The Impact of Diversity on Distributive Perceptions and Preferences for Redistribution

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Abstract

Does socioeconomic diversity affect people's perceptions of income distribution and redistributive preferences? I leverage a financial aid reform that drastically boosted the share of low-income students at selective universities in Colombia. Unlike affirmative action, the admissions process remained unaffected, which enables identifying the causal effect of diversity. I combine original survey data with administrative microdata to examine high-income students' outcomes as a function of exposure to low-income peers, leveraging treatment variation across cohorts and majors using difference-in-differences. Diversity caused high-income students to have more accurate perceptions of poverty, raised their concerns about fairness, and boosted their support for progressive redistribution.

JEL codes: D31, D63, I22, I24

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1 Introduction

What drives people's preferences for redistribution? Researchers have shown that individual preferences can respond to (mis)perceptions about the distribution of income and social mobility, which are formed endogenously through people's access to information and social interactions (Alesina et al., 2018; Cruces et al., 2013; Kuziemko et al., 2015). Thus, can changing people's social interactions—specifically, exposing them to a more socioeconomically diverse group of individuals—correct these misperceptions and alter their support for redistribution? Identifying the causal effect of diversity on individual perceptions and preferences is challenging due to the endogeneity of social interactions and peer groups. Indeed, previous studies have rarely manipulated these outside the lab or field experiment. As a result, we know little about how people's preferences respond to real-life policies promoting diversity, such as need-based financial aid and affirmative action.

This paper overcomes these challenges to estimate the effect of exposing high-income individuals to low-income peers on their perceptions of the income distribution and social mobility, and their support for progressive redistribution. In 2015, the Colombian government implemented a massive tertiary education financial aid program for low-income high achievers to attend selective universities. The policy generated an unprecedented and unanticipated influx of low-income students into elite institutions, boosting the socioeconomic diversity of their student body (Londoño-Vélez et al., 2020). Unlike affirmative action, which usually trades off diversity for average quality, Colombia's financial aid policy left the college admissions process virtually unaffected. Low-income students were not given preferential treatment in admissions, enabling me to disentangle between having socioeconomically diverse versus lower-achieving peers. This provides an ideal setting to evaluate how perceptions and preferences are causally influenced by socioeconomic diversity.

I focus on a university that historically catered to high-income students and that, as a result of the policy, quadrupled its share of entering low-income students. I collect original survey data six and twelve months after the policy rollout. I survey students who began their studies before or after the policy and measure their social networks, beliefs, and preferences using survey experiments. I combine these survey records with the partner university's administrative records on admissions and classroom composition to create a measure of a student's exposure to low-income peers—the main treatment variable.

I leverage three key institutional features for identification. First, the policy raised diversity for cohorts entering college in Spring 2015, whereas older cohorts were significantly less affected by the policy. Second, the composition of *high*-income students did not change immediately after the policy, allowing me to cleanly compare high-income students across cohorts. Third, there is little room for self-selection into courses with more or less low-income peers. These crucial features are leveraged by a difference-in-difference design that compares high-income students' outcomes as a function their degree of exposure to low-income students across cohorts (before and after the policy rollout) and majors (with smaller and greater shocks in diversity).

To examine people's awareness of others' SES, I exploit a unique feature of this setting: Colombia's socioeconomic stratification system. This system explicitly stratifies households from 1 to 6 by affluence (1 being the poorest) based on neighborhood and dwelling characteristics. Most Colombians are well aware of their stratum, making this information easy to collect. Moreover, they likely are able to infer others' stratum (based, for instance, on where they live) better than other measures of SES, like household income or wealth. For this reason, the stratum is a popular measure of SES among researchers and policy-makers in Colombia. Its salience makes it ideal to study perceptions of SES and inequality.

There are three main findings. First, exposure to low-income peers fostered interactions among students of diverse socioeconomic backgrounds. A greater share of high-income students named a low-income student among their five closest friends or study partners. While previous research has shown that changing the group of potential peers does not necessarily change the peers one chooses to associate with, or may change them in unexpected ways (Carrel et al., 2013), I find that high income students have meaningful increased interactions with lower income students as a result of the policy. Second, exposing high-income students to low-income peers reduced the (upward) bias in their perception of the income distribution, translating into more accurate beliefs about the national share of low-income families. Third, exposure to low-income peers also raised concerns about fairness—specifically, an awareness of the difficulty of overcoming poverty without government intervention. This, coupled with a null result on perceptions of upward social mobility, resulted in high income students becoming more supportive of progressive redistribution.

These findings contribute to the literature on how individuals form preferences for redistribution. Previous studies using surveys, lab or field experiments have shown that preferences for redistribution respond to subjective perceptions of one own's position in the income distribution (Cruces et al., 2013; Meltzer and Richard, 1981), social justice (Alesina and Ferrara, 2005; Alesina and Angeletos, 2005; Alesina et al., 2001), social mobility (Alesina et al., 2018; Benabou and Ok, 2001; Piketty, 1995), the perception of the income distribution (Ariely and Norton, 2011; Kuziemko et al., 2015), culture (Luttmer and Singhal, 2011), interpersonal preferences (Luttmer, 2001), and reference points (Charite et al., 2016). In contrast, I study the formation of beliefs and preferences using naturally ocurring variation. This is crucial because how people behave in the lab or the field might differ from how they react to government interventions in practice. Specifically, I evaluate how a real-life, large-scale policy intervention—a financial aid program for low-income students—affects individuals' beliefs and preferences. This natural experiment is ideal to study the causal effects of peer composition on beliefs and preferences. It is also especially policy relevant, given recent evidence of high income segregation across colleges (Chetty et al., 2020) and the prospect of fostering diversity through financial aid (Hoxby and Avery, 2013).

A related literature in behavioral economics studies the effects of affirmative action—which directly promote socioeconomic and/or racial diversity often at the expense of quality—on social behaviors, like generosity, discrimination, stereotypes, and prejudice (Boisjoly et al., 2006; Burns et al., 2019; Rao, 2019).[1] In particular, I extend Rao (2019) by studying a policy that left the admissions process virtually unaffected, enabling me to cleanly disentangle between having socioeconomically diverse versus lower-achieving peers. Moreover, I measure beliefs about the distribution of income and fairness, and show how changes in beliefs also shape preferences for redistribution. Lastly, I show that it is possible to affect political preferences in adults, not only by integrating at a young age. This is particularly relevant given adults may exercise their democratic right to vote.

The remainder of the paper is organized as follows. Section 2 introduces the intuition for how reference groups affect individuals' perception of the income distribution and their redistributive preferences. Section 3 provides some institutional background and describes the financial aid program. Section 4 presents the data, while Section 5 describes the methodology used. Section 6 desribes social interactions between high- and low-income students and their awareness of others' SES. Section 7 presents the results on beliefs about the income distribution and preferences for redistribution. Section 8 explores the mechanisms and offers a brief discussion. Finally, Section 9 concludes.

[1] In addition to recent works by economists (see, for instance, Bazzi et al., 2019; Burns et al., 2019; Carrell et al., 2019; Finseraas et al., 2019; Lowe, 2021; Rao, 2019, and references therein), the study of contact theory (Allport, 1954) has also been explored by psychologists, sociologists, and political scientists (see Paluck et al., 2019, for a recent review). I bring together the literatures on intergroup contact theory and beliefs about inequality and support for redistribution in the context of a real-world public policy.

2 Conceptual Framework

This section summarizes the statistical inference problem in individuals' assessment of the income distribution. Agents infer the distribution of income based on their access to information about individuals' level of income and their ability to process this information. In the presence of limited information, agents observe the income levels of only a subset of the population and apply Bayes' rule to infer the entire distribution from the subset they observe (the "reference group"). If agents are fully rational, they arrive at consistent estimates of the income distribution by accounting for the relative size of the reference group, the selection or non-representativeness of this reference group, and their ability to make probability judgements.[2] If, instead, agents are naïve—i.e., they fail to properly apply Bayes' rule—they have systematically biased inferences of the income distribution.

Selection into a reference group is likely a function of income: agents who have "rich" reference groups are more likely to observe higher-income individuals and vice-versa. Thus, naïve agents with rich reference groups will overestimate the share of high-income individuals and have biased estimates of many moments of the income distribution, such as the mean, dispersion, and fraction of individuals under the poverty line (for an illustration, see Figure A.1). More generally, if reference groups are more homogeneous in income than the total population, perceptions about income inequality will be biased downward. Indeed, survey evidence shows individuals systematically underestimate the level of inequality in OECD (Ariely and Norton, 2011) and non-OECD countries (Cruces et al., 2013).

Applying this framework to my empirical setting, consider a college student who infers the income distribution from their reference group, which includes friends and classmates. A high-income student might have rich reference groups given friendship homophily and, especially if higher education is segregated, exposure to classmates of similar socioeconomic background. The above model offers two testable predictions:

Prediction 1: A naïve high-income student with rich reference groups systematically overestimates the share of high-income individuals and underestimates the fraction of the population below the poverty line.

Prediction 2: Exogenously exposing the naïve high income student to low-income peers reduces their misperception.

Correcting the bias might impact individuals' stated preferences for redistribution. In the self-interested model by Meltzer and Richard (1981), making high-income individuals more aware of their relative position in the income distribution *reduces* their support for

[2]For a more detailed discussion, see Cruces et al. (2011, 2013) and references therein.

redistribution. Preferences for redistribution also weakens if the treatment strengthens the perception of upward mobility (POUM) (Benabou and Ok, 2001; Hirschman and Rothschild, 1973; Piketty, 1995). If, instead, interacting with heterogeneous groups affects their views on the fairness of the economic system (Alesina and Angeletos, 2005), exposure to low-income peers *raises* support for redistribution. This leads to the third and final testable prediction:

Prediction 3: Exogenously exposing the naïve high income student to low-income peers boosts support for redistribution if fairness concerns are sufficiently large.

3 Background

This section describes the setting of this study; specifically, the segregation of Colombia's higher education system. It then describes the reform-induced shock in socioeconomic diversity that took place at an elite university, henceforth referred to as the partner university, and which is used to estimate effects.

Colombia's college admission process begins with SABER 11, the national standardized high school exit exam. SABER 11 is taken by virtually all high school seniors, regardless of their postsecondary intentions, and it has widespread use in colleges' admissions processes (OECD and The World Bank, 2012). Applications are decentralized, major-specific, and biannual, with college beginning in the spring (fall) for most public (private) high school graduates. At the partner university, SABER 11 is the sole condition for admissions and applicants who score above their intended major's cutoff are admitted. These cutoffs, which depend on the supply of seats available each semester, are unknown and unpredictable by applicants at the time of application (Barrera-Osorio and Bayona-Rodriguez, 2019).

Private high-quality universities are costly in Colombia; their average tuition fee is over tenfold the public equivalent. A lack of financial aid available excludes low-income students from these universities (Melguizo et al., 2016; Sanchez and Velasco, 2014).[3] While public high-quality universities are more affordable thanks to heavy government subsidies, they are over-subscribed and reject most applicants. As a result, the overwhelming majority of low-income students are left with the alternative of attending a medium- or low-quality postsecondary institution (Ferreyra et al., 2017). Thus stems Colombia's severe de facto segregation in postsecondary education.

[3]Less than 10 percent of high school graduates from strata 1 and 2 received financial aid (Melguizo et al., 2016; Sanchez and Velasco, 2014) and only a handful of private universities offered resources to low-income students. For instance, the University of Los Andes' *Quiero Estudiar* aid program covered less than one in 20 students by 2014.

In October 2014, the government announced the introduction of *Ser Pilo Paga* (roughly “hard work pays off” in Spanish, and henceforth referred to as SPP), Colombia’s first large-scale need- and merit-based college financial aid program. To be eligible, applicants had to score among the top 9 percent of the SABER 11 distribution and be sufficiently low-income. They also had to be admitted at one of Colombia’s 33 government-certified “high quality" universities.[4] Between 2014 and 2018, roughly 40,000 students benefited from SPP. Londoño-Vélez et al. (2020) show that the policy radically changed the student body composition at private high-quality universities, historically reserved for those who could afford their pricey tuition fees: their share of entering low-income students increased by 46 percent.

The unprecedented boost in socioeconomic diversity was exceptionally pronounced at the partner university. By January 2015—barely three months after the announcement of SPP—roughly one-third of new entrees were beneficiaries of SPP. Figure 1 plots Spring freshmen students by their socioeconomic stratum (a measure of SES) and shows that the share of low-income students—henceforth defined as those from the bottom two strata—almost quadrupled from 7.1 percent to 27.3 percent between 2014 and 2015, and further reached 33.3 percent in 2016. Reflecting heterogeneity in tastes, Figure 2 shows that the share of SPP recipients varies substantially across majors. For instance, while 71.4 percent of the entering Philosophy majors were beneficiaries of SPP, none of the entering Art History majors were beneficiaries of SPP at the partner university. Critically, the share of SPP students in a given major is not correlated with the SABER 11 admission cutoff of that major (the p-value on that regression is 0.148).

Five features of SPP are particularly important for the analysis. First, the boost in diversity was *not* offset by a decrease in the average quality of new enrollees at the partner university.[5] Unlike affirmative action, SPP beneficiaries received no preferential treatment in college admissions, which remained based solely on SABER 11 standardized test scores.

Second, high-income students did not immediately modify their application and enrollment decisions in response to the policy (based, for instance, on their affinity for low-income peers): the number of applications, the admission rate, and the yield rate all

[4] Insofar as High Quality Accreditation status was awarded well in advance of the announcement of SPP, universities could not immediately self-select into receiving or not beneficiaries of SPP.

[5] If anything, *average* cognitive ability increased. To illustrate why, Figure A.2 presents applicants’ standardized test scores for those seeking to enroll between Spring 2013 and Spring 2016 immediately after graduating high school. While the distribution of applicants’ scores did not change much prior to SPP, SPP raised the number of applicants just above the program’s eligibility cutoff: as soon as low-income students scored in the top 9 percent of national test scores (specifically, a score of 310/500), they sent their application to the partner university. The greater demand for admission shifted the admission cutoff towards the right.

remained constant for high-income applicants (see Figure A.3).[6] This reflects the surprise nature of the policy: SPP was announced *after* students had taken the SABER 11 exam and shortly before the partner university's admission deadline (see the timeline of events in Figure A.5). News reports on how SPP had diversified elite universities were published only *after* the spring 2015 term had begun (La Silla Vacía, January 13, 2015).

Third, the policy did not affect the composition of *high-income* students at the partner university. High-income applicants were ex-ante scoring well above SPP's eligibility cutoff; on average in the 98th percentile of national test scores both in Spring 2014 and Spring 2015. Moreover, the university somewhat expanded the supply of its seats available in 2015 in response to the increased demand triggered by the policy (see Figure A.6 and Londoño-Vélez et al. (2020)).

Fourth, financial aid was only awarded to students enrolling in college for the first time in Spring 2015. Thus, the policy did not significantly change the composition of cohorts that began college *before* Spring 2015.

Lastly, high-income students have little ability to self-select into exposure to low-income peers. Colleges were not permitted to track students by their SES and SPP beneficiaries were integrated in the same classrooms as non-beneficiaries. At the partner university, course curriculum is relatively set within a major and students have significantly less freedom to choose their courses than traditional American universities (and especially so during their freshman year).

Together, these institutional features generate a unique opportunity to identify the causal effect of diversity. As Section 5 details, the difference-in-difference approach will leverage both the within-cohort, across-major *and* the within-major, across-cohort variation in the share of SPP classmates to estimate effects.

4 Data

This section describes the administrative and survey data used. The data for this paper come from four main sources:

1. **Administrative records from the partner university on undergraduate admissions and enrollment.** The admissions records include detailed student-by-semester level information about applications, admissions, and matriculation for 2010–2016. These

[6]While students who find that they particularly dislike low-income classmates may transfer to a major with a smaller prevalence of SPP recipients, there was no increase in switching to majors with fewer SPP beneficiaries (see Figure A.4). The possibility of transfering to a non-SPP-receiving university is also unlikely, as there are large long-term costs of attending a university without High Quality certification (Camacho et al., 2017).

records include applicants' sociodemographic characteristics (e.g., sex, date of birth, socioeconomic stratum, parental education), SABER 11 test score, and major, as well as the university's admission score (i.e., a major-by-semester-specific weighted average of the different components of SABER 11) and the major-by-cohort admission cutoff. For students ever enrolled between 2000 and 2016, I observe detailed semesterly information about the courses taken, which is used to construct the main treatment variable (the share of SPP classmates) as well as alternative treatment variables (e.g., the share of low-income classmates).[7]

2. **Administrative micro-data from Colombia's Ministry of Education and ICETEX, the institutions in charge of the SPP program.** This includes student-level information about all SPP beneficiaries and is used to build measures of intensity of social interaction between high-income students and their SPP peers.

3. **Administrative data from ICFES, the institution in charge of delivering the SABER 11 high school exit exam.** It contains information for all students taking the SABER 11 standardized exam between 2003 and 2016. I use this data to normalize test scores.

4. **Survey data collected by myself specifically for this research project using Qualtrics online survey software.** The remainder of this section describes the survey design and implementation.

I sampled high-income students—henceforth defined as belonging to socioeconomic strata 4, 5, or 6—matriculated in any undergraduate program at the partner university. I sampled students from all majors and three cohorts: those who entered in Spring 2014, Fall 2015, or Spring 2015, that is, before and after SPP was implemented. The questionnaire collected information on students' beliefs about the income distribution, social justice, and redistributive preferences. To measure how intensely high-income students interact with low-income peers, the survey recorded students' social and study networks as well as their perceptions about their SPP classmates. Appendix B includes the screenshots of the Qualtrics survey.

The link to the online survey was sent to students' institutional email from the university's Office of Admissions and Registration. To avoid experimenter demand effects, the survey consent form explained that the purpose of the survey was to "gather

[7] The treatment variable is computed using the partner university's administrative data on course enrollment. Since, as I will explain, students were surveyed in the first week of each term, I define the treatment as the share of SPP classmates in the previous term. For instance, survey wave 1 was collected in the first week of the fall 2015 term and I use information on course enrollment in the spring 2015 term to construct the instrument.

information on college students' beliefs and political attitudes." There was no mention of SPP. For their participation, respondents were compensated in cash (2015 COP 10,000 or roughly 2015 US$ 3.4) or in kind (a burger combo at a popular burger chain near campus). They were allowed to donate their compensation.

I collected two waves of survey data in the first week of instruction in the fall and spring semesters. Wave 1 was completed in August 2015, that is, after one semester of treatment (see Figure A.5 for a timeline of events). Wave 2 was collected in early February 2016, that is, after one year of treatment. I pool both waves in my main estimates and include the results for each wave separately in Appendix A.

In all, 20.2 percent of the 4,993 students who were sent the survey link (2,200 in wave 1 and 2,793 in wave 2) answered the survey. Appendix Table A.1 shows there is balance in the response rate across cohorts. Indeed, I cannot reject the null hypothesis that the coefficients on the three cohort dummies are the same: the p-value on the joint F-statistic is 0.4453 without controls in Column (1) and 0.8790 with controls in Column (2). Moreover, the treatment (i.e., the share of SPP classmates) does not influence the likelihood of responding to the survey: the p-value is 0.157 without controls and 0.338 with controls.

5 Empirical Strategy

This section describes the empirical approach used to estimate the effect of socioeconomic diversity on beliefs about the income distribution and redistributive preferences. I exploit the plausibly exogenous exposure of high-income students to low-income peers introduced by the SPP financial aid policy as well as variation in the treatment intensity using the following difference-in-difference specification:

$$y_{imkw} = \alpha + \beta \text{ Share of SPP Classmates}_i + \delta_m + \psi_k + \theta_w + \mathbf{X}_i'\Gamma + e_{imkw} \qquad (1)$$

where y_{imkw} is outcome y for student i in major m and cohort k surveyed in wave w, Share of SPP Classmates$_i$ is the student's average share of classmates that receive SPP financial aid (the main treatment variable), δ_m are major fixed effects, ψ_k are cohort fixed effects, θ_w are survey wave fixed effects, $\mathbf{X}_i$ is a vector of individual controls, and e_{imkw} is a student-specific error term.[8] The β coefficient in Specification (1) is thus the average effect on outcome y of a one percentage point increase in the share of classmates that are SPP

[8]The vector $\mathbf{X}$ contains sex, age and its quadratic term, a migrant dummy, SABER 11 percentile, dummies for parental education, risk aversion (from a heads or tails game), and socioeconomic stratum.

recipients and is the key parameter of interest. This approach identifies the average effect on high-income college students of adding low-income classmates (who are of similar ability), which is a relevant estimate for common policies.

Note that this difference-in-difference approach exploits two sources of variation in the treatment variable. First, it leverages the within-major, across-cohort variation that accounts for any cross-cohort change in the composition of high-income students or any other cohort-specific shock that could drive the estimates. Second, it uses the within-cohort, across-major variation in the influx of low-income students described in Section 3 and plotted in Figure 2.[9]

To support the validity of this empirical design, I show that the treatment is *not* correlated with student observable characteristics. Indeed, a common approach to validate the quasi-random nature of a treatment is to examine balance in observable characteristics between treated and control units. Figure 3 plots the coefficients and associated 95 percent confidence intervals from regressing the predicted value of the outcome using a given baseline covariate, $\hat{y}_{imkw}$, on the treatment using Specification (1).[10] The first line in each panel shows the result when $\hat{y}_{imkw}$ is based on all the covariates. The following rows separately use a single covariate to predict $\hat{y}_{imkw}$ at a time. There is balance in observable covariates between students exposed to more versus less SPP peers, which supports the validity of my empirical design.

6 Social Interactions between High- and Low-Income Peers

This section documents the extent to which the policy fostered socioeconomically diverse interactions. This point is important because one could be concerned that high-income students simply do not observe low-income students, either because they cannot infer others' SES or because they do not interact with them (as would be the case, for instance, under extreme homophily). Either of these scenarios would bias my estimates towards zero.

Table 1 presents summary statistics combining both survey waves for the three cohorts of high-income students separately. The first row reports the average share of SPP classmates—the main treatment variable. For students entering college in Spring 2014, i.e., a year before SPP was implemented, only 2.88 percent of their classmates in 2015 were SPP beneficiaries. In contrast, this share is 14.03 percent for students in the Spring 2015 cohort.

[9] Figure A.7 illustrates the variation in the treatment variable leveraged in the regression analysis.

[10] Following Chetty et al. (2014), I use the predicted outcomes, $\hat{y}_{imkw} = \mathbf{X}_i'\hat{\Omega}$, to have all the covariates on the same scale.

On average, the Spring 2015 cohort is five times more exposed to SPP beneficiaries.

To measure social networks and examine students' awareness of others' SES, I asked survey participants to list their five closest friends and study partners (see Figures B.1 and B.2) as well as the socioeconomic strata of their listed friends (see Figure B.3). The second row of Table 1 shows that only 5.1 percent of the Spring 2014 cohort and 3.8 percent of the Fall 2014 cohort report having a low-income friend, i.e., a friend from stratum 1 or 2. Relative to older cohorts, students from the Spring 2015 cohort are almost twice as likely to have low-income friends and this difference is statistically significant (the p-value is 0.017). This reflects the impact of the policy on friendship formation among students with diverse socioeconomic backgrounds.

I next asked students about their perception of SPP classmates and their personal interactions with them. Specifically, I asked them to report what share of their classmates were SPP beneficiaries (see Figure B.4) and how many times they had worked with SPP beneficiaries (see Figure B.5). The results, reported in the third and fourth rows in Table 1, show that high-income students are well aware of classmates' SPP status. Sociological work by Alvarez (2019) finds this is often inferred from the clothing and mobile phone brands students use, the high school they attended, and the way they speak Spanish and English. While students from the Spring 2015 cohort perceive a significantly higher prevalence of SPP classmates than students from older cohorts, all cohorts overestimate the actual share—particularly older students. Lastly, consistent with the policy leading to more interactions of high-income students with their low-income peers, the Spring 2015 cohort is three times more likely to have worked with a SPP beneficiary (the p-value is 0.000).

The final rows compare the likelihood that a high-income student named a SPP beneficiary among their five closest friends or study partners. Reflecting the extent to which the policy diversified social networks, students from the Spring 2015 cohort are tenfold as likely to name a SPP beneficiary among their closest friends or study partners.[11] Thus, to the extent that peer group formation is inherently endogenous, Table 1 suggests that the policy substantially influenced social interactions between high- and low-income

[11] A back-of-the-envelope calculation suggests that if students selected their friends/study partners at random among their classmates, then students from the Spring 2015 cohort would have a 54.6 percent chance of having at least one SPP recipient among their five closest friends/study partners. The Fall and Spring 2014 cohorts would have a 23.5 percent and 13.6 percent chance of having at least one SPP beneficiary among their five closest friends/study partners, respectively.

students and generated more socioeconomically diverse peer groups.[12] The following section will show how this exposure to diversity influenced people's beliefs about the income distribution and their preferences for redistribution.

7 Results

In this section, I test whether exposure to socioeconomic diversity affects high-income students' beliefs about the distribution of income and their preferences for redistribution.

7.1 Beliefs about the Distribution of Income

To measure perceptions of the income distribution, the survey respondents were asked: "*What percentage of Colombians do you think are poor* (*that is, those earning less than 200 thousand pesos* [*2014 USD 84.16*] *per month*)*?*" (see Figure B.6). To map their beliefs about the entire distribution, respondents were then asked: "*What share of Colombians do you think belong to each socioeconomic stratum?*" (see Figure B.7).

Figure 4 plots the responses given by the Spring 2014 cohort. The gray bars report the actual distribution of socioeconomic strata, using information from all students graduating high school in 2014. The black bars plot the mean perceived distribution. Following prediction # 1 from the conceptual framework, high-income students barely exposed to SPP classmates have biased beliefs about the distribution of SES: they severely underestimate the share of low-income individuals (i.e., strata 1 and 2) and significantly overestimate the share of individuals similar to them (i.e., strata 4, 5, and 6). This is consistent with high-income students having high-income reference groups and failing to properly apply Bayes' rule in their assessment of the income distribution.[13]

To test prediction #2—that exposing high-income individuals to low-income peers shifts their reference groups and lessens this bias—I use the difference-in-difference approach described in Section 5. The main dependent variable for the analysis consists of a summary measure of these two outcomes following the procedure described in Anderson (2008). I standardize using the mean and standard deviation of each outcome among

[12]Following the rollout of SPP, several media outlets expressed their concern that SPP recipients would be bullied or discriminated against by traditional students at elite universities. To examine these concerns, I included a module about students' views on college financial aid and their attitudes towards SPP recipients in the first survey wave. The results, presented in Appendix C, are not supportive of out-group prejudice as a result of the policy. Instead, high-income students were generally supportive of SPP recipients, financial aid, and diversity. The treatment had no impact on these attitudes. See also Alvarez (2019).

[13]Figure A.8 presents the distribution of the perceived poverty incidence and the perceived distribution of socioeconomic strata. Again, the figure shows that high-income students underestimate the incidence of poverty.

the Spring 2014 cohort. I then create a weighted average using all of the outcomes in the domain, using the inverse of the covariance matrix of the transformed outcomes in the domain.

The results are displayed in Table 2. Column (1) shows that a one percentage point increase in the share of SPP classmates raises the perceived incidence of poverty by 0.012 standard deviations (the p-value is 0.011). This coefficient is significant and stable when progressively adding wave fixed effects in Column (2), major fixed effects in Column (3), baseline controls in Column (4), and cohort fixed effects in Column (5). Column (5), which reports the results from Specification (1), suggests that a one percentage point increase in exposure to diversity raises the perceived incidence of poverty by 0.013 standard deviations (the p-value is 0.062). Thus, exposing high-income individuals to low-income peers shifts their reference groups and lessens the (upward) bias in their perceived distribution of income.[14]

Alternatively, the analysis using the summary index can be done separately for each of the two variables that make up this index, i.e., the perceived poverty incidence and the perceived share of the population in strata 1 and 2. Tables A.2 and A.3 show a similar pattern of results. Moreover, the results are robust to changing the definition of the treatment variable: Table A.4 shows that substituting the share of SPP classmates with the share of low-income classmates—defined as those from strata 1 and 2—produces the same point estimate of 0.013 (the standard errors are slightly larger for the full difference-in-difference specification).

Next, I test whether this exposure to more diversity influences individuals' preferences for redistribution.

7.2 Preferences for Redistribution

To measure individuals' preferences for redistribution, the survey respondents were asked to report, on a scale from 1 (strongly disagree) to 7 (strongly agree), how strongly did they agreed or disagreed with the following statements: "*The state should tax the rich*" and "*The state should subsidize the poor*" (see Figure B.8).

Table 3 presents the results when the dependent variable is a summary measure of these two outcomes. Column (1) shows that a one percentage point increase in the share of SPP classmates raises support for redistribution by 0.006 standard deviations. The inclusion of controls improves the precision of the estimate, as columns (2) through (4) show. Column (5), which reports the difference-in-difference estimates using Specification

[14]Table A.8 presents the results from Table 2 separately by survey wave. The effects are broadly consistent.

(1), shows that a one percentage point increase in the share of SPP classmates raises support for redistribution by 0.016 standard deviations (the p-value is 0.018).

The analysis using the two variables that make up that index—support for taxing the rich and subsidizing the poor—separately suggest similar patterns, as Tables A.5 and A.6 report. Moreover, the results from Table 3 are robust to the definition of the treatment variable: Table A.7 shows that substituting the share of SPP peers with the share of low-income classmates does not affect neither the direction nor the significance of the estimated coefficient (the p-value of the estimate in Column (5) is 0.032). I therefore conclude that the shock in socioeconomic diversity boosted support for redistribution.[15]

8 Discussion

This section discusses the mechanisms through which diversity affects people's perceptions of the income distribution and their preferences for progressive redistribution.

The findings from above suggest that boosting socioeconomic diversity influences high-income individuals' beliefs about the distribution of income and their support for progressive redistribution. These effects might be driven by the extent to which exposure to diversity influences people's *perception* of having more low-income peers. Indeed, Section 6 showed that high-income students do perceive their SPP peers (and, in fact, they overestimate their prevalence). To examine this, Table 4 reports the results from Specification (1) when replacing the *actual* share of SPP classmates with the *perceived* share as the treatment variable. Columns (1) and (3) report the OLS estimates when the dependent variable is the index for perception of poverty and the index for support for progressive redistribution, respectively. Columns (2) and (4) report the 2SLS estimates, which instrument the *perceived* share of SPP classmates with the *actual* share. The 2SLS coefficients are almost identical in both magnitude and significance as those using the actual share in Tables 2 and 3. The OLS coefficients are biased toward zero, consistent with attenuation due to measurement error in people's perceptions of their peers.

To further examine the mechanisms, recall from Section 2 that exposure to low-income peers might affect high-income students' preferences for redistribution due to self-interest (Meltzer and Richard, 1981), changes in people's perceptions of upward mobility (Benabou and Ok, 2001; Piketty, 1995), or by influencing their concerns for fairness (Alesina and Angeletos, 2005). The remainder of this section explores and discusses each of these channels.

[15]Table A.9 presents the results from Table 3 separately by survey wave. Again, the effects are broadly consistent.

First, if exposure to low-income peers made people more aware of their own position in the socioeconomic ladder, we would expect diversity to *weaken* high-income individuals' support for progressive redistribution. Instead, Table 3 shows that exposure to low-income classmates *raised* high-income students' support for redistribution, which is inconsistent with the Meltzer and Richard (1981) model of self-interested voters.

A similar argument can be made against the POUM hypothesis: if the policy—by virtue of improving access to high-quality education for low-income high-achievers—made people more optimistic about upward social mobility, then we would expect the treatment to *decrease* people's support for progressive redistribution. To examine whether the treatment affected people's perceptions of upward mobility, I asked students: "*Suppose a baby is born in stratum [1/2/3/4/5/6] in Colombia. Where do you think he or she will end up as an adult?*" (see Figure B.9). Panel (a) of Table 5 presents the results from Specification (1) when the dependent variable is an index for perceptions of upward social mobility among the poor, i.e., an indicator that an individual born in strata 1 or 2 ends up in a higher stratum as an adult. The treatment had no statistically significant effect on high-income students' perceived upward mobility (the p-value is 0.236).[16] I can rule out effects smaller than -0.006 and larger than 0.02.

Lastly, to examine people's concerns for fairness, I asked respondents how often they believed the economic system provided equal opportunity to overcome poverty (on a scale from "always" to "never", see Figure B.10).[17] Panel (b) of Table 5 presents the results from Specification (1) when the dependent variable is an indicator for whether the student believes the economic system "never" or "almost never" provided equal opportunity. Column (5), which reports the results from the full difference-in-difference specification, suggests that a one percentage point increase in the treatment raises the outcome by 0.012 percentage points relative to a mean of 46.3 percent from the Spring 2014 cohort (the p-value is 0.013). This result suggests that exposure to socioeconomic diversity in the classroom raised skepticism towards equal opportunity without government intervention.[18] Consistent with prediction #3, a greater concern for

[16]This does *not* mean the policy did not influence people's perception of equity in access to quality education: Column (5) of Table C.1 shows that the treatment did increase students' perception of college admissions becoming more meritocratic.

[17]I focus on this particular outcome in lieu of more commonly used measures, like lack of effort vs. luck determining income (Alesina and Angeletos, 2005), because it is the most interpretable given the policy. For instance, exposure to low-income peers might raise the perception that poverty is due to lack of effort, since hard-working low-income students are now able to attend their selective university thanks to the policy. Or it can make them more likely to report luck as a determining factor, if exposure to SPP recipients make them more aware of their own privilege.

[18]Unfortunately, this question was only asked in the first survey wave. Despite the drop in the number of observations, the results are highly statistically significant.

fairness made students more supportive of progressive redistribution.

9 Conclusion

This paper investigates whether socioeconomic diversity affects individuals' perception of the income distribution and their preferences for progressive government redistribution. In my setting—characterized by high inequality and a de facto segregation of higher education—boosting diversity had considerable impacts on who high-income students interact with, how unequal they perceive income to be distributed, and how supportive they become of progressive redistributive policy. By promoting social interactions among students with heterogeneous family backgrounds, exposure to diversity drastically reduced high-income students' upwardly biased perception of the income distribution. As they perceived more inequality and became more concerned the lack of equal opportunity without government intervention, diversity strengthened their support for redistribution.

A caveat from these results is that the high-income students I study are not exposed to a truly diverse set of representative low-income individuals. Instead, they interact with a positively selected sample of low-income individuals characterized by a high cognitive ability, stronger parental backgrounds and, arguably, better non-cognitive skills (e.g., grit, motivation, perseverance). These characteristics might induce more sympathy from their high-income peers than if, for instance, they interacted with the average low-income individual of the same age or with a more diverse group of low-income individuals. I leave a study of the effect these other types of interactions might have for future research.

References

Alesina, A. and E. La Ferrara, "Preferences for redistribution in the land of opportunities," *Journal of Public Economics*, 2005, *89*, 897–931.

_ **and G. Angeletos**, "Fairness and redistribution: US versus Europe," *American Economic Review*, 2005, *95* (4), 960–980.

_ **, E. Glaeser, and B. Sacerdote**, "Why doesn't the United States have a European-style welfare state," *Brookings Papers on Economic Activity*, 2001, *2*, 1–69.

_ **, S. Stantcheva, and E. Teso**, "Intergenerational Mobility and Preferences for Redistribution," *American Economic Review*, February 2018, *108* (2), 521–54.

Allport, G.W., *The Nature of Prejudice*, Addison-Wesley Publishing Company, 1954.

Alvarez, M.J., "Los becados con los becados y los ricos con los ricos? Interacciones entre clases sociales distintas en una universidad de élite," *Desacatos. Revista de Ciencias Sociales*, 2019, *59*, 50–67.

Anderson, M., "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American Statistical Association*, 2008, *103*, 1481–1495.

Ariely, D. and M. Norton, "Building a better America – One wealth quintile at a time," *Perspectives on Psychological Science*, 2011, *6* (1), 9–12.

Barrera-Osorio, F. and H. Bayona-Rodriguez, "Signaling or better human capital: Evidence from Colombia," *Economics of Education Review*, June 2019, *70*, 20–34.

Bazzi, S., A. Gaduh, A.D. Rothenberg, and M. Wong, "Unity in Diversity? How Intergroup Contact Can Foster Nation Building," *American Economic Review*, November 2019, *109* (11), 3978–4025.

Benabou, R. and E. Ok, "Social mobility and the demand for redistribution: The POUM hypothesis," *The Quarterly Journal of Economics*, 2001, *116* (2), 447–487.

Boisjoly, J., G.J. Duncan, M. Kremer, D.M. Levy, and J. Eccles, "Empathy or Antipathy? The Impact of Diversity," *American Economic Review*, December 2006, *96* (5), 1890–1905.

Burns, J., L. Corno, and E. La Ferrara, "Interaction, stereotypes and performance: Evidence from South Africa," 2019. IFS Working Paper W19/03.

Camacho, A., J. Messina, and J.P. Uribe, "The Expansion of Higher Education in Colombia: Bad Students or Bad Programs?," February 2017. Documento CEDE No. 13.

Carrel, S.E., B.I. Sacerdote, and J.E. West, "From Natural Variation to Optimal Policy? The Importance of Endogenous Peer Group Formation," *Econometrica*, 2013, *81* (3), 855–882.

Carrell, S.E., M. Hoekstra, and J.E. West, "The Impact of College Diversity on Behavior toward Minorities," *American Economic Journal: Economic Policy*, November 2019, *11* (4), 159–82.

Charite, J., R. Fisman, and I. Kuziemko, "Reference points and redistributive preferences: Experimental evidence," March 2016. NBER Working Paper 21009.

Chetty, R., J.N. Friedman, and J.E. Rockoff, "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates," *American Economic Review*, September 2014, *104* (9), 2593–2632.

_ , _ , E. Saez, N. Turner, and D. Yagan, "Income Segregation and Intergenerational Mobility Across Colleges in the United States," *The Quarterly Journal of Economics*, 2020, *135*, 1567–1633.

Cruces, G., R. Perez-Truglia, and M. Tetaz, "Biased perceptions of income distribution and preferences for redistribution: Evidence from a survey experiment," May 2011. IZA DP No. 5699.

_ , _ , and _ , "Biased perceptions of income distribution and preferences for redistribution: Evidence from a survey experiment," *Journal of Public Economics*, 2013, *98*, 100–112.

DANE, "Actualización metodológica de la medición de pobreza monetaria," 2020.

Ferreyra, M.M., C. Avitabile, J. Botero, F. Haimovich, and S. Urzúa, *At a Crossroads: Higher Education in Latin America and the Caribbean*, The World Bank, 2017.

Finseraas, H., T. Hanson, A. Johnsen, A. Kotsadam, and G. Torsvik, "Trust, ethnic diversity, and personal contact: A field experiment," 2019, *173*, 72–84.

Hirschman, A. and M. Rothschild, "The changing tolerance of income inequality in the course of economic development," *The Quarterly Journal of Economics*, 1973, *87* (4), 544–566.

Hoxby, C. and C. Avery, "The Missing "One-Offs": The Hidden Supply of High-Achieving, Low-Income students," *Brookings Papers on Economic Activity*, 2013.

Kuziemko, I., M. Norton, E. Saez, and S. Stantcheva, "How elastic are preferences for redistribution? Evidence from randomized survey experiments," *American Economic Review*, 2015, *105* (4), 1478–1508.

La Silla Vacía, "Las becas obligan a las universidades a actualizarse," January 13 2015.

Londoño-Vélez, J., C. Rodríguez, and F. Sanchez, "Upstream and Downstream Impacts of College Merit-Based Financial Aid for Low-Income Students: Ser Pilo Paga in Colombia," *American Economic Journal: Economic Policy*, 2020, *12* (2), 1–37.

Lowe, M., "Types of Contact: A Field Experiment on Collaborative and Adversarial Caste Integration," *American Economic Review*, June 2021, *111* (6), 1807–44.

Luttmer, E.F.P., "Group Loyalty and the Taste for Redistribution," *Journal of Political Economy*, 2001, *109* (3), 500–528.

_ **and M. Singhal**, "Culture, Context, and the Taste for Redistribution," *American Economic Journal: Economic Policy*, February 2011, *3* (1), 157–79.

Melguizo, T., F. Sanchez, and T. Velasco, "Credit for low-income students and access to and academic performance in higher education in Colombia: A regression discontinuity approach," *World Development*, 2016, *80*, 61–77.

Meltzer, A. and S. Richard, "A rational theory of the size of government," *Journal of Political Economy*, 1981, *89*, 914–927.

OECD and The World Bank, *Reviews of National Policies for Education: Tertiary Education in Colombia*, OECD Publishing, 2012.

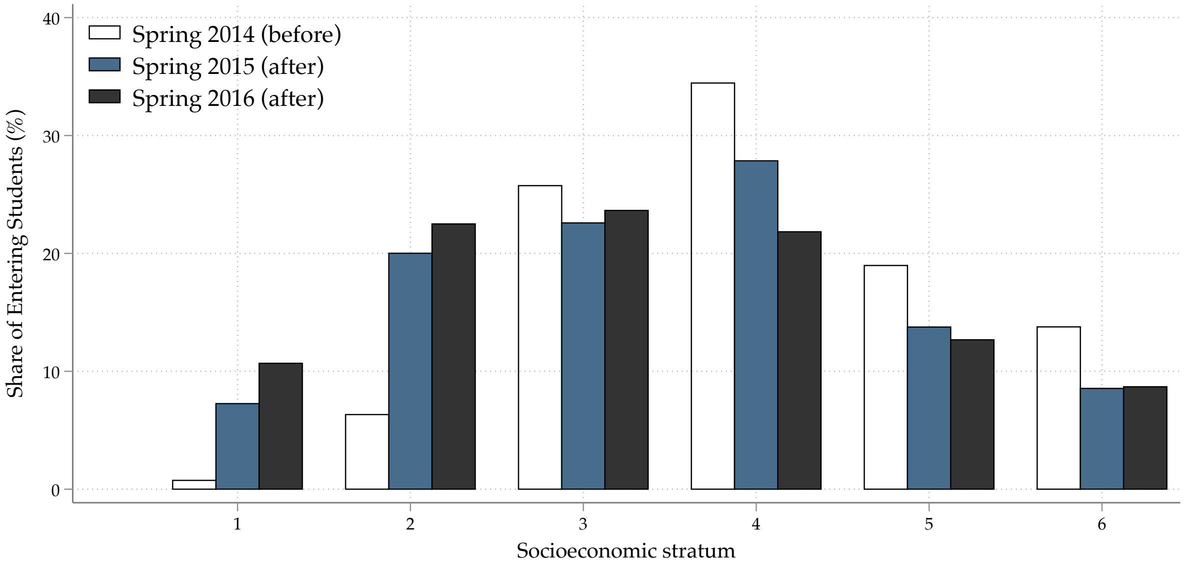
Paluck, B.E., S.A. Green, and D.P. Green, "The contact hypothesis re-evaluated," *Behavioural Public Policy*, 2019, *3* (2), 129–158.

Piketty, T., "Social mobility and redistributive politics," *The Quarterly Journal of Economics*, 1995, *111*, 551–584.

Rao, G., "Familiarity does not breed contempt: Diversity, discrimination, and generosity in Delhi Schools," *American Economic Review*, March 2019, *109* (3), 774–809.

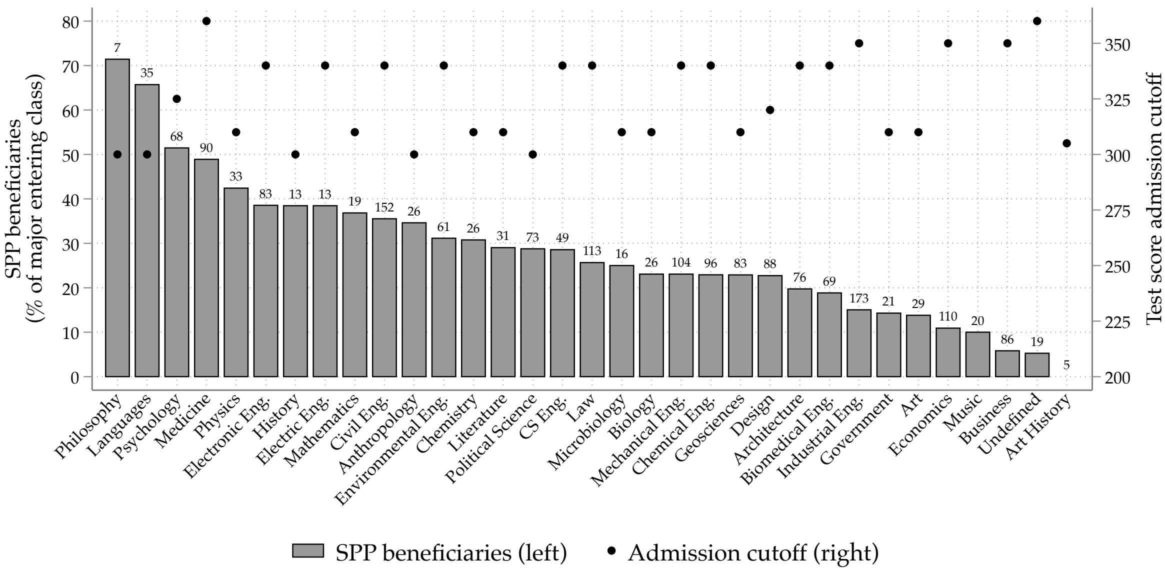
Sanchez, F. and T. Velasco, "Do loans for higher education lead to better salaries? Evidence from a regression discontinuity approach for Colombia," October 2014.

Figure 1: A Dramatic Increase in Socioeconomic Diversity at an Elite University



Notes: This figure plots the distribution of entering students at an elite university by their socioeconomic stratum (1 is the poorest, 6 is the wealthiest) in Spring 2014 (before SPP financial aid program), Spring 2015 (after), and Spring 2016 (after). Financial aid dramatically promoted socioeconomic diversity, almost quadrupling the share of low-income students (i.e., strata 1 and 2) from 7.1 percent in 2014 to 27.3 percent in 2015 and further 33.3 percent in 2016.
Sources: Author's calculations using college admissions records.

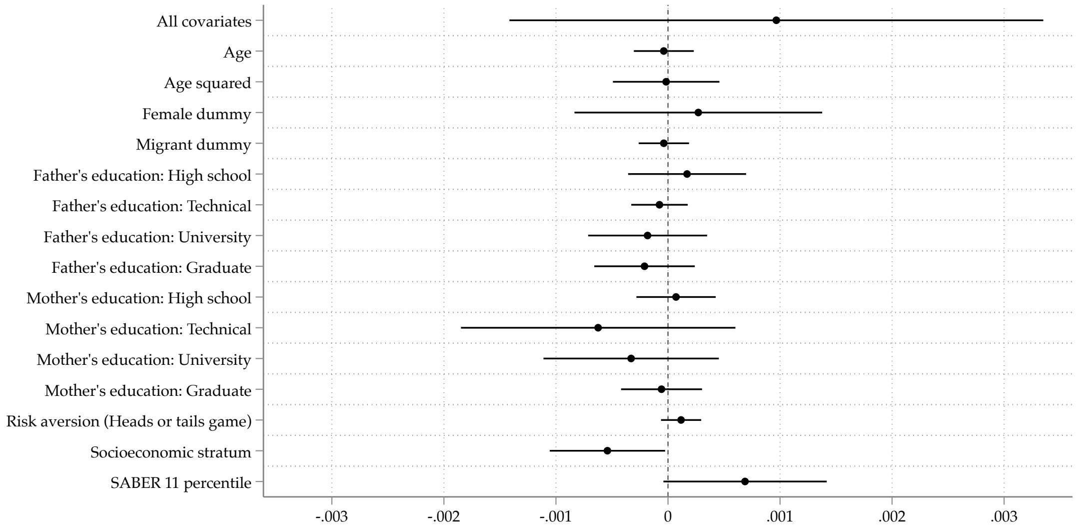
Figure 2: The Share of SPP Beneficiaries Varies Across Majors



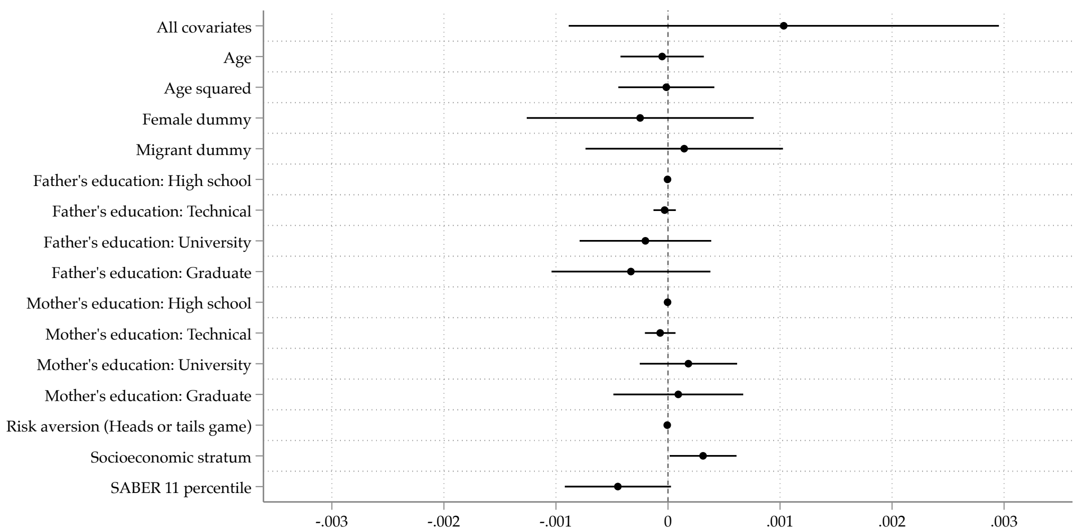
Notes: The left axis in this figure plots the share of entering students in Spring 2015 at the partner university who are beneficiaries of SPP financial aid program by major (in gray bars). This share ranges from 71.4 percent in Philosophy to 0 percent in Art History. The numbers above the bars represent the total number of students enrolling for the first time in a given major in Spring 2015. Thus, 10.9 percent of the 110 students entering Economics in Spring 2015 were beneficiaries of SPP. The right axis plots the major-specific admission cutoff for Spring 2015 (in black round markers). The admission cutoff does not predict the share of SPP recipients in a major ($p = 0.148$).
Sources: Author's calculations using college admissions records.

Figure 3: Balance in Baseline Observable Characteristics

(a) Beliefs about the income distribution

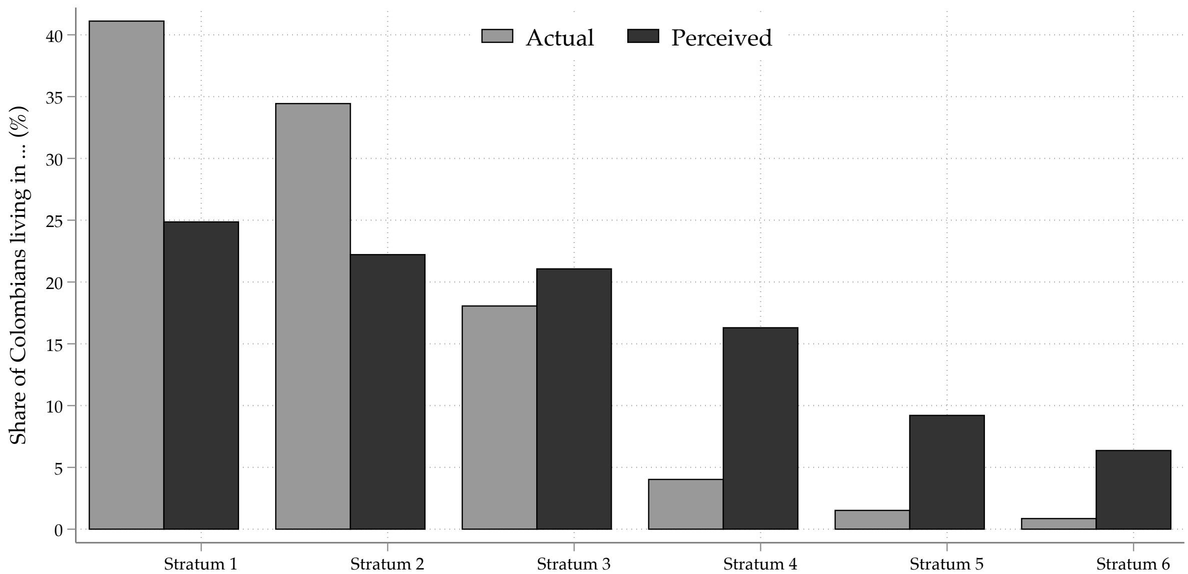


(b) Preferences for redistribution



Notes: This figure plots the coefficients and associated 95 percent confidence intervals from regressing the predicted value of the outcome—the index of beliefs about the income distribution in Panel (a) or the index of redistributive preferences in Panel (b)—using a given baseline covariate on the observed share of SPP classmates using cohort fixed effects, wave fixed effects, and major fixed effects as in specification (1). Standard errors are clustered at the major-by-cohort level. Each row is a separate regression that uses a different observable characteristic to generate the predicted outcome; the first row uses all of the observable covariates to calculate the predicted outcome, while the rest use one covariate at a time. It is common to use the predicted outcomes when assessing balance to rescale the covariates to the same scale as the outcome (e.g., Chetty et al., 2014). The sample uses waves 1 and 2 and is composed of survey respondents from high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP) or Spring 2015 (after SPP).
Sources: Author's calculations using college records and student survey data.

Figure 4: High-Income Individuals have Biased Beliefs about the Income Distribution



Notes: This figure plots the actual versus perceived distribution of individuals by socioeconomic stratum (1 is the poorest, 6 is the wealthiest). The gray bars report the actual distribution for all SABER 11 test takers (ICFES, 2014). The black bars plot the average response by high-income students (strata 4, 5, and 6) from the Spring 2014 cohort.
Sources: Author's calculations using college records and student survey data.

Table 1: Intensity of Interactions with SPP Recipients by Entry Cohort

	Entering Cohort		
	Spring 2014 Cohort (1)	Fall 2014 Cohort (2)	Spring 2015 Cohort (3)
Share of SPP Classmates (%)	2.88	5.22	14.03
	(3.43)	(3.58)	(5.21)
Reports friends' stratum is 1 or 2	.051	.038	.084
	(.22)	(.19)	(.28)
Perceived Share of SPP Classmates (%)	15.564	17.724	34.407
	(14.89)	(14.04)	(18.62)
No. times worked with SPP recipient	1.225	1.131	3.343
	(2.27)	(2.22)	(3.19)
$\mathbb{1}$(SPP recipient among 5 closest friends)	.022	.062	.241
	(.15)	(.24)	(.43)
$\mathbb{1}$(SPP recipient among 5 study partners)	.033	.052	.273
	(.18)	(.22)	(.45)
N	275	291	344

Note: This table presents means (and standard deviations in parentheses) for high-income students by entering cohort, i.e., the semester in which they first began their studies at University X.
Sources: Author's calculations using college records and student survey data.

Table 2: Exposure to Low-Income Peers Raises Perceived Poverty

	(1)	(2)	(3)	(4)	(5)
Share of SPP classmates (%)	0.012**	0.010**	0.010**	0.012***	0.013*
	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	910	910	909	900	900

Notes: This table presents the β coefficient from Specification (1) when the dependent variable is the index of beliefs about the income distribution, i.e., the perceived share of Colombians living under poverty and in strata 1 and 2, following the procedure described in Anderson (2008). The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table 3: Exposure to Low-Income Peers Boosts Support for Redistribution

	(1)	(2)	(3)	(4)	(5)
Share of SPP classmates (%)	0.006*	0.006	0.009***	0.012***	0.016**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	910	910	909	900	900

Notes: This table presents the β coefficient from Specification (1) when the dependent variable is the index of support for redistribution, i.e., taxing the rich and subsidizing the poor, following the procedure described in Anderson (2008). The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college admissions records and student survey data.

Table 4: Perceived versus Actual Share of SPP Classmates as the Treatment Variable

	Panel A: Perceived Poverty		**Panel B:** Support for Redistribution	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Perceived share of SPP classmates (%)	0.006***	0.012*	-0.003*	0.015**
	(0.002)	(0.007)	(0.002)	(0.007)
Wave FE	X	X	X	X
Major FE	X	X	X	X
Controls	X	X	X	X
Cohort FE	X	X	X	X
FS F-Stat		36.6		36.6
N	897	897	897	897

Notes: This table presents the β coefficient from Specification (1) when using the *perceived* share of SPP classmates as the main treatment variable. The dependent variable is the index for perception of poverty in Panel A and the index of support for progressive redistribution in Panel B. Columns (1) and (3) report the OLS estimates. Since the *perceived* share of SPP classmates is measured with error, Columns (2) and (4) report the 2SLS estimates using the actual share of SPP classmates as an instrument. The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table 5: Mechanisms

	Panel A: Perception of Upward Social Mobility					**Panel B:** Concern for Fairness				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of SPP classmates (%)	0.004	0.007	0.005	0.004	0.008	0.008***	0.008***	0.008***	0.009***	0.012**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Wave FE		X	X	X	X		X	X	X	X
Major FE			X	X	X			X	X	X
Controls				X	X				X	X
Cohort FE					X					X
N	910	910	909	900	900	457	457	456	453	453

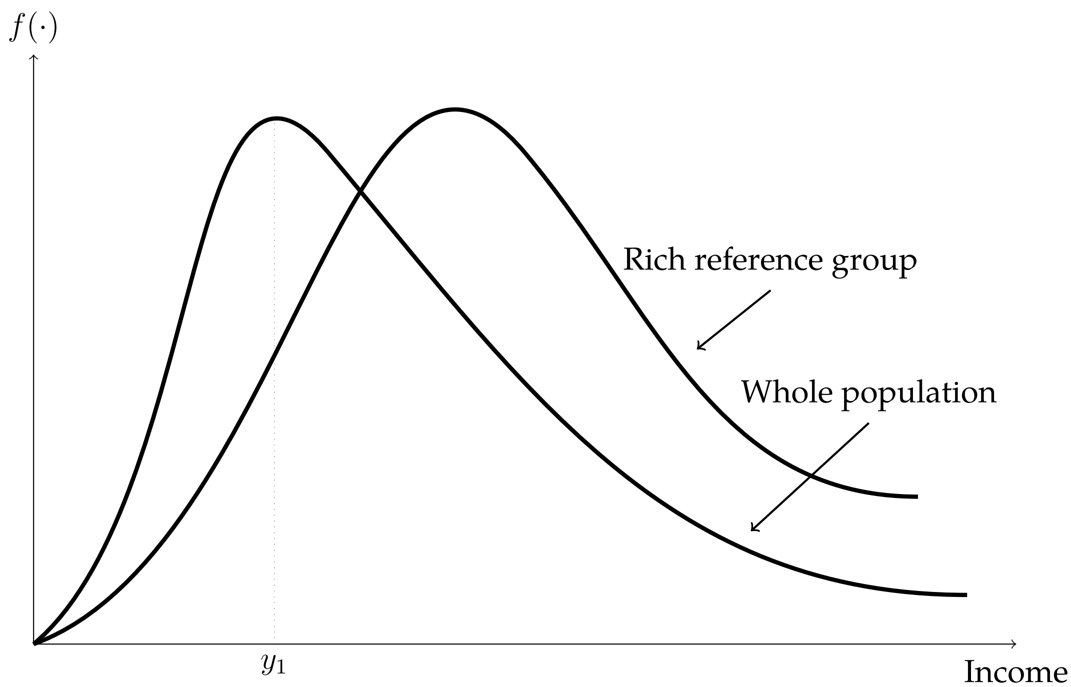
Notes: This table presents the β coefficient from Specification (1). In Panel A, the dependent variable is the index of perception of upward social mobility among the poor, i.e., that an individual born in strata 1 and 2 can end up in a higher stratum as an adult, following the procedure described in Anderson (2008), and the sample includes both survey waves. In Panel B, the dependent variable is an indicator for whether the respondent believes the economic system "never" or "almost never" *"provides equal opportunity to overcome poverty."* Unfortunately, this question was only asked in the first survey wave, which halves the number of observations. The sample for both panels is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$

Sources: Author's calculations using college records and student survey data.

Appendices

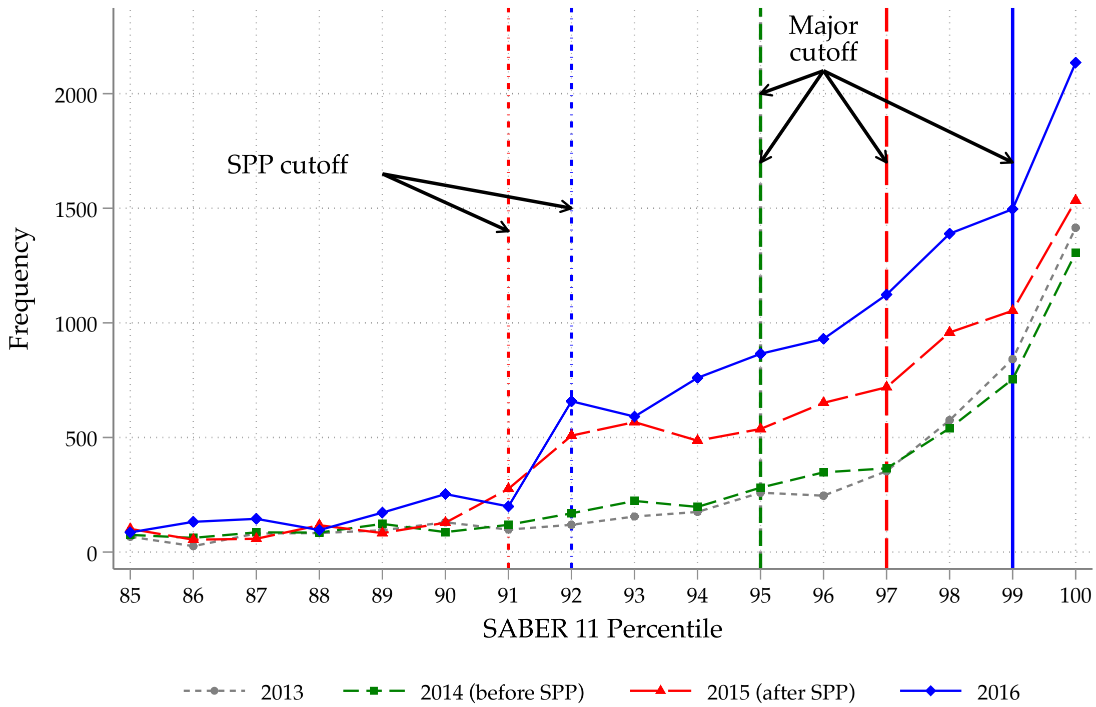
A Additional Figures and Tables

Figure A.1: Illustration of Biases with a Rich Reference Group



Source: Figure 1a in Cruces et al. (2013).

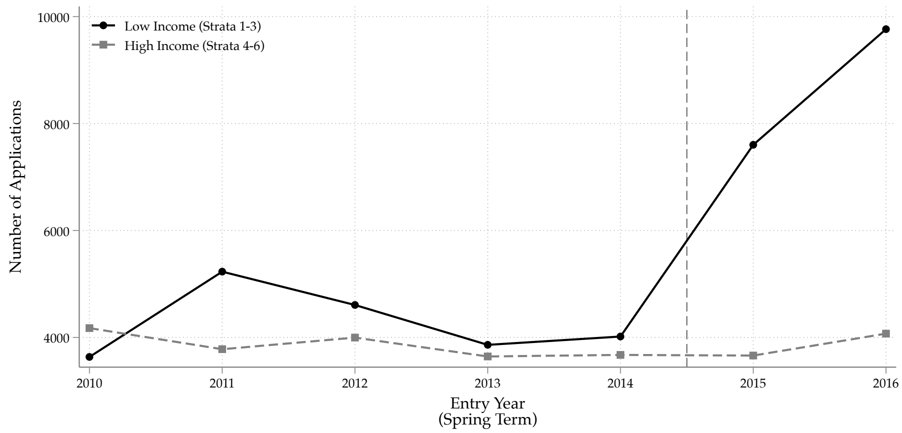
Figure A.2: SPP Raised Admission Thresholds



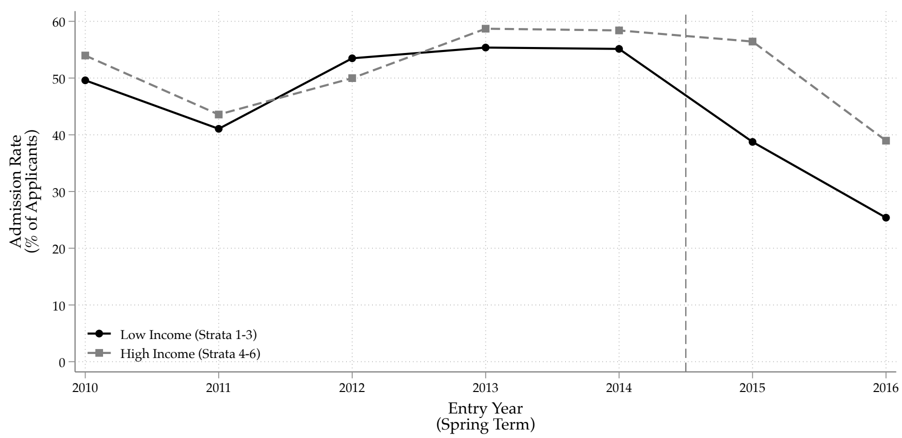
Note: This figure plots the distribution of SABER 11 test score percentiles for Fall high school test-takers that applied to the partner university for the Spring term in 2013 (in gray), 2014 (in green), 2015 (in red), or 2016 (in blue). The short dashed and dotted vertical lines mark the SPP eligibility cutoffs in 2015 and 2016. The other vertical lines depict the admission cutoff in the four years for the Civil Engineering major, as an illustration. The figure shows that the number of undergraduate applications increased significantly in 2015 and 2016 after SPP was introduced, with applications spiking after surpassing the eligibility cutoffs. This pushed the admission cutoff rightward; while the cutoff did not change prior to SPP (the gray and green vertical lines perfectly overlay each other), it significantly increased in 2015 and 2016.
Sources: Author's calculations using college admissions records and ICFES.

Figure A.3: The Admissions Process for Low- and High-Income Applicants

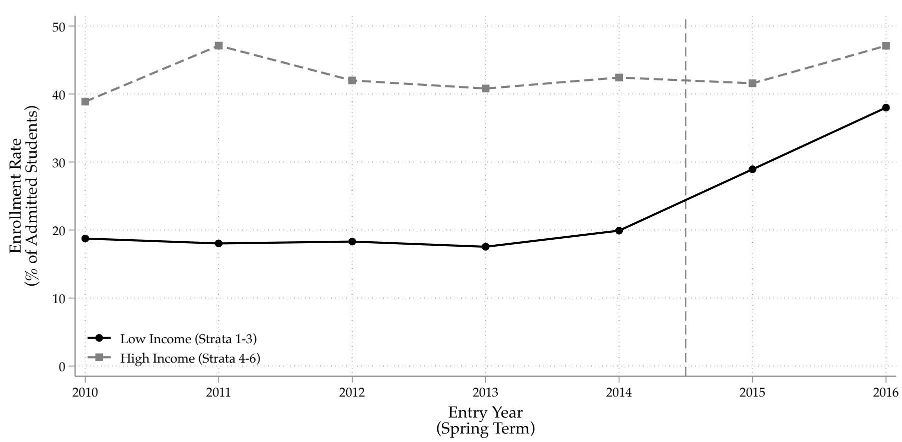
(a) Number of Applications



(b) Admission Rate



(c) Yield Rate

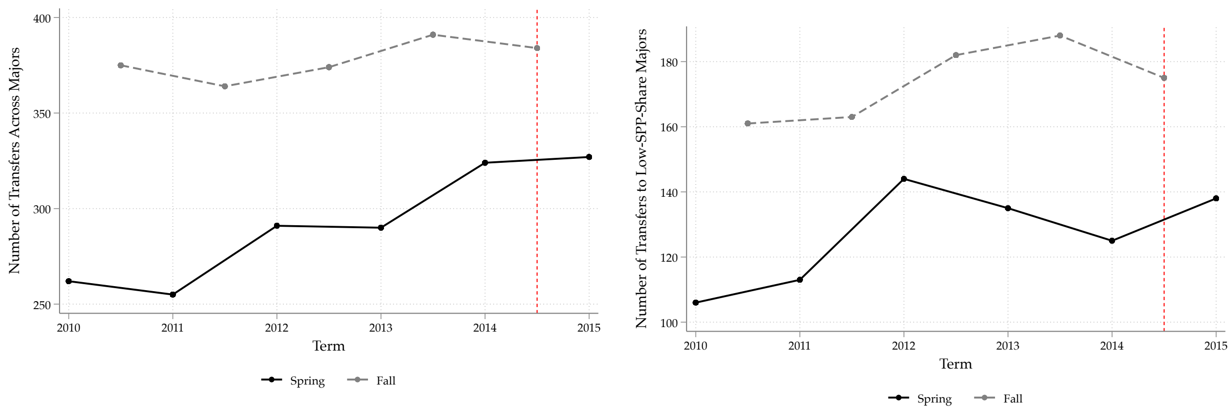


Notes: This figure compares the admissions process for low- and high-income applicants; specifically, the number of applications in Panel (a), the share of applicants who are granted admission in Panel (b), and the share of admitted applicants who enroll in Panel (c). The vertical red line represents SPP.
Sources: Author's calculations using college admissions records.

Figure A.4: There is No Increase in Transfers Across Majors

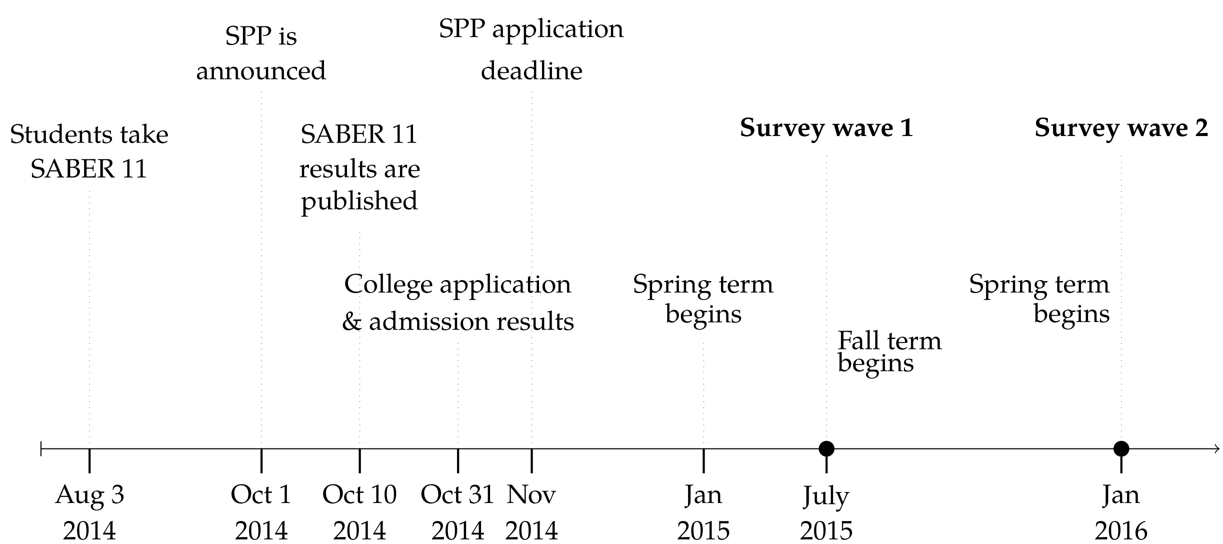
(a) All Transfers

(b) Transfers to Majors with Less than 20 Percent SPP Share



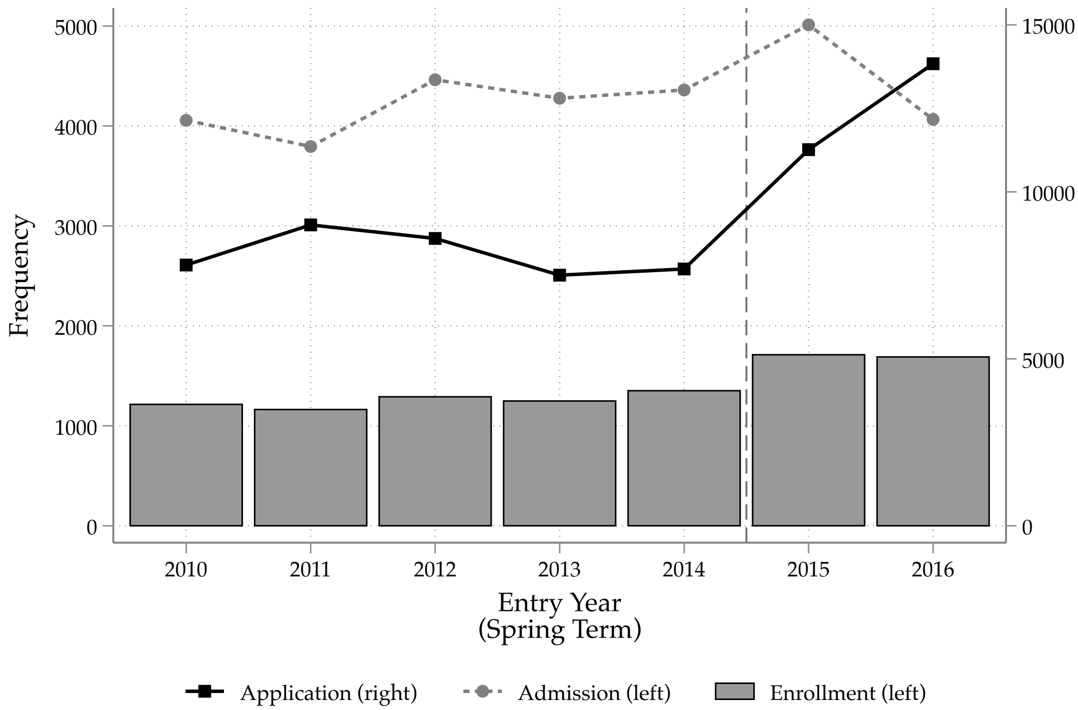
Note: Panel A plots the total number of transfers across majors within the partner university by academic term. Panel B restricts to transfers to majors where less than 20 percent of Freshmen in Spring 2015 are SPP recipients, according to Figure 2: Architecture, Art, Art History, Biomedical Engineering, Business, Undefined, Music, Economics, Government, and Industrial Engineering.
Sources: Author's calculations using college records.

Figure A.5: Timeline of Events



Notes: This figure plots a timeline of events taking place between August 2014 and January 2016 (not drawn to scale). SPP recipients began attending classes in mid to late January 2015. The first survey wave took place six months later, in early August 2015. The second survey wave took place one year later, in early February 2016.

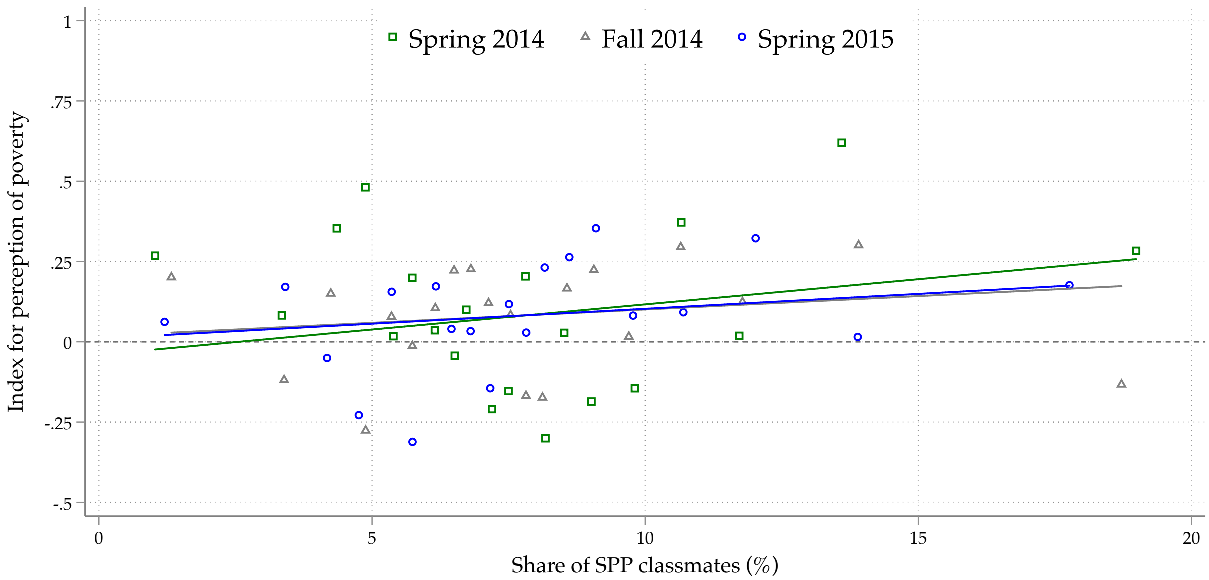
Figure A.6: A Small Increase in Cohort Size



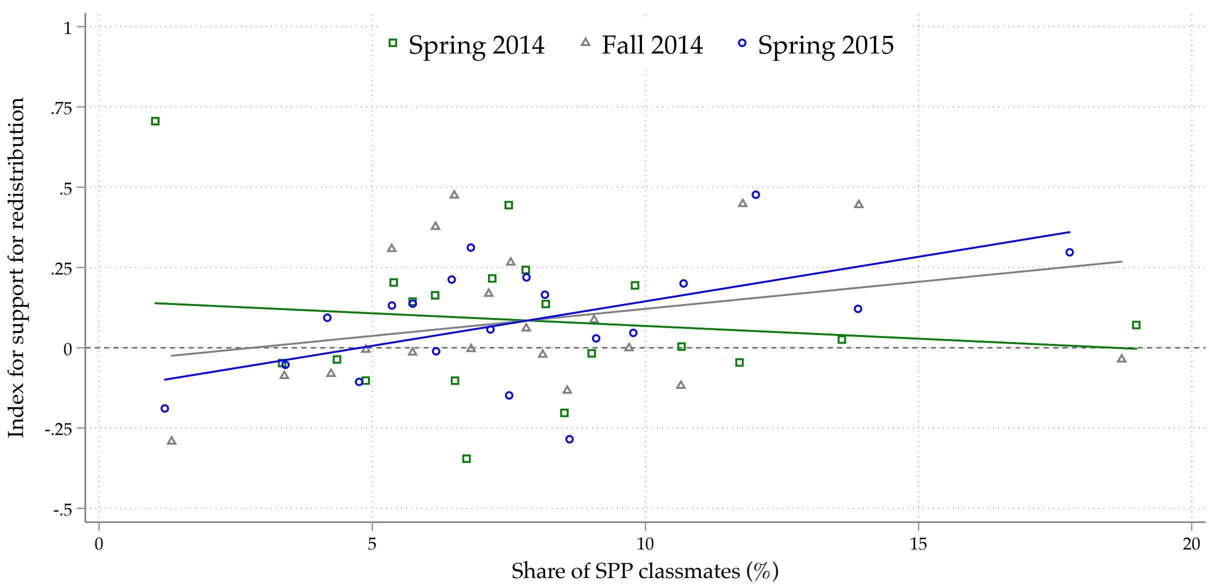
Notes: This figure compares the number of students who apply (solid black line), receive admission (dashed gray line), and enroll (gray bar) in the partner university every Spring term between 2010 and 2016. The vertical red line represents SPP. The figure shows that, despite the increase in number of applicants, class size remained relatively constant throughout this time period at this university.
Sources: Author's calculations using college admissions records.

Figure A.7: Correlation between Index Outcomes and the Treatment Variable

(a) Perception of Poverty



(b) Support for Progressive Redistribution

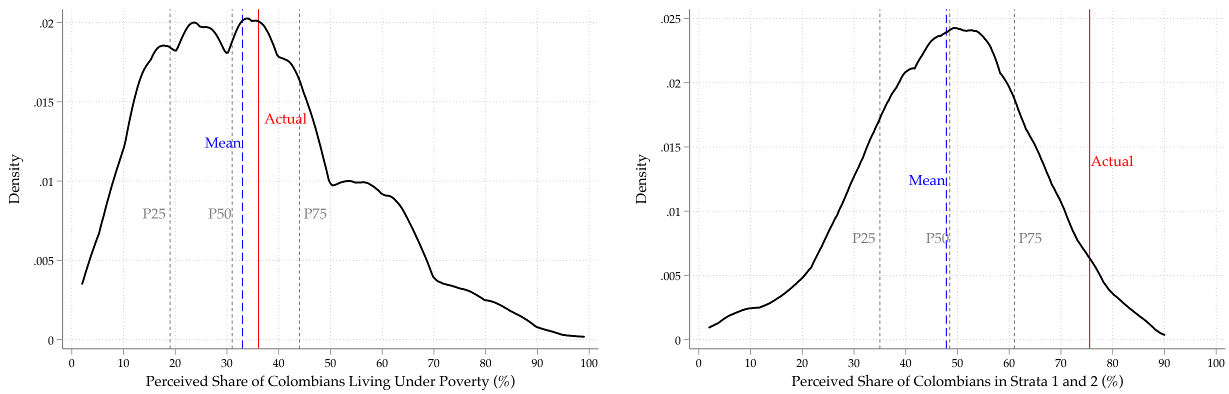


Note: This figure illustrates the variation in the share of SPP classmates—the treatment variable—leveraged in the regression analysis. The outcome variable is the index of perception of poverty in Panel A and the index of support for progressive redistribution in Panel B. The plotted lines show the correlation between the treatment and the outcome within a major-cohort-wave cell for each cohort; the β coefficient from Specification (1) captures the average slope of the plotted lines.
Sources: Author's calculations using college records and student survey data.

Figure A.8: Distribution of Beliefs about the Distribution of Income

(a) Perceived Poverty Incidence

(b) Perceived Share Living in Strata 1 and 2



Note: This figure plots the kernel density of the perceived share of Colombians living under poverty in Panel (a) and the perceived share of Colombians living in strata 1 and 2 in Panel (b). The dashed blue vertical line reports the mean response, the gray lines report the responses at P25, P50, and P75 of the distribution, and the red vertical line reports the actual rates. The sample is composed of high-income survey respondents from the Spring 2014 cohort six months after SPP was implemented.
Sources: Author's calculations using college records, DANE (2020), and ICFES (2014).

Table A.1: Survey Response Balance Test

	Dependent variable: Responded survey			
	(1)	(2)	(3)	(4)
Spring 2014 cohort	0.01	-0.022		
	(0.014)	(0.015)		
Spring 2015 cohort	0.017	-0.008		
	(0.014)	(0.014)		
Share of SPP classmates (%)			0.001	0.002
			(0.001)	(0.002)
Controls		X		X
Wave FE		X		X
Major FE		X		X
Cohort FE				X
N	4993	4959	4928	4895
R^2	0	0.02	0	0.02

Note: This table shows the survey response balance test for the 4,993 students who were emailed a link to the survey in waves 1 and 2. Column (1) reports the coefficients and standard errors on the cohort dummies (Fall 2014 is the omitted category), while Column (2) adds observable covariates (sex, socioeconomic stratum, SABER 11 score), wave fixed effects, and major dummies. The p-value on the joint F-statistic is 0.4453 in Column (1) and 0.8790 in Column (2). Column (3) and (4) test whether the main treatment variable, the share of SPP classmates, affects the survey response rate. Again, I cannot reject the null hypothesis: the p-value is 0.157 without controls and 0.338 with controls.
Sources: Author's calculations using college records and student survey data.

Table A.2: Exposure to Low-Income Classmates Raises Perceived Poverty Incidence

	(1)	(2)	(3)	(4)	(5)
Share of SPP classmates (%)	0.281**	0.253**	0.212**	0.263***	0.286**
	(0.112)	(0.113)	(0.100)	(0.093)	(0.143)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	903	903	902	893	893

Notes: This table presents the β coefficient from Specification (1) when the dependent variable is the perceived share of Colombians living under poverty. The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table A.3: Exposure to Low-Income Classmates Raises Perceived Share in Strata 1 and 2

	(1)	(2)	(3)	(4)	(5)
Share of SPP classmates (%)	0.135*	0.109	0.145*	0.181**	0.198
	(0.080)	(0.082)	(0.081)	(0.087)	(0.143)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	908	908	907	898	898

Notes: This table presents the β coefficient from Specification (1) when the dependent variable is the perceived share of Colombians living in strata 1 and 2. The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table A.4: Robustness of Effects on Beliefs to the Treatment Variable

	(1)	(2)	(3)	(4)	(5)
Share of strata 1 or 2 classmates (%)	0.014**	0.012**	0.011**	0.014**	0.013
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	910	910	909	900	900

Notes: This table presents the β coefficient from Specification (1) when the treatment variable is the share of classmates from strata 1 or 2. The dependent variable is the index of beliefs about the income distribution, i.e., the perceived share of Colombians living under poverty and in strata 1 and 2, following the procedure described in Anderson (2008). The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college admissions records and student survey data.

Table A.5: Exposure to Low-Income Classmates Boosts Support for Taxing the Rich

	(1)	(2)	(3)	(4)	(5)
Share of SPP classmates (%)	0.002	0.002	0.003*	0.005**	0.009**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	910	910	909	900	900

Notes: This table presents the β coefficient from Specification (1) when the dependent variable is an indicator variable that equals one if the respondent supports taxing the rich. The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table A.6: Exposure to Low-Income Classmates Boosts Support for Subsidizing the Poor

	(1)	(2)	(3)	(4)	(5)
Share of SPP classmates (%)	0.004	0.004	0.005**	0.006**	0.006
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	910	910	909	900	900

Notes: This table presents the β coefficient from Specification (1) when the dependent variable is is an indicator variable that equals one if the respondent supports subsidizing the poor. The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table A.7: Robustness of Effects on Preferences to the Treatment Variable

	(1)	(2)	(3)	(4)	(5)
Share of strata 1 or 2 classmates (%)	0.007*	0.007	0.011**	0.014***	0.017**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Wave FE		X	X	X	X
Major FE			X	X	X
Controls				X	X
Cohort FE					X
N	910	910	909	900	900

Notes: This table presents the β coefficient from Specification (1) when the treatment variable is the share of classmates from strata 1 or 2. The dependent variable is the index of preferences for redistribution, i.e., their support for taxing the rich and subsidizing the poor, following the procedure described in Anderson (2008). The sample includes both survey waves and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college admissions records and student survey data.

Table A.8: Effects on Perceptions of Poverty by Survey Wave

	Panel A: Wave 1				**Panel B:** Wave 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of SPP classmates (%)	0.011**	0.012**	0.014**	0.012	0.008	0.007	0.01	0.014
	(0.006)	(0.006)	(0.006)	(0.009)	(0.006)	(0.007)	(0.007)	(0.011)
Major FE		X	X	X		X	X	X
Controls			X	X			X	X
Cohort FE				X				X
N	457	456	453	453	453	449	443	443

Notes: This table presents the results from Table 2 separately by survey wave. Students from the Spring 2014 cohort become *more* exposed to SPP classmates over time, which shrinks the treatment gap across cohorts in the second wave compared to the first wave. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

Table A.9: Effects on Support for Redistribution by Survey Wave

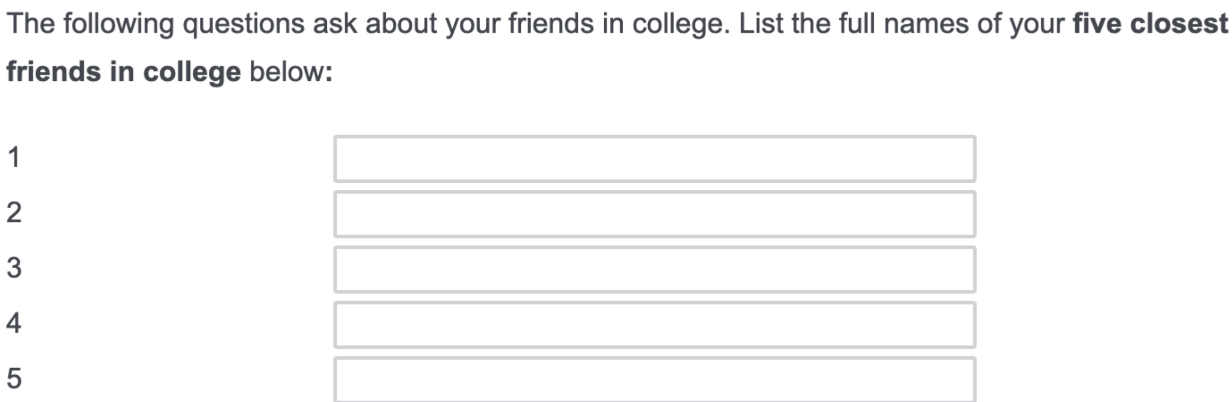
	Panel A: Wave 1				**Panel B:** Wave 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of SPP classmates (%)	0.009**	0.010**	0.012**	0.009	-0.001	0.005	0.01	0.019**
	(0.004)	(0.004)	(0.005)	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)
Major FE		X	X	X		X	X	X
Controls			X	X			X	X
Cohort FE				X				X
N	457	456	453	453	453	449	443	443

Notes: This table presents the results from Table 3 separately by survey wave. Students from the Spring 2014 cohort become *more* exposed to SPP classmates over time, which shrinks the treatment gap across cohorts in the second wave compared to the first wave. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$
Sources: Author's calculations using college records and student survey data.

B Screenshots of the Qualtrics Survey Questionnaire

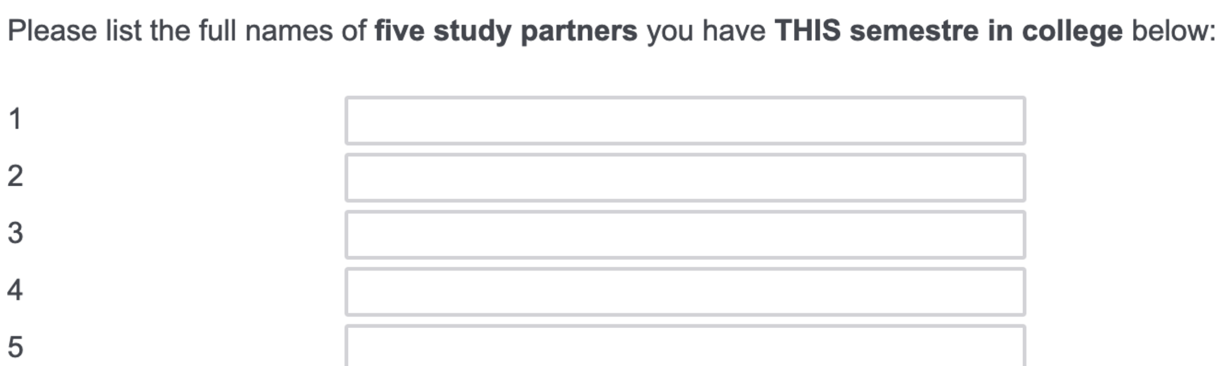
This section shows the screenshots of the Qualtrics survey. The questions have been translated from Spanish to English by the author.

Figure B.1: Question on List of Friends


The following questions ask about your friends in college. List the full names of your **five closest friends in college** below:

1
2
3
4
5

Figure B.2: Question on List of Study Partners


Please list the full names of **five study partners** you have **THIS semestre in college** below:

1
2
3
4
5

Figure B.3: Question on Friends' Socioeconomic Strata

Think about the **five closest friends in college** you listed above. What **socioeconomic stratum** do you think they belong to? (Check all that apply)

- Stratum 1
- Stratum 2
- Stratum 3
- Stratum 4
- Stratum 5
- Stratum 6

Figure B.4: Question on Perceived Share of SPP Classmates

Now think about your classmates. What percentage of your **classmates** do you think are receiving "Ser Pilo Paga" scholarship?

Recall that "Ser Pilo Paga" refers to the recent government program that awarded 10,000 scholarship-loans to low income, achieving students to study at high-quality universities.

Percentage (%)

0 20 40 60 80 100

Percentage of classmates receiving Ser Pilo Paga scholarship

Figure B.5: Question on Number of Times Worked with SPP Beneficiary

How many times have worked in a group project with a student with "Ser Pilo Paga" scholarship?

- Never
- 1 or 2 times
- 3 or 4 times
- 5 or 6 times
- 7 or 8 times
- 9 or 10 times
- More than 10 times

Figure B.6: Question on Perceived Poverty Incidence

What percentage of **Colombians** do you think are **poor** (that is, those earning less than $200 thousand pesos per month)?

Percentage that are poor (%)

0 20 40 60 80 100

Entire population in Colombia

Figure B.7: Question on Perceived Distribution of Socioeconomic Strata

What share of **Colombians** do you think belong to each **socioeconomic stratum**?

Please make sure that the 5 numbers entered below add up to 100%.

Percentage of Colombians in each stratum (%)

	0 10 20 30 40 50 60 70 80 90 100	
Stratum 1		0
Stratum 2		0
Stratum 3		0
Stratum 4		0
Stratum 5		0
Stratum 6		0
Total:		**0**

Figure B.8: Question on Preferences for Redistribution

This question asks your opinion on certain state policies. Please indicate your views on the scale provided.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The state should tax the rich	○	○	○	○	○	○	○
The state should subsidize the poor	○	○	○	○	○	○	○

Figure B.9: Question on Perception of Social Mobility

Suppose a baby is born in a given stratum in Colombia. Where do you think he or she will end up as an adult?

Then the baby, as an adult, is likely to end up in:

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5	Stratum 6
If a baby is born in stratum **1...**						
If a baby is born in stratum **2**...						
If a baby is born in stratum **3**...						
If a baby is born in stratum **4**...						
If a baby is born in stratum **5**...						
If a baby is born in stratum **6...**						

Figure B.10: Question on Perception of Fairness

How often do you think...

	Never	Almost never	Rarely	Sometimes	Most of the time	Almost always	Always
... the economic system provides Colombians equal opportunity to exit poverty?							

Figure B.11: Question on Being Uncomfortable Working with Classmates of Different Socioeconomic Background

Pedro says that, students in his classroom feel "uncomfortable" having classmates from different socioeconomic backgrounds in their study groups.

	Strongly Agree	Agree	Somewhat Agree	Neither Agree nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
Do you agree or disagree with him?	○	○	○	○	○	○	○

Figure B.12: Question on Whether Diversity is Important

How important is it that **your university** bring together students from all socioeconomic backgrounds?

Not at all Important	Very Unimportant	Somewhat Unimportant	Neither Important nor Unimportant	Somewhat Important	Very Important	Extremely Important
○	○	○	○	○	○	○

Figure B.13: Question on Support for Need-Based Financial Aid

This question asks your opinion on certain state policies. Please indicate your views on the scale provided.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The state should offer financial aid for poor students	○	○	○	○	○	○	○

Figure B.14: Question on Expanding SPP

The Colombian government is considering a financial aid policy that would allow more poor students with high Saber 11 scores to afford attending a college like yours. What is your view of this?

Strongly Opposed	Opposed	Somewhat Opposed	Neither Favor nor Oppose	Somewhat Favor	Favor	Strongly Favor

Figure B.15: Question on Meritocracy in University Admissions

How often do you think...

	Never	Almost never	Rarely	Sometimes	Most of the time	Almost always	Always
... the most talented students get into the best universities in Colombia?	○	○	○	○	○	○	○

Figure B.16: Question on Donation

Thank you very much for your time. You can now collect your $10,000 pesos as compensation for answering this questionnaire.

Would you like to donate part of this amount to fund poor, high-achieving students studying at high-quality universities in Colombia? If so, what percentage would you like to donate? (Otherwise, simply mark 0).

Percentage Donated (%)

0 20 40 60 80 100

I will donate this percentage of $10,000 pesos

C Attitudes Towards SPP Recipients and Financial Aid

This section examines high-income students' attitudes towards SPP recipients, need-based financial aid policy, and promoting socioeconomic diversity in colleges. I included this module in the first survey wave to address the concern, expressed in various media outlets soon after SPP was implemented, that low-income students would be bullied or discriminated against by traditional students at elite universities or that the policy would foster negative interactions and out-group prejudice. In short, I find no evidence of such effects.

First, it is possible that group work among students of heterogeneous family backgrounds raises coordination problems. For instance, since high- and low-income students likely live in far away from each other (as on-campus housing was uncommon by 2015), a group project would require students work on campus. I therefore asked students whether they agreed or not with "Pedro" in that working with students from different socioeconomic backgrounds was "uncomfortable" (see Figure B.11). Column (1) of Table C.1 shows that only 10 percent of students from the Spring 2014 cohort agreed with this statement and the treatment had no effect on the likelihood of agreeing with it.

Second, I asked students how important it was that their university bring together students from all socioeconomic backgrounds (see Figure B.12). Column (2) of Table C.1 shows that 75 percent of students from the Spring 2014 cohort believe that diversity is important and the treatment had no statistically significant impact on this outcome.

Third, I asked whether students thought the state should offer financial aid for low-income students (see Figure B.13). Column (3) of Table C.1 shows that 78 percent consider the state should offer need-based financial aid and the treatment had no impact.

Fourth, I asked students whether they would support a policy that would allow more low-income high-achievers to afford attending a university like theirs (see Figure B.14). Column (4) of Table C.1 shows that 83 percent of students from the Spring 2014 cohort reported to support such a policy and the treatment had no impact on this outcome.

Fifth, I asked students how often they believed the most talented students were admitted in the best universities in the country (see Figure B.15). Column (5) of Table C.1 shows there is widespread skepticism towards meritocracy in college admissions: only 28 percent of students from the Spring 2014 cohort believe the best students get into the best universities. However, the treatment appears to have raised the perception that the college admission process had become more meritocratic. This is consistent with the evidence from Londoño-Vélez et al. (2020) showing how SPP leveled the playing field, eliminating the SES gradient in college admissions for high-achievers.

Sixth, respondents who completed the survey received a compensation of 10,000 pesos (2015 US$ 3.4, which roughly covers the cost of a cheap lunch in Bogotá). Students could donate part of their compensation "to fund poor, high-achieving students studying at high-quality universities in Colombia" (see Figure B.16). Column (6) of Table C.1 shows that 60 percent of students from the Spring 2014 cohort chose to donate some fraction of their compensation to this purpose. However, the treatment had no statistically significant effect on likelihood of donating.

In sum, the findings from Table C.1 show that high-income students' have generally positive attitudes towards SPP recipients, need-based financial aid policy, and promoting socioeconomic diversity in colleges. The last column of this table uses a summary index of these six measures of attitudes (see Anderson, 2008). The treatment had no statistically significant impact on this index (the p-value is 0.496).

Table C.1: Attitudes Towards SPP Recipients, Diversity, and Need-Based Financial Aid

	Dependent variable						
	Uncomfortable working w/ SPP peers (1)	Diversity is important (2)	State should offer need-based financial aid (3)	Supports expanding financial aid (4)	Meritocracy in college admissions (5)	Donated compensation to SPP (6)	Index (7)
Share of SPP classmates (%)	0	-0.002	0.005	0.001	0.010**	0.002	0.005
	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)	(0.007)	(0.007)
Major FE	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
N	453	453	453	453	453	453	453
$\bar{y}_{\text{Spring 2014}}$	0.1	0.75	0.78	0.83	0.28	0.6	0

Notes: This table presents the β coefficient from Specification (1) without wave fixed effects as only survey wave #1 is included. Each column represents a separate regression using a different dependent variable. The sample includes only survey wave #1 and is composed of high-income students (strata 4, 5, and 6) who first enrolled in the partner university in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Controls include age, age squared, sex, SABER 11 test score percentile, socioeconomic stratum, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Standard errors, in parentheses, are clustered at the major-by-cohort level. $***p < 0.01, **p < 0.05, *p < 0.1$

Sources: Author's calculations using college records and student survey data.