Data Appendix for Deservingness and the Politics of Student Debt Relief
Perspectives on Politics
Mallory E. SoRelle and Serena Laws

A. Survey Administration and Sample

The data for our study were collected between May 20-26, 2022, three months prior to President Biden's announced debt cancellation, using an online survey administered to a sample of 1,503 U.S. adult respondents from Prolific. Prolific is an online recruitment platform for survey samples built explicitly to cater to academic research. Unlike several other platforms, Prolific requires minimum payments by time of required survey task. Consistent with Prolific guidelines, participants were paid $1.20 for completing the survey. While scholars have noted concerns about the use of convenience samples, there is considerable evidence that the conclusions drawn from experiments conducted using these samples are typically consistent with those derived from probability samples (e.g., Krupnikov et al. 2021). Moreover, recent studies have found that Prolific samples outperform peer platforms in data quality, exhibiting consistently high rates of attention, comprehension, honesty, and reliability among survey takers (Eyal et al. 2021). Several indicators suggest a high quality of data for our sample. We enabled Qualtrics bot detection, which employs Google reCAPTCHA technology to rate the likelihood that a response was provided by a bot. Responses that score below .5 on a scale from 0-1 are considered highly likely to be a bot. Only four responses out of 1,503 were flagged as bots, and we removed them from our analysis. Furthermore, 98 percent of participants responded substantively to an open-end probe following the conjoint.

We employed a representative sample from Prolific, wherein survey takers are matched to U.S. Census categories for race, gender, age, and their intersections at the point of administration. Prolific gathers basic demographic information about survey participants upon their registration for the platform. Thus, screening characteristics are collected independently from their participation in specific projects. When researchers elect to use a representative sample, Prolific calculates the necessary subgroups by stratifying the requested sample size (in our case, 1,500) across age, sex, and ethnicity characteristics. Based on the US Census, Prolific approximates the percentage of respondents who should fall into each intersectional category, cross-stratifying into five age brackets, five ethnicity brackets, and two sex brackets for a total of fifty subgroups. Participants are still allocated on a largely first-come-first-serve basis until the subgroups are complete.

Table A.1: Descriptive Statistics of Survey Sample

		Survey Sample (%)
Gender		
	Female	52
	Male	48
Race		
	White	74
	Black	13
	Latinx	5
	AAPI	6
	Other	2
Age		
	Range	18-93
	Mean	45
Education		
	Some High School	1
	High School Credential	9
	Some College	21
	Associates	11
	Bachelors	38
	Masters	16
	Doctoral or other terminal	4
Income		
	<$25,000	17
	$25,000-49,999	25
	$50,000-74,999	20
	$75,000-99,999	15
	$100,000-124,999	8
	$125,000-149,999	5
	$150,000+	9
Party ID		
	Democrat	49
	Republican	18
	Independent/Other	33

*Columns may not total to 100 due to rounding.

More information about their stratification and sampling process is available here: https://researcher-help.prolific.co/hc/en-gb/articles/360019238413. We did not employ any posthoc weighting for the sample. The survey contains several demographic variables for participants. Income is measured on a seven-point scale where each one-point increase corresponds to $25,000 of annual household income. A person's highest level of education is measured on a seven-point scale from some high school to Doctoral or terminal degree. Age is a continuous variable. Gender is a dummy variable where one equals male. Race is a five-category variable capturing participant's primary racial identity. Party identification is imputed to create a five-point scale from strong Democrat to strong Republican. Figure A.1 shows the resulting descriptive statistics for our survey sample.

While our survey sample is 1,500 participants, only half were randomly assigned to receive the deservingness conjoint analyzed in this paper. With 750 participants completing six pairs of the conjoint, the total number of profiles captured by our study is 9,000. This is, of course, fewer than the number of possible combinations of profiles in our design. However, conjoint analysis does not require the sample to approximate or exceed the number of potential profiles. The typical conjoint experiment contains many more unique profiles than are observed in the actual study (Hainmueller and Hopkins 2015). For example, in Hainmueller et al. 2014, which serves as the main primer on conjoint analysis in political science experiments, the candidate experiment they employ has 3,466 profiles rated despite the design generating 186,624 unique profiles. The randomization of attributes and levels produces an orthogonal relationship among attributes, allowing for valid estimation of average marginal component effects without capturing all unique profiles (Hainmueller et al. 2014). The primary concern for power in conjoint analysis is the highest number of levels, which in our case is four. The number of profiles viewed in our sample relative to the highest number of levels contained is consistent with other conjoint studies published in political science (e.g., Hainmueller et al. 2014; Hainmueller and Hopkins 2015; Sen 2017).

B. Additional Details of Conjoint Design and Analysis

Identifying an appropriate number of conjoint attributes must balance concerns over masking—the possibility that one attribute is capturing the effect of another omitted attribute—with the problem of satisficing—wherein participants engage in time saving behaviors that may reduce response quality. Studies of this tradeoff in the conjoint context have shown that satisficing is not likely to occur until the number of attributes reaches 35 (Bansak et al. 2019), well outside the range our conjoint. Survey takers evaluated six pairs of borrowers, which is also within the standard range. Due to an issue with the embedded data for the race variable for pairs five and six, the models in the main text will be run using the first four pairs. (To be clear, this did not affect survey takers, only the choices recorded for analysis for the race variable for the final two pairs.) The results are consistent when running the models across all six pairings without the race variable.

Attributes were chosen to eliminate implausible profiles; therefore, we impose no restrictions on the randomization of attributes and levels within our conjoint. This allows us to meet the assumptions for analysis with completely independent randomization (see Hainmueller et al. 2014), meaning we can estimate the AMCE using standard linear regression techniques while clustering standard errors by participant. Given the wide range of demographic characteristics for student borrowers, as described in the main text of the paper, we do not have external validity concerns about atypical profiles. We also keep that attribute order fixed both within and across respondents. Maintaining attribute order within respondent is common practice to reduce the cognitive load for participants. Studies have also found that in conjoint experiments with fewer than ten attributes (as ours is) row-order effects are not a concern (e.g., Hainmueller et al. 2014; Malhotra 1982). The distribution of statistically meaningful differences in outcomes corresponding with attributes across the rows in our experiment is consistent with this finding. We also consider the possibility that there are profile order effects, wherein participants might be more likely to select the first profile in the forced choice response. We construct a dummy variable to capture which profile was displayed as "borrower A" and run our analyses with this control. We find no statistically significant differences in which profile is chosen based on the order of profiles.

Figure A.1 on the following page provides an example how the conjoint appeared to participants. As described in the main text, participants reviewed six pairs of borrower profiles. After viewing each profile, they were asked to 1) choose which borrower was most deserving of student debt forgiveness and 2) rate the deservingness of each borrower separately on a scale from one to five, where one equals very undeserving and five equals very deserving of debt relief.

Figure A.1: Screenshot of Sample Conjoint Profile

Policymakers are considering a proposal to forgive student loan debt for certain types of borrowers. Please consider the following two people with student loan debt:

	Borrower A	**Borrower B**
Current or most recent occupation	Small Business Owner	Small Business Owner
Race	Asian	Hispanic
Employment status	Employed	Employed
Type of institution attended	Public 2- or 4-year College	For-profit College
Type of debt (undergraduate, graduate, or both)	Undergraduate	Undergraduate
Amount of debt remaining	$25,000-50,000	<$10,000
How long borrower has been repaying debt	1-5 years	5-10 years
Borrower payment history	Never missed a payment	Is currently behind on repayment

Which borrower most deserves to have a significant portion of their outstanding student loan debt forgiven?

- ○ Borrower A
- ○ Borrower B

How deserving of student loan debt forgiveness do you think each borrower described above is?

	Very Undeserving	Somewhat Undeserving	Neither Deserving Nor Undeserving	Somewhat Deserving	Very Deserving
Borrower A	○	○	○	○	○
Borrower B	○	○	○	○	○

C. Additional Details of Open-End Coding

After completing the conjoint exercise (viewing and evaluating 6 borrower pairs), respondents were asked the following open-ended question: "Still thinking about the questions you just answered, I'd like you to tell me what ideas came to mind as you were making those choices. Exactly what things went through your mind?" The question was not required, but if participants initially left the answer blank they were prompted (once) to ask if they really wanted to move on. Of the 750 participants assigned to this conjoint, 732 (98.1 percent) offered a substantive open-ended response. Responses varied in length and detail—some were just a phrase or sentence, others several paragraphs long.

The open-end responses provide context to better understand participants' thought processes in making their choices as to which borrower in each pair was most deserving. They offer an additional way of gauging which of the many borrower attributes was most important to participants in making their deservingness judgments—some attributes were mentioned often in the responses (such as employment status); others were not mentioned much at all (such as race). In some cases, they offered a space for participants to comment on the exercise itself and what was frustrating or difficult about it. These responses also help illuminate how participants interpreted different borrower attributes, suggesting which mechanisms were at work. For example, open-ended responses helped clarify whether the participant saw the amount of debt remaining as an indication of the borrower's need or as an indication the borrower had made a bad choice in taking out too large a loan.

We systematically analyzed the open-ended responses by identifying key themes from the CARIN typology and coding each response for whether it mentioned a particular theme. We coded the response one if it exhibited a given theme and zero if it did not. For example, one common theme in the open-ended responses was assessing which borrower seemed to need debt relief most. Thus, if an open-ended response mentioned any evaluation of need as part of the decision-making process it was coded “1” for need. Categories were not mutually exclusive, so a single response could receive multiple yes codes, and each response was evaluated for the presence of all codes. For example, it is quite possible an open-ended response indicated that assessments of need *and* employment status were both important in making judgments. Most responses were complex and touched on many themes. While categories were chosen by both authors, all coding was completed by a single author. Table A.2 describes all of the themes we identified by the CARIN category they tap into and the number and percentage of instances we found.

Table A.2: Descriptive Statistics of Open-end Probes

***Control*-related categories**	#	%
Mentions borrower’s responsibility or choices (borrower made the decision; their choices; their responsibility to repay)	68	9.3
Mentions school type (public/private/Ivy/for-profit AND graduate/professional degree)	102	13.9
Total responses containing one or more control-related comments (duplicates excluded)	158	21.1

***Reciprocity*-related categories**	#	%
Mentions employment status	268	36.6
Mentions repayment time (how long has been repaying)	170	23.2
Mentions repayment status (in default, current, delinquent, etc.)	239	32.7
Mentions public service	39	5.3
Total responses containing one or more reciprocity-related comments (duplicates excluded)	449	60.0

***Identity*-related categories**	#	%
Mentions race (as a positive factor for being deserving)	23	3.1
Mentions that race should not be a factor	30	4.1
Total responses containing one or more race-related comments (duplicates excluded)	54	7.2

***Need*-related categories**	#	%
Mentions perceived need (broadly defined)	59	8.1
Mentions amount of debt remaining	193	26.4
Mentions occupation	201	27.5
Discusses who's more/less likely to be able to pay off debt	47	6.4
Mentions that paying back would be a hardship for the person	13	1.8
Total responses containing one or more need-related comments (duplicates excluded)	361	48.3

D. Tabular Results for Figures

Table A.3: Tabular Results for Figure 1

	Support Relief	Borrower Ranking
Male (1=yes)	-0.239 *	-0.087
	(0.061)	(0.089)
White (1=yes)	-0.095	-0.069
	(0.073)	(0.502)
Income	-0.112 *	-0.047 $^{+}$
	(0.018)	(0.103)
Education	-0.037	-0.132 *
	(0.025)	(0.036)
Age	-0.013 *	-0.011 *
	(0.002)	(0.003)
Party ID	-0.456 *	-0.321 *
	(0.020)	(0.030)
Had Student Debt (1=yes)	0.291 *	0.287 *
	(0.065)	(0.095)
Constant	5.542	4.774
	(0.119)	(0.169)
N	1,492	741
R^2	.35	.21

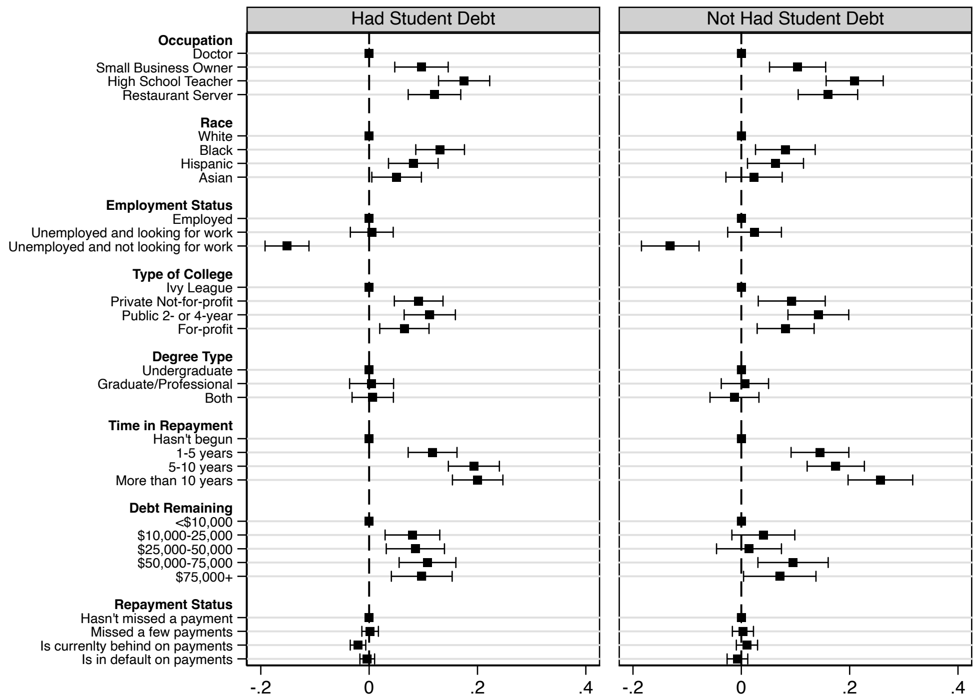
Notes: Base categories in parentheses. Figures in columns are coefficients from OLS regression. Coefficient standard errors are in parentheses
*p<.05 $^{+}$p<.1

Table A.4: Tabular Results for Figures 2 and 3

	Figure 2		Figure 3: Party		Figure 3: Race	
	FC	Rating	Dem	Rep	White	Non-White
Occupation (Doctor)						
Small Business	0.099* (.02)	0.170* (.05)	0.089* (.02)	0.100* (.04)	0.114* (.02)	0.054 (.03)
Teacher	0.188* (.02)	0.223* (.05)	0.170* (.02)	0.160* (.04)	0.208* (.02)	0.131* (.03)
Server	0.137* (.02)	0.162* (.05)	0.146* (.02)	0.106* (.04)	0.157* (.02)	0.082* (.03)
Race (White)						
Black	0.110* (.02)	0.088^{+} (.05)	0.135* (.02)	0.069^{+} (.04)	0.102* (.02)	0.127* (.03)
Latinx	0.073* (.02)	0.069 (.05)	0.088* (.02)	0.073^{+} (.04)	0.068* (.02)	0.091* (.04)
AAPI	0.039* (.02)	0.056 (.05)	0.043^{+} (.02)	0.070* (.04)	0.047^{+} (.02)	0.023 (.03)
Employed (yes)						
Unemployed, looking	0.013 (.02)	0.026 (.04)	0.026 (.02)	-0.034 (.03)	0.002 (.02)	0.050 (.03)
Unemp., not looking	-0.143* (.02)	-0.420* (.05)	-0.138* (.02)	-0.149* (.03)	-0.165* (.02)	-0.077* (.03)
College (Ivy)						
Private	0.093* (.02)	0.143* (.05)	0.097* (.02)	0.086* (.04)	0.101* (.02)	0.072^{+} (.04)
Public	0.123* (.02)	0.154* (.05)	0.123* (.02)	0.133* (.04)	0.140* (.02)	0.081* (.03)
For Profit	0.073* (.02)	0.115* (.05)	0.060* (.02)	0.112* (.04)	0.085* (.02)	0.035 (.03)
Degree (Undergrad)						
Grad/Professional	0.006 (.02)	-0.001 (.04)	0.018 (.02)	-0.021^{+} (.03)	-0.003 (.02)	0.023 (.03)
Both	-0.001 (.01)	0.026 (.04)	0.002 (.01)	-0.035 (.03)	0.007 (.02)	-0.030 (.03)
Repayment (none)						
1-5 years	0.130* (.02)	0.187* (.05)	0.128* (.02)	0.180* (.04)	0.124* (.02)	0.142* (.03)
5-10 years	0.187* (.02)	0.323* (.05)	0.178* (.02)	0.246* (.04)	0.169* (.02)	0.233* (.03)
10+ years	0.224* (.02)	0.317* (.05)	0.230* (.02)	0.263* (.04)	0.211* (.02)	0.255* (.03)
Debt (<$10k)						
$10-25k	0.064* (.02)	-0.046 (.05)	0.074* (.02)	0.059 (.04)	0.024 (.02)	0.064* (.04)
$25-50k	0.056* (.02)	-0.085^{+} (.05)	0.098* (.03)	-0.006 (.04)	0.067^{+} (.02)	0.056* (.04)
$50-75k	0.103* (.02)	-0.030 (.05)	0.147* (.03)	0.014 (.04)	0.126* (.03)	0.103* (.04)
$75k+	0.086* (.02)	-0.041 (.05)	0.122* (.03)	0.058 (.05)	0.078* (.03)	0.113* (.04)
Status (never missed)						
Missed some payments	0.002 (.01)	-0.122^{+} (.01)	0.001 (.01)	0.003 (.01)	0.001 (.01)	0.010 (.01)
Currently behind	-0.009 (.01)	-0.106^{+} (.01)	-0.014 (.01)	-0.004 (.01)	-0.007 (.01)	-0.016 (.01)
In default	-0.005 (.01)	-0.108^{+} (.01)	-0.011 (.01)	-0.004 (.01)	-0.005 (.01)	-0.002 (.01)
n	5,968	5,975	3,776	1,360	4,296	1,656
R^2	0.09	0.04	0.10	0.09	0.09	0.09

Notes: Base categories in parentheses. Figures in columns are coefficients from OLS regression. Coefficient standard errors are in parentheses
*p<.05 $^{+}$p<.1

E. Supplemental Analysis of Student Borrowers



F. References

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