The Impact of Diversity on Distributive Perceptions and Preferences for Redistribution

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Abstract

Does socioeconomic diversity affect individuals' perceptions of income distribution and redistributive preferences? I leverage a massive financial aid policy that drastically boosted the share of low-income students at elite universities in Colombia. Unlike affirmative action, the admissions process remained unaffected, enabling identifying the causal effect of diversity. I survey high-income students and compare beliefs and preferences across those entering college before and after policy rollout and those more or less exposed to low-income peers. Diversity caused high-income students to have more accurate perceptions of poverty and inequality, raising their concerns about fairness and boosting support for progressive taxation.

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What drives people's preferences for redistribution? If individual preferences respond to perceptions of poverty and inequality, which are formed endogenously through access to information and social interactions with peers (Cruces et al., 2013; Kuziemko et al., 2015), can changing people's peer groups alter their support for redistribution? Specifically, can exposing high-income individuals to low-income peers shape their perceptions of the income distribution and their support for progressive redistributive policy?

Identifying the causal effect of socioeconomic diversity on individual perceptions and preferences is challenging due to the endogeneity of peer groups. As a result, previous studies have rarely manipulated these outside the lab or field experiment. Indeed, we know little about how people's preferences respond to real-life policies promoting diversity, such as need-based financial aid and affirmative action in colleges.

This paper overcomes these challenges by exploiting a reform that exogenously exposed people to low-income peers. In 2015, the Colombian government implemented a massive tertiary education financial aid program for low-income high achievers to attend high-quality universities. The policy generated an immediate, unanticipated, and unprecedented influx of low-income students into private and selective universities, boosting the socioeconomic diversity of the student body at elite institutions (Londoño-Vélez et al., 2020) and induced more interactions between high- and low-income students. 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 an elite university that ex-ante catered to predominantly high-income students and whose share of entering low-income students quadrupled from 7 percent in 2014 to 33 percent in 2016 as a result of the expansion of financial aid. I began collecting original survey data in August 2015—roughly six months after the policy rollout. My survey experiments measure students' social networks, as well as their perceptions, attitudes, and preferences for redistribution. Combining the survey records with administrative microdata on admissions and classroom composition for cohorts entering college before and after the policy, I compare high-income students' outcomes as a function of their exposure to low-income peers. I leverage four 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 mean composition of high-income students did not change immediately after the policy, allowing me to cleanly compare high-income students across time. Third, students have little ability to self-select into being exposed to more low-income peers. Fourth, college admission is based solely on standardized high school exit test scores, which are observable to me (the econometrician). These four features enable me to exploit the exogenous variation in the degree of exposure to low-income students across cohorts (before and after the policy rollout) and majors (with smaller and greater shocks in diversity). Moreover, Colombians' awareness of their own and others' socioeconomic status makes it an ideal setting to study perceptions of inequality.

I find that exposure to low-income peers fostered interactions among students of different socioeconomic backgrounds, with a greater share of high-income students naming a low-income student among their five closest friends or study partners. Such an exposure to diversity reduced high-income individuals' upward bias in their perception of the income distribution. The extensive margin effects of initial exposure to diversity are particularly large, with the effects being more than twofold the size from a move from 0 to 1 percent than a move from 10 to 11 percent. I argue, and show, that exposure to low-income peers also raised concerns about fairness—specifically, an awareness of the difficulty of overcoming poverty without government intervention. As a result, high income students became more supportive of progressive taxation. These findings are robust across a range of specifications that alter the comparison sample, modify the functional form of the treatment variable, and control for any potential sorting of students into exposure to low-income peers.

This paper contributes 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 extent of inequality or poverty (Ariely and Norton, 2011; Kuziemko et al., 2015), culture (Luttmer and Singhal, 2011), interpersonal preferences (Luttmer, 2001), and reference points (Charite et al., 2016). This study evaluates how a real-life, large-scale policy intervention—a financial aid program—shapes people's stated redistributive preferences. My findings highlight the potential externalities from policies that increase diversity. This is crucial because how people behave in the lab or the field might differ from how they react to government interventions in practice. Further, the natural experiment I study—financial aid for low-income students—is particularly policy relevant, given recent evidence of high income segregation across colleges (Chetty et al., forthcoming) and the prospect of fostering diversity through financial aid policy (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) in three main ways. First, unlike India's affirmative action, the policy I study left the admissions process virtually unaffected, enabling me to cleanly disentangle between having socioeconomically diverse versus lower-achieving peers. Second, I measure beliefs about the distribution of income and fairness, and show how changed beliefs shape preferences for redistribution. Third, 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 the adults in my study, unlike the population in Rao (2019), may exercise their democratic right to vote.

The remainder of the paper is organized as follows. Section 1 introduces the intuition for how reference groups affect individuals' perception of the income distribution and their redistributive preferences. Section 2 provides some institutional background and describes the financial aid program. Section 3 presents the data, while Section 4 describes the methodology used. Section 5 presents the results on perceptions of the income distribution and preferences for redistribution. Section 6 explores the mechanisms and offers a brief discussion. Finally, Section 7 concludes.

1 Conceptual Framework

In this section, I briefly summarize 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

[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, 2019; 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.

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, median, dispersion and fraction of individuals under the poverty line (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).

In my setting, college students infer the income distribution from their reference groups, including friends and classmates. Consider a naïve high-income student with rich reference groups given, for instance, friendship homophily or having classmates of similar socioeconomic background (e.g., due to segregation in higher education). 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: An exogenous increase in her exposure to low-income peers reduces these biases.

Correcting these biases might impact individuals' stated preferences for redistribution. For instance, 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 redistribution. Similarly, raising the perception of social mobility should also negatively impact redistributive preferences (Benabou and Ok, 2001; Hirschman and Rothschild, 1973; Piketty, 1995). If, instead, interacting with heterogeneous groups raises fairness concerns (Alesina and Angeletos, 2005), then it *raises* support for redistribution. This leads to the third and final testable prediction:

Prediction 3: Raising high-income individuals' exposure to low-income peers might have a positive effect on their support for redistribution if fairness concerns are sufficiently large.

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

2 Background

Segregation in Colombia's Higher Education System

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 has widespread use in colleges' admissions processes: four-fifths of postsecondary institutions use SABER 11 scores as an admission criterion (OECD and The World Bank, 2012). College applications are decentralized, major-specific (i.e., students apply to a college-major pair) and biannual—Spring and Fall—since there are two graduating cohorts per year.[3]

High-quality private universities are costly in Colombia, with the average tuition fee being more than tenfold its public equivalent. This, coupled with scarce resources available, excludes low-income students from high-quality private universities. Being heavily subsidized, high-quality public universities are over-subscribed and reject most applicants. The overwhelming majority of low-income students are left with the alternative of attending medium- or low-quality postsecondary institutions (Ferreyra et al., 2017). This results in a severe de facto segregation of postsecondary education in Colombia.

A Reform-Induced Shock in Socioeconomic Diversity

In October 2014, the government announced the introduction of *Ser Pilo Paga* (roughly, "hard work pays off" in Spanish, henceforth SPP), Colombia's first large-scale need- and merit-based college financial aid program.[4] To receive this scholarship-loan, applicants had to score among the top 9 percent of the SABER 11 distribution (merit), be sufficiently low-income (need), and be admitted at one of the 33 "High Quality" universities in the country, as certified by the central government.[5] Between 2014 and 2018, roughly 40,000 students benefited from SPP. The policy dramatically changed the student body composition at high-quality private universities, historically reserved for those who could afford their pricey tuition fees—on average, their share of entering low-income students increasing by 46 percent (Londoño-Vélez et al., 2020).

[3]College begins in the spring (fall) for most public (private) high school students.

[4]Before SPP, 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 1 in 20 students by 2014.

[5]Note that, insofar as High Quality Accreditation status was awarded well in advance of the announcement of SPP, universities could not self-select into receiving or not students from SPP.

The boost in diversity was exceptionally pronounced at an elite university in Bogotá D.C., henceforth referred to as University X. Although its average annual tuition cost exceeds Colombia's per capita GDP of PPP $15,000 (The World Bank, 2018), prospective students pay no fee to apply to this university. Applicants, who declare their major when submitting their application, are ranked within their major based solely on their SABER 11 test score. Depending on the supply of seats available, a major-specific admission cutoff is generated; those scoring above that cutoff are admitted, whereas those scoring below it are rejected. These cutoffs are unknown at the time of application and cannot not be predicted by applicants (see Barrera-Osorio and Bayona-Rodriguez, 2019). Around 1,200–1,400 of admitted high school students enroll each term (see Figure A.2).

By January 2015—barely three months after SPP had been publicly announced—roughly one-third of students enrolling at University X were beneficiaries of SPP. Reflecting differences in tastes for particular majors, there was large variation of SPP recipients across majors, as depicted in Figure 1. 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 University X. Importantly, the share of SPP students in a given major is not correlated with the admission cutoff of that major (the p-value on that regression is 0.148).

By relaxing credit constraints, SPP significantly raised the share of low-income entering students. Figure 2, which plots Spring freshmen students by their socioeconomic stratum (a measure of SES), shows that the share of low-income students—henceforth defined as those in the bottom two strata—almost quadrupled immediately after SPP, jumping from 7.1 percent to 27.3 percent between 2014 and 2015, and further to 33.3 percent in 2016.[6] This constitutes an unprecedented increase in socioeconomic diversity. Importantly, this boost in diversity was not offset by a decrease in the average quality of new enrollees; if anything, *average* cognitive ability increased (although, as I discuss below, the composition of *high-income* students was not affected).[7]

Five features of SPP are particularly important for my analysis. First, the policy was announced *before* most college admissions deadlines, but *after* students had taken the

[6]"Stratum" is a measure of socio-economic status designed to target public service subsidies in Colombia. The system classifies dwellings into 6 strata (1 being the poorest) according to their physical characteristics and surroundings. While correlation with income is imperfect, one advantage of using the strata system is straightforwardness: most Colombians are well aware of their stratum, making this information easy to collect and Colombia an ideal setting to study perceptions of inequality. I henceforth use strata as my measure of SES.

[7]To illustrate why this is the case, Figure A.4 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 University X. The greater demand for admission shifted the admission cutoff towards the right.

SABER 11 exam (see the timeline of events in Figure A.3). This short timespan made it very difficult for high-income students to modify their (university-by-major) application and enrollment decisions in response to the policy based on their affinity for low-income peers. In fact, the impact of SPP on socioeconomic diversity only became known a few days *after* the spring term began (La Silla Vacía, 2015).[8] This helps explain why the number of high-income students applying to University X remained constant after SPP was rolled out (see Figure A.5) and why the yield rate—i.e., the share of admitted applicants who enroll—remained constant for high-income students between Spring 2014 and Spring 2015 (see Figure A.6).[9]

Second, 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, a feature I leverage for identification.

Third, the policy did not significantly affect the composition of *high-income* students enrolling in Spring 2015 relative to Spring 2014. Indeed, while the admission rate for *low-income* students dropped, the share of high-income admitted applicants remained constant (see Figure A.7). This reflects the fact that, unlike low-income applicants—who applied as soon as their test score made them eligible to receive SPP—high-income students' test scores were located well above SPP's eligibility cutoff. For instance, high-income students who enrolled at University X scored on average in the 98th percentile of national test scores both in Spring 2014 and Spring 2015. Thus, very few *high-income* students were displaced by low-income students in Spring 2015 (see Londoño-Vélez et al., 2020). In addition, the university somewhat expanded the supply of its seats in 2015 in response to the increased demand (see Figure A.2). This absence of compositional changes among *high-income* students for the Spring 2015 cohort is another key feature I leverage for identification.

Fourth, insofar as SPP was a financial aid program—not affirmative action—SPP beneficiaries received no preferential treatment in college admissions, which are always based solely on SABER 11 standardized test scores. Thus, unlike in Rao (2019), high-income students in my setting share their classroom with low-income students that are ex-ante similar in cognitive ability (as measured by SABER 11); the main difference is their socioeconomic background.

The final feature is that colleges were not permitted to track students by their socioeconomic status (SES). Instead, SPP beneficiaries were integrated in the same

[8]Note that the potential long-term costs of attending a university that did not qualify to receive SPP beneficiaries—that is, universities without High Quality certification—are high (Camacho et al., 2017).

[9]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 after SPP was introduced (see Figure A.8).

classrooms as non-beneficiaries. At University X in particular, 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). This severely limits high-income students' capacity to self-select into exposure to low-income peers, a point I return to when analyzing the results.

Together, these five features of the institutional setting produce a unique opportunity to identify the causal effect of socioeconomic diversity on student interactions and high-income individuals' perceptions, attitudes, and preferences.

3 Data

The data for this paper comes from four main sources. First, I use administrative records from University X, which include detailed student-by-semester level information about undergraduate applications, admissions, matriculation, and course enrollment. The admissions records, available 2010 through 2016, include student-by-semester information on applicants' sociodemographic characteristics (e.g., sex, date of birth, socioeconomic stratum, parental education), SABER 11 standardized test score, the university's admission score (i.e., a major-by-semester-specific weighted average of the different components of SABER 11), major, the major-by-cohort admission cutoff, and indicators for whether the applicant received admission and enrolled. For students ever enrolled between 2000 and 2016, I observe detailed semesterly information about the courses taken, their performance in each course, and other information (e.g., double major, internal transfers).

Second, I use administrative micro-data from Colombia's Ministry of Education. This includes student-level information about all SPP beneficiaries.

Third, to normalize SABER 11 test scores, I use 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.

Lastly, I use survey data collected by myself specifically for this research project using Qualtrics online survey software. I collected survey wave 1 in August 2015, that is, one semester after high-income students first shared a classroom with low-income peers (see Figure A.3 for a timeline of events). The survey sampled high-income students (i.e., strata 4, 5, and 6) attending University X in Fall 2015 and who began their undergraduate studies in either Spring 2014, Fall 2015, or Spring 2015, that is, before and after SPP was implemented. Survey wave 2 was collected in February 2016, i.e., one year after the first cohort of SPP beneficiaries began their studies. The survey questionnaires collected information on students' social and study networks, as well as their perceptions, attitudes, and preferences.[10] I use the survey information about participants' networks and merge it with the list of SPP beneficiaries to construct a measure of intensity of interaction between SPP beneficiaries and non-beneficiaries.

4 Empirical Strategy

This section describes the empirical strategy used to identify the effect of socioeconomic diversity on individuals' perceptions of the income distribution and their preferences for redistribution. I exploit the plausibly exogenous exposure to low-income peers introduced by SPP financial aid at this elite university, as well as treatment intensity from variation in the share of SPP classmates students are exposed to. Restricting the sample to high-income students (i.e., strata 4, 5, and 6) enrolled in a given term in University X, I estimate the following specification by OLS:

$$y_{imk} = \alpha + \beta \text{ Share of SPP Classmates}_{imk} + \mathbf{X}'_{imk}\gamma + \delta_m + \epsilon_{imk} \tag{1}$$

where y_{imk} is outcome y for student i in major m and cohort k, Share of SPP Classmates$_{imk}$ is the average share of classmates that receive SPP financial aid (the main treatment variable), $\mathbf{X}_{imk}$ is a vector of controls, δ_m are major fixed effects, and ϵ_{imk} is a student-specific error term.[11] I cluster standard errors at the major-by-cohort level, since this is the unit of treatment. The β coefficient is thus the average effect on outcome y of a one percentage point increase in the share of classmates that are SPP recipients and is the key parameter of interest. This approach identifies the average effect on high-income college students of adding low-income classmates of similar ability, which is a relevant estimate for policy.

One concern with the cross-cohort comparison in specification (1) is that the composition of high-income students might have changed between Spring 2014 and 2015. While I provided evidence against this in Section 2, I can test whether the policy affected the composition of high-income students in my survey sample. I do this by putting the covariates in vector $\mathbf{X}$ on the left hand side and regressing each one on a dummy for being in the Spring 2015 cohort (see Table A.1). While the Spring 2014 cohort is roughly one year older than the Spring 2015 cohort, which is to be expected, there are little baseline differences between the two groups. In particular, the cognitive ability, socioeconomic

[10] Appendix B describes the survey questionnaire and procedure, and shows there is balance in the response rates across cohorts.

[11] For instance, I flexibly control for students' standardized SABER 11 test score by including SABER 11 fixed effects in $\mathbf{X}_{imk}$ based on deciles of the sample of survey respondents.

stratum, migrant status, paternal education, and risk aversion are the same between the two cohorts (although there appear to be some differences in maternal education). We control for all of these baseline covariates in my main regressions.

An additional concern that might emerge is that specification (1) is picking up cohort-specific trends. Intuitively, this is unlikely for high-income students—the population I survey—given that, as shown, the policy did not change the composition of high-income students enrolling in Spring 2015. Notwithstanding, I consider an alternative empirical strategy that exploits the within-cohort, across-major variation in the share of SPP classmates by implementing a difference-in-differences approach that augments specification (1) with cohort fixed effects ψ_k:

$$y_{imk} = \alpha + \beta \text{ Share of SPP Classmates}_{imk} + \mathbf{X}'_{imk}\gamma + \delta_m + \psi_k + e_{imk} \tag{2}$$

The identifying variation in specification (2) comes from majors that were differentially affected by the shock in socioeconomic diversity. Importantly, I can show that the share of SPP classmates is *not* correlated neither with the competitiveness of the major (recall Figure 1) nor with student observable characteristics (see Table A.2). As a robustness exercise I report the results using both specifications (1) and (2) and, reassuringly, find that both types of analyses produce quantitatively similar results.

4.1 Interactions between Low- and High-Income Students

Before presenting the results, I first show that the policy raised high-income students' exposure to low-income peers and fostered interactions with them. This point is important because one could be concerned that high-income students simply do not observe low-income students, either because they do not interact with them (e.g., extreme homophily) or because they cannot infer classmates' socioeconomic status, biasing my estimates towards zero. To examine this, I asked respondents about their friendship networks and their interactions with SPP recipients. The evidence, summarized in Table 1, shows that, in fact, high-income students are well aware of their classmates' SPP status.[12] Consistent with the increased number of low-income students being felt at the university level, all three cohorts overestimate the actual share of SPP classmates.[13] However, students from the "treated" cohort (i.e., Spring 2015) perceive a significantly higher prevalence of SPP classmates than students from "control" cohorts (i.e., Fall 2014 and Spring 2014). They are

[12] In-depth interviews and ethnographic observation suggest socioeconomic status can be inferred at this elite university, *inter alia*, by the clothing brands students wear, the mobile phone brands they use, the high school they attended, and the way they speak Spanish and English (Alvarez, 2019).
[13] Note that such spillovers bias against finding effects.

also ten times more likely to have SPP beneficiaries in their social networks and have twice as many low-income friends—i.e., friends in stratum 1 or 2—as the “control" cohort.[14] In addition, students from the “treated" cohort report having worked with a SPP beneficiary an average of three times, compared to only once for students in older cohorts. Thus, to the extent that peer group formation is inherently endogenous, Table 1 suggests high-income students in the “treated" cohort substantially interacted with SPP recipients and, furthermore, have peer groups that are more heterogeneous in SES.

5 Results

5.1 Perception of the Income Distribution

In this section, I test whether exposure to socioeconomic diversity affects high-income students' perceptions of the income distribution; specifically, the incidence of poverty and the distribution of individuals across socioeconomic strata.

Poverty Incidence

Table 2 presents the results from specification (1) when the dependent variable is the perceived share of Colombians that are living under poverty.[15] Consistent with prediction # 1 from the conceptual framework, high-income students from the Spring 2014 cohort have a biased perception of the incidence of poverty: their perceived rate of 32.99 percent is 3.2 percentage points below the actual rate of 36.1 percent in 2015 (DANE, 2020), i.e., a 9.4 percent underestimate. This is consistent with a segregated education system where high-income students have similarly-rich reference groups and fail to properly apply Bayes' rule in their assessment of the income distribution.

Moreover, and consistent with prediction # 2, an exogenous increase in high-income students' exposure to low-income peers shifts their reference groups and lessens the bias in their perceived distribution of income: a 1 percentage point increase in SPP classmates raises the outcome by 0.304 percentage points or 0.9 percent relative to the control mean.

[14] A back-of-the-envelope calculation suggests that if students selected their friends/study partners at random among their classmates, then the Spring 2015 Freshmen would have a 57.8 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 23.1 percent and 12.8 percent chance of having at least one SPP beneficiary among their five closest friends/study partners, respectively.

[15] To guide students, the survey questionnaire noted that this share could be defined as the share of Colombians earning less than 200 thousand pesos (2014 USD 84.16) per month. Figure A.9 presents the distribution of this dependent variable across all survey respondents.

The identification strategy underlying specification (1) could face three potential challenges, which I now address. First, if the perception of the income distribution is correlated with baseline covariates (e.g., cognitive ability), the cross-cohort comparison might conflate the effect of socioeconomic diversity with compositional changes induced by the financial aid program. However, the coefficient from Column (1) is not affected when excluding the baseline controls: the p-value from a hypothesis test that the β coefficients with and without controls are the same is 0.2834.

Second, although high-income students cannot self-select into *majors* based on their affinity for low-income students (applicants received admission and enrolled before learning of the increase in SES diversity), they might self-select into *courses*. While course curriculum is relatively set within a major at this university, I deal with this potential concern by instrumenting the *actual* share of SPP classmates with the *predicted* share using the pre-reform distribution of students across classes within a major-by-cohort pair. That is, given a student's major m and cohort k, I predict her share of SPP classmates absent sorting in response to SPP (Appendix C further describes this methodology).[16] Column (2) shows accounting for any potential selection has no effect on β: the p-value of the Hausman test is 0.73.

Third, even though my sample is restricted to high-income students, *Spring* and *Fall* cohorts may differ in observable and non-observable characteristics (e.g., Spring cohorts are more likely to have graduated from international high schools). For this reason, Columns (3) and (4) restrict the estimation sample to Spring entry students only. Despite the loss in sample size from dropping Fall entry students, the magnitude and significance of the coefficient is remarkably robust to this restriction. Even controlling for any potential sorting of students across classrooms in response to the reform, Column (4)—my preferred specification—suggests that a 1 percentage point increase in the share of SPP classmates raises the perceived poverty incidence by 0.31 percentage points (0.9 percent).

Interestingly, I observe nonlinear impacts of exposure to low-income peers on high-income students' perception of the income distribution. Specifically, the magnitude and significance of the β coefficient is driven by the extensive margin of the initial exposure of high-income students to socioeconomic diversity. Increasing the share of low-income classmates from 0 to 1 percent has 2.5 times the effect of an increase from 10 to 11 percent and more than ninefold the effect of an increase from 15 to 16 percent (see Table A.3).

Further, the results from Table 2 are robust to changes in the definition of the treatment variable. For instance, substituting the share of SPP classmates with the share

[16] Inter alia, this accounts for any concern that the increase in exposure to low-income peers might be due to any orientation course developed by the university in response to SPP.

of low-income classmates—defined as being from strata 1 and 2—produces very similar results (see Table A.4). The results are also robust across different functional form specifications, such as collapsing the share of SPP classmates to an indicator that equals one if at least 5 percent of classmates are SPP recipients (see Table A.5), which is roughly the median share of SPP classmates in the surveyed sample and turns 1 for 99.5 percent of the Spring 2015 cohort versus only 13.8 percent of the Spring 2014 cohort (see Table 1). This suggests most of the variation in my analysis comes from the within-major, across-cohort comparison.[17]

As explained in Section 4, an alternative empirical strategy would be to implement a difference-in-differences approach that exploits the within-cohort, across-major variation in the share of SPP classmates, as in specification (2). An advantage of this approach is that it enables addressing the concern that the results presented above are picking up cohort-specific trends. Its disadvantage is that it compares low versus high shares of SPP classmates, which does not take into account potential extensive-margin impacts of diversity and the concave returns to diversity documented above. Notwithstanding, Table A.6 presents the results using specification (2). The last row of Column (1) shows that the estimates are quantitatively similar: while the β coefficient is less precisely estimated, the p-value of the null hypothesis that the estimates with and without cohort fixed effects are equal is 0.21.

Socioeconomic Strata

To further explore the effects of diversity on the perception of the income distribution, I ask students to plot the distribution of the population across socioeconomic strata, a proxy for SES that is arguably more salient for Colombians. For ease of exposition, Figure 3 plots the results collapsing the treatment to an indicator that equals 1 for having at least 5 percent of SPP classmates. The black bars represent the distribution of socioeconomic strata for all students graduating high school in 2014, taken from the ICFES data described in Section 3. The white bars represent the mean perceived distribution from high-income students in the Spring 2014 cohort (i.e., before SPP). Again, consistent with prediction # 1 of naïve agents failing to fully apply Bayes' rule, high-income students' perception of the income distribution is substantially upward-biased: they severely underestimate the share of low-income individuals (i.e., strata 1 and 2) and overestimate the share of high-income individuals (i.e., strata 4, 5, and 6).

[17] The last row of Table 2 reports the p-value from 1,000 permutations of the predicted share of SPP classmates at the major-by-cohort level, i.e., the same level in which standard errors are clustered. Reassuringly, the p-values are similar or even smaller relative to standard inference.

The gray bars add the estimated OLS coefficient from a regression using specification (1) to the control cohort mean, comparing Spring entry cohorts only. Consistent with the prediction # 2—namely, that an exogenous increase in socioeconomic diversity reduces high-income individuals' bias in the perceived income distribution—exposure to low-income peers narrows the gap between the perceived and the actual distributions of socioeconomic strata. Indeed, the β coefficient is positive and significant for the lowest stratum, while it is negative and significant for highest three strata—the strata of the surveyed students.[18] The results are quantitatively similar when instrumenting the actual treatment indicator with the predicted indicator using pre-reform data (see Table A.7). Reassuringly, the results hold when augmenting specification (1) by including cohort fixed effects for a difference-in-differences-type analysis that accounts for possible cohort-specific trends: the estimates with and without cohort fixed effects are quantitatively similar (see Table A.6).

5.2 Preferences for Redistribution

In this section, I test whether exposure to socioeconomic diversity affects high-income individuals' preferences for redistribution.

Table 3 presents the results from specification (1) when the dependent variable is an indicator of support for taxing the rich. Column (1) shows that a 1 percentage point increase in the share of SPP classmates raises support for taxation of the rich by 0.008 percentage points or 1.2 percent from a base of 68 percent, and this effect is significant at the 1 percent level.[19] Even restricting the sample to Spring cohorts only and accounting for any potential sorting, Column (4) shows that a 1 percentage point increase in the share of SPP classmates raises support for taxation of the rich by 0.011 percentage points or 1.6 percent from a base of 68 percent.

Neither substituting the share of SPP classmates with the share of low-income classmates (see Table A.8) or with an indicator for having least 5 percent of SPP classmates (see Table A.9) affect the direction nor significance of the estimated coefficient. Further, as with the outcomes on perceptions analyzed in the previous section, these results are also robust to including cohort fixed effects in the difference-in-differences-type analysis from

[18] An alternative interpretation is that students incorrectly believe that the population is distributed uniformly among socioeconomic strata. Thus, the white bars in Figure 3 would reflect a misunderstanding of the strata system in Colombia rather than an actual biased perception of the income distribution caused by a failure to fully apply Bayes' rule. However, even if this were the case, the fact that the β coefficients are positive and significant at the bottom and negative and significant at the top suggests exposure to a more diverse peer group affects students' perception of the distribution of strata in Colombia.

[19] Again, this finding is not driven by changes in the sample composition: the p-value from a hypothesis test that the β coefficients with and without controls are the same is 0.3574.

specification (2): Column (8) in Table A.6 shows that the resulting β coefficient has the same magnitude as the specification without cohort fixed effects displayed in Table 3, and the p-value of a test of equality that the β coefficients are the same with and without cohort fixed effects is 0.92. I therefore conclude that exposure to socioeconomic diversity in the classroom raises high-income students' support for redistribution.[20]

6 Mechanisms and Discussion

Why would exposure to socioeconomic diversity affect individuals' preferences for redistribution? In the classic Meltzer and Richard (1981) model with self-interested voters, the demand for redistribution falls with the level of income. Thus, if exposure to socioeconomic diversity raised high-income students' awareness of own high position in the socioeconomic ladder, the treatment should make them less—not more—supportive of government redistribution. Similarly, if exposure to low-income classmates raised their prospect of upward social mobility (POUM), the treatment should have a negative impact on redistributive preferences (Benabou and Ok, 2001; Hirschman and Rothschild, 1973; Piketty, 1995). Indeed, Panel (a) of Table 4 shows that the treatment raised high-income students' POUM for low-income individuals; specifically, from stratum 2, the modal stratum among SPP recipients and where Figure 2 documented the largest shock in diversity.[21] Notwithstanding, I find that the treatment had a *positive* impact on high-income students' support for redistribution, which is inconsistent with both the self-interested model and the POUM hypothesis.

Instead, I find evidence that exposure to low-income students—and its subsequent effect on the perceived income distribution—raises concerns for fairness. Specifically, it raises the notion that, absent government intervention, individuals do not share the same opportunity of overcoming poverty. Panel (b) in Table 4 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 provides equal opportunity for

[20] I focus on this measure of redistributive preferences because it is the most interpretable given the policy. While I obtain quantitatively similar (but less precisely estimated) results when respondents are asked whether the government should subsidize the poor (see survey questionnaire in Appendix B), unfortunately this question could be interpreted as subsidizing the poor by providing *more support in addition to SPP*. Given the mixed results with respect to attitudes towards SPP in particular (see Appendix E), interpreting this outcome is not straightforward in my setting.

[21] The effect on stratum 1's mobility is similar in magnitude but imprecisely estimated (not reported).

individuals to overcome poverty (see the survey questionnaire in Appendix B).[22] A 1 percentage point increase in the share of SPP classmates raises this outcome by 0.012 percentage points (2.6 percent). These results are robust to instrumenting the treatment variable with the predicted share of SPP classmates using pre-reform information (see Table 4, Column 8), substituting the share of SPP classmates with the share of low-income classmates (see Table A.10), and substituting the continuous treatment with an indicator for having at least 5 percent SPP classmates (see Table A.11).

Moreover, these findings are not statistically different when augmenting specification (1) with cohort fixed effects for a difference-in-differences-type analysis, i.e., using specification (2) (the p-value for this comparison is 0.69): as in Table 4, a 1 percentage point increase in the share of SPP classmates increases this outcome by 0.011 percentage points or 2.4 percent (see Table A.6). Thus, and consistent with prediction # 3, exposure to socioeconomic diversity in the classroom raised skepticism towards equal opportunity without government intervention, making students more supportive of progressive redistribution.

In Appendix D, I show that these impacts from the financial aid policy took place without affecting students' own academic achievement, a concern often brought up with other diversity-promoting policies, like affirmative action. Moreover, and consistent with sociological work by Alvarez (2019), I find no evidence that exposure to low-income peers triggered negative interactions among students of different socioeconomic backgrounds—a fear often voiced by critics of SPP. In fact, in Appendix E I document a widespread support among both treated and control students for policies promoting and expanding financial aid for low-income, high-achieving students. In line with SPP's large impacts on enrollment of low-income high-achievers at high-quality universities (Londoño-Vélez et al., 2020), exposure to SPP classmates significantly raised high-income students' perception that the college admission process had become more meritocratic, enabling the most talented students enroll in the nation's top schools.

Lastly, the immediate effects of exposure to socioeconomic diversity persist over time, even as control students "catch up" and become more exposed to SPP peers and as new friendships form past students' first semester in college. In Appendix F, I compare the results from the first wave with those from second survey wave I collected six months later, i.e., after a year of being exposed to SPP classmates (these are not necessarily the

[22] 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.

same survey respondents). The results generally point in the same direction: students exposed to low-income classmates over a year have more accurate perceptions of the income distribution. Although the effects on redistributive preferences have attenuated (at least in part due to catch up by controls), exposure to diversity has raised high-income students' willingness to donate to a charity of their choice.

7 Conclusion

This paper tested 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 redistribution. 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 students perceived more inequality and became more concerned about fairness, diversity strengthened their support for redistribution.

A caveat from these results is that the high-income students I study are not exposed to a diverse set of representative low-income individuals. Instead, they interact with a 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 interacting 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 on high-income individuals for future research.

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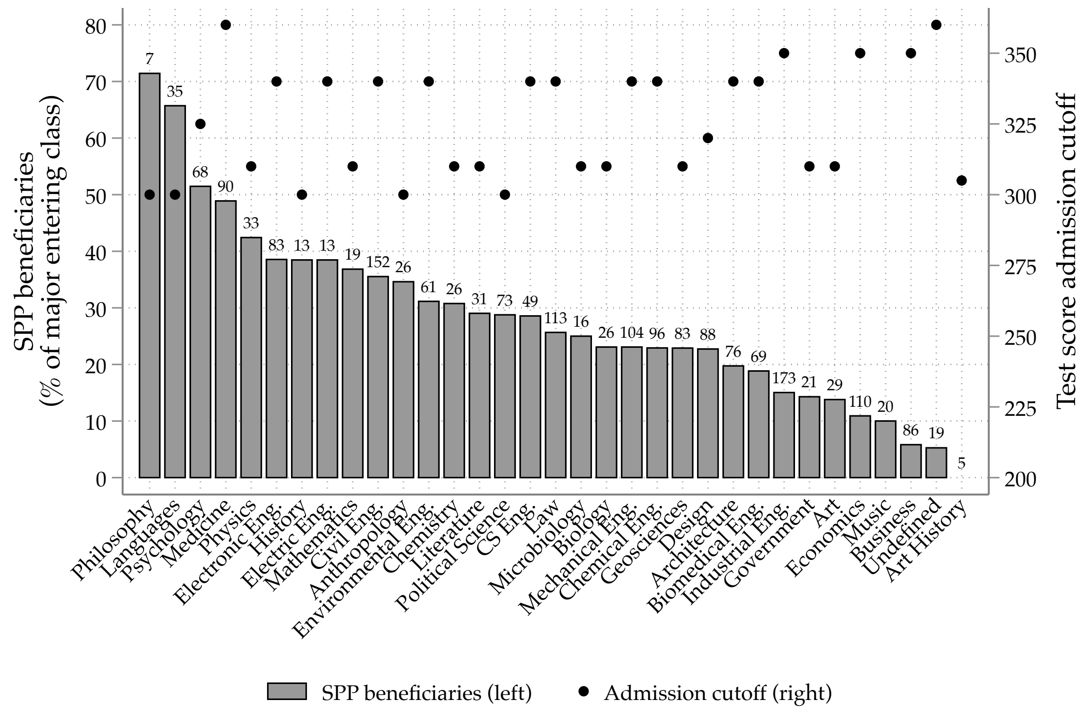
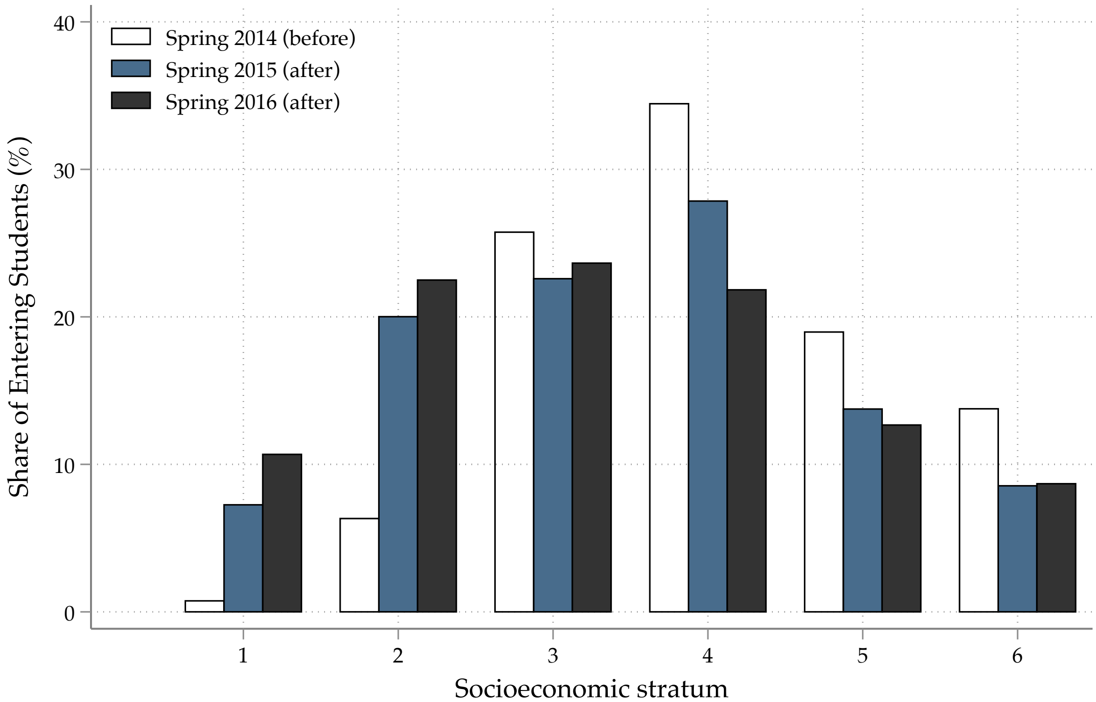
Figure 1: The Share of SPP Beneficiaries Varies Across Majors



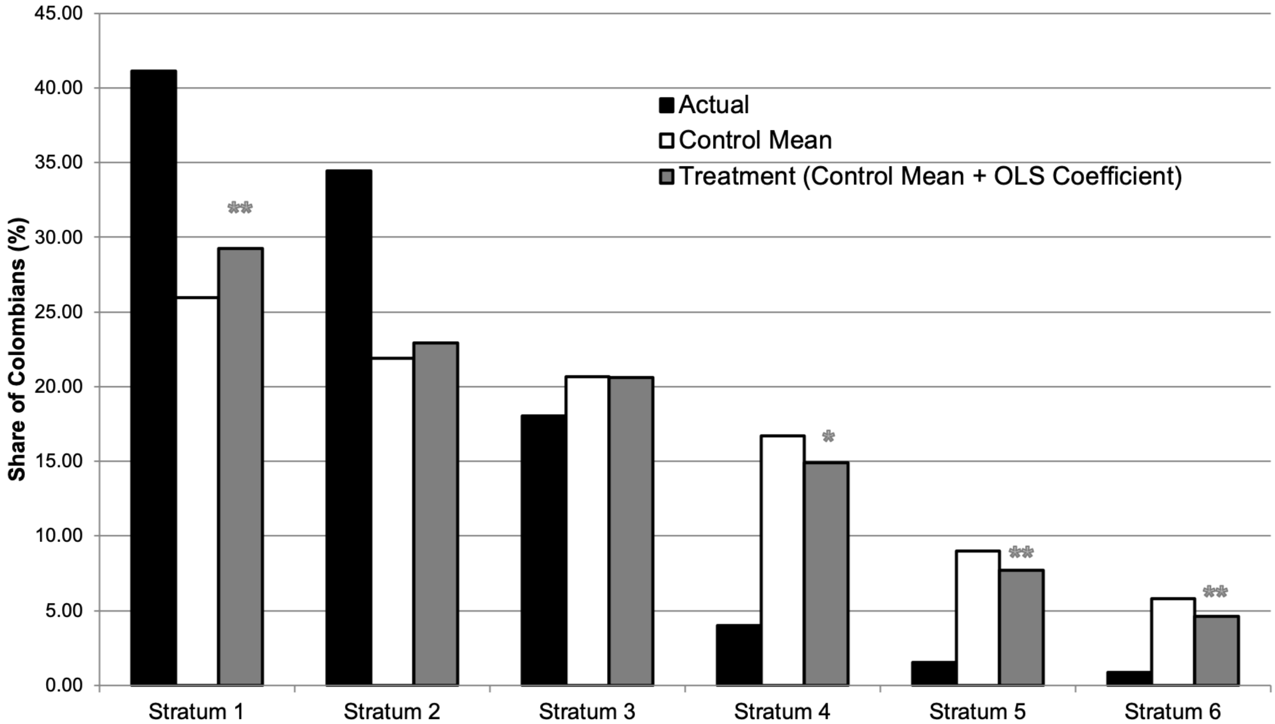
Note: The left axis in this figure plots the share of entering students in Spring 2015 at University X who are beneficiaries of SPP financial aid program by major (in gray bars). This share ranges from 71.4 percent in Philosophy to 0 percent in Art History. The numbers above the bars represent the total 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 2: 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 3: Exposure to Low-Income Classmates Reduces Bias in Perceived Income Distribution



Note: This figure plots the actual versus perceived distribution of individuals by socioeconomic stratum (1 is the poorest, 6 is the wealthiest). The black bar represents the actual distribution for all SABER 11 test takers in 2014. The white bar represents the average response by students in the Spring 2014 cohort, while the "Treatment" bar adds the estimated coefficient from the regression using a dummy for having at least 5 percent of SPP classmates. See description in Table A.7. $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Table A.7, based on 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)
Actual Share of SPP Classmates (%)	2.695	5.127	15.785
	(3.575)	(3.653)	(5.706)
Perceived Share of SPP Classmates (%)	12.511	16.388	34.477
	(13.771)	(14.086)	(19.21)
$\mathbb{1}$(Actual Share of SPP Classmates $\geq$ 5%)	.138	.393	.995
	(.346)	(.49)	(.072)
$\mathbb{1}$(SPP recipient among 5 closest friends)	.022	.067	.292
	(.146)	(.25)	(.456)
$\mathbb{1}$(SPP recipient among 5 study partners)	.043	.067	.328
	(.205)	(.25)	(.471)
No. times worked with SPP recipient	1.138	1.134	3.031
	(2.312)	(2.352)	(3.134)
Reports friends' stratum is 1 or 2	.058	.037	.103
	(.235)	(.19)	(.304)
N	138	135	195

Note: This table presents means (and standard deviations in parentheses) by entering cohort, i.e., the semester in which they first began their studies at University X. Note that the differences between these shares and those plotted in Table C.1 are driven by differences in major composition among the sample of high-income survey respondents and the full student population. *Sources:* Author's calculations using college records and student survey data.

Table 2: Exposure to Low-Income Classmates Raises Perception of Poverty Incidence

	Colombians Living Under Poverty (%)			
	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)
Share of SPP classmates (%)	0.304**	0.281**	0.346***	0.310**
	(0.123)	(0.133)	(0.124)	(0.140)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.14	0.04	0.21	0.05
$\bar{y}_{\text{Spring 2014}}$	32.99	32.99	32.99	32.99
FS F-Stat		947.25		808.15
Hausman Test p-val.		0.73		0.61
Permutation inference p-value		0.003		0.059

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 is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual share of SPP classmates with the predicted share using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3) and (4) restrict the sample to Spring cohorts only. Standard errors, in parentheses, are clustered at the major-by-cohort level. The permutation inference p-value is based on 1,000 permutations of the predicted share of SPP classmates at the major-by-cohort level, i.e., the same level standard errors are clustered. $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college records and student survey data.

Table 3: Preferences for Redistribution

	The State Should Tax the Rich			
	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)
Share of SPP classmates (%)	0.008***	0.006	0.011***	0.011**
	(0.003)	(0.004)	(0.003)	(0.004)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.11	0.02	0.15	0.07
$\bar{y}_{\text{Spring 2014}}$	0.68	0.68	0.68	0.68
FS F-Stat		947.25		808.15
Hausman Test p-val.		0.27		0.66
Permutation inference p-value		0.037		0.022

Notes: This table presents the β coefficient from specification (1) when the dependent variable is support for the statement *"The state should tax the rich."* The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual share of SPP classmates with the predicted share using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3) and (4) restrict the sample to Spring cohorts only. Standard errors, in parentheses, are clustered at the major-by-cohort level. The permutation inference p-value is based on 1,000 permutations of the predicted share of SPP classmates at the major-by-cohort level, i.e., the same level standard errors are clustered. $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college admissions records and student survey data.

Table 4: Mechanisms

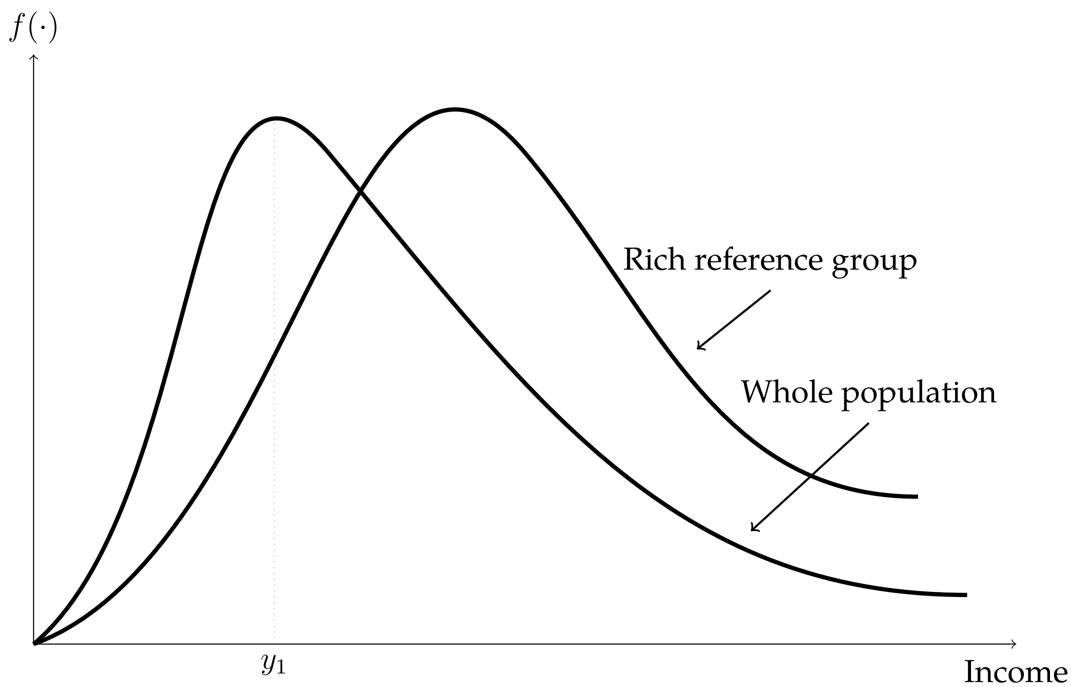
	Panel A: Upward Social Mobility for Stratum 2				**Panel B:** System Does Not Offer Equal Opportunity			
	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of SPP classmates (%)	0.007*	0.010**	0.009*	0.011**	0.009***	0.006*	0.012***	0.011***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)
Major FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X
Spring Cohort Only			X	X			X	X
N	453	453	319	319	453	453	319	319
R^2	0.14	0.04	0.16	0.05	0.12	0.04	0.2	0.07
$\bar{y}_{\text{Spring 2014}}$	0.53	0.53	0.53	0.53	0.46	0.46	0.46	0.46
FS F-Stat		947.25		808.15		947.25		808.15
Hausman Test p-val.		0.2		0.28		0.13		0.64
Permutation Inference p-val.		0.009		0.052		0.034		0.011

Notes: This table presents the β coefficient from specification (1). In Panel A, the dependent variable is an indicator for perceiving upward social mobility for individuals from stratum 2. 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."* The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual share of SPP classmates with the predicted share using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3), (4), (7), and (8) restrict the sample to Spring cohorts only. Standard errors, in parentheses, are clustered at the major-by-cohort level. The permutation inference p-value is based on 1,000 permutations of the predicted share of SPP classmates at the major-by-cohort level, i.e., the same level standard errors are clustered. $***p < 0.01, **\,p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college records and student survey data.

Appendices

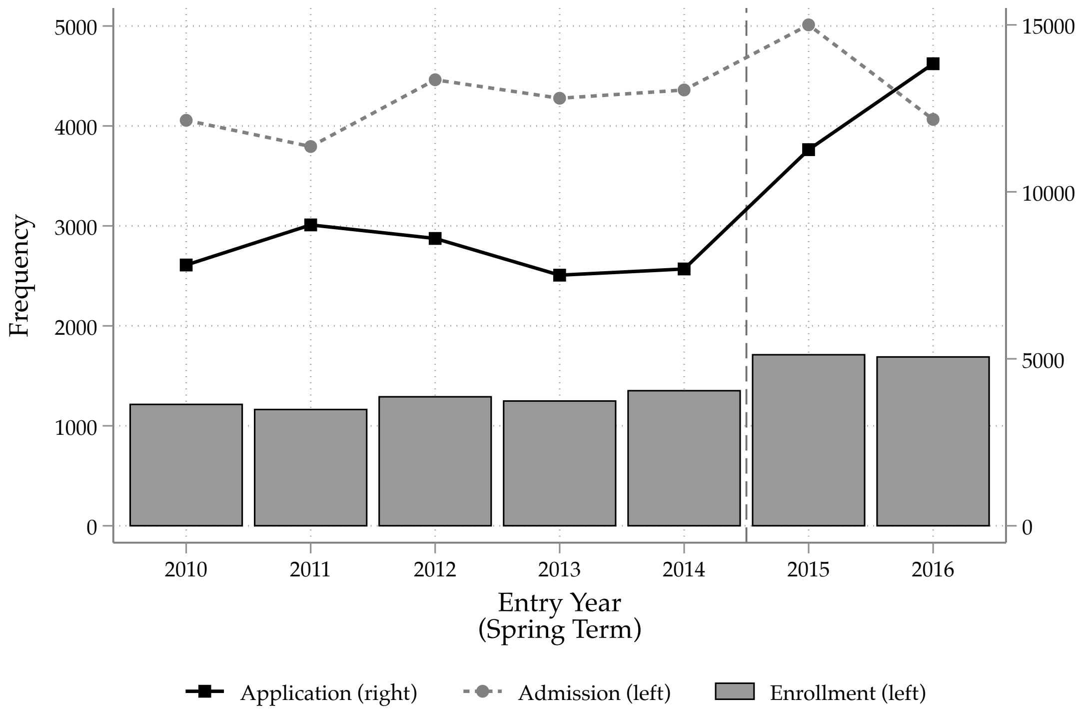
A Online Tables and Figures

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



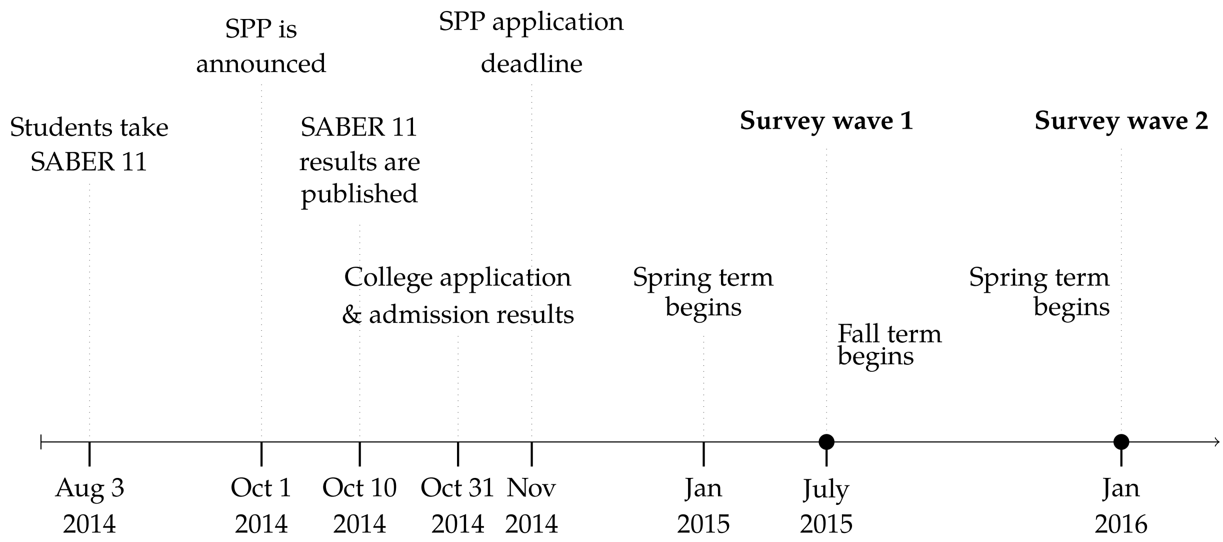
Source: Figure 1a in Cruces et al. (2013).

Figure A.2: Cohort Size Remained Constant



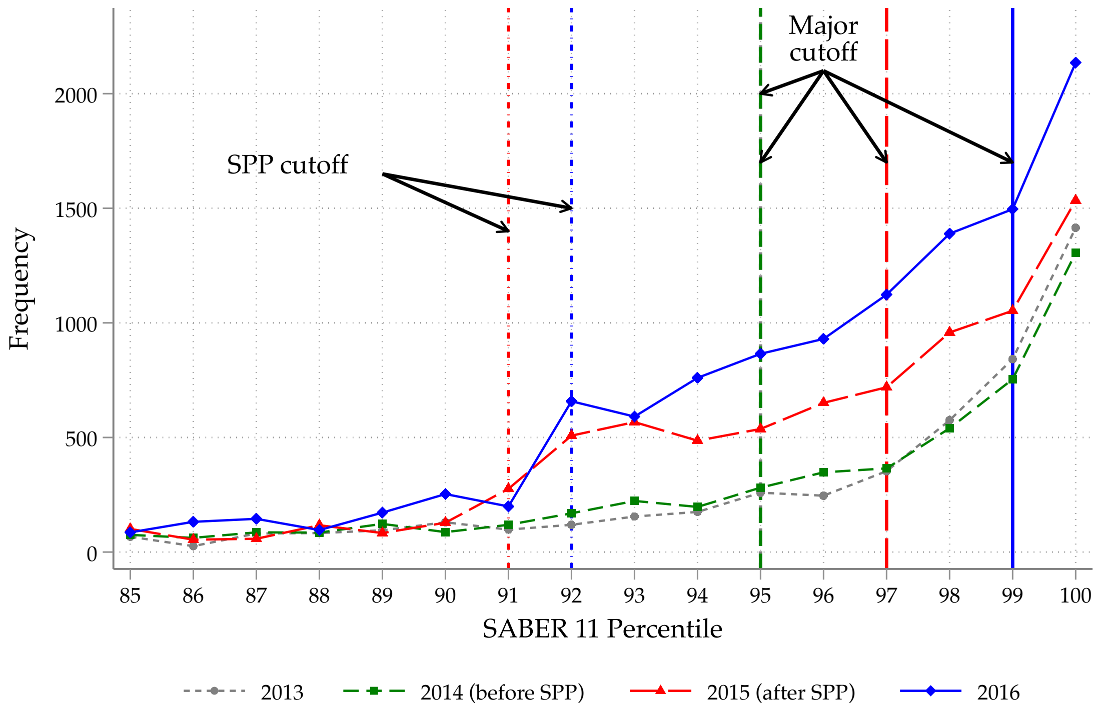
Notes: This figure compares the number of students who apply (solid black line), receive admission (dashed gray line), and enroll (gray bar) in University X every Spring term between 2010 and 2016. The vertical red line represents SPP. The figure shows that, despite the increase in number of applicants,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

Figure A.3: Timeline of Events



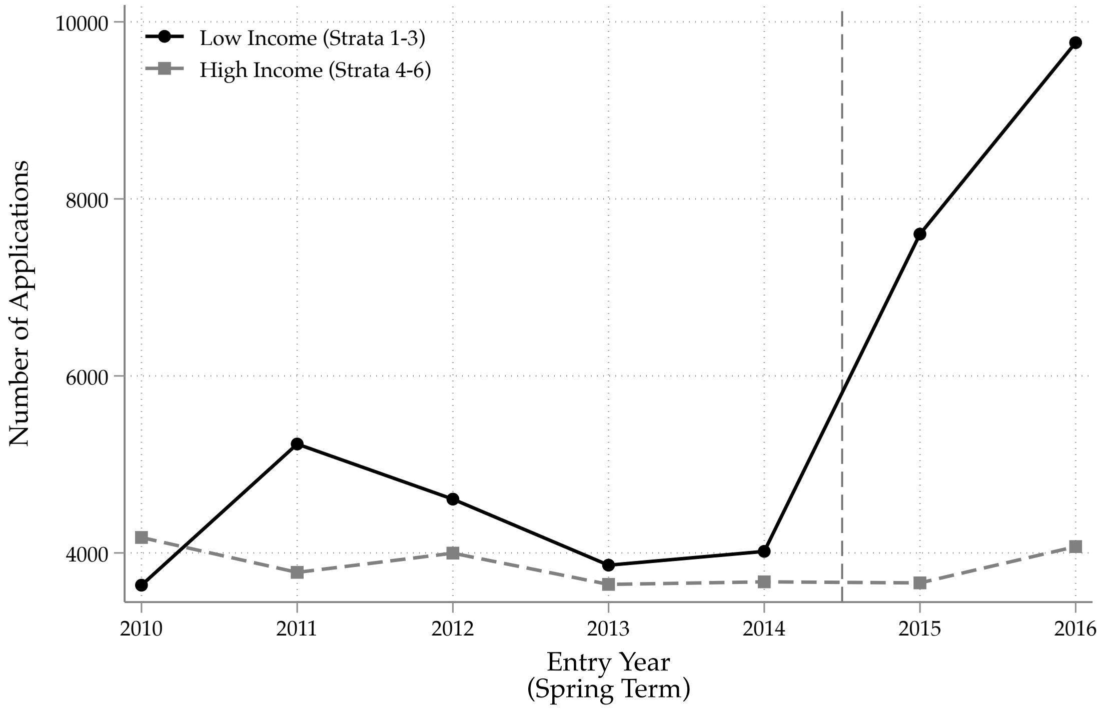
Notes: This figure plots a timeline of events taking place between August 2014 and January 2016 (not drawn to scale). SPP recipients began attending classes in mid to late January 2015. The first survey wave took place six months later, in early August 2015. The second survey wave took place one year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

Figure A.4: SPP Raised Admission Thresholds



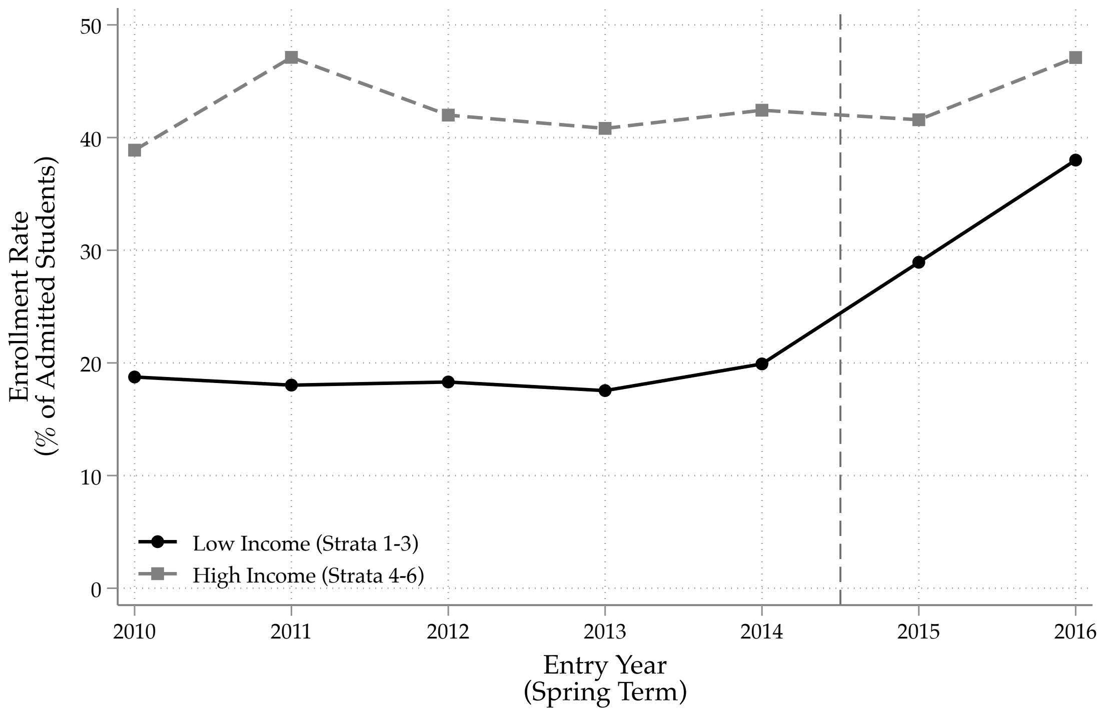
Note: This figure plots the distribution of SABER 11 test score percentiles for Fall high school test-takers that applied to University X for the Spring term in 2013 (in gray), 2014 (in green), 2015 (in red), or 2016 (in blue). The short dashed and dotted vertical lines mark the SPP eligibility cutoffs 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.5: An Increase in the Number of Low-Income (But Not High-Income) Applicants



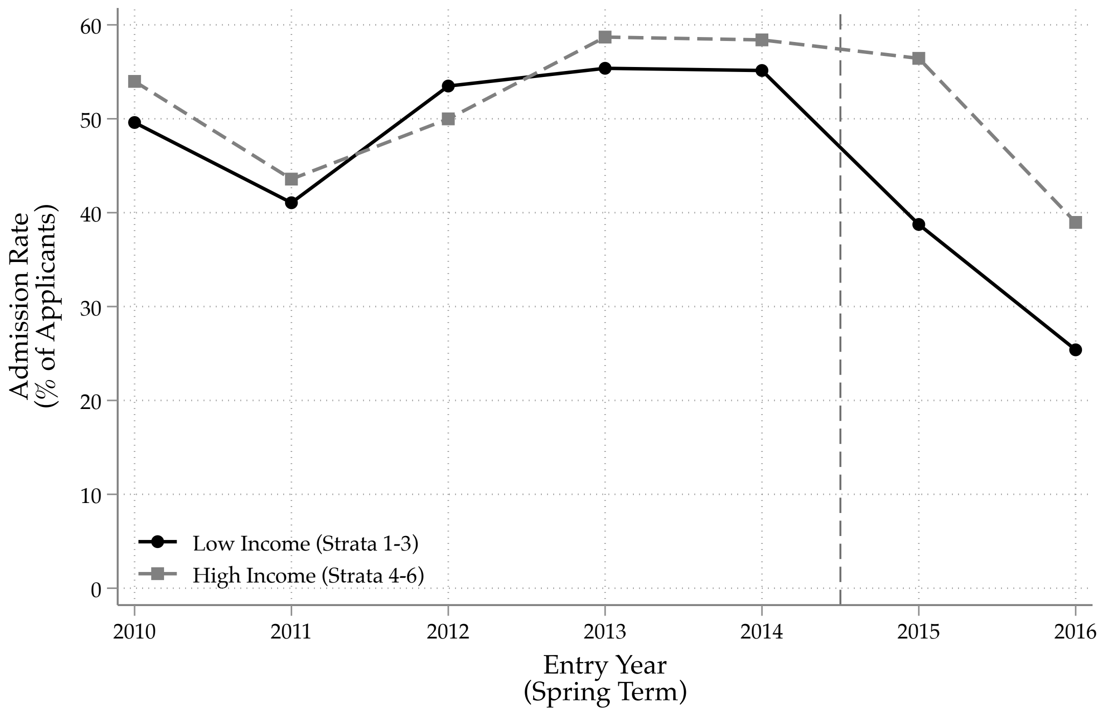
Notes: This figure plots the number of applications received by University X for Spring admissions by socioeconomic stratum.“Poor" refers to strata 1–3, while “rich" refers to strata 4–6. The vertical red line represents SPP. The figure shows that the number of applicants from relatively poor households doubled from 4,000 to almost 8,000 between Spring 2014 and 2015, and further to 10,000 the following year. As expected, the number of applicants from relatively wealthy households was unaffected by the announcement of SPP and only slightly increased in 2016. *Sources:* Author’s calculations using college admissions records.

Figure A.6: SPP Raised the Share of Low-Income (But Not High-Income) Admits that Enroll



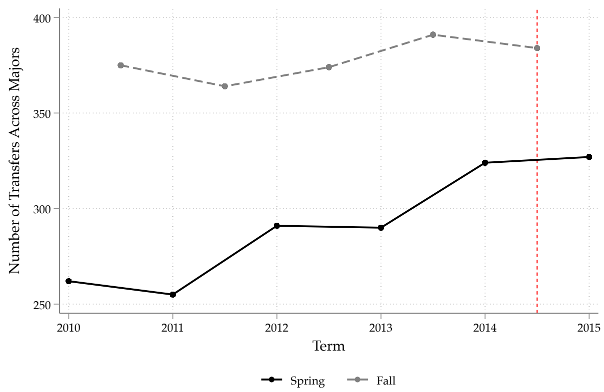
Note: This graph plots the fraction of low- and high-income admitted Spring applicants who enroll between 2010 and 2016. Low-income refers to strata 1–3, while high-income refers to strata 4–6. The vertical red line represents SPP. The figure shows that the share of high-income admits who enroll is twice the share of low-income admits who enroll. While this share did not change immediately after SPP for high-income admits, it increased significantly for low-income admits.

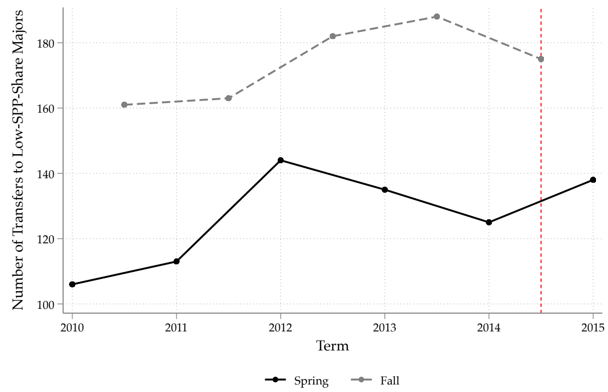
Figure A.7: Admission Rates Decreased for Low-Income (But Not High-Income) Students



Note: This figure plots the share of applicants who are awarded admission at University X over time (Spring cohorts only). The vertical red line represents SPP. For high-income applicants (strata 4–6), the admission rate did not change between 2014 (before SPP) and 2015 (after SPP). Instead, for low-income applicants (strata 1–3), the admission rate dropped significantly after SPP. *Sources:* Author's calculations using college records.

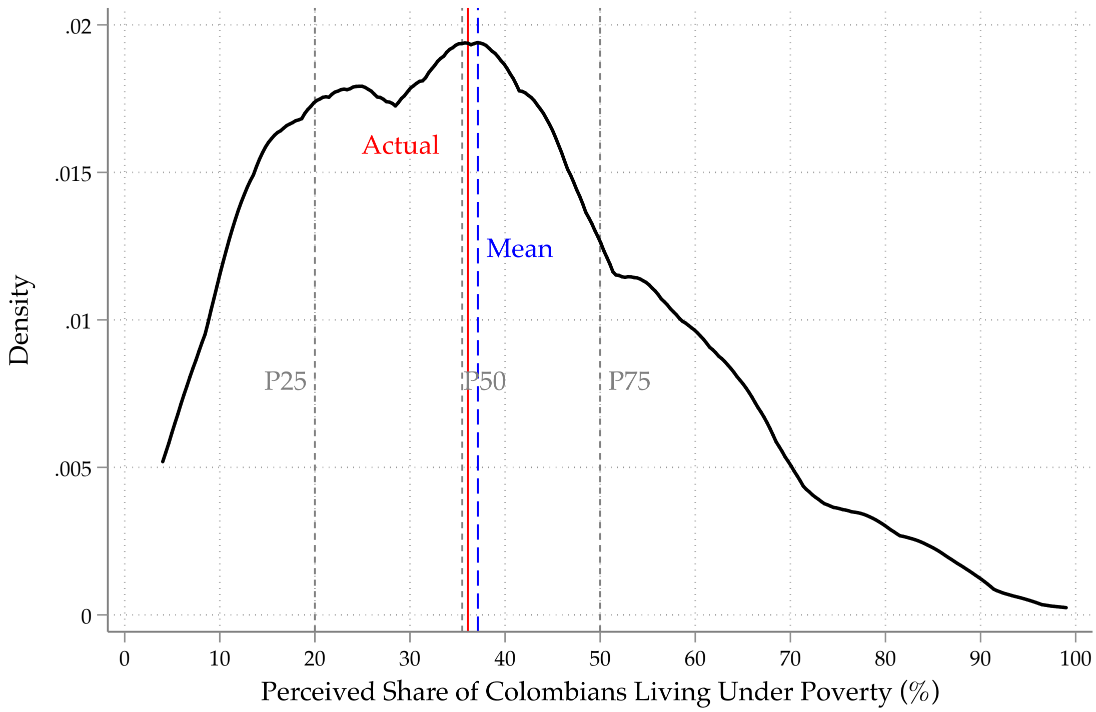
Figure A.8: There is No Increase in Transfers Across Majors





Note: Panel A plots the total number of transfers across majors within University X 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 1: Architecture, Art, Art History, Biomedical Engineering, Business, Undefined, Music, Economics, Government, and Industrial Engineering. *Sources:* Author's calculations using college records.

Figure A.9: Distribution of the Perceived Poverty Incidence



Note: This figure plots the kernel density of the perceived share of Colombians living under poverty for all surveu respondents. The dashed blue vertical line reports the mean response, while the gray lines report the responses at P25, P50, and P75 of the distribution. The red vertical line reports the actual poverty rate in 2015 (DANE, 2020). *Sources:* Author's calculations using college records.

Table A.1: Cohort Balance Test in Baseline Observable Characteristics for Specification (1)

Baseline covariate	Spring 2014 Cohort (1)	Spring 2015 Cohort (2)	p-value (no major FE) (3)	p-value (w/ major FE) (4)
Age (Aug 15, 2015)	18.800	18.011	0.000	0.000
Female dummy	0.422	0.497	0.391	0.045
Migrant dummy	0.259	0.212	0.248	0.652
Father's education: Technical	0.052	0.053	0.976	0.932
Father's education: University	0.437	0.413	0.700	0.796
Father's education: Graduate	0.452	0.492	0.512	0.418
Mother's education: Technical	0.052	0.095	0.098	0.015
Mother's education: University	0.585	0.402	0.002	0.000
Mother's education: Graduate	0.289	0.450	0.004	0.000
Risk aversion (Heads or tails game)	2.319	2.407	0.697	0.631
Decile of respondents' SABER 11 score	5.090	5.326	0.407	0.103
Socioeconomic stratum	4.541	4.587	0.618	0.488
N	135	189		

Notes: This table compares baseline characteristics between students in the Spring 2014 cohort in Column (1) and Spring 2015 cohort in Column (2). Column (3) reports the p-value from an OLS regression of the outcome on a dummy for being in the Spring 2015 cohort, i.e., without any major fixed effects. Column (4) reports the p-value when including major fixed effects. The sample is composed of survey respondents from high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP) or Spring 2015 (after SPP). $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college records and student survey data.

Table A.2: Balance Test in Baseline Observable Characteristics for Specification (2)

Dependent variable	Share of SPP classmates	
	Coef/SE	p-value
	(1)	(2)
Age (Aug 15, 2015)	-0.004	0.854
	(1.041)	
Female dummy	0.012	0.102
	(0.007)	
Migrant dummy	0.005	0.469
	(0.007)	
Father's education: Technical	0.001	0.659
	(0.003)	
Father's education: University	0.005	0.503
	(0.008)	
Father's education: Graduate	-0.008	0.300
	(0.007)	
Mother's education: Technical	0.005	0.296
	(0.005)	
Mother's education: University	-0.010	0.179
	(0.007)	
Mother's education: Graduate	0.006	0.424
	(0.007)	
Risk aversion (Heads or tails game)	-0.063	0.002
	(0.019)	
Decile of respondents' SABER 11 score	-0.038	0.130
	(0.025)	
Socioeconomic stratum	-0.017	0.137
	(0.011)	

Notes: This table shows the results from regressing a given baseline covariate on the observed share of SPP classmates using cohort fixed effects and major fixed effects. Each row is a separate regression that uses a different observable characteristic as the dependent variable. Column (1) reports the coefficient and associated standard error in parentheses, while Column (2) reports the p-value. The sample is composed of survey respondents from high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP) or Spring 2015 (after SPP). $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college records and student survey data.

Table A.3: Non-Linearities

	Share of Colombians... (%)			
	Living Under Poverty		In Stratum 1	
	OLS (1)	IV-2SLS (2)	OLS (3)	IV-2SLS (4)
Share of SPP classmates (%)	1.076***	1.933***	0.708***	1.293***
	(0.250)	(0.378)	(0.199)	(0.313)
Squared share of SPP classmates (%)	-0.031***	-0.077***	-0.026***	-0.057***
	(0.010)	(0.018)	(0.008)	(0.013)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only	X	X	X	X
N	319	319	319	319
R^2	0.22	0.03	0.18	0.04
$\bar{y}_{\text{Spring 2014}}$	32.99	32.99	25.93	25.93
FS F-Stat		129.54		129.54
Hausman Test p-val.		0.01		0.03
Effect of 0 to 1 percent	1.045	1.856	0.682	1.236
	[0.000]	[0.000]	[0.001]	[0.000]
Effect of 5 to 6 percent	0.734	1.085	0.425	0.662
	[0.000]	[0.000]	[0.002]	[0.001]
Effect of 10 to 11 percent	0.423	0.314	0.167	0.088
	[0.000]	[0.019]	[0.088]	[0.378]
Effect of 15 to 16 percent	0.112	-0.457	-0.091	-0.487
	[0.376]	[0.069]	[0.417]	[0.001]

Notes: This table presents the results when augmenting specification (1) with the squared share of SPP classmates. The dependent variable is the perceived share of Colombians living under poverty in Columns (1) and (2) and the perceived share of Colombians in stratum 1 in Columns (3) and (4). The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual share of SPP classmates with the predicted share using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, 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. Two-tail p-values in brackets. $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college records and student survey data.

Table A.4: Robustness: Share of Classmates from Strata 1 or 2

	Colombians Living Under Poverty (%)			
	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)
Share of strata 1 or 2 classmates (%)	0.368**	0.370**	0.419**	0.406**
	(0.157)	(0.176)	(0.168)	(0.186)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.14	0.04	0.21	0.05
$\bar{y}_{\text{Spring 2014}}$	32.99	32.99	32.99	32.99
FS F-Stat		580.05		480.66
Hausman Test p-val.		0.98		0.89

Notes: This table presents the β coefficient from specification (1) when the dependent variable is the perceived share of Colombians living under poverty, and the independent variable of interest is the share of classmates from stratum 1 or 2. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual share of classmates from stratum 1 or 2 with the predicted share of SPP classmates using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3) and (4) restrict the sample to Spring cohorts only. 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: Robustness: At Least 5 Percent of SPP Classmates

	Colombians Living Under Poverty (%)			
	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)
1(Share SPP classmates $\geq 5\%$)	3.881**	7.949***	5.697***	7.546***
	(1.888)	(2.500)	(1.985)	(2.120)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.14	0.02	0.21	0.05
$\bar{y}_{\text{Spring 2014}}$	32.99	32.99	32.99	32.99
FS F-Stat		261.92		240.38
Hausman Test p-val.		0.03		0.23

Notes: This table presents the β coefficient from specification (1) when the dependent variable is the perceived share of Colombians living under poverty, and the independent variable of interest is an indicator for whether at least 5 percent of classmates are SPP recipients. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual dummy with the predicted dummy using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3) and (4) restrict the sample to Spring cohorts only. 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.6: Including Cohort Fixed Effects in Specification (1)

	Dependent variable:								
	Perceived share of Colombians... (%)							State	No
	Below Poverty	In Stratum 1	In Stratum 2	In Stratum 3	In Stratum 4	In Stratum 5	In Stratum 6	Should Tax the Rich	Equal Opportunity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of SPP classmates (%)	0.182	0.029	0.083	0.154*	-0.139	-0.106**	-0.022	0.008*	0.011**
	(0.164)	(0.169)	(0.066)	(0.090)	(0.088)	(0.051)	(0.042)	(0.005)	(0.005)
Major FE	X	X	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X	X
N	453	453	453	453	453	453	453	453	453
R^2	0.15	0.12	0.14	0.12	0.13	0.15	0.14	0.12	0.12
$\bar{y}_{\text{Spring 2014}}$	32.99	25.93	21.91	20.66	16.68	8.99	5.82	0.68	0.46
Equal to w/out cohort FE (p-val)	0.21	0.66	0.45	0.07	0.38	0.27	0.70	0.92	0.69

Notes: This table presents the β coefficient from specification (2). The dependent variable changes in each column. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, 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. The last row presents the p-values of a test of equality between the regression with and without cohort fixed effects. $***p < 0.01, **p < 0.05, *p < 0.1$ *Sources:* Author's calculations using college records and student survey data.

Table A.7: Perceived Distribution of Income

	Perceived Share of Colombians in Each Socioeconomic Stratum (%)											
	Stratum 1		Stratum 2		Stratum 3		Stratum 4		Stratum 5		Stratum 6	
	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1(Share SPP classmates $\geq$ 5%)	3.316**	3.702*	1.034	1.325	-0.056	-1.184	-1.791*	-1.227	-1.306**	-1.446**	-1.197**	-1.17
	(1.554)	(1.867)	(0.797)	(0.985)	(0.937)	(1.150)	(0.935)	(1.165)	(0.560)	(0.672)	(0.556)	(0.748)
Major FE	X	X	X	X	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X	X	X	X	X
Spring Cohort Only	X	X	X	X	X	X	X	X	X	X	X	X
N	319	319	319	319	319	319	319	319	319	319	319	319
R^2	0.18	0.07	0.19	0.04	0.13	0.05	0.16	0.05	0.22	0.07	0.18	0.03
$\bar{y}_{\text{Spring 2014}}$	25.93	25.93	21.91	21.91	20.66	20.66	16.68	16.68	8.99	8.99	5.82	5.82
FS F-Stat		240.38		240.38		240.38		240.38		240.38		240.38
Hausman Test p-val.		0.73		0.61		0.17		0.44		0.75		0.94

Notes: This table presents the β coefficient from specification (1) when the dependent variable is the perceived share of Colombians in each socioeconomic stratum, and the independent variable of interest is an indicator for whether at least 5 percent of classmates are SPP recipients. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual dummy with the predicted dummy using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. The sample is restricted to Spring cohorts only. 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: Robustness: Share of Classmates from Strata 1 or 2

	State Should Tax the Rich			
	OLS (1)	IV-2SLS (2)	OLS (3)	IV-2SLS (4)
Share of strata 1 or 2 classmates (%)	0.010***	0.008	0.014***	0.014**
	(0.004)	(0.005)	(0.004)	(0.005)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.11	0.02	0.15	0.07
$\bar{y}_{\text{Spring 2014}}$	0.68	0.68	0.68	0.68
FS F-Stat		580.05		480.66
Hausman Test p-val.		0.4		0.97

Notes: This table presents the β coefficient from specification (1) when the dependent variable is support for the statement *"the government should tax the rich"*. The independent variable of interest is the share of classmates from stratum 1 or 2. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the share of classmates from strata 1 or 2 with the predicted share of SPP classmates using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. The sample is restricted to Spring cohorts only. 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.9: Robustness: At Least 5 Percent of SPP Classmates

	State Should Tax the Rich			
	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)
1(Share SPP classmates $\geq 5\%$)	0.114***	0.102	0.185***	0.224***
	(0.039)	(0.074)	(0.053)	(0.069)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.11	0.03	0.15	0.07
$\bar{y}_{\text{Spring 2014}}$	0.68	0.68	0.68	0.68
FS F-Stat		261.92		240.38
Hausman Test p-val.		0.83		0.36

Notes: This table presents the β coefficient from specification (1) when the dependent variable is support for the statement *"the government should tax the rich"*. The independent variable of interest is an indicator for whether at least 5 percent of classmates are SPP recipients. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual dummy with the predicted dummy using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. The sample is restricted to Spring cohorts only. 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.10: Robustness: Share of Classmates from Strata 1 or 2

	System Does Not Offer Equal Opportunity			
	OLS (1)	IV-2SLS (2)	OLS (3)	IV-2SLS (4)
Share of strata 1 or 2 classmates (%)	0.013***	0.009*	0.015***	0.015***
	(0.004)	(0.005)	(0.005)	(0.005)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.13	0.05	0.2	0.07
$\bar{y}_{\text{Spring 2014}}$	0.46	0.46	0.46	0.46
FS F-Stat		580.05		480.66
Hausman Test p-val.		0.1		0.79

Notes: This table presents the β coefficient from specification (1) when the dependent variable is an indicator for whether the respondent believes the economic system "never" or "almost never" *"provides equal opportunity to overcome poverty"* and the independent variable of interest is the share of classmates from stratum 1 or 2. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual share of strata 1 and 2 classmates with the predicted share using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3) and (4) restrict the sample to Spring cohorts only. 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.11: Robustness: At Least 5 Percent of SPP Classmates

	System Does Not Offer Equal Opportunity			
	OLS (1)	IV-2SLS (2)	OLS (3)	IV-2SLS (4)
1(Share SPP classmates $\geq$ 5%)	0.111** (0.045)	0.144* (0.075)	0.148*** (0.046)	0.200*** (0.060)
Major FE	X	X	X	X
Controls	X	X	X	X
Spring Cohort Only			X	X
N	453	453	319	319
R^2	0.12	0.04	0.19	0.06
$\bar{y}_{\text{Spring 2014}}$	0.46	0.46	0.46	0.46
FS F-Stat		261.92		240.38
Hausman Test p-val.		0.58		0.29

Notes: This table presents the β coefficient from specification (1) when the dependent variable is an indicator for whether the respondent believes the economic system "never" or "almost never" *"provides equal opportunity to overcome poverty"* and the independent variable of interest is an indicator for whether at least 5 percent of classmates are SPP recipients. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP), Fall 2014 (before SPP), or Spring 2015 (after SPP). Each column represents a separate regression. Odd columns present the OLS coefficient, while even columns present the IV-2SLS coefficient when instrumenting the actual dummy with the predicted dummy using pre-reform data, as described in Appendix C. Controls include age, age squared, sex, SABER 11 test score fixed effects, socioeconomic stratum fixed effects, an indicator for having attended high school outside of Bogotá D.C., a measure of risk aversion, and dummies for parental education. Columns (3) and (4) restrict the sample to Spring cohorts only. 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 Survey Description and Validity Checks

This section describes the survey data I collected for this research project. The data was collected using Qualtrics online survey software.

Wave 1 was collected in August 2015, that is, one semester after high-income students first shared a classroom with low-income peers due to the SPP financial aid program (see Figure A.3 for a timeline of events). I surveyed a random sample of high-income undergraduate students (i.e., strata 4, 5, and 6) who had first attended in Spring 2014, Fall 2015, or Spring 2015. That is, I surveyed two cohorts before SPP and one cohort after SPP. The link to the Qualtrics survey was sent to 2,200 students: 689 from Spring 2014 cohort, 662 from Fall 2014 cohort, and 849 from Spring 2015 cohort. 469 of these 2,200 students responded the survey, i.e., a response rate of 21.3 percent. Table B.2 shows there is balance in the response rate across cohorts. Further, I cannot reject the null hypothesis that the three cohort dummies are the same: the p-value on the joint F-statistic is 0.3237 without controls and 0.3434 with controls.

To avoid experimenter demand effects, the survey consent form explained the purpose of the survey was to "gather information on college students' beliefs and political attitudes." There was no mention of SPP. The survey questionnaire collected information on students' social and study networks, as well as their perceptions about the income distribution and their attitudes towards government redistribution. Table B.1 presents these questions asked in the survey. For their participation, respondents who completed the survey were compensated in cash (COP 10,000 or roughly US$ 3.4), and were allowed to donate their compensation to college financial aid programs for low-income, high-achieveing students.

Survey wave 2 was collected in early February 2016, i.e., one year after the first cohort of SPP beneficiaries began their studies. This survey wave again sampled from high-income students (i.e., strata 4, 5, and 6) but expanded the number of cohorts to all those beginning their studies between 2013 and 2016 (i.e., 7 cohorts). To make the results more comparable to those from Table B.2, Table B.3 restricts to all 2,790 students from entering cohorts Spring 2014, Fall 2014, and Spring 2015 enrolled in Spring 2016. 540 of these 2,790 students responded the survey, i.e., a response rate of 19.35 percent. Table B.3 shows there is balance in the response rate across the three cohorts. Further, I cannot reject the null hypothesis that the three cohort dummies are the same: the p-value on the joint F-statistic is 0.5322 without controls and 0.7809 with controls.

The survey questionnaire for the second wave also collected information on students' social and study networks, as well as their perceptions and their attitudes. Students were compensated in kind (a burger combo at a popular burger chain near campus, costing 12,600 pesos US $4.3). They were also allowed to donate their compensation.

Table B.1: Survey Wave 1: Questions on Social Interactions, Perceptions, Beliefs, and Attitudes

Social Interactions with SPP Recipients	
1	List the full names of your five closest friends in college. [*Text*]
2	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 1/2/3/4/5/6*]
3	Please list the full names of five study partners you have THIS semestre in college below. [*Text*]
4	Now think about your classmates. What percentage of your classmates do you think are receiving "Ser Pilo Paga" scholarship? [*Scale from 0 to 100%*]
5	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*]
Perception of the Income Distribution	
6	What share of Colombians do you think belong to each socioeconomic stratum? [*Scale from 0 to 100%*]
7	What percentage of Colombians do you think are poor (that is, those earning less than 200 thousand pesos per month)? [*Scale from 0 to 100%*]
Social Justice, Social Mobility, and Redistributive Preferences	
8	How often do you think the economic system provides Colombians equal opportunity to exit poverty? [*Scale from 1 (Never) to 7 (Always)*]
9	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? [*Stratum 1/2/3/4/5/6*]
10	The state should tax the rich. [*Scale from 1 (Strongly disagree) to 7 (Strongly agree)*]
11	The state should subsidize the poor. [*Scale from 1 (Strongly disagree) to 7 (Strongly agree)*]
Attitudes Towards SPP Recipients, Financial Aid Policy, and Socioeconomic Diversity, and Perception of Meritocracy	
12	Pedro says that, students in his classroom feel "uncomfortable" having classmates from different socioeconomic backgrounds in their study groups. Do you agree or disagree with him? [*Scale from 1 (Strongly agree) to 7 (Strongly disagree)*]
13	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? [*Scale from 1 (Strongly opposed) to 7 (Strongly favor)*]
14	The state should offer financial aid for poor students. [*Scale from 1 (Strongly disagree) to 7 (Strongly agree)*]
15	How important is it that your university bring together students from all socioeconomic backgrounds? [*Scale from 1 (Not at all important) to 7 (Extremely important)*]
16	How often do you think the most talented students get into the best universities in Colombia? [*Scale from 1 (Never) to 7 (Always)*]
17	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.) [*Scale from 0 to 100%*]

Notes: This table presents questions asked in survey wave 1, collected in August 2015. The questions were translated from Spanish to English by the author.

Table B.2: Wave 1 Survey Response Balance Test

	Responded Survey			
	b	se	t	p
Spring 2014	-0.016	0.023	-0.696	0.486
Spring 2015	0.015	0.022	0.7	0.484
Female	0.029	0.019	1.506	0.132
Stratum 5	-0.019	0.021	-0.931	0.352
Stratum 6	-0.041	0.023	-1.77	0.077
Mother has college degree	0.009	0.025	0.374	0.708
Father has college degree	-0.003	0.027	-0.108	0.914
Business	-0.103	0.118	-0.872	0.383
Anthropology	-0.207	0.133	-1.56	0.119
Architecture	-0.129	0.119	-1.087	0.277
Art	-0.268	0.118	-2.267	0.023
Biology	-0.144	0.132	-1.091	0.276
Political Science	0.018	0.123	0.143	0.886
Law	-0.113	0.118	-0.957	0.339
Design	-0.165	0.118	-1.391	0.164
Economics	-0.028	0.118	-0.236	0.814
Philosophy	0.116	0.219	0.529	0.597
Physics	-0.104	0.135	-0.765	0.444
Geosciences	-0.095	0.124	-0.767	0.443
Government	-0.174	0.142	-1.229	0.219
History	-0.225	0.144	-1.562	0.118
Environmental Eng.	-0.179	0.12	-1.49	0.136
Biomedical Eng.	-0.046	0.124	-0.369	0.712
Civil Eng.	-0.168	0.116	-1.441	0.15
Electronic Eng.	-0.112	0.125	-0.892	0.372
Electric Eng.	0.021	0.159	0.131	0.896
Industrial Eng.	-0.107	0.115	-0.927	0.354
Mechanical Eng.	-0.142	0.118	-1.199	0.231
Chemical Eng.	-0.129	0.118	-1.091	0.275
CS Eng.	-0.246	0.119	-2.078	0.038
Literature	-0.048	0.142	-0.337	0.736
Mathematics	-0.061	0.16	-0.378	0.705
Medicine	-0.128	0.12	-1.064	0.288
Microbiology	-0.107	0.164	-0.651	0.515
Music	0.075	0.151	0.5	0.617
Psychology	-0.143	0.124	-1.156	0.248
Chemistry	-0.05	0.151	-0.329	0.742
Constant	0.322	0.118	2.726	0.006
N	2200			
R^2	0.03			

Note: This table shows the results of regressing, for the 2,220 students who were emailed a link to the survey, the likelihood of responding the survey on observable covariates (academic term, sex, socioeconomic stratum, parental education, and major). Fall 2014 is the omitted academic term category, and Languages is the omitted major category. I cannot reject the null hypothesis that the three cohort dummies are the same: the p-value on the joint F-statistic is 0.3237 without controls and 0.3434 with controls. *Sources:* Author's calculations using college records and student survey data.

Table B.3: Wave 2 Survey Response Balance Test

	Responded Survey			
	b	se	t	p
Spring 2014	0.008	0.019	0.442	0.659
Spring 2015	-0.005	0.018	-0.261	0.794
Female	-0.018	0.016	-1.096	0.273
Stratum 5	-0.015	0.019	-0.814	0.416
Stratum 6	-0.051	0.019	-2.665	0.008
Business	0.06	0.113	0.529	0.597
Anthropology	0.011	0.123	0.092	0.927
Architecture	0.077	0.114	0.674	0.501
Art	0.049	0.119	0.412	0.68
Biology	0.013	0.121	0.109	0.913
Political Science	0.159	0.117	1.355	0.176
Law	0.064	0.113	0.562	0.574
Design	0.006	0.113	0.056	0.955
Economics	0.129	0.114	1.136	0.256
Undefined	0.099	0.138	0.716	0.474
Philosophy	0.062	0.153	0.406	0.685
Physics	0.071	0.126	0.56	0.575
Geosciences	0.071	0.119	0.594	0.552
Government	0.132	0.139	0.95	0.342
History	-0.022	0.139	-0.16	0.873
Environmental Eng.	0.084	0.119	0.708	0.479
Biomedical Eng.	0.099	0.12	0.825	0.41
Civil Eng.	0.133	0.114	1.17	0.242
Electronic Eng.	0.092	0.121	0.762	0.446
Electric Eng.	0.041	0.142	0.289	0.772
Industrial Eng.	0.063	0.111	0.569	0.569
Mechanical Eng.	0.187	0.116	1.604	0.109
Chemical Eng.	0.021	0.113	0.188	0.851
CS Eng.	0.084	0.121	0.692	0.489
Language and Culture	0.148	0.188	0.788	0.431
Literature	0.073	0.127	0.575	0.565
Mathematics	0.017	0.141	0.124	0.902
Medicine	0.101	0.117	0.863	0.388
Microbiology	0.026	0.143	0.182	0.855
Music	0.122	0.133	0.916	0.36
Psychology	0.076	0.117	0.648	0.517
Chemistry	0.011	0.138	0.078	0.938
Constant	0.138	0.11	1.252	0.211
N	2790			
R2	0.02			

Note: This table shows the results of regressing, for the 2,790 students who were emailed a link to the survey in entering cohorts Spring 2014, Fall 2014, and Spring 2015, the likelihood of responding the survey on observable covariates (academic term, sex, socioeconomic stratum, and major). Fall 2014 is the omitted academic term category, and Languages is the omitted major category. I cannot reject the null hypothesis that the three cohort dummies are the same: the p-value on the joint F-statistic is 0.5322 without controls and 0.7809 with controls. *Sources:* Author's calculations using college records and student survey data.

C Predicting the Distribution of Pilo Classmates

The objective is to exploit pre-reform data to predict the share of classmates who receive SPP financial aid. I do this using the distribution of students of major m and cohort k across courses c in Spring 2014 (i.e., one year before SPP). The estimation proceeds as follows (see Altonji and Card, 1991):

Step 1 Using data from Spring 2014, estimate the probability that a student enrolled in major m from cohort k enrolls in course c, s^c_{mk}.

Step 2 Predict the number of SPP recipients enrolled in each course, SPP^c. To do this, multiply the number of Spring 2015 SPP recipients in each major by s^c_{mk}:
$SPP^c = SPP_{m,\text{Spring 2015}} \times s^c_{mk}$.

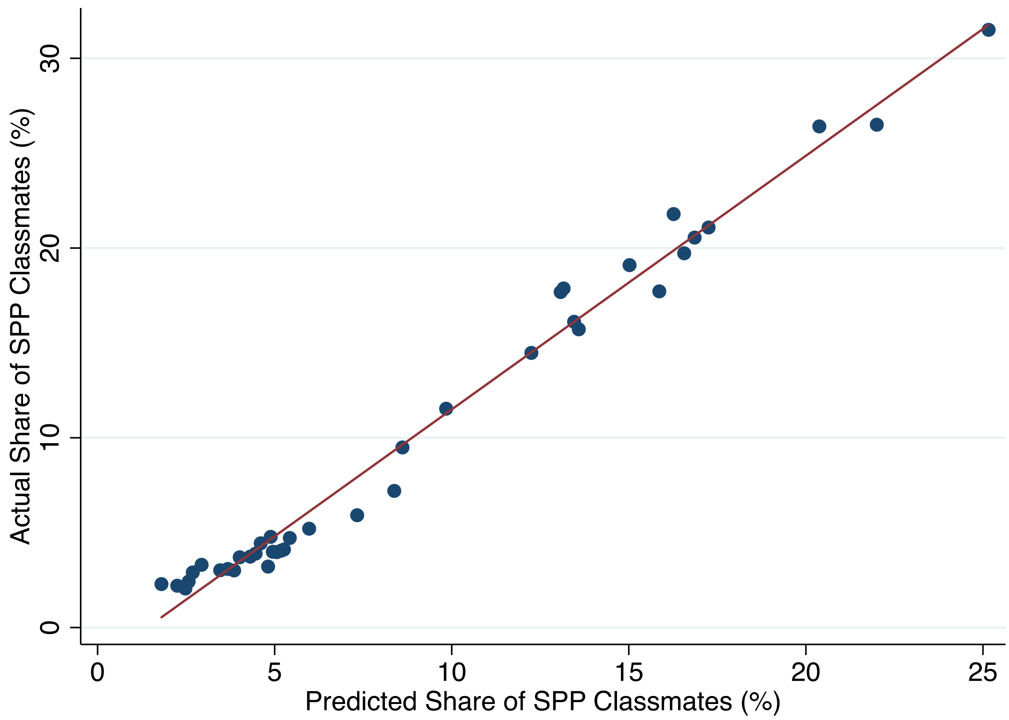
Step 3 Predict the share of SPP recipients in each course, d^c. To do this, for each course offered in the Spring 2015 term, divide SPP^c by the total number of students enrolled in each class, N^c: $d^c = SPP^c/N^c$. Note that, because s^c_{mk} used to predict SPP^c is based on Spring 2014 data, d^c will not be available for courses that were not offered in Spring 2014.

Step 4 For each student enrolled in Spring 2015, predict the mean share of SPP classmates, d_{mk}. To do this, collapse d^c by m-k pair, using s^c_{mk} as a probability weight. Thus, given a student's major m and cohort k, I have predicted her share of SPP classmates absent sorting in response to SPP.

Figure C.1 plots the correlation between the actual and predicted shares of SPP classmates for all students enrolled in Spring 2015 from the Spring 2014, Fall 2014, and Spring 2015 entering cohorts. There is almost a one-to-one relationship between the two shares. Any differences stem from a combination of the following. First, two new majors were created between Spring 2014 and Spring 2015; Government and Art History majors did not exist in Spring 2014 and, for this reason, there is no prediction available for these majors. Second, new courses were offered in Spring 2015. Some of these new courses were created in response to SPP (e.g., "Tools for College Life", offered for the first time in Spring 2015, was aimed at helping new students in their transition from high school into college). Lastly, the two shares may differ due to sorting in response to SPP.

Table C.1 presents the result of this exercise separately by entering cohort. Columns (1) through (4) show that the aforementioned exercise slighly overpredicts the share of SPP classmates for older cohorts. In contrast, Columns (5) and (6) show that the exercise underpredicts the actual shares of SPP classmates for the Spring 2015 cohort. This is partly due to the aforementioned creation of new classes in response to SPP aimed at entering students, which the pre-reform distribution of students across classes does not predict.

Figure C.1: Correlation of Actual and Predicted Shares of SPP Classmates



Note: This binscatter plots actual share of SPP classmates against the predicted share. The sample is students from Spring 2014, Fall 2014, and Spring 2015 cohorts enrolled in Spring 2015 term. The differences reflect some combination of new classes opening in Spring 2015, new majors (Government, Art History) and, possibly, sorting in response to SPP.
Source: Author's calculation using college records.

Table C.1: Actual vs. Predicted Share of SPP Classmates in Spring 2015 Term

	Share of SPP Classmates By Entering Cohort (%)					
	Spring 2014 Cohort		Fall 2014 Cohort		Spring 2015 Cohort	
	Actual (1)	Predicted (2)	Actual (3)	Predicted (4)	Actual (5)	Predicted (6)
Mean	3.076	3.541	4.486	5.365	19.102	15.425
Median	2.17	3.56	3.735	4.824	17.167	15.019
SD	3.384	1.237	3.457	1.635	8.215	4.067
Min	0	1.395	0	2.599	0	8.612
Max	33.81	9.546	36.435	10.529	77.535	29.41
$\mathbb{1}[\text{Share} \geq 5\%]$	.191	.192	.336	.42	.99	.989
N	1398		1332		1913	

Notes: Differences between actual and predicted shares of SPP classmates reflect some combination of new classes opening in Spring 2015, new majors (Government, Art History) and, possibly, sorting in response to SPP.
Source: Author's calculation using college records.

D Impacts on High-Income Students' Academic Performance

In this section, I test whether the SPP financial aid program affected high-income students' academic performance and persistence in college. Specifically, I study grades obtained during the first year in college and the likelihood of not being enrolled one year after first entering college. The sample consists of high-income students (socioeconomic strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP) or Spring 2015 (after SPP).

To explore effects on grades, I estimate the following specification by OLS:

$$g_{imc} = \alpha + \beta \cdot 1(\text{After SPP})_i + \gamma_{mc} + \mathbf{X}_i'\gamma + \psi_{imc} \tag{3}$$

where g is the grade obtained by student i from major m in course c, 1(After SPP) is a dummy that equals one for students from the Spring 2015 cohort, and γ are major-by-course fixed effects. This means I am comparing, for instance, the course obtained in ECON 1 among Economics majors who entered college before or after SPP. $\mathbf{X}$ is a vector of student characteristics, including age at first enrollment in college, sex, and parental education. I also control non-parametrically for socioeconomic stratum. To control for the increase in average test scores induced by SPP, $\mathbf{X}$ also includes SABER 11 percentile fixed effects, where the percentile is defined relative to the universe of SABER 11 test takers in Colombia in a given cohort. ψ is the error term. Lastly, grades are weighted by course credit.

Column (1) in Table D.1 presents the β coefficient from specification (3), where the outcome variable is the grade obtained by a student in a given course. High-income students entering college immediately after SPP was implemented do not have lower grades than equivalent students from the previous cohort. Even despite any potential grading on a curve, the β coefficient from specification (3) is close to zero and not statistically significant at conventional levels. Although most courses are graded on a scale from 1.5 to 5 (with 3 being a passing grade), a minority of courses have a pass-fail grading system. For these pass-or-fail courses, Column (2) shows that the likelihood of passing drops by 1.5 percentage points (2 percent from a base of 73 percent), but again the effect is not statistically significant at conventional levels. Therefore, high-income students who entered college at the same time as SPP recipients did not have lower academic performance during their first year than similar students entering one year before.

Did the SPP financial aid program increase high-income students' likelihood of dropping out during their first year in college? To assess this question, I estimate a linear probability model with the following specification by OLS:

$$d_{im} = \alpha + \beta \cdot 1(\text{After SPP})_i + \Omega_m + \mathbf{X}_i'\gamma + e_{im} \tag{4}$$

where d is an indicator for whether student i from major m entering college in the Spring term is no longer enrolled the following Spring, 1(After SPP) is a dummy that equals one for students from the Spring 2015 cohort, and Ω are major fixed effects. $\mathbf{X}$ is a vector of student characteristics, including age at first enrollment in college, sex, and parental education. As before, I also include fixed effects for socioeconomic stratum and for SABER

11 test score percentile. e is the error term.

Table D.2 presents the results of this linear probability model. On average, high-income students from the Spring 2014 entering cohort have a 9 percent chance of not being enrolled in University X two semesters later. The β coefficient in Column (1) is 0.009 and not statistically significant, which suggests high-income students entering college after SPP are not more likely to drop out after their first year of college than similar students from their previous cohort. I therefore conclude that SPP had no statistically significant effect on high-income students' academic performance nor their persistence during the first year in college.

Table D.1: Grades During First Year of College

	Dependent variable	
	Grade (1)	Passed (2)
After SPP	-0.004	-0.015
	(0.012)	(0.022)
Course-by-Major FE	X	X
Controls	X	X
N	127,322	6,789
R^2	0.4	0.26
$\bar{y}_{\text{Spring 2014}}$	3.85	0.73

Notes: This table presents the β coefficient from specification (3). In Column (1), the dependent variable is the grade obtained in a given course. Most courses are graded numerically, with the grade ranging from 1.5 to 5. For the minority of courses with a pass-fail grading system, Column (2) presents the likelihood of passing that course. Grades are weighted by course credit. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP) or Spring 2015 (after SPP). Controls include age, age squared, sex, dummies for parental education, stratum fixed effects, as well as SABER 11 test score percentile fixed effects. 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.

Table D.2: Not Enrolled 1 Year After First Entering College

	Not Enrolled
	(1)
After SPP	0.009
	(0.008)
Major FE	X
Controls	X
N	2,015
R^2	0.05
$\bar{y}_{\text{Spring 2014}}$	0.09

Notes: This table presents the β coefficient from specification (4). The dependent variable is an indicator that equals one if a student first enrolled in University X in Spring of year t is no longer enrolled by Spring $t+1$. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP) or Spring 2015 (after SPP). Controls include age, age squared, sex, dummies for parental education, stratum fixed effects, as well as SABER 11 test score percentile fixed effects. 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.

E Attitudes Towards SPP Recipients Financial Aid Policy

In this section, I present results for outcomes related to high-income students' views on college financial aid in general and SPP in particular as well as their attitudes towards SPP recipients (see survey questionnaire in Table B.1). I included this module in the survey to test for evidence of the concern, expressed in various media outlets soon after SPP was implemented, that low-income students could be bullied or discriminated against by high-income students at elite universities. In short, I find no evidence of such behavior in my data and these null results are robust to changing the sample and the definition of the treatment variable.

First, group work among students with different socioeconomic backgrounds could raise some coordination issues, as students often live in distant neighborhoods and thus must resort to staying on campus to work on the group project (Alvarez, 2019). For this reason, I asked high-income students whether they agreed or not with "Pedro" when he said that working with students from different socioeconomic backgrounds could be "uncomfortable." Column 1 of Table E.1 shows that only 10 percent of control students agreed with this statement, and the treatment had no effect on the likelihood of agreeing with it.

Second, there is widespread support for SPP and colleged merit-based financial aid programs for low-income students. Column (2) of Table E.1 shows 83 percent of control students would support a government proposal to expand financial aid programs for low-income high-achieving students to attend a "university like theirs." Column (3) shows 78 percent consider that the state should offer need-based financial aid. The treatment had no impact on support for neither of these outcomes.

Third, as described in Appendix B, 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." Column (4) of Table E.1 shows 60 percent of control students donated some fraction of their compensation to this purpose and the treatment had no statistically significant effect on likelihood of donating.

Fourth, Column (5) suggests 75 percent of control students believe that socioeconomic diversity in college is important and the treatment had no statistically significant impact on this outcome.

Lastly, Column (6) shows there is widespread skepticism towards meritocracy in college access is widespread; almost three-quarters of control students reported that the most talented students rarely access the best universities in Colombia. This skepticism is consistent with the severe segregation in the postsecondary education system prior to SPP described in Section 2. Instead, exposure to SPP classmates raises the perception that the most talented students access the best universities: a 1 percentage point increase in the share of SPP classmates increases the perception of meritocracy by almost 0.01 percentage points (3.2 percent). This effect is significant at the 1 percent level and robust to the usual robustness checks.

In sum, the findings from Table E.1 suggest exposure to low-income students did not generate negative attitudes towards SPP recipients among high-income students. There is widespread support for policies promoting and expanding financial aid for low-income, high-achieving students, and an awareness of the importance of having SES diversity in college, and the treatment had no impact on these already highly supported outcomes. Instead, exposure to SPP classmates did significantly raise the perception that the college admission process had become more meritocratic, such that the most talented students attend the nation's best universities. This is in line with the large enrollment impacts of SPP for low-income high-achievers documented in Londoño-Vélez et al. (2020)

Table E.1: Attitudes Towards SPP Recipients, Financial Aid, and Socioeconomic Diversity, and Perception of Meritocracy

	Dependent variable					
	Uncomfortable working with SPP recipients (1)	Supports expanding financial aid (2)	State should offer need-based financial aid (3)	Donated to financial aid program (4)	SES diversity in college is important (5)	Meritocracy in college access (6)
Share of SPP classmates (%)	0.003	-0.002	0.004	0	0.001	0.009***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Major FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X
Spring Cohort Only	X	X	X	X	X	X
N	319	319	319	319	319	319
R^2	0.16	0.16	0.11	0.16	0.17	0.13
$\bar{y}_{\text{Spring 2014}}$	0.1	0.83	0.78	0.6	0.75	0.28

Notes: This table presents the β coefficient from OLS specification (1) using five different dependent variables. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X in Spring 2014 (before SPP) or Spring 2015 (after SPP). Controls include age, age squared, sex, SABER 11 standardized test score, 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.

F Results from the Second Survey Wave (1 Year After Policy Rollout)

In this section, I present results from the second survey wave, collected six months after the first wave and a full year after the policy rollout (Figure A.3 plots a timeline of the events). As in the first survey wave, this second wave sampled from high-income students (i.e., strata 4, 5, and 6) but expanded the number of cohorts to all those beginning their studies between 2013 and 2016 (see Appendix B). To make the results from this analysis more comparable to those presented in the main text, I restrict the sample to students from the same entering cohorts: Spring 2014, Fall 2014, and Spring 2015.[23]

A potential concern would be that a disproportionate dropping out of SPP beneficiaries (whether for financial, personal or psychological reasons) would compromise the intensity of the interaction between low- and high-income students over time. However, the dropout rate of SPP beneficiaries was *lower* for SPP beneficiaries than for non-beneficiaries, a point discussed in Londoño-Vélez et al. (2020).

To observe high-income students' interactions with SPP recipients, Table F.1 plots the mean and the standard deviation of variables measuring such interaction separately by cohort of entry, that is, when a student first enrolled in University X (Spring 2014, Fall 2014, or Spring 2015), as in Table 1. The first row shows that, in the first year after the policy rollout, respondents from the Spring 2015 cohort had on average 12.4 percent of SPP classmates, which is 3.4 percentage points less than six months prior. In contrast, students from the Spring 2014 cohort are *more* exposed to SPP classmates: on average, 3.5 percent of their classmates are SPP recipients (relative to 2.7 percent six months prior) and 19 percent of them have at least 5 percent of SPP classmates (relative to 13.8 percent six months prior). Indeed, since students may start taking courses attended by students from both control and treated cohorts, the gap in exposure to SPP classmates between treated and control cohorts shrank a year after policy rollout.[24] As a result of becoming more exposed to SPP recipients, control students start perceiving a greater share of SPP classmates. For my estimation strategy, this implies a shrinking treatment difference over time between "treated" and "control" cohorts.

Further, Table F.1 suggests some homophily, that is, high-income students have befriended peers of similar SES over time. Indeed, 7.9 percent of students from the "treated" Spring 2015 cohort report having friends from stratum 1 or 2, which is 2.4 percentage points less than in the first survey wave. Further, the likelihood of having at least one SPP recipient among the five closest friends and study partners has also dropped six months later. This, coupled with the greater exposure to SPP recipients for control students, suggests the effects of diversity on treated high-income students *relative to control students* could be smaller than before, possibly attenuating some of the effects on perceptions of the income distribution and redistributive preferences reported in Section 5.

Starting with perceptions of the income distribution, Columns (1)–(2) of Table

[23] Table B.3 shows there is balance in the response rate across the three cohorts.

[24] The decrease over time in exposure to SPP classmates is *not* due to SPP recipients dropping out from college—they are in fact *less* likely to drop out than non-recipients (Londoño-Vélez et al., 2020).

F.2 present the β coefficient from specification (1) when the dependent variable is the perceived share of Colombians living under poverty. In line with greater exposure to diversity, the control mean has increased from 32.99 percent (an underestimate of poverty incidence) to 34.3 percent. Further, the β coefficient is quantitatively similar although less precisely estimated. Columns (4)–(14) present the results for the perceived distribution of Colombians by socioeconomic stratum. Once again, I find that one year of exposure to low-income peers has reduced the upward bias in high-income students' perception of the income distribution. Consequently, they perceive a significantly larger share of Colombians from strata 1 and 2 and a significantly smaller share from stratum 4 and 6.

While I find that the β coefficient on support for taxation of the rich is no longer statistically significant (available upon request)—at least in part due to catch up by controls—the treatment did increase willingness to make a charitable donation. Unlike in the first wave, in the second wave I allowed survey respondents to donate 100 percent of their compensation to an organization of their choosing among the following three alternatives: (i) SPP scholarships or the university's own need-based financial aid program; (ii) *Fundación Ayuda por Colombia*, which contributes to the educational and emotional development of poor children and youth; and (iii) GiveDirectly, an organization that directly sends money to the extreme poor. The results from Table F.3 confirm that a one percentage point increase in exposure to low-income classmates raised the likelihood of donating by 0.014 percentage points or 3.5 percent relative to the control mean. Further, Table F.3 provides some evidence that students chose to donate more to GiveDirectly rather than SPP and other financial aid programs offered by the university. This is again consistent with diversity increasing the perception of poverty and concerns about poverty more generally, rather than SPP recipients specifically (see Appendix E).

Table F.1: Intensity of Interactions with SPP Recipients by Entry Cohort, Wave 2

	Entering Cohort		
	Spring 2014 Cohort (1)	Fall 2014 Cohort (2)	Spring 2015 Cohort (3)
Actual Share of SPP Classmates (%)	3.5	6.444	12.404
	(2.563)	(2.665)	(3.574)
Perceived Share of SPP Classmates (%)	18.578	19.201	33.953
	(15.227)	(13.912)	(18.163)
$\mathbb{1}$(Actual Share of SPP Classmates $\geq$ 5%)	.19	0.699	.994
	(.393)	(.46)	(.075)
$\mathbb{1}$(SPP recipient among 5 closest friends)	.028	.054	.169
	(.165)	(.226)	(.376)
$\mathbb{1}$(SPP recipient among 5 study partners)	.022	.032	.192
	(.148)	(.177)	(.395)
No. times worked with SPP recipient	1.29	1.179	3.609
	(2.192)	(2.118)	(3.178)
Reports friends' stratum is 1 or 2	.039	.038	.079
	(.194)	(.191)	(.271)
N	179	186	177

Note: Using data from the second survey wave (one year after the policy rollout), this table presents means (and standard deviations in parentheses) 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 F.2: Perception of the Income Distribution

	Dependent variable: Perceived Share of Colombians... (%)													
	Under Poverty		In Stratum 1		In Stratum 2		In Stratum 3		In Stratum 4		In Stratum 5		In Stratum 6	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Share of SPP classmates (%)	0.163	0.148	0.147	0.255*	0.052	0.127*	0.048	0.01	-0.069	-0.167**	-0.084	-0.101**	-0.094	-0.124
	(0.168)	(0.169)	(0.121)	(0.146)	(0.072)	(0.070)	(0.088)	(0.102)	(0.077)	(0.079)	(0.053)	(0.048)	(0.085)	(0.084)
Major FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Spring Cohort Only		X		X		X		X		X		X		X
N	485	311	491	314	491	314	491	314	491	314	491	314	491	314
R^2	0.15	0.13	0.1	0.17	0.11	0.21	0.13	0.15	0.07	0.14	0.14	0.2	0.11	0.21
$\bar{y}_{\text{Spring 2014}}$	34.3	34.3	23.93	23.93	22.6	22.6	21.73	21.73	15.63	15.63	9.4	9.4	6.71	6.71

Notes: Using data from the second survey wave (one year after the policy rollout), this table presents the β coefficient from specification (1) for seven different dependent variables. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X 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 fixed effects, socioeconomic stratum fixed effects, 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 F.3: Exposure to Low-Income Classmates Increases Likelihood of Donating Compensation, Survey Wave 2

	Dependent variable:							
	Any donation		Donation to GiveDirectly		Donation to SPP or other aid program		Donation to Low-Income Youth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of SPP classmates (%)	0.011**	0.014***	0.009**	0.006	-0.002	0.003	0.004	0.005
	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)
Major FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X
Spring Cohort Only		X		X		X		X
N	500	321	500	321	500	321	500	321
R^2	0.16	0.21	0.13	0.23	0.08	0.13	0.14	0.18
$\bar{y}_{\text{Spring 2014}}$	0.4	0.4	0.12	0.12	0.08	0.08	0.2	0.2

Notes: Using data from the second survey wave (one year after the policy rollout), this table presents the β coefficient from specification (1) when the dependent variable is an indicator for choosing to donate his or her compensation for responding the survey. The sample is composed of high-income students (strata 4, 5, and 6) who first enrolled in University X 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 fixed effects, socioeconomic stratum fixed effects, 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.