelated regression models, is that the joint maximization should be similar to a two-stage model.[4] As such, we attempt a two-stage model which parallels the original model, the results for which are reported in the appendix. Using this method, we do not find that support for redistribution is higher for those individuals who express fear of crime; this is irrespective of individual income.

[1] We also prune about 5,000 (of $\sim$ 96,000) observations from the original dataset because, upon investigating subjective attitudes towards immigration, we found a couple measures to be severely mean-inflated (on a 10-point scale). We hypothesized that some respondents might have chosen 5 as a form of "don't know" (don't know was not an option), rather than a true preference. Thus we identify and remove observations of respondents that answered 5 on three related immigration questions. We then use the new, pruned dataset in multiple imputation (Honaker, King, and Blackwell 2009). The pruning does not affect the results.

[2] See Roodman (2011) for cmp documentation, and Greene and Hensher (2010, Ch. 10) for a brief overview of the math of the bivariate ordered probit model.

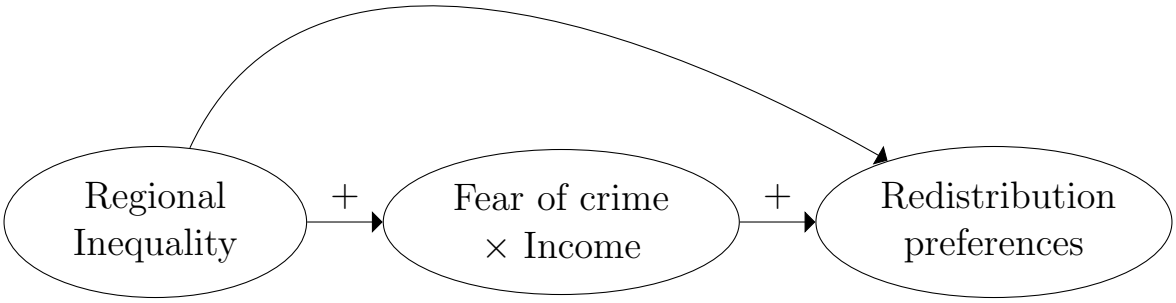
[3] It does appear that an exclusion restriction applies, which Rueda and Stegmueller claim to satisfy using an indicator variable for whether a respondent was a victim of a crime. We note that this appears to be quite a weak instrument for fear of crime (*cor(fear, victim)* = 0.08).

[4] Rueda and Stegmueller cite Yatchew and Griliches (1985) for a discussion on the disadvantages of two-step estimation. However, Yatchew and Griliches (1985) is a paper on the effects of omitted variable bias and violations of homoskedasticity in the probit model, and has nothing on two-stage models.

Testing the Theory: Causal Mediation

Our inability to discern the exact structure of the model or models underlying the cmp function used in the original paper and our inability to replicate their results using a two-stage model (laid out in detail in the appendix) raises questions about the validity of the authors' empirical approach. Yet, this does not invalidate the underlying theory − that regional inequality affects preferences for redistribution (among the wealthy) through fear of rising crime. In fact, Rueda and Stegmueller (2016) make an implicit claim throughout their paper that fear of crime is a mediator for the causal effect of inequality on redistribution. In this section, we test this causal claim using what we argue to be a more appropriate empirical strategy: causal mediation analysis.

Figure 1: Model Implied by Rueda and Stegmueller (2016)



Causal mediation provides an appropriate framework for testing theories with a particular structure: where a treatment variable (i.e. regional inequality) is claimed to influence an outcome variable (i.e. redistribution preferences), through a particular mediator variable (i.e. fear of crime). Figure 1 offers a graphical representation of Rueda and Stegmueller's causal mediation argument.

We can frame this in more formal terms by appealing to the concept of potential outcomes (Imai et al. 2011). In this setting, we let R_i denote a binary outcome variable

which takes on the value of 1 if an individual supports redistribution and 0 otherwise. Similarly, let T_i denote a continuous treatment variable which represents the level of inequality ($Rgini$) in individual i's region. M_i represents a binary mediator variable that is equal to 1 if an individual fears crime and 0 otherwise. We can thus define $M_i(t)$ as the potential value of fear of crime under treatment status $T_i = t$. Likewise, $R_i(t, m)$ denotes the potential outcome that would be realized if $T_i = t$ and $M_i = m$. Finally, then, we can define two quantities of interest:

$$\delta_i(t) \equiv R_i(t, M_i(1)) - R_i(t, M_i(0)) \tag{1}$$

$$\phi_i(t) \equiv R_i(1, M_i(t)) - R_i(0, M_i(t)) \tag{2}$$

$\delta_i(t)$ is defined as the causal mediation effect for each individual i. More concretely, in words, equation (1) calculates this effect by holding constant treatment status, t, and measuring the difference in support for redistribution if fear of crime were changed from its true value, $M_i(1)$, to the value that would be realized under the relevant control status, $M_i(0)$. In this paper, we focus primarily on the average causal mediation effect (ACME), $\bar{\delta}(t)$, which represents the average indirect effect of regional inequality on support for redistribution through the fear of crime variable.

Equation (2) defines the direct effect of treatment for individual i. That is, it represents the difference in support for redistribution under the treatment and control levels of inequality, holding the value of the mediator, fear of crime, at its true treatment value. As above, we focus on the average direct effect (ADE), $\bar{\phi}(t)$, in the foregoing analysis.

To estimate these quantities, we use the R *mediation* package (Tingley et al. 2014). Using this approach, we first fit a probit regression model to the the mediator (fear of crime) as a function of treatment (regional inequality) and a range of pre-treatment control variables. This model is the same fear of crime model estimated

by Rueda and Stegmueller in the original paper.[5] Second, we fit a probit regression to the outcome variable (support for redistribution), which we model as a function of the mediator, treatment and pre-treatment covariates. The underlying structure of the original theoretical argument implies that the ACME varies systematically as a function of an individual's distance from mean income, $(v_i - \bar{v})$. We account for this by using a particular form of mediation analysis, referred to as moderated mediation analysis. In this approach, we allow the ACME to vary with income by interacting the mediator (fear of crime) with income. The mediator and outcome models can therefore be written as:

$$M_i = \delta_0 + \delta_1 T_i + \delta_2 (v_i - \bar{v}) + \delta_3 R_i + \gamma' X_i + \epsilon_{iM} \tag{3}$$

$$R_i = \beta_0 + \beta_1 T_i + \beta_2 M_i + \beta_3 M_i * (v_i - \bar{v}) + \beta_4 T_i * M_i + \lambda' Q_i + \epsilon_{iY} \tag{4}$$

where Q_i and X_i denote a vector of additional covariates (as in the original Rueda and Stegmueller paper) that serve as controls. Based on the mediator model, the algorithm estimates a prediction for M_i under treatment and control. These predictions are then used to calculate the ACME by applying equation (1) to quantities simulated from the estimated outcome model.

It is worth emphasizing that for us to claim that we have estimated the true ACME, we need to assume sequential ignorability. This requires that, first, conditional on pre-treatment confounders, treatment assignment (i.e., regional inequality) is independent of potential mediator values (i.e., fear of crime), and of potential outcomes (i.e., redistribution preferences). Second, conditional on treatment and pre-treatment covariates, the mediator is as good as randomly assigned (Imai et al. 2011). We acknowledge that this is a strong assumption and can think of numerous ways in which it might be violated. For instance, regions with a lot of inequality are likely to be urbanized, which could simultaneously increase the likelihood that an individual fears crime *and* the likelihood that an individual supports redistribution. Nevertheless, we justify making this

[5]Unlike in Rueda and Stegmueller's model, though, mediation analysis does not require that this model be an effective predictive model. Instead, we require that the model satisfies sequential ignorability. We discuss this in some detail below.

assumption on the basis that Rueda and Stegmeuller require this to hold too, and hence this seems a reasonable assumption to make for the purposes of testing their findings.[6]

Before presenting the main results results of the mediation analysis, we also test our mediator and outcome models (equations 3 and 4 respectively) for the existence of the necessary but insufficient correlations that should hold if there is a mediated causal effect going from regional inequality to redistribution preferences, via fear of crime.[7] These conditions are the following: (1) the probability that a rich individual supports redistribution should be higher in more unequal regions than in equal regions; (2) the probability that an individual reports a significant fear of crime should be increasing in the level of regional inequality; and (3) individuals who fear crime should, in expectation, be more likely to support redistribution.

[6]Rueda and Stegmeuller might respond that including *victim* of crime in their *crime* model is a sufficient source of exogeneity to justify this assumption. However, *victim* is an extremely weak instrument for *crime* and so doesn't plausibly ensure that Rueda and Stegmeuller satisfy as-good-as random assignment in the original paper.

[7]We do so to provide reassurance that our findings, which support a different conclusion to the original paper, are not being driven by the fact that our mediator and outcome models are specified slightly differently (though we believe consistently with the causal mediation argument) to Rueda and Stegmeuller's models.

Results

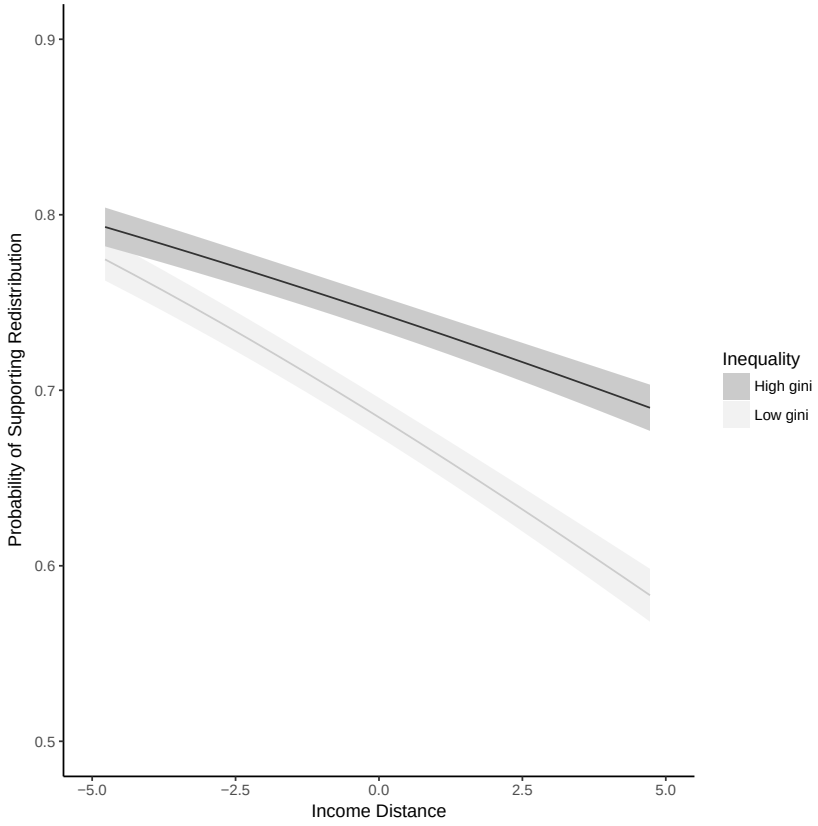


Figure 2: Simulated predicted probability of supporting redistribution (from Table 1 in Appendix), holding all other covariates at their median. Standard errors calculated according to appropriate metric for multiply imputed dataset.

As Rueda and Stemeuller suggest, there does appear to be strong correlational evidence that, all else equal, support for redistribution among the rich is considerably higher in unequal regions than in equal regions. This is shown by the divergence, as income distance increases, between the predicted probability lines of unequal and equal region in Figure 2. Likewise, Figure 3 shows that, according to our model, the probability of fearing crime is increasing in regional inequality, as predicted. Finally, figures 4a and 4b below show that, consistent with Rueda and Stegmueller's argument, all else equal, support for redistribution among the rich is highest in regions of high inequality and

where individuals fear crime.[8]

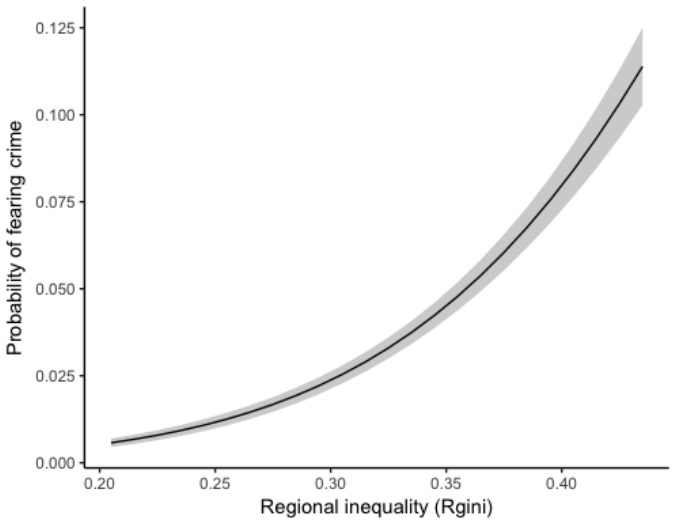


Figure 3: Simulated predicted probabilities from Table 2 (Appendix), holding all other covariates at their median.

While it is tempting to interpret figure 4b as showing no significant difference in support for redistribution between equal and unequal regions for those who fear crime, we caution that the errors are especially large due to the triple interaction. We find it more informative to look at the point estimates, which point to increased support for redistribution in unequal regions for those who fear crime. It is, however, notable that while fear of crime may increase the probability of supporting redistribution among the rich, especially in unequal regions, the regional heterogeneity of preferences remains after accounting for fear. In other words, even where respondents do not fear crime, there remains a significant difference in preferences among the rich according to levels of inequality.

[8]To make all these plots, we implement the following procedure (Honaker, King, and Blackwell 2009). We first run the model on each of the 5 imputed data sets and then simulate predicted probabilities, q_j, from each model, using standards methods and holding all but the covariates of interest at their median. The final predicted probabilities presented, $\bar{q}$, take an average over the 5 data sets, by calculating $\frac{1}{5}\sum_{j=1}^{5} q_j$. Similarly, the standard errors are calculated by taking the square root of the average squared standard error over the 5 models, plus an additional component to account for the variance of the error across the models. That is, we apply the formula: $\sqrt{se(\bar{q}) = \frac{1}{5}\sum_{j=1}^{5} se(q_j)^2 + s_q^2(1+1/5)}$ where $s_q^2 = \sum_{j=1}^{5}(q_j - \bar{q})^2/(5-1)$. This is the method we implement throughout the rest of the paper.

At this stage, then, we have for the most part demonstrated the existence of the correlations proposed by Rueda and Stegmueller. But, even prior to running the mediation analysis, there is some evidence to suggest that the mediation effect going through fear of crimes offers relatively little explanatory power for the overall effect.[9] However, we turn to causal mediation to explicitly test this causal argument, using the mediator and outcome models defined above.

A table with detailed mediation results are reported in Table 4 in the appendix. Figure 6 alone is however sufficient to demonstrate confirmation of our prediction that the mediation effect is weak: the total effect of regional inequality on preferences for redistribution is driven entirely by the direct effect of regional inequality on preferences (see Figure 1). The average causal mediation effect − the effect of treatment (regional inequality) on outcome (support for redistribution) that flows through fear of crime − is effectively zero. We also test whether there is a significant difference in the mediation effect for high-income and low-income individuals as Rueda and Stegmeuller predict, and again find no significant mediation effect for either level of income.[10]

[9]There remains a significant difference in preferences among the rich according to levels of inequality.

[10]We used the test.modmed() function from the R *mediation* package (Tingley et al. 2014), with 10th and 90th income-distance percentiles. This function tests the difference in the ACME at two levels of mediator-moderator (i.e., *incdist*).

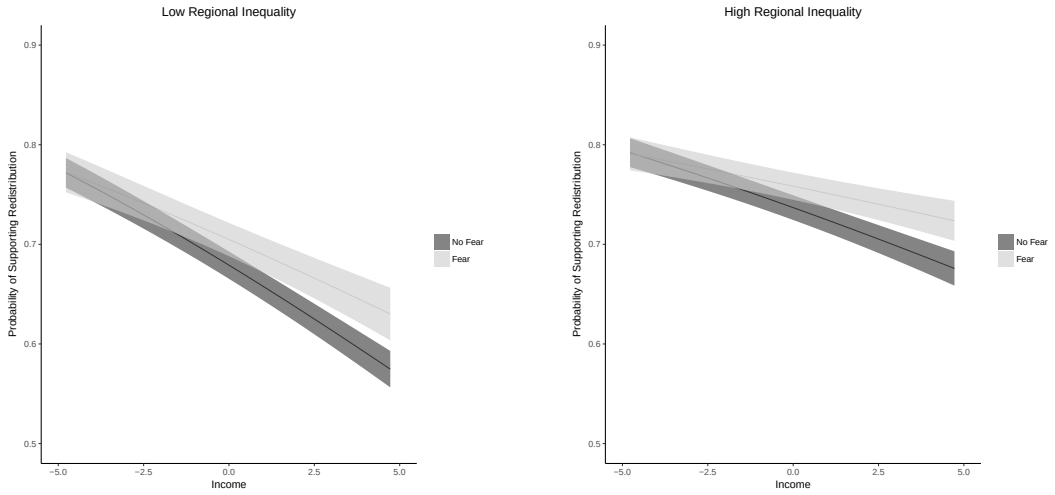


Figure 4: Simulated predicted probabilities from Table 1 (appendix), holding all other covariates at their median. Left hand side: Low Gini (10th percentile); Right hand side: High Gini (90th percentile)

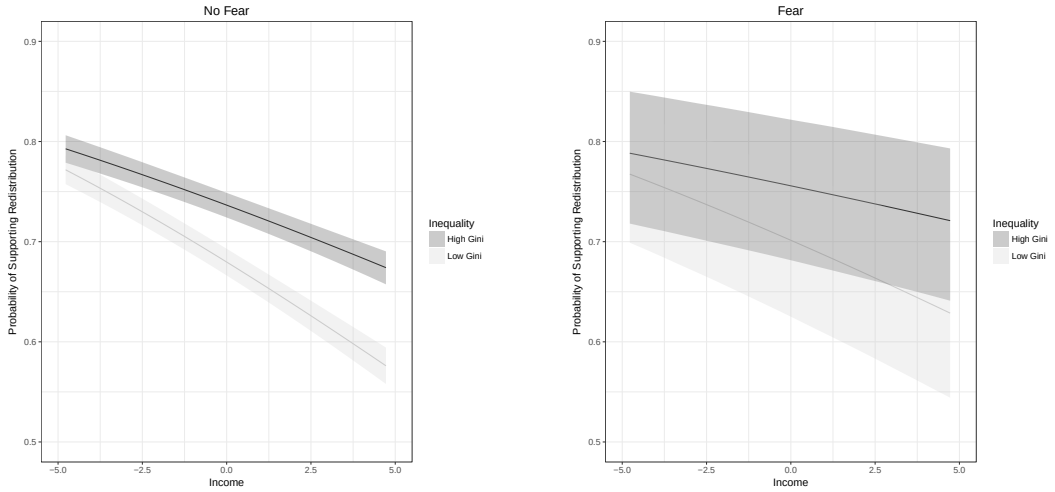


Figure 5: Simulated predicted probabilities from Table 1 (appendix), holding all other covariates at their median and subsetting by respondents who fear crime and those who don't.

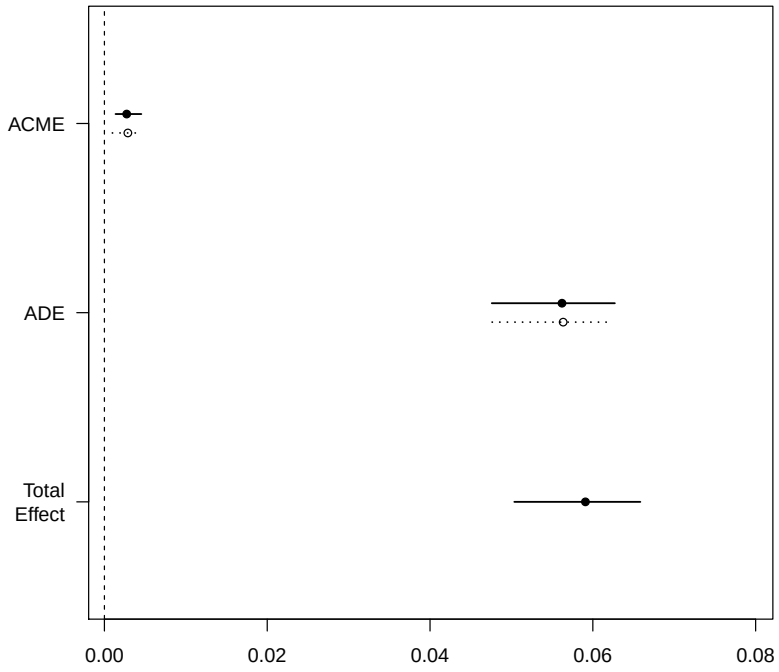


Figure 6: Average causal mediation effect, average direct effect, and total effect (with confidence intervals) of regional inequality (control and treatment) on support for redistribution. Note that a 0.06 effect implies a 6% difference in the probability of supporting redistribution.

As discussed above, the key assumption for causal mediation to be a valid causal identification approach is sequential ignorability. This is, of course, a very strong assumption in this case, and normally we would conduct sensitivity analysis to test it. Sensitivity analysis tests the degree to which the identification assumption must be violated for the original conclusions to be reversed. Unfortunately, it is not possible to run sensitivity analysis when both the outcome and mediator are modeled using probit regression (Tingley et al. 2014). However, given that our ACME is 0, sensitivity analysis doesn't make a lot of sense anyway, as the results cannot make us conclude a mediation effect where there is none.

We have thus subjected Rueda and Stegmueller's theory to two empirical analyses:

first, a modified version of the model used in the original paper (detailed in the appendix) and second, causal mediation analysis. We find similar correlations between regional inequality, fear of crime interacted with income, and preferences for redistribution, but fail to replicate the authors' main causal claim: that fear of crime mediates the effect of inequality on redistribution. In the following section we briefly explore alternative explanations.

Alternative Hypotheses and Potential Confounders

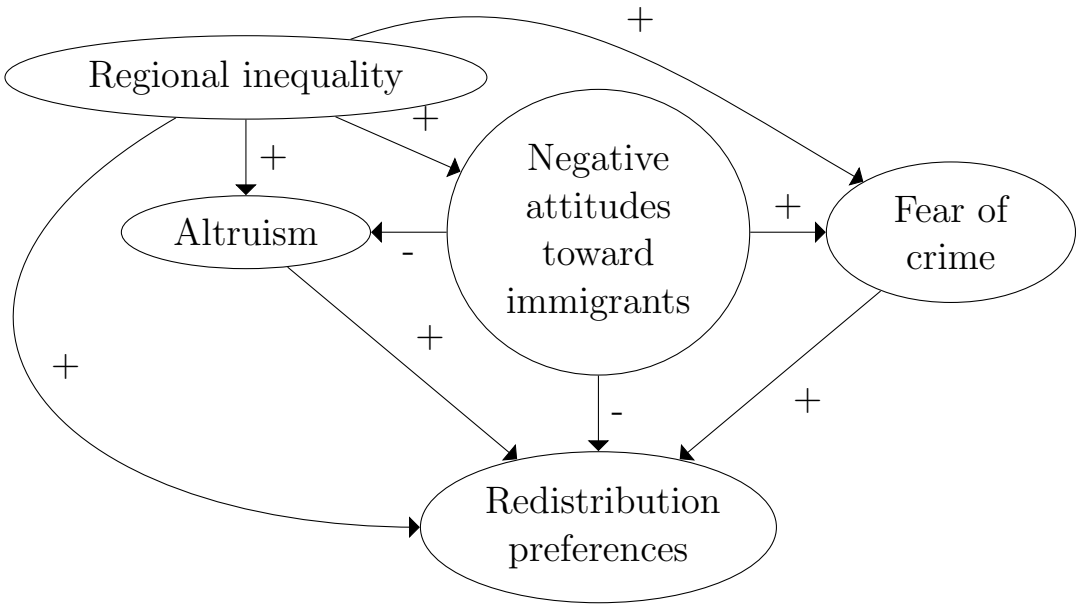
Thus far, we find robust empirical evidence that the rich in unequal regions are more supportive of redistribution than the rich in more equal regions. Our results also reveal that very little of this effect is explained by increased fear of crime. Rueda and Stegmueller's original puzzle persists: why does the relationship between inequality and preferences for redistribution exist for the rich?

Although fear of crime does not appear to be a significant driver of redistribution preferences, other externalities might plausibly explain the observed relationship. A more recent paper by Rueda (2018) advances a similarly structured argument to Rueda and Stegmueller (2016), proposing that the income effects (among the rich) on preferences for redistribution are mediated by altruism rather than fear of crime. In his argument, the identity and similarity of the individuals receiving benefits moderates rich respondents' feelings of altruism, which in turn influences their preferences for redistribution. Using percentage of foreign-born residents at the country level, Rueda (2018) finds that support for redistribution is lower among the rich where the percentage of foreign-born residents is higher. But by not including regional inequality, Rueda (2018) fails to address the central wealth-redistribution paradox we are interested in.

In this section we attempt to put both Rueda and Stegmueller (2016) and Rueda (2018) in conversation with each other. Altruism may be another externality of inequal-

ity – that is, the rich's increased concern for the poor may be the mechanism through which inequality increases preferences for redistribution among the rich in unequal regions. We add measures of altruism and attitudes toward immigrants to Rueda and Stegmueller's (2016) model tested above and hypothesize that the effect of regional inequality on redistribution preferences might be mediated by altruism, attitudes toward immigrants, and fear of crime.

Figure 7: Adjusted Model



Unfortunately, this model of the relationship between regional inequality and redistribution preferences does not lend itself to mediation analysis for several reasons. First, like the original model we tested above, the model in Figure 7 likely violates sequential ignorability, as several of the mediators in the model likely influence each other, regional inequality, and redistribution preferences all at the same time. Negative attitudes toward immigrants, for example, might cause individuals to self-sort into regions with fewer immigrants or less inequality. This model also presents potential confounders for fear of crime as a mediator of regional inequality. For instance, regional inequality

may increase both altruism and fear of crime, and therefore support for redistribution. However, both mediators are affected − in opposite directions − by attitudes towards immigration. Negative attitudes towards immigration may increase support for redistribution by driving up fear of crime, as well as decrease support by limiting altruistic feelings. Failing to account for these potential confounders likely influences the estimated mediation effect of fear of crime. Second, we do not have a good measure of altruism. In Rueda (2018), percentage foreign-born is used as a proxy for altruism, but does not clearly have a mediating relationship between inequality and preferences for redistribution. In fact, the number of foreign-born residents in a region might influence both regional inequality, altruism, and redistribution preferences.

While we would prefer to conduct a mediation analysis, we are able to explore this model briefly without mediation analysis to examine whether the correlation between altruism and redistribution preferences from Rueda (2018) holds when including regional inequality. We estimate a probit model for redistribution preferences equivalent to Rueda's (2018) model, but including fear of crime and a measure of subjective attitudes toward immigrants.[11] We then estimate an identical model, but include regional inequality.

Table 5 of the appendix reports the regression results for both models. The inclusion of regional inequality in the model reduces the influence of percentage foreign-born by approximately two-thirds and renders it statistically insignificant. Figure 8 shows the differences in the predicted probability of supporting redistribution as an individual moves from a country with a low foreign-born population to a country with a high foreign-born population, holding all other factors at their means and broken out by income. We can see that when we control for regional inequality, there is little expected change in preferences for redistribution as the foreign-born population increases. We find it puzzling that Rueda excluded regional inequality in the models for the 2018 paper.

[11]We use ESS data which asks whether respondents believe that their "country's cultural life is undermined or enriched by immigrants" (10-point scale). This data is available for all waves of ESS; we continue to use data for 2002-2008.

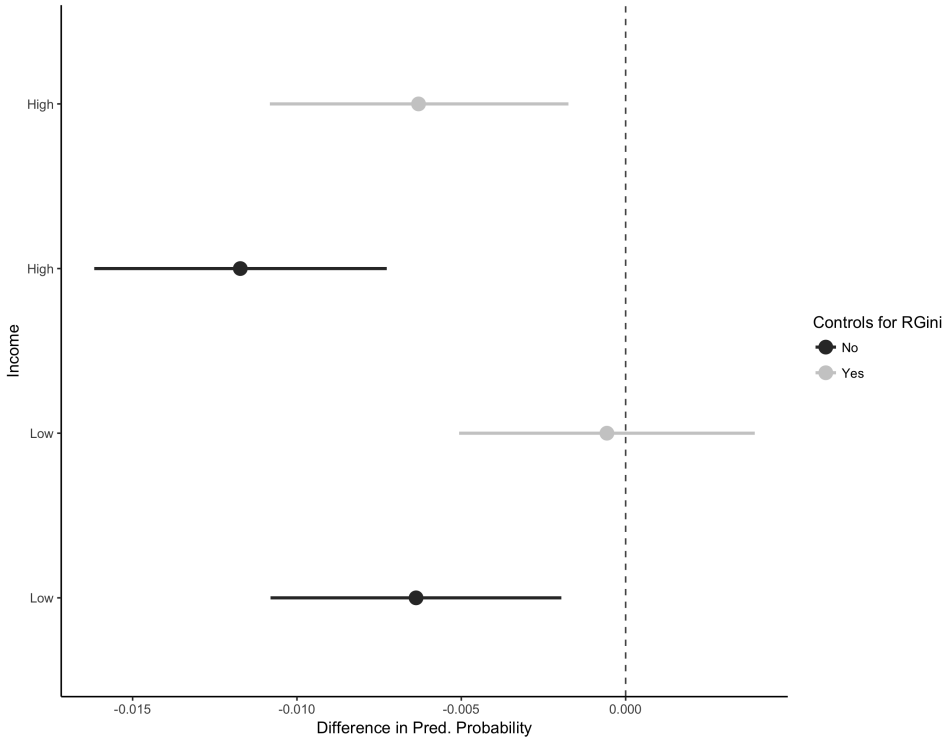


Figure 8: Simulated differences in predicted probabilities of supporting redistribution from Table 5 (appendix) going from 20th to 80th percentile in percent foreign-born, holding all other covariates at their median.

The fact that the relationship between foreign-born population and income distribution preferences disappears once regional inequality is included illustrates how potential causes of inequality are related in complex ways. Regional inequality and foreign-born population likely influence each other at the same time as each influences preferences for redistribution. A mediation analysis that satisfies methodological requirements would be the ideal way to disentangle the effect of each variable, but is not an easy task in reality. Using current ESS data we have no way to do so.

Conclusion

In this paper, we replicated the Rueda and Stegmueller's correlations between regional inequality, fear of crime, relative income, and preferences for redistribution. Contrary

to the theory posited in Rueda and Stegmueller (2016), we failed to find a plausible causal relationship between regional inequality and preferences for redistribution that is mediated by fear of crime using causal mediation analysis. Though fear of crime does not appear to be a mediator, we found the logic of negative externalities of inequality mediating regional inequality and redistribution plausible. We therefore tried to lay out a new model (Figure 7) that included altruism and attitudes toward immigrants, drawing on Rueda (2018). We were unfortunately unable to test the new model using causal mediation due to clear violations of sequential ignorability as well as insufficient data.

Although we were unable to replicate the central causal claim of Rueda and Stegmueller (2016), we believe that we have clearly laid out why such claims are difficult to convincingly demonstrate. As discussed above, Rueda and Stegmueller's model (see Figure 5 for a stylized version) likely does not meet the criteria required for a valid mediation analysis. If we assume that the model does meet the criteria, as we did when running the analysis, the effect of regional inequality on redistribution preferences mediated by fear of crime is negligible.

The central paradox of Rueda and Stegmueller (2016) and this paper therefore remains unanswered: why are wealthy individuals in more unequal regions more likely to favor redistribution? We suggest that future attempts to answer this question more transparently acknowledge the challenges in analyzing the relationship, as regional inequality and preferences for redistribution are likely influenced by a number of other confounding factors.

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Appendix

Table 1: Redistribution Probit Regression Results

	Dependent variable:
	support for redistribution
Rgini	1.946^{***}
	(0.196)
income distance	-0.133
	(0.138)
Rgini*income distance	0.261^{*}
	(0.146)
Constant	-0.147
	(0.150)
Controls?	yes
Observations	92,116
Log Likelihood	$-54{,}605.740$
Akaike Inf. Crit.	109,253.500
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: Two-Stage Probit Regression Results

	Dependent variable:	
	fear of crime	support for redistribution
	(1)	(2)
modeled fear		0.007
		(0.317)
Rgini	5.324***	1.949***
	(0.209)	(0.341)
income distance	−0.023	−0.133
	(0.146)	(0.301)
modeled fear*income distance		0.0003
		(0.300)
income distance*Rgini		0.261
		(0.304)
modeled fear*Rgini		−0.008
		(0.430)
Constant	−3.210***	−0.148
	(0.160)	(0.308)
Controls?	yes	yes
Observations	92,116	92,116
Log Likelihood	−42,800.470	−54,604.250
Akaike Inf. Crit.	85,634.930	109,256.500
Note:		*p<0.1; **p<0.05; ***p<0.01

Understanding the Two-Stage Model

In order to approximate the joint estimation of Rueda and Stegmueller's (2016) bivariate ordered probit, we run a two-stage model. For the two-stage model, we first model fear of crime using the same model and covariates as the original paper but binarizing fear of crime. The results of the first-stage probit model are in Table 2. The results are consistent with Rueda and Stegmeuller's original analysis. We estimate the second stage by feeding the predicted values from the first model into the equation modeling support for redistribution. Our two-stage probit regression produces significantly different results than Rueda and Stegmueller's bivariate model. The modeled treatment (fear) is statistically and substantively insignificant, while regional inequality continues to be (independently) significantly correlated with support for redistribution, all else equal. Figure 9 shows that, while support for redistribution is more likely in highly-unequal regions, fear (as modeled) has no effect on preferences. We note again that the difference between our model and the original is independent versus joint maximization.

We briefly investigate whether our modeling choices for translating predicted probabilities into predicted binary values affect the second stage of the model by plotting an ROC curve. Figure 10 shows, surprisingly, that Rueda and Stegmueller's model of fear of crime is not a good predictor of fear of crime. In fact, correlation between the modeled treatment and the actual data is effectively zero, regardless of the cutoff point used. Of course, the outcome from the second-stage (or in an ideal world, joint) model is the point of interest, but the theoretical argument relies on believing that we are indeed modeling fear of crime. We should be cautious about results from models that do not resemble the data, as is the case for Rueda and Stegmueller's model of fear.

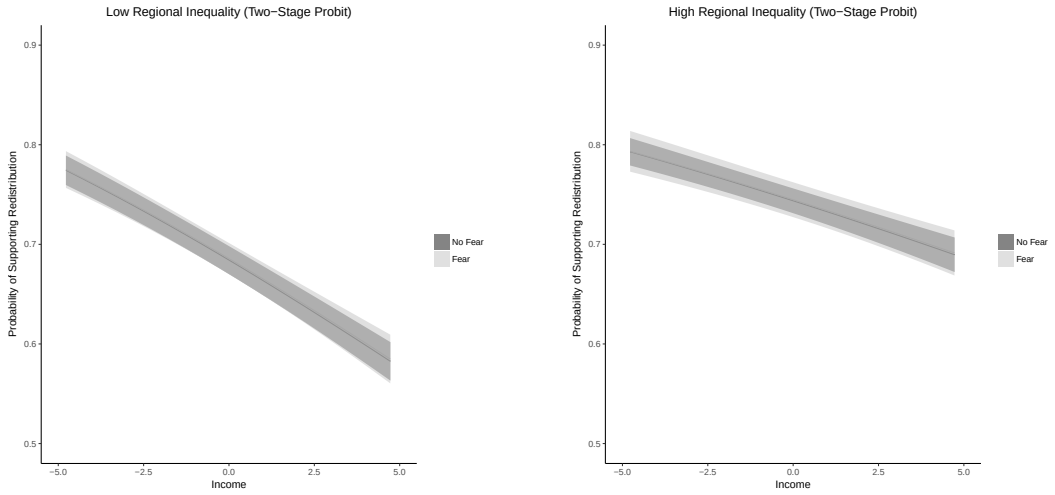

Figure 9: Simulated predicted probabilities from Table 2 (appendix), holding all other covariates at their median. Left hand side: Low Gini (10th percentile); Right hand side: High gini (90th percentile)

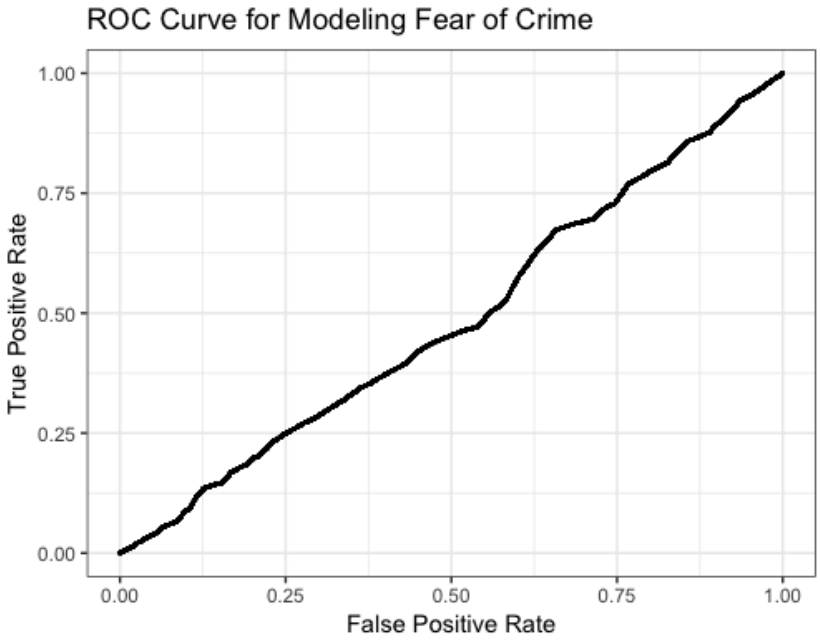

Figure 10: ROC curve using ESS fear of crime data and modeled treatment from first-stage probit model.

Table 3: Mediation Model: Probit Regression Results

	Dependent variable:
	support for redistribution
fear of crime	0.093
	(0.333)
income distance	−0.126
	(0.315)
Rgini	1.873***
	(0.353)
fear*income distance	0.015
	(0.314)
income distance*Rgini	0.233
	(0.318)
fear of crime*Rgini	−0.066
	(0.452)
Constant	−0.131
	(0.321)
Controls?	yes
Observations	92,116
Log Likelihood	−54,582.090
Akaike Inf. Crit.	109,212.200
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Causal Mediation Analysis

	Estimate	95% Conf Int
ACME (control)	0.003	$(0.001, 0.00)^{***}$
ACME (treated)	0.003	$(0.001, 0.00)^{***}$
ADE (control)	0.056	$(0.048, 0.06)^{***}$
ADE (treated)	0.056	$(0.048, 0.06)^{***}$
Total Effect	0.059	$(0.05, 0.07)^{***}$
Prop. Mediated (control)	0.049	$(0.017, 0.07)^{***}$
Prop. Mediated (treated)	0.046	$(0.023, 0.08)^{***}$
ACME (average)	0.003	$(0.002, 0.00)^{***}$
ADE (average)	0.056	$(0.048, 0.06)^{***}$
Prop. Mediated (average)	0.048	$(0.033, 0.07)^{***}$
Observations		92,116
Note:		***p<0.0001

Table 5

	Dependent variable:	
	support for redistribution	
	(1)	(2)
pct. foreign-born	-0.364^{***}	-0.136
	(0.085)	(0.087)
income distance	-0.040^{***}	-0.040^{***}
	(0.003)	(0.003)
Rgini		1.916^{***}
		(0.141)
fear of crime	0.089^{***}	0.072^{***}
	(0.012)	(0.012)
immigration att.	0.050^{***}	0.060^{***}
	(0.012)	(0.012)
	(0.008)	(0.008)
pct. foreign-born*income distance	-0.056^{**}	-0.065^{**}
	(0.026)	(0.026)
Constant	0.443^{***}	-0.185^{***}
	(0.041)	(0.062)
Observations	92,116	92,116
Log Likelihood	$-54{,}677.775$	$-54{,}585.663$
Akaike Inf. Crit.	109,399.550	109,217.327
Note:	*p<0.1; **p<0.05; ***p<0.01	