Replication:Becker, B., 2024. International inequality and demand for redistribution in the Global South. *Political Science Research and Methods*, 12, pp.407-415.

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Roadmap

Presentation Roadmap

1. **Introduction of the Paper**
    - Overview of the research theme and the pivotal questions the paper addresses.
    - Presentation of the core hypotheses: H1 , H2 , H3.
    - Summary of the key findings that highlight the paper's contributions to the field.
    - Examination of the dataset and methods used for analysis.
2. **Replication of the Paper**
    - Detailed replication of the original study's quantitative findings to deepen our understanding and verify the results.

Presentation Roadmap

3. **Extension Part**

    - Extending the study by applying binary logistic regression to Table 2.
    - Introduction of a new hypothesis on education and inequality.

Introduction of the Paper

Introduction of the Paper:Research Question

How do perceptions of international inequality influence attitudes toward inequality and redistribution in recipient countries of the Global South? Specifically, it explores the relationship between Kenyans' perceptions of international income differences and their attitudes towards international aid, an instrument for redistribution.

Independent Variable (X): Perceptions of international inequality.

Dependent Variables (Y):

- Attitude toward international inequality.
- Demand for international redistribution.

figure:The gap between rich and poor.

[0]Source: https://kenyanwallstreet.com/higher-taxes-kenyas-rich-can-lower-extreme-inequality-oxfam/

Introduction of the Paper:Hypotheses

1. The higher individuals perceive between-country inequality to be, the less accepting they are of the status quo.
2. The higher individuals perceive between-country inequality to be, the more they demand international redistribution.
3. The higher individuals perceive between-country inequality to be, the more they demand international redistribution from former colonial powers.

Introduction of the Paper:Key Contributions

- **Underestimation of Inequality:** The study sheds light on the Global South's perception, particularly in Kenya, about international income differences.
- **Impact of Information:** Presentation of factual data significantly decreases the acceptance of inequality among Kenyan respondents.
- **Aid Demand Complexity:** Counter to conventional beliefs, enhanced awareness does not straightforwardly lead to a greater demand for international aid.
- **Methodological Innovation:** The adoption of SMS-based surveys in the study paves the way for cost-effective and broad-reaching data gathering in challenging research contexts.
- **Impetus for Further Research:** The findings suggest a need for more in-depth analysis into attitudes towards various forms of international redistribution, extending beyond traditional aid.

Introduction of the Paper:Data Review

A pre-registered SMS survey conducted in Kenya provided insights into citizens' perceptions of international income differences and their preferences for redistribution. The survey specifically addressed:

- Comparative living standards within the country, ranging from "Much lower" (1) to "Much higher" (5).
- Frequency of religious service attendance, from "Never" (1) to "Every day" (5).
- According to official statistics by the World Bank, average incomes in Western Europe are 25 times higher than in Kenya. [RANDOMIZED TREATMENT]
- Levels of agreement with statements regarding the acceptability of income differences and the demand for financial aid from countries like the UK and USA, rated from "Strongly disagree" (1) to "Strongly agree" (5).

These questions aimed to gauge the subjective and objective understanding of international economic disparities and the subsequent effect on attitudes towards international aid and inequality.

Data Review

DAT ×

Filter

	respID	age	female	edu_low	edu_high	employment	region	relig	living	ineqtreat	guess_recode	incdiff	aidUK	aidUS	aid
1	1	25	1	0	1	Own my own company	nairobi	4	2	1	0.60	4	2	2	2.0
2	2	26	1	0	1	Other/Unemployed	western	2	3	1	6.00	2	1	1	1.0
3	3	25	1	0	1	Other/Unemployed	central	4	2	1	10.00	4	4	5	4.5
4	4	NA	NA	NA	NA	NA	NA	4	1	1	0.50	4	4	4	4.0
5	5	30	0	0	1	Other/Unemployed	riftvalley	4	2	1	1.00	5	2	2	2.0
6	6	26	1	0	1	Student	nyanza	3	3	1	10.00	4	4	2	3.0
7	7	NA	NA	NA	NA	NA	NA	4	1	1	3.00	1	2	4	3.0
8	8	25	0	0	1	Other/Unemployed	riftvalley	3	1	1	2.00	4	4	3	3.5
9	9	35	0	0	1	Skilled worker	eastern	2	2	1	1.00	4	1	1	1.0
10	10	27	0	0	1	Student	western	4	3	1	1.00	1	2	2	2.0
11	11	23	1	0	1	Student	eastern	4	1	1	1000.00	4	4	3	3.5
12	12	NA	NA	NA	NA	NA	NA	4	1	1	3.00	1	5	5	5.0
13	13	25	1	0	0	Student	riftvalley	4	1	1	10.00	4	5	5	5.0
14	14	NA	NA	NA	NA	NA	NA	4	2	1	0.40	4	1	1	1.0

Figure: Dataset snapshot showcasing respondents' views on living standards, religious attendance, income disparities, and attitudes towards aid.

Replication of the Paper

Replication: Attitudes Toward Inequality and Demand for Aid

The data visualization reflects the distribution of opinions on whether such inequality is acceptable and whether there should be increased aid from countries like the UK and the USA. Differences in the acceptance of inequality and the demand for international aid are evident, with nuances in opinion possibly relating to the country of aid origin.

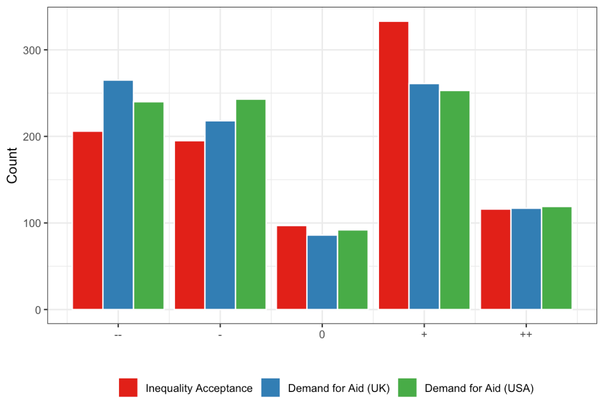

Figure: Aggregate frequencies of attitudes towards inequality acceptance and demand for aid from the UK and USA.

Replication:Table 1: OLS Regression Models

Table 1: Average Treatment Effects (OLS)

	Inequality Acceptance	Demand for aid	Aid (UK)	Aid (USA)	Aid (UK) - Aid (USA)
Treatment	-0.189*	-0.048	-0.002	-0.094	0.092
	(0.090)	(0.086)	(0.093)	(0.092)	(0.066)
R^2	0.005	0.000	0.000	0.001	0.002
Adj. R^2	0.004	-0.001	-0.001	0.000	0.001
Num. obs.	947	947	947	947	947

Note: Ordinary least squares regression. indicates acceptance of income differences between Kenya and Western Europe; indicates demand for international financial transfers. (*=0.05)

Figure: OLS Estimates of Treatment Effects on Inequality Acceptance and Demand for Aid.

```
# OLS regression models
mod01 <- lm(incdiff ~ ineqtreat, DAT)
mod02 <- lm(aid ~ ineqtreat, DAT)
mod03 <- lm(aidUK ~ ineqtreat, DAT)
mod04 <- lm(aidUS ~ ineqtreat, DAT)
mod05 <- lm(aidUK - aidUS ~ ineqtreat, DAT)
```

Replication:Table 2: Linear Probability Models

Table 2: Average Treatment Effects (LPM)

	Inequality Opposition	Demand for aid	Aid (UK)	Aid (USA)	Aid (UK) - Aid (USA)
Treatment	0.086*	-0.008	0.034	-0.012	0.032
	(0.032)	(0.032)	(0.032)	(0.032)	(0.022)
R^2	0.008	0.000	0.001	0.000	0.002
Adj. R^2	0.006	-0.001	0.000	-0.001	0.001
Num. obs.	947	947	947	947	947

* *Note:* Linear probability models (OLS). All dependent variables are dummy-coded. *Inequality Opposition* indicates opposition to income differences between Kenya and Western Europe; *Aid* indicates demand for international financial transfers; all dependent variables are dichotomized. (*=p¡.05)

Figure: Linear Probability Estimates of Dichotomized Treatment Effects.

```
# Linear Probability Models
mod01 <- lm(I(incdiff < 3) ~ ineqtreat, DAT)
mod02 <- lm(I(aid > 3) ~ ineqtreat, DAT)
mod03 <- lm(I(aidUK > 3) ~ ineqtreat, DAT)
mod04 <- lm(I(aidUS > 3) ~ ineqtreat, DAT)
mod05 <- lm(I(aidUK - aidUS > 0) ~ ineqtreat, DAT)
```

Replication:Interpreting Regression Results

- **Inequality Acceptance:**
  - The treatment reduced inequality acceptance, consistent with H1.
  - Significance suggests information impacts perceptions of inequality.
- **Demand for Aid:**
  - No significant effect from the treatment on aid demand from either the UK or USA.
  - Findings imply a more complex decision-making process for aid demand.
- **Dichotomized Variables Analysis:**
  - Further supports increased opposition to inequality with information.
  - LPM confirms lack of significant change in aid demand.

Replication:Visual Analysis: Perceived Inequality and Attitudinal Shifts

- The histograms show perceptions of inequality with varying attitudes towards acceptance and aid demand.
- The regression line for perceived inequality versus inequality acceptance suggests a negative correlation.
- There is no clear relationship between perceived inequality and aid demand, indicating other factors at play.

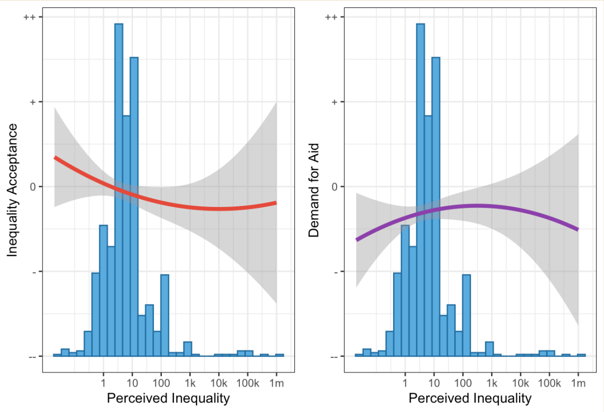

Figure: Distributions and Regression Lines: Perceived Inequality vs. Acceptance and Aid Demand.

Replication:Table3:Examining Information Dosage Effects

- Examines the effect of the amount of information on attitudes.

```
# Regression models with interaction for treatment dosage
mod01 <- lm(incdiff ~ ineqtreat * guess_recode, DAT)
mod02 <- lm(aid ~ ineqtreat * guess_recode, DAT)
mod03 <- lm(aidUK ~ ineqtreat * guess_recode, DAT)
mod04 <- lm(aidUS ~ ineqtreat * guess_recode, DAT)
mod05 <- lm(aidUK - aidUS ~ ineqtreat * guess_recode, DAT)
```

Table 3: Treatment Effects by Dosage (OLS)

	Inequality Acceptance	Demand for aid	Aid (UK)	Aid (USA)	Aid (UK) - Aid (USA)
Treatment	-0.162	-0.034	0.027	-0.095	0.121
	(0.097)	(0.092)	(0.099)	(0.097)	(0.070)
Perceived Inequality (PI)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treatment × PI	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.005	0.002	0.003	0.002	0.006
Adj. R^2	0.002	-0.002	-0.000	-0.002	0.003
Num. obs.	838	838	838	838	838

Note: Ordinary least squares regression. indicates pretreatment perception of income differences between Kenya and Western Europe; indicates acceptance to these income differences; indicates demand for international financial transfers. (*=0.05)

Replication:Table 4:Effects Across Economic Standing and Religiosity

- Assesses how economic status and religiosity affect the treatment impact.

```r
# Regression models with interaction for economic standing and religiosity
mod01 <- lm(incdiff ~ ineqtreat * living, DAT)
mod02 <- lm(aid ~ ineqtreat * living, DAT)
mod03 <- lm(incdiff ~ ineqtreat * relig, DAT)
mod04 <- lm(aid ~ ineqtreat * relig, DAT)
```

Table 4: Treatment Effect Heterogeneity (OLS)

	Inequality Acceptance	Demand for aid		
	(1)	(2)	(3)	(4)
Treatment	0.125	-0.767*	0.089	-0.273
	(0.223)	(0.310)	(0.213)	(0.297)
Economic Standing (ES)	0.016		-0.099	
	(0.069)		(0.066)	
Religiosity		-0.091		0.059
		(0.062)		(0.059)
Treatment × ES	-0.135		-0.047	
	(0.095)		(0.090)	
Treatment × Rel.		0.173*		0.065
		(0.088)		(0.084)
R^2	0.007	0.008	0.009	0.006
Adj. R^2	0.004	0.005	0.005	0.003
Num. obs.	899	939	899	939

Note: Ordinary least squares regression. indicates acceptance of income differences between Kenya and Western Europe; indicates demand for international financial transfers. (*=0.05)

Replication:Interpreting the Effects of Treatment Dosage and Heterogeneity

- The level of information provided (treatment dosage) did not significantly alter inequality acceptance or aid demand.
- Economic status does not uniformly influence attitudes, suggesting nuanced individual-level variations.
- Religiosity's interaction with treatment increases demand for aid, indicating different impacts across religious beliefs.
- These findings point to the complexity of socioeconomic factors in shaping attitudes towards inequality and aid.

Extension

Extension:R Code for Binary Logistic Regression Model (Comparative Analysis with Table 2's Linear Probability Model)

```
# Set up binary variables for logistic regression
DAT$incdiff_binary <- factor(DAT$incdiff < 3)
DAT$aid_binary <- factor(DAT$aid > 3)
DAT$aidUK_binary <- factor(DAT$aidUK > 3)
DAT$aidUS_binary <- factor(DAT$aidUS > 3)
DAT$aid_diff_binary <- factor(DAT$aidUK - DAT$aidUS > 0)

# Fit GLM models for binary dependent variables
mod01_glm <- glm(incdiff_binary ~ ineqtreat, family=binomial(link="logit"), data=DAT
mod02_glm <- glm(aid_binary ~ ineqtreat, family=binomial(link="logit"), data=DAT)
mod03_glm <- glm(aidUK_binary ~ ineqtreat, family=binomial(link="logit"), data=DAT)
mod04_glm <- glm(aidUS_binary ~ ineqtreat, family=binomial(link="logit"), data=DAT)
mod05_glm <- glm(aid_diff_binary ~ ineqtreat, family=binomial(link="logit"), data=DA
```

Extension:Binary Logistic Regression Model Output from R

Table 5: Comparative Model Output

	Dependent variable:				
	(Inequality Opposition)	(Demand for Aid)	(Aid UK)	(Aid USA)	(Aid UK - Aid USA)
	(1)	(2)	(3)	(4)	(5)
Treatment	0.353***	−0.033	0.141	−0.052	0.270
	(0.132)	(0.134)	(0.133)	(0.133)	(0.191)
Constant	−0.490***	−0.481***	−0.481***	−0.409***	−1.991***
	(0.095)	(0.095)	(0.095)	(0.095)	(0.142)
Observations	947	947	947	947	947

Note: *p<0.1; **p<0.05; ***p<0.01

Note: GLM with binomial family. All dependent variables are dummy-coded. Inequality Opposition indicates opposition to income differences between Kenya and Western Europe; Aid indicates demand for international financial transfers. Significance levels: *p¡0.1; **p¡0.05; ***p¡0.01.

Figure: Comparative Model Output for Binary Dependent Variables

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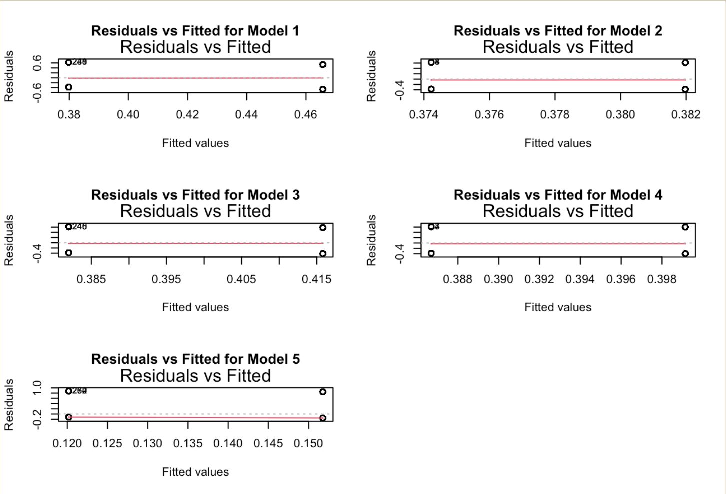
Extension:Insights from Binary Logistic Regression Model

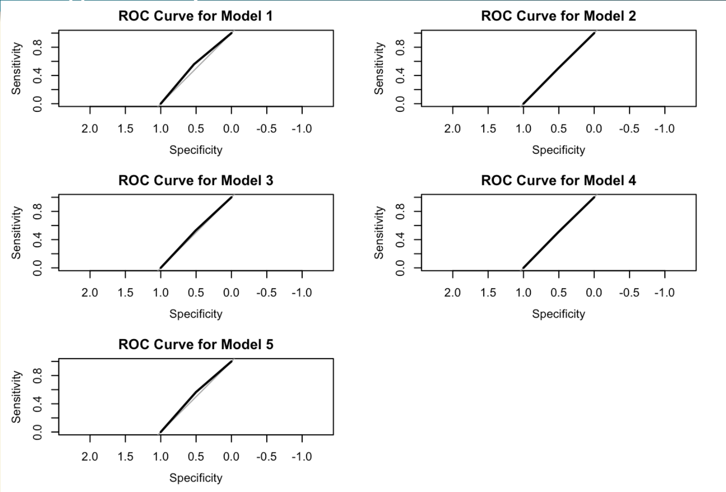
- The logistic regression provides a nuanced understanding of the treatment effects.
- Treatment significantly increases the probability of opposing inequality, aligning with Hypothesis 1.
- The lack of significant change in aid demand across both models suggests complex underlying dynamics influencing aid preferences.

Extension:Residuals Analysis for LM Model Fit (Table 2)



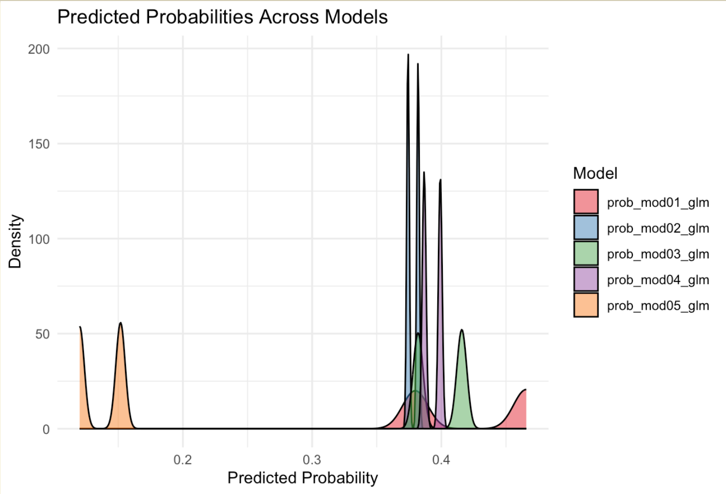
- Residual plots for each model help check the assumptions of linear regression.
- Ideally, residuals should be randomly distributed with no clear pattern.
- Patterns in the plots may indicate model misspecification or need for a different modeling approach.

Extension:ROC Curves for Classification Effectiveness(Binary Logistic Regression)



- ROC curves evaluate the diagnostic ability of binary classifiers.
- A curve closer to the top-left corner indicates a more effective model.
- The area under the ROC curve (AUC) quantifies the overall performance of the models. (Model 1: AUC = 0.544 Model 2: AUC = 0.5041 Model 3: AUC = 0.5176 Model 4: AUC = 0.5065 Model 5: AUC = 0.5336) (AUC values closer to 1 indicate a good model. Values below 0.7 typically indicate poor discrimination)

Extension:Predicted Probabilities Distribution(Binary Logistic Regression)



- Distributions of predicted probabilities for binary outcomes from GLM.
- Probabilities close to 0 or 1 suggest a strong predictive model.
- Wide distributions can indicate uncertainty in the model's predictions.

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Extension:Comparative Insights from Linear Probability and Logistic Regression Models

- Extension analysis utilizes logistic regression to explore factors affecting inequality acceptance and aid demand.
- Model diagnostics alongside ROC curves evaluated the suitability of GLM for binary outcomes.
- Predicted probabilities from GLM demonstrate the model's varying confidence levels in classifying outcomes.
- The detailed examination of socio-economic influences elucidates the complex nature of public responses to information on inequality.

Extension:A new hypothesis:Higher education would lead to less acceptance of inequality.

```r
DAT$ineqtreat <- factor(DAT$ineqtreat)
DAT$incdiff_binary <- factor(DAT$incdiff < 3, labels = c("0", "1"))
mod01 <- glm(ineqtreat ~ incdiff_binary + edu_low + edu_high,
             family = binomial, data = DAT)
summary(mod01)
```

Table 6: GLM Model Summary

Variable	Estimate	Std. Error	z value	Pr(¿—z—)
Intercept	0.4758	0.2268	2.098	0.03594 *
incdiff_binary1	0.3340	0.1673	1.996	0.04592 *
edu_low	-0.9100	0.3753	-2.425	0.01533 *
edu_high	-0.6439	0.2418	-2.663	0.00775 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Dispersion parameter for binomial family taken to be 1.

Null deviance: 835.56 on 602 degrees of freedom.

Residual deviance: 823.70 on 599 degrees of freedom.

344 observations deleted due to missingness.

AIC: 831.7.

Figure: GLM Model Summary with Education Variables

Extension:Odds Ratios for Education Levels on Inequality Acceptance

```r
# Calculate odds ratios and confidence intervals
odds_ratios <- exp(coef(mod01))
conf_int <- exp(confint(mod01))

cbind(odds_ratios, conf_int)
```

Table 7: Odds Ratios and 95% Confidence Intervals

Variable	Odds Ratios	2.5%	97.5%
Intercept	1.6092968	1.0382871	2.5348830
incdiff_binary1	1.3965640	1.0068642	1.9409184
edu_low	0.4025184	0.1906322	0.8345698
edu_high	0.5252496	0.3240232	0.8383815

Figure: Odds Ratios and Confidence Intervals for Education Variables

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Educational Impact on Inequality Acceptance: A Broader Perspective

- **Initial Hypothesis:** It was anticipated that higher education correlates with a lesser acceptance of inequality.
- **Revised Findings:** Empirical data shows that both lower and higher education levels lead to a reduced acceptance of inequality.
- **Interpretation:** This contradicts the initial assumption, suggesting a universal educational influence on perceptions of inequality, irrespective of the education level.
- **Conclusion:** The findings highlight the pervasive impact of education on societal attitudes toward income disparity, emphasizing the role of education in shaping collective consciousness about equity.