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A Comment on "Acceptance of Inequality between Children: Large-Scale Experimental Evidence from China and Norway" by Cappelen et al. (2025)

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A Comment on “Acceptance of Inequality between Children: Large-Scale Experimental Evidence from China and Norway” by Cappelen et al. (2025)*

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Abstract

Cappelen et al. (2025) conduct an online experiment among Chinese and Norwegian adults to measure and compare the acceptance of inequality among children in the two societies. They find a significantly higher acceptance of inequality among children in China. The acceptance of inequality among children is also affected by the source of inequality and the costs associated with redistribution and is found to predict respondents’ attitudes towards child policies. In this discussion paper, we first successfully reproduce the main results of the paper. Doing so, we uncover a minor coding error, which, however, leaves the main results unchanged. We then conduct a number of robustness checks, including a redefinition of the main outcome variable and of some of the regressors. The main findings of the paper hold up to these robustness checks.

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1 Introduction

Cappelen *et al.* (2025) design and evaluate a large online experiment which is simultaneously conducted in China and Norway in two waves. The experiment aims to measure respondents' attitudes towards inequality among children. Respondents are presented with a scenario where two children receive different payoffs after completing a task and the respondents have to choose whether to redistribute the payoffs among the two children. The authors introduce several additional treatments which vary the age of the children, the source of inequality (luck or merit) and the cost of redistribution. They find that Chinese respondents are much more willing to accept inequality among children: they redistribute only half as often compared to Norwegian respondents. This finding persists across the different treatments. Moreover, respondents are found to redistribute less as the children get older, when the source of inequality is merit, and when redistribution is costly.

Cappelen *et al.* (2025) find that only 18.7% of adult respondents in Shanghai implement perfect equality, compared with 61.6% of adults in Norway. The authors depict the 95% confidence intervals of their estimates in all figures and refer to the 1%, 5% and 10% significance level using ***, **, and * in their tables. However, they also consistently report p-values in the discussion, creating transparency around the significance level of their results.

In the present report prepared for the Institute for Replication (Brodeur *et al.* 2024), we investigate whether their analytical results are computationally reproducible and further test their replicability and robustness to: (1) re-defining the main outcome, using the Theil index instead of the Gini index, (2) re-estimating all main regressions without covariates, and (3) re-defining the self-reported attitudes measures.

As reported in Section 2, we successfully reproduced all main tables and figures and would like to acknowledge Cappelen *et al.* (2025)'s diligence in preparing the replication package. All the data and codes are publicly available and easy to access. We uncovered one minor coding mistake: the variable identifying right-wing voters in the Norwegian sample codes respondents who either did not want to answer the question, declared they did not want to vote, were not allowed to vote, or did not remember who they voted for as “not right-wing”. We argue that the variable should

be coded as missing for these categories of respondents and test the robustness of the authors' results to re-coding this variable. However, we find that this coding decision does not impact the main results of the study.

We then turn to sensitivity analysis in Section 3. We first test the robustness of the results to using an alternative definition of the main outcome, the Theil index, which is more sensitive to extreme values than the Gini index, employed by the authors. This redefinition impacts some minor findings, especially in heterogeneity and subsample analysis, however, the main results of the study are robust. Second, we estimate all main regressions without covariates, with very reassuring results. Finally, we test the robustness of the paper's result to re-defining the self-reported attitudes measure, which play a crucial role in the authors' discussion of potential mechanisms. Again, all main findings survive this robustness check.

We conclude that Cappelen et al. (2025) is perfectly reproducible. The authors' results are also robust to the proposed robustness checks. Overall, we note the authors' exemplary use of pre-registration, diligence in data collection and documentation, and transparency with respect to how their analysis are performed.

2 Computational Reproducibility

Our reproduction relies on the replication package publicly provided [here](#). The raw data as well as the cleaning codes are included in the replication package and clearly explained in the Readme-file. The analysis do-files are clearly structured. The replication package also contains IRB approvals and experimental instructions for the participants in Norwegian, Chinese as well as an English translation. We note that not all variables in the final dataset are sufficiently labeled. For example "RS4", which corresponds to the main variable of interest ("Learn life is not fair") in Table 3 of the original paper, is not labeled in the dataset. Several other variables are only labeled in Norwegian, with no further explanations.

Based on the raw data, data cleaning do-files and analysis do-files, we successfully computationally reproduced all the main results in Figures 1-4 and Tables 1-3 from the raw data. See Table 1 for details. We found only one coding error in the data cleaning files. The variable identifying right-wing voters in the Norwegian

sample (“right”) was coded as “1” when respondents reported that they had voted for one of the right-wing parties, Høyre and FrP. All other respondents are coded as “0”, including those who reported that they did not want to vote (“Vil ikke stemme”, N=63 in the 2018 sample), did not want to answer the question (“Vil ikke si”, N=87 in the 2018 sample), were not sure (“Ikke sikker”, N=493 in the 2018 sample) and were not allowed to vote (“Har ikke stemmerett”, N=61 in the 2018 sample). Together these categories make up 30.5% of the 2018 sample of Norwegian respondents. In the 2023 sample, N=43 reported that they did not want to vote, N=45 did not want to answer the question, N=295 were unsure, and N=28 reported that they were not allowed to vote. Together, these categories make up for 26.0% of the 2023 Norwegian sample. We find it problematic to assume that these voters are not leaning to the extreme-right, especially for respondents who refused to answer the question. We therefore suggest to instead code the variable as missing for these categories of respondents.¹

The right-wing dummy is only included in Figure 2(b) and (d) of the original paper. We reproduce the figure using our preferred definition of the right-wing dummy, See Figure A1. Reassuringly, the results are very similar.

2.1 Discrepancies Between Pre-analysis Plan and Article

The authors uploaded two pre-analysis plans to the Social Science Registry, which were immediately shared with us upon our request. The pre-analysis plans are very detailed and systematic and contain all relevant details on the recruitment of participants and the experimental design. The first pre-analysis plan, which can be requested [here](#), provides details on the experiment carried out in China. The second pre-analysis plan which can be requested [here](#), provides further information

¹In a similar vein, the variable “child” was coded as “1” for respondents who did not want to report how many children were living in their household (“Vil ikke svare”). However, we consider this issue to be very minor, since only 1 respondent in the 2023 Norwegian sample refused to report on their number of children. Similarly, in the same experiment, 217 respondents refused to report their income before tax and 56 said they did not know, 17.7% of the total sample. The main regressions reported in the paper only control for a binary variable coded as “1” when respondents earn less than the median income. The respondents who refused to report their income or reported not knowing their income are coded as “0”, not below the median income. The authors acknowledge the imputation of missing education and income - not the imputation of missing family size - in the notes of Figure 2: “Adults with missing information on education or income are included in the above-median subgroup in the main analysis, but the results are robust to excluding these adults.”

on the experiment carried out in Norway.

The pre-analysis plans are broadly consistent with the article, with one minor exception: in Section 4.3 of the pre-analysis plan of the Chinese experiment, [Cappelen et al. \(2025\)](#) write “We employ two different approaches when coding the self-reported measures on attitudes that are on the form of agreement on a scale from 1-10. First, we consider them as continuous, coding answers 1-10 as 1-10. Second, we create dummy variables for each of the questions. When deciding on the cut-off for the dummies, we will take into considerations that we would like the groups to be similar in size.” In the published paper, the authors code the dummy as 1 whenever a respondent gave an answer above the median and 0 otherwise, consistent with the second part of the statement. However, they did not publish the results using the statements as continuous variables. This discrepancy between pre-analysis plan and article motivates our third robustness check, as described in the following section.

3 Robustness Reproduction

We now turn our attention to robustness replication. We first test the robustness of the results to changing the definition of the main outcome variable. [Cappelen et al. \(2025\)](#) compute inequality as the Gini index, which appears as a sensible choice given the widespread use of this index. We propose to test the robustness of their results to using an alternative, also widely used measure of inequality, the Theil index ([Theil 1967](#)). This measure is well-established in the economics literature ([Shorrocks 1980](#), [Milanovic 2002](#), [Cowell 2011](#)). Compared to the Gini index, the Theil index is similarly sensitive to the distribution of outcomes but places relatively greater weight on disparities at different points of the distribution. The first proposed robustness check therefore provides a meaningful test of whether the results hinge on the specific choice of inequality measure.

Second, we re-estimate all results without covariates. Given that randomization was fairly successful (Table A3 in the Online Appendix only shows imbalances with respect to the existence of children in the respondents’ households in the Norwegian sample), this should theoretically leave the main results unchanged. Estimating

results without covariates is a standard procedure allowing us to verify whether some of the results of the study are driven by the choice of covariates.

Third, we test the sensitivity of the study’s results to recoding the question items which serve as main regressors in Tables 3 and 5 of the original paper. We recode the variables following the instructions given in the authors’ pre-analysis plan as described in Subsection 2.1. This is a sensible robustness check since it is not clear why only one of the pre-registered ways of coding the regressor was reported in the study.²

3.1 Redefining the main outcome: inequality

We compute an alternative index of inequality following Theil (1967):

$$u_i = \frac{1}{2} \left(\frac{IncomeChildA_i}{MeanIncome} \cdot \ln \left(\frac{IncomeChildA_i}{MeanIncome} \right) + \frac{IncomeChildB_i}{MeanIncome} \cdot \ln \left(\frac{IncomeChildB_i}{MeanIncome} \right) \right)$$

where u_i indicate the inequality measure for individual i ’s choice, where she allocates income between child A and child B . We examine the distributions of the two inequality measures (Gini index and Theil index) separately for Shanghai and Norway. Figure A2 presents the kernel density plots of both measures by country. For Shanghai, the distributions of both the Gini and Theil indices are shifted to the right relative to Norway, indicating a generally higher level of accepted inequality among adult decision-makers. In contrast, the Norwegian distributions are more concentrated around lower values, consistent with a lower average acceptance of inequality. This ordered ranking is consistent with the reproduction of Figure 1 using the Theil index, shown in Figure A3. Although both Gini and Theil indices capture the same cross-country ranking, the Theil index exhibits somewhat greater dispersion, reflecting its higher sensitivity to tail differences in the distribution. As we can see the level of inequality acceptance in Figure A3, both Shanghai and Norway exhibit lower levels and the gap is narrower as compared to Gini measure.

The results using the Theil index are broadly consistent with those obtained using the Gini index. In particular, as shown in Figure A4, the associations between a set of background characteristics and implemented inequality remain robust. The

²The decision to conduct these three robustness checks was taken after reading the original paper and after verifying the codes/programs. The robustness analyses were not pre-registered.

direction and significance level for the coefficients of background characteristics are quite similar for both societies as compared to using Gini index. The effects by age groups also show similar patterns, as shown by Figure A5 Panel (a): individuals are more likely to accept inequality as children approach adulthood and the levels of inequality acceptance in Shanghai are still much higher than in Norway. The reproduction of Table 1 using the Theil index shown in Table A1 shows smaller magnitudes but at similar levels of statistical significance - adults' acceptance of inequality between children is causally affected by children's age. Moreover, the Theil index confirms the conclusions regarding the effects of efficiency concerns: Table A2 shows that making redistribution costly significantly increases inequality acceptance in both societies. Moreover, Cappelen et al. (2025)'s mechanism analysis is quite robust. We find similar magnitudes of coefficients and significance levels, as shown in Table A3. The only exception is the coefficient on "Norway", which surprisingly switches signs while staying highly significant. The results regarding the policy preferences for helping low-performing children in Norway are very robust and quite robust in Shanghai, as shown in Table A4. Taken together, these findings suggest that the main conclusions are not an artifact of the specific inequality measure employed.

However, some differences emerge when using the Theil index. Specifically, we find the effect of merit is higher in Shanghai than in Norway (Figure A5 panel (b)), while producing no significant merit treatment effects in estimations (Table A2). Additionally, we find no statistically significant interaction effects as shown in Figure A5 (c). The estimated effect of the interaction of the merit treatment and being confronted with a 17-year old child in Norway, as well as the interaction of the efficiency-treatment and being confronted with a 17-year old in Shanghai switch signs when using Theil index. While the latter was far from statistical significance in the original estimates, the former result was marginally statistically significant. Finally, after controlling for covariates, the Theil index cannot statistically significantly predict the policy preferences for children in Shanghai, while the direction of the coefficient is in line with the original results. Thus, while most results still hold, the strength of the evidence is somewhat weaker under the Theil specification.

3.2 Results without covariates

We re-ran all main regressions without control variables to test whether the results are driven by imbalances in observable characteristics across treatments. Tables A5 - A7 report the reproduced results for Tables 1 - Table 3 from the original paper. We find that the regression results without covariate adjustment are mostly consistent with the original results.

Table A5 checks for the causal effect of children's age without covariates. The pattern remains largely consistent with the main specifications. In both Shanghai and Norway, participants show more inequality acceptance as children's ages increase. The 17-year-old coefficient remains statistically significant in both societies for implemented inequality. The cross-societal difference in inequality acceptance remains substantial and highly significant. For the share-equalizing outcome, the age gradient in Norway remains strong and statistically significant, with adults becoming progressively less likely to equalize as children age.

Table A6 presents estimates of the effects of the economic environment without controls. The merit treatment effect remains positive and significant in Norway and marginally significant in Shanghai, as in the covariate-adjusted regressions. The efficiency treatment continues to yield highly significant effects in both societies. These results confirm the authors' conclusion that the source of inequality and the cost of redistribution causally affect inequality acceptance independent of participant characteristics.

Table A7 reproduces the mechanism analysis from Table 3 in the original paper without covariates. The coefficient on "Learn life is unfair" remains positive and highly significant, and the interaction with Norway remains negative and significant. This confirms that the learning mechanism plays a more important role in Shanghai than in Norway. The cross-societal difference in inequality acceptance persists across all specifications, even when no further covariates are included.³

³Note that Table 4 of the original paper already shows results without covariate adjustment. We therefore do not include the table in this analysis.

3.3 Redefining self-reported measures on attitudes

As noted in Section 2.1, the pre-analysis plan specified that attitude measures would be analyzed both as continuous variables and as binary variables. While Cappelen et al. (2025) only report results using continuous measures in Tables 3-4, we test the robustness of their findings by recoding these measures as binary indicators. Specifically, on a scale of 10, 1-5 are recoded as 0 while 6-10 are recoded as 1.

Table A8 reproduces Table 3 from the original paper using the binary coding of “Learn life is unfair”. Column (1) shows one noticeable change: the coefficient on the recoded “Learn life is unfair” variable for the pooled sample loses its statistical significance, though it remains positive and of similar size. This indicates that the relationship between learning attitudes and inequality acceptance may be more nuanced than what a binary split would capture. However, the interaction effect with the “Norway” indicator remains negative and highly statistically significant, which confirms that there are strong differences across societies, even with the binary coding. These patterns are consistent with the continuous variable results, though the statistical significance decreases for the learning mechanism reported in Column (1).

Table A9 reproduces Table 4 from the original paper using the binary coding of the policy preference variable “Helping Low-Performing Children”. As before, we code the variable as 0 when respondents gave an answer between 1 and 5 and 1 when respondents gave an answer between 6 and 10. The results remain fairly robust to this alternative specification. In both Shanghai and Norway, adults who implement more inequality in the experiment are significantly less likely to strongly support policies helping low-performing children. The magnitudes are somewhat smaller than with the continuous measure, but the direction and significance of the relationships persist.

4 Conclusion

Cappelen et al. (2025) conduct several independent experiments to investigate adults’ preferences towards inequality among children in Norway and China. Their study is backed up by two detailed pre-analysis plans and a comprehensive and

diligently prepared replication package, which allowed us to reproduce all of their results. We detect one coding error, which however does not impact the findings of the study. The main findings of the study are also robust to the sensitivity analyses we conduct.

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5 Tables

Table 1: Replication Package Contents and Reproducibility

Replication Package Item	Fully	Partial	No
Raw data provided	✓		
Analysis data provided	✓		
Cleaning code provided	✓		
Analysis code provided	✓		
Reproducible from raw data	✓		
Reproducible from analysis data	✓		

Notes: This table summarizes the replication package contents contained in [Cappelen et al. \(2025\)](#).

6 APPENDIX

Table A1: Reproduction of Table 1 with Theil index

	Shanghai (1)	Norway (2)	Pooled (3)
Norway			-0.146*** (0.010)
9 years	0.012 (0.020)	0.008 (0.019)	0.011 (0.014)
13 years	0.037* (0.020)	0.053*** (0.019)	0.046*** (0.014)
17 years	0.055*** (0.020)	0.049** (0.019)	0.052*** (0.014)
Constant	0.259*** (0.028)	0.243*** (0.024)	0.336*** (0.019)
Observations	3000	3014	6014
R^2	0.015	0.012	0.042

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Reproduction of Table 2 with Theil index

	Shanghai (1)	Norway (2)	Pooled (3)
Norway			-0.146*** (0.010)
Merit	0.010 (0.018)	-0.011 (0.016)	-0.001 (0.012)
Efficiency	0.077*** (0.018)	0.050*** (0.018)	0.063*** (0.012)
Constant	0.256*** (0.028)	0.259*** (0.023)	0.343*** (0.019)
Observations	3000	3014	6014
R^2	0.019	0.013	0.044

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Reproduction of Table 3 with Theil index

	(1)	(2)	(3) $I_B > 0$	(4) $I_B \leq I_A$
Norway	-0.139*** (0.010)	0.072*** (0.027)	-0.092*** (0.003)	-0.157*** (0.010)
Learn life is unfair	0.012*** (0.002)	0.029*** (0.003)		
Norway x Learn life is unfair		-0.030*** (0.004)		
Constant	0.272*** (0.022)	0.155*** (0.026)	0.117*** (0.006)	0.373*** (0.018)
Observations	6014	6014	4713	5878
R^2	0.045	0.056	0.163	0.044

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Reproduction of Table 4 with Theil index

	(1) Shanghai	(2) Shanghai	(3) Norway	(4) Norway
Inequality Theil Measure	-0.219* (0.112)	-0.104 (0.110)	-0.446*** (0.156)	-0.529*** (0.154)
Constant	7.001*** (0.056)	6.876*** (0.156)	6.957*** (0.069)	7.891*** (0.168)
Controls	No	Yes	No	Yes
Observations	3000	3000	3014	3014
R^2	0.001	0.053	0.003	0.039

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Reproduction of Table 1 without covariates

	Inequality			Share equalising		
	Shanghai (1)	Norway (2)	Pooled (3)	Shanghai (4)	Norway (5)	Pooled (6)
Norway			-0.281*** (0.010)			0.429*** (0.011)
9y	-0.002 (0.018)	0.038** (0.019)	0.018 (0.013)	0.025 (0.021)	-0.095*** (0.025)	-0.035** (0.016)
13y	0.022 (0.018)	0.074*** (0.020)	0.048*** (0.014)	0.003 (0.020)	-0.112*** (0.025)	-0.055*** (0.016)
17y	0.052*** (0.018)	0.072*** (0.020)	0.062*** (0.013)	-0.027 (0.020)	-0.113*** (0.025)	-0.069*** (0.016)
Controls	No	No	No	No	No	No
Constant	0.524*** (0.013)	0.216*** (0.014)	0.511*** (0.010)	0.187*** (0.014)	0.696*** (0.017)	0.227*** (0.012)
Observations	3000	3014	6014	3000	3014	6014
R^2	0.004	0.006	0.129	0.002	0.009	0.194

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Reproduction of Table 2 without covariates

	Inequality			Share equalising		
	Shanghai (1)	Norway (2)	Pooled (3)	Shanghai (4)	Norway (5)	Pooled (6)
Norway			-0.281*** (0.010)			0.429*** (0.011)
Merit	0.029* (0.016)	0.056*** (0.016)	0.043*** (0.011)	-0.049*** (0.018)	-0.192*** (0.021)	-0.121*** (0.014)
Efficiency	0.108*** (0.016)	0.065*** (0.018)	0.086*** (0.012)	-0.086*** (0.017)	-0.081*** (0.021)	-0.084*** (0.014)
Constant	0.497*** (0.012)	0.222*** (0.012)	0.500*** (0.010)	0.232*** (0.013)	0.707*** (0.014)	0.255*** (0.011)
Controls	No	No	No	No	No	No
Observations	3000	3014	6014	3000	3014	6014
R^2	0.016	0.006	0.133	0.008	0.026	0.202

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Reproduction of Table 3 without covariates

	(1)	(2)	(3) $I_B > 0$	(4) $I_B \leq I_A$
Norway	-0.277*** (0.010)	-0.114*** (0.026)	-0.280*** (0.007)	-0.289*** (0.010)
Learn life is unfair	0.006*** (0.002)	0.020*** (0.003)		
Norway \times Learn life is unfair		-0.023*** (0.004)		
Constant	0.498*** (0.014)	0.401*** (0.019)	0.384*** (0.006)	0.547*** (0.007)
Controls	No	No	No	No
Observations	6014	6014	4713	5878
R^2	0.127	0.134	0.260	0.130

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Reproduction of Table 3 with binary coding

	(1)	(2)	(3) $I_B > 0$	(4) $I_B \leq I_A$
Norway	-0.280*** (0.010)	-0.198*** (0.018)	-0.280*** (0.007)	-0.288*** (0.010)
Learn life is unfair (Recoded)	0.006 (0.011)	0.066*** (0.015)		
Norway \times Learn life is unfair (Recoded)		-0.113*** (0.021)		
Constant	0.566*** (0.019)	0.523*** (0.020)	0.392*** (0.012)	0.578*** (0.017)
Controls	Yes	Yes	Yes	Yes
Observations	6014	6014	4713	5878
R^2	0.130	0.134	0.266	0.136

Recoded “Learn life is unfair” as binary

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Reproduction of Table 4 with binary coding

	(1) Shanghai	(2) Shanghai	(3) Norway	(4) Norway
Inequality	-0.118*** (0.022)	-0.094*** (0.021)	-0.057** (0.022)	-0.066*** (0.022)
Constant	0.817*** (0.013)	0.850*** (0.029)	0.703*** (0.010)	0.846*** (0.024)
Controls	No	Yes	No	Yes
Observations	3000	3000	3014	3014
R^2	0.010	0.051	0.002	0.032

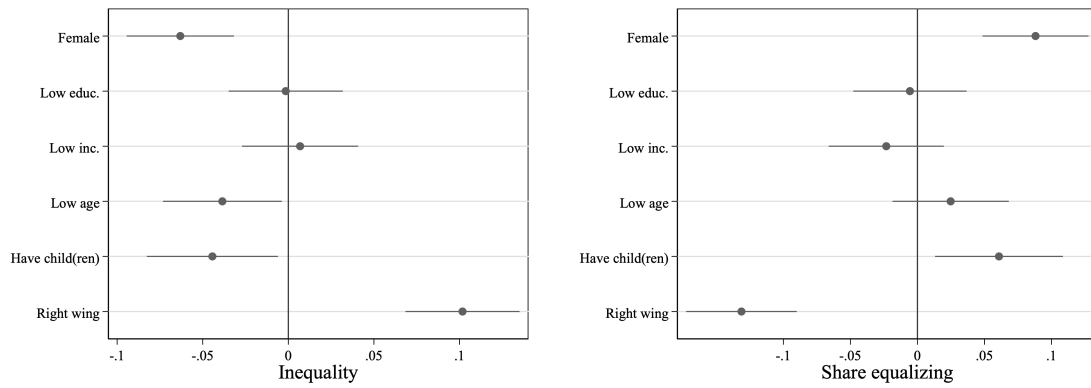
Recoded "Helping Low-Performing Children" as binary

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Appendix Figures

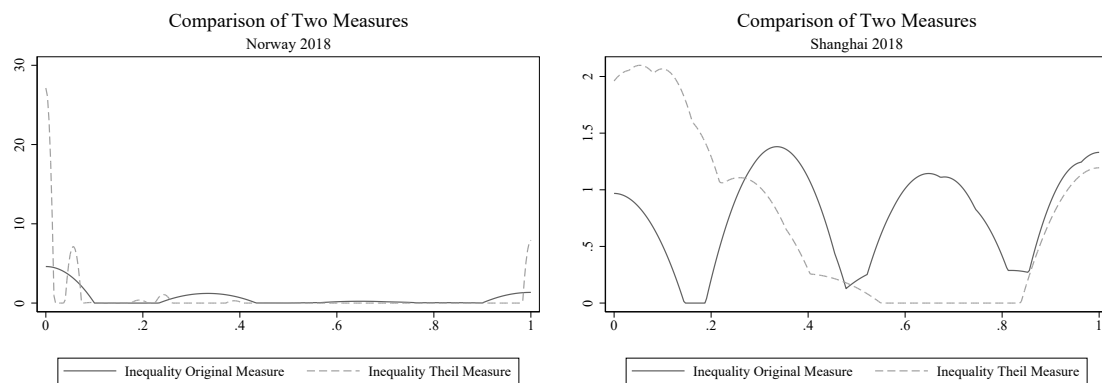
Figure A1: Reproduction of Fig.2, accounting for missing values in “Right-wing” variable



(a) Fig.2 (b) revised

(b) Fig.2 (d) revised

Figure A2: Kernel density plots of Gini and Theil indices by country



(a) Norway

(b) Shanghai

Figure A3: Reproduction of Figure 1 with Theil index

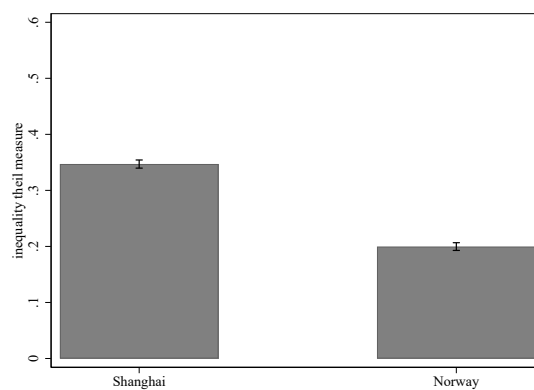


Figure A4: Reproduction of Figure 2 with Theil index

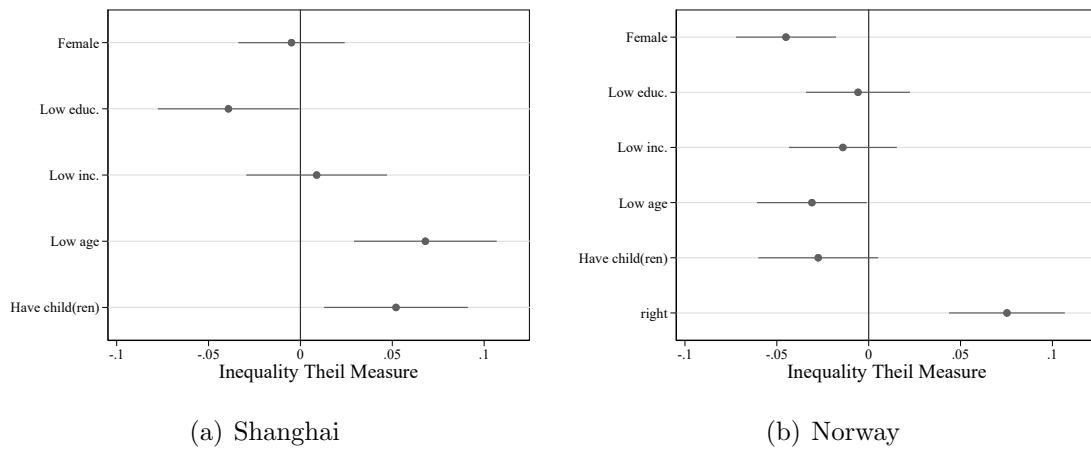


Figure A5: Reproduction of Figure 3 with Theil index

