Academic Aspirations and Income Inequality: Spillover Effects of a Video-Based Role Model Intervention Among Teenagers

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Abstract

This article examines the influence of poverty on academic aspirations by introducing a novel approach that links academic preferences with potential economic returns. Using data from 16,570 Ecuadorian high school students, I document that low-income students set lower aspirations than their high-income peers only because of their position in the income distribution. Moreover, I report inconsistencies between academic preferences and earning expectations, making students, especially low-income students, susceptible to experiencing frustration. Data from a stratified randomized control trial indicate that video-based content featuring role models cannot reduce the gap between poor and rich students. However, it exhibits positive subgroup effects for low-income students. For instance, the aspiration level is 7% (midline) and 11.6% (endline) higher for low-income treatment than for low-income placebo students. It suggests that treated students could earn about 270.33 US$ more than their placebo peers each month. The increase accounts for 68% of the Ecuadorian basic salary. I report similarly positive results with different magnitudes for the subsample of mid-low and mid-high-income students. However, the estimates for the last two subgroups exhibit attrition bias. Findings suggest that media content exhibit promising potential to influence low-income adolescents' decisions and economic outcomes through reinforcing aspirations.

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1. Introduction

In 2019, approximately 1.68 billion people around the globe were living on less than 3.50 US$ per day (World Bank, 2020). The lack of monetary resources impacts different well-being dimensions, such as cognitive function (Mani et al., 2013) or life expectancy (Chetty et al., 2016) (see a comprehensive review in Banerjee and Duflo 2007). In the words of Deaton (2004), the lack of income makes "the poor even poorer."

Escaping this situation would be impossible without even aspiring for a better future. But, poverty curtails individuals' capacity to aspire (see a discussion in Vakis, Rigolini, and Lucchetti 2016).[1] Poverty limits access to information or successful examples (henceforth, role models), hindering the formation of aspirations (see Ray 2006; Duflo 2012). Low aspirations reduce the incentives to work hard, leading to poor economic results (Genicot & Ray, 2020). Poor outcomes and low aspirations form a feedback loop that traps individuals into vicious cycles (Dalton et al., 2014).

Facilitating the formation of aspirations through, for instance, role models can improve economic outcomes (see recent reviews in Serra 2022; and Mani and Riley 2019). Indeed, media content like soap operas (Chong & La Ferrara, 2009; La Ferrara et al., 2012), documentaries (Ahmed et al. 2022; Bernard et al. 2015), or movies (Riley, 2022) have proven to be effective in changing behavior by introducing external (unfamiliar) role models. However, only a handful of studies formally capture the role of aspirations in these behavioral change (for instance, see Bernard et al. 2014; Golan and You 2020).[2] I aim to extend this evidence by examining the spillover effects of a video-based intervention featuring role models. In particular, whether the media content can reshape the influence of poverty on aspirations even when it was not designed to target low-income students.

The proposed research is distinct because it presents a pecuniary perspective on measuring academic aspirations. The existing literature on aspirations focuses solely on the highest level of education that an individual desires to achieve (see Bernard and Taffesse 2014; Fruttero, Muller, and Calvo-González 2021). However, this approach overlooks the vast array of academic majors available. This heterogeneity becomes evident when considering the varying values of different majors within the job market. For instance, the difference in economic returns between a social science major and a life science major could be as large as the difference between attending college education or not (see more details in Kirkeboen, Leuven, and Mogstad 2016; Hastings et al. 2016; Altonji, Blom, and Meghir 2012). The aim of this research is to expand the concept of academic aspirations by examining how ambitious the students' preferences for college education are by

[1] Aspirations are forward-looking goals (evolving reference points) that determine individuals' investment of effort and the subsequent economic outcome (Dalton et al., 2014; Genicot & Ray, 2020).
[2] Most studies assume that aspirations trigger a behavior change, but evidence testing this hypothesis is scarce.

linking them to labor market returns.[3] It is essential to note that no mention of financial rewards was made during the data collection, making this approach a depiction of students' academic rather than economic aspirations. The approach measures aspirations on a scale of one to six, where one indicates that the student intends to forego college, and six represents a plan to pursue a major in life science. To the extent that academic aspirations translates into actual choices,[4] this outcome enables quantifying the consequences of setting low aspirations and the economic effects of the video-based content.

I test the reliability of my approach by mirroring the analysis proposed by Guyon and Huillery (2020).[5] The authors study the association between inequality and academic aspirations among French adolescents by dividing the sample into three income groups. The authors do so since examining how aspirations differ according to income level offers a good approximation of the consequences of poverty on the state of mind. Using the data from the project Showing Life Opportunities (SLO) (Asanov & McKenzie, 2020), I replicate the analysis proposed by Guyon and Huillery (2020) but introducing the abovementioned pecuniary approach to measuring academic aspirations. The SLO project collects data from a stratified randomized control trial that recruited a representative sample of 16,570 students in 610 classes and 115 schools in Ecuador.[6] An asset index allows classifying the sample into four wealth groups (for simplicity: income groups), where high-income students are the comparison group.

The project recruits adolescents in the last three years of education (K10 to K12) and introduces a video-based role model intervention as part of the general curricula (in-school intervention). Half of the classes were assigned to the treatment group. Students in treatment classes watched video interviews with role models from high-rewarding professions. The other half watched placebo videos with young individuals discussing unrelated topics (i.e., democracy or love). By introducing professionals in high-rewarding occupations, the hope is that role models illustrate what is possible and inspire students to pursue a high-rewarding major (see a comprehensive role model theory in Morgenroth, Ryan, and Peters 2015).

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[3] The academic aspiration outcome accounts for two elements: preferences for entering college education (i.e., enrolling in college education) and preferences for a major (i.e., Arts or Health). Most evidence studies academic aspirations by assessing the years of schooling one would like to achieve (see Fruttero, Muller, and Calvo-González 2021). Even though this evidence is relevant, it is still However, as Altonji, Blom, and Meghir (2012) suggest, data is scarce on the choice of major, even when it could be crucial for economic returns (see more details in Kirkeboen, Leuven, and Mogstad 2016; Hastings et al. 2016; Conlon and Patel 2023).

[4] Assuming that preferences are related to actual choices might not be a strong assumption (see theoretical propositions in Altonji, Blom, and Meghir 2012; and empirical evidence in Porter and Serra 2020)

[5] By replicability, I mean answering the following question, are the results found here consistent with those found using similar measures elsewhere? (see T. Bernard and Taffesse 2014). Capturing a similar pattern to Guyon and Huillery (2020) could be a way to validate the index. Indeed, even when capturing the same pattern, it is likely that results differ in magnitudes since Ecuador exhibits a higher level of inequality (0.45 Gini Index) and poverty (9.04%) than France (0.32 Gini Index and 0.74% poverty), according to the World Bank.

[6] I assess treatment effects on half of the sample who watch the videos at the beginning of the Showing Life Opportunities project. It allows measuring impacts about two months (midline) and four months (endline) after watching the videos.

My main findings are as follows. Firstly, I was able to successfully replicate Guyon and Huillery's (2020) patterns. The results reveal a significant gap in academic aspirations between low and high-income students, even when they have comparable intellectual skills and environmental conditions.[7] Low-income students report academic aspirations 0.21 points lower than their high-income peers (3.58). This means that most low-income students prefer not to enter college education (38.9%). However, if they plan to enter college education, substantially more low-income than high-income students plan to study low-rewarding majors, such as Services (4.85%), Education (3.2%), or Arts (6%). The evidence also suggests that low-income students who manage to set high aspirations despite their prevalent conditions also exhibit high school performance. High aspirations are associated with test scores 0.04 SD higher.

As for earning expectations, equally capable low-income students exhibit lower earnings expectations than their high-income peers, with a gap of over 132 US$.[8] Although academic aspirations and income expectations reveal a gap between rich and poor students, I found a major inconsistency between the two. Low-income students might earn less than 50% of their expected wages due to low academic aspirations. This suggests that low-income students do not internalize the consequences of their decisions, making them more susceptible to experiencing frustrated aspirations (or aspiration failures, as proposed by Ray 2006).

Secondly, I discovered that video-based content reinforces students' academic aspirations. The treatment cannot reduce the aspirations gap between high and low-income students. However, it exhibits positive impacts when examining the treatment effects within income groups. For low-income students, the treatment increases academic aspirations by 0.23 points at the midline (two months after treatment) and 0.37 points at the endline (four months after treatment). In other words, academic aspirations are 7% and 11.5% higher for treatment than for placebo students (mean aspirations of 2.7 points). Findings suggest that substantially more treated than placebo low-income students prefer to enroll in high-rewarding majors like Engineering or Health. In contrast, more placebo than treatment low-income students opted for low-rewarding options like Arts and Humanities and Services. Due to this difference, treated students could earn about 270.33 US$ more than their placebo peers each month. This accounts for 68% of the Ecuadorian basic salary (395 US$). Notice that treatment effects increase over time, suggesting the intervention produces a cumulative impact.

Regarding mid-low-income students, academic aspirations are 7% (midline) and 12.5% (endline) higher for treatment than for placebo students. Meanwhile, the aspiration level is 6.1% (midline)

[7] The estimation accounts for intellectual skills by including cognitive and non-cognitive skills. Moreover, it controls for external factors by controlling for family level of education and peers, teachers, and the school environment.
[8] The average earnings expectation for high-income students is 1,409.85 US$.

and 8.4% (endline) higher for treated than placebo mid-high-income students. However, caution is needed when assessing the results for the last two groups since the Ghanem, Hirshleifer, and Ortiz-Becerra's (2021) attrition test suggests that the treatment effects might suffer from attrition biases.

Third, I examine heterogeneous treatment effects using a Generic Machine Learning inference (Chernozhukov et al. 2020) and an interaction analysis. I capture meaningful effects only for the subsample of mid-high-income students. Results suggest that the higher aspirations are driven by students with high cognitive ability and a growth mindset. However, one should see results as suggestive since a multiple inference test could not reject the null hypothesis.

This paper relates to studies aiming to reshape low-income individuals' aspirations. Most studies assess aspirations following the approach in Bernard and Taffesse (2014) by accounting for years of schooling (Bernard et al. 2019; Chiapa, Garrido, and Prina 2012; Cuevas, Favara, and Rosero 2016; Kosec 2018). Others have used alternative approaches, such as occupation preference (Ahmed et al., 2022; Beaman et al., 2012; Hoff et al., 2022; Mann et al., 2020), preferred education levels (Carlana et al., 2013; Guyon & Huillery, 2020; Kipchumba et al., 2021), preferred university (Jerrim et al., 2020), or financial goals (McKenzie et al., 2021).

My distinctive feature uses a pecuniary approach to account for aspirations in a sample with diverse socioeconomic backgrounds. This unique scenario allows studying the influence of poverty on the state of mind, illustrating how the poor can become even poorer when their prevailing circumstances curtail their capacity to aspire (see a broader discussion in Appadurai 2004; Nathan 2005). In this regard, the evidence contributes empirical evidence aligned with the Scarcity Theory (Bertrand et al., 2004; Mullainathan & Shafir, 2014).

This work is also related to the literature studying post-secondary choices. Empirical evidence in Blau and Kahn (2017), Kirkeboen, Leuven, and Mogstad (2016), or Hastings et al. (2016), and theoretical propositions in Altonji, Blom, and Meghir (2012) argue that educational preferences (in my case, aspirations) determine the choice of major and subsequent economic outcomes. Relative to this literature, my findings explain how preferences can affect economic outcomes. Moreover, they reinforce the theory that students, particularly those from disadvantaged backgrounds, are unaware of the consequences of academic preferences in long-term outcomes, making them susceptible to frustration (i.e., earning substantially less than expected). Furthermore, my results show that setting ambitious preferences motivate students to exert higher academic effort (i.e., higher test scores), expanding the opportunities to entering top-ranked college institutions or high-demanding majors (see how universities use test scores as signaling in Schwerdt and Woessmann, 2017).

Finally, the paper contributes to the extensive literature on video-based and media content (DellaVigna & La Ferrara, 2015; Enikolopov & Petrova, 2017; Ozgun & Broekel, 2022). This evidence suggests that media affects individuals through two channels: providing information and spurring preferences (La Ferrara, 2016). Although I cannot disentangle the effect of the video-based intervention on information or preferences, my findings extend the evidence on how educational media contributes to alleviating poverty by reshaping aspirations. Since the intervention was not designed to reshape aspirations, findings can extend to media pieces exhibiting similar content.[9]

2. Institutional context

Since 2014, Ecuador has rapidly deteriorated its social conditions (Gachet et al., 2019; Jara et al., 2021). Lack of employment opportunities or the degradation of public services (Díaz Pabón & Palacio Ludeña, 2021) can explain part of the rising inequality and poverty.[10] Accelerated by the coronavirus outbreak, this situation impacted individuals' state of mind. As a result, the population exhibits signs of anxiety (Chocho-Orellana et al., 2022; Mautong et al., 2021) or depression (Asanov et al., 2021). The detrimental situation is expected to negatively influence individuals' aspirations, as Cuevas, Favara, and Rosero (2016) reported. In particular, adolescents can make biased post-secondary decisions due to rising poverty and inequality.

I assess adolescents' academic aspirations since it is one of the determinants of post-secondary choices (Altonji et al., 2012). To do so, I explore the data from the Showing Life Opportunities project (SLO), an RCT that gathers students in the last three years of secondary education (Asanov & McKenzie, 2020).[11] Since students receive the program as part of the general curricula, it captures the entire student population within selected schools. Due to its nature (online project), only schools with a running computer laboratory could participate.[12] In collaboration with the Ministry of Education, the SLO project gathers 115 schools located in two out of nine administrative zones, reaching about 36% of the student population in these zones.[13]

[9] The content and structure of the intervention are very close to other educational and mass-media programs. For instance, Ecuador: "Yo soy hecho en Ecuador", "Soy Ciencia", "Ellas hacen ciencia"; Colombia: "Emprendedores en acción", "Conversaciones"; Argentina: "Mi oficio, mi historia", "Aca estamos"; Spain: "trabajo temporal", "Arts i oficis". Indeed, literature suggests that the simple expansion of cable TV already influence choices (Jensen & Oster, 2009)

[10] According to the ECLAC (Economic Commission for Latin America Caribbean), poverty grew from 23.4% in 2014 to 30.6% in 2020. Furthermore, the GINI coefficient raised from 0.45 points in 2014 to 0.47 in 2020.

[11] The SLO project promotes entrepreneurship and science-related professions among high school students. It features three online components, training, information, and role models. I study the role models component. It consists of video interviews with STEM scientists and Entrepreneurs. The videos were embedded in an e-learning platform.

[12] To participate in the program, schools had to guarantee an Internet connection speed of at least 30Mbps. The technical team in Zone 2 expanded the computer laboratories and improved the internet speed in 34 schools. The research team tested the improvements during a pilot phase and teacher training.

[13] The SLO project gathered a representative sample in Zone 2 and Quito, the capital city. The Municipality of Quito operates a group of city-based schools, while Zone 2 comprises public and (a few) private schools in three states (Pichincha, Napo, and Orellana). A zone is the highest territorial structure in Ecuador. The country has nine zones. Each zone is subdivided into states. Ecuador has 24 states (see Appendix E).

Until 2021, entering college education required that students achieve a competitive grade in the national standardized exam. The exam accounts for 60% of the student's overall score (INEVAL, 2017; Senescyt, 2020). One can apply to up to five academic programs in multiple universities. A centralized system offers a place in the preferred option (first choice), but this depends on the quota availability. The SLO project simulates this procedure by designing a standardized exam mirroring the national test and motivating students to declare their post-secondary plans (i.e., whether they plan to enter college education and, if so, which academic major they would like to choose). This allows examining students' academic aspirations based on their post-secondary preferences.

The SLO project started in September 2019 and was extended until June 2020. Although the program was intended to last three months, exogenous issues forced some schools to delay the intervention.[14] After March 13, 2020, a school closure mandate was in place due to the coronavirus outbreak. The Ministry of Education called off educational activities for six weeks in all schools at the national level. The learning process resumed in a virtual format on May 4, 2020. Since that day to June 30, students worked with the e-learning platform to complete their learning process from home.

3. Experimental Design

The experimental participants were all students in the 115 selected high schools who attended the last three years of secondary education. Overall, it comprises 16,570 students in 610 classes. Once students register to the e-learning platform, they complete a baseline survey. This is the first time students declare their college education preferences. Immediately after the baseline, half of the sample watched the video-based content. The SLO project randomly allocates classes into treatment (155) or placebo content (145).[15] I follow this cohort until the end of the project to capture the intervention's effectiveness over time (see Figure 5).[16]

Lesson design. Overall, the video-based intervention lasted 60 minutes, divided into two 30-minute lessons. Each lesson contains two parts, entrepreneurs and STEM scientists. Each 15-minute part includes five segments. Each segment narrates a story of personal success. Since the

[14] The project suffered two major setbacks. In September 2019, it experienced conflicts with large schools' agendas since the Ministry of Education simultaneously evaluated teachers' performance. Second, on October 2, 2019, Ecuador faced a violent riot against the government. The situation delayed the regular progress of the intervention, particularly in the 25% of schools that started before the protests. A small fraction of the 65% of schools that started the SLO project after the riots experienced issues due to the coronavirus outbreak. I avoided the health emergency affecting the treatment by working with the sample that watched the role model component at the beginning of the SLO project (September – October). Despite that, I could not prevent the pandemic influences the endline responses.

[15] The study uses two-stage randomization. First, it allocates schools into treatment and placebo arms based on the strata of random allocation. Second, within each experimental arm, the SLO project randomly assigns the role model component (treatment and placebo) at the class level.

[16] The SLO project collected midline data about two months after students watched the video-based intervention. Moreover, they collected endline information about four months after showing the video-based content. Less than 30% of students provide the information after a longer period due to the learning disruption explained in Section 2.

20 role models tell the same story from their perspective, the lesson alternates between them, keeping the message intact. In this way, one increases the likelihood that a student identifies with any role model (see Appendix E). The second lesson is a repetition of the first lesson.

Content of the intervention. The experimental video-based intervention featured interviews with 20 Ecuadorian entrepreneurs and STEM scientists in high-rewarding industries. The role models reflect diversity in sex, ethnicity, place of birth, and age.[17] The SLO project did not consider diversity in the socioeconomic background. Does it imply that this content is ineffective for reshaping non-high-income students' aspirations? I can shed light on this question with my research.[18]

Each interview included five segments, two aiming to reshape students' beliefs about the profession. The remaining three explored role models' reasons for choosing their career (preferences), the academic preparation needed to follow their professional path (origins), and the inspiration to enter their work activity (motivation) (see Appendix E). Besides unveiling alternative career paths, role models illustrate a representation of what is possible and become a source of inspiration. In particular, the content can update students' preferences toward college education and high-rewarding majors by sharing an implicit message, choosing high-rewarding majors could increase the likelihood of achieving financial success and, in parallel, contributing to society. At the same time, the role models highlight hard work as the key element to success.

The placebo intervention featured a set of young people discussing topics related to "love," "gender equality," "freedom," or "discrimination." The Ministry of Education produced and piloted the videos in a target group similar to our participants. Hence, one can argue that both interventions are similarly appealing, but the placebo content is orthogonal to the treatment.

4. Data and empirical strategy

4.1. Outcome variables

Academic aspirations. I developed a novel approach to assess how ambitious post-secondary preferences are. In a simulation, students declare their plans for college education. It asks whether students plan to enter college education. If so, it invites students to select their preferred academic major (open question). I classified students' preferences for majors according to UNESCO's (2015)

[17] The project selected young professionals (24 to 35 years old), so students could relate to them (i.e., big brother or sister rather than parents or grandparents). It recruits successful professionals by imposing a threshold for Entrepreneurs (annual revenue of US$ 300,000 or more) and STEM scientists (H-index ≥ 5 or having a patent).

[18] Prior research stresses the importance of students watching role models from similar social backgrounds to produce meaningful results (for instance, see Bernard et al. 2015; Nguyen 2008). It implies tailoring specific content to multiple population segments, for instance, role models from low-SES backgrounds to low-SES individuals. However, this might not be the most efficient way to distribute mass media content. First, recent evidence suggests that irrespective of the social background, the audience can relate to the role models (Peter & Pierk, 2021; Pietro, 2016). Second, most of the existing media content might also overlook the SES dimension.

International Standard Classification of Education (ISCED). It narrowed down the open responses to ten groups.

I link this data with the Ecuadorian National Employment Survey (INEC, 2019), which collects economic returns per ISCED field. Since some fields exhibit statistically similar returns, I condensed them into five groups (see Appendix A). Overall, a highly ambitious student holds an index of five. It is associated with majors such as Natural Science, Health, and Computer Science (IT). On the other side, the least ambitious student reports an index of one, accounting for a plan of not entering college education.[19] I compute academic aspirations using baseline, midline, and endline information. Hence, I can compare the causal effects of the treatment on students' ambitions at different points in time.

Since this is a novel approach, I run through a replicability process to identify whether the results are consistent with those found using similar measures elsewhere. Thus, I replicate Guyon and Huillery's (2020) analysis with my baseline data. I expect a qualitative validation (i.e., patterns) since the outcome variable and the context of the samples are different.[20]

Earning expectations. I compute earnings expectations by assessing the question, "*How much do you expect to earn per month 10 years from now?*" Since the National Employment Survey unveiled the market wage per major, I can study how far expected returns are from actual salaries. The wider the gap, the less consistent the academic aspirations with expected earnings.

School performance. I measure school performance (test scores) as a proxy of effort. I assess students' test scores in a standardized mini-test. It assesses individuals' knowledge of Statistics, Spanish (native language), and English (foreign language).[21] I standardized each component (z-scores) and combined them into a single index of mean 0 and standard deviation of 1.

Additional covariates. I highlight two key covariates, socioeconomic level (for simplicity, income level) and academic ability. Income level allows splitting the sample into four comparable bins, low, mid-low, mid-high, and high-income (omitted group).[22] Examining how aspirations differ according to income level offers a good approximation of the consequences of poverty on the state of mind.

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[19] Notice that students unsure of entering college education or those who cannot (do not) name any major were also assigned to the first category (least ambitious student).

[20] According to the World Bank, Ecuador exhibits a higher level of inequality (0.47 Gini Index) and poverty (9.04%) than France (0.32 Gini Index and 0.74% poverty).

[21] The test is similar to the one developed by the Secretary of Higher Education of Ecuador. Until 2021, this grade determined the chances of pursuing college education, choosing a high-ranked college institution, and studying the preferred major.

[22] The asset index is formed as the first principal component of the following seven assets measured in the baseline survey: washing machine; air conditioning/dryer; flat screen television; family car; domestic employees; number of bathrooms; number of bedrooms.

When determining aspirations, academic ability plays a crucial role as it gives an estimate of what students can achieve (Guyon and Huillery 2020). However, it is unknown to the student and can be a source of uncertainty, leading to a high chance of over or understating their ability (Altonji, Blom, and Meghir 2012). Therefore, it is necessary to control for academic ability to produce accurate results. To create a proxy for academic ability, I take into account both cognitive and non-cognitive skills. The former accounts for the results from the Cognitive Reflection Test proposed by Frederick (2005). The latter includes results from an incentivized task that measures perseverance (Grit) (Ubfal et al. 2020). It also includes a standardized index measuring Growth Mindset (Paunesku et al. 2015), Self-Construal (Singelis 2016), and Self-Efficacy (Baessler and Schwarzer 1996). On top of that, I account for the level of education of close relatives (parents and siblings). The variables aim to construct a similar ability index as in Guyon and Huillery (2020), mitigating the noise in the replicability process.

4.2. Sample description

Attrition and data manipulation. Multiple strategies tried to minimize the risk that a whole school or class drop out of the intervention. Hence, I account as an attritor to the student who skips one or several questions necessary to construct the outcome variable (academic aspirations). The overall attrition test indicates that about 29.2% of students failed to answer one or several questions to compute their academic aspirations. Since attrition can affect the experiment's internal validity, notably when correlated with treatment, I double-check whether this is an issue by running the Ghanem, Hirshleifer, and Ortiz-Becerra's (2021) test. This test accounts for the internal validity of the subgroup of respondents (IV-R) and the internal validity of the population (IV-P). The test indicates that the treatment effects for low-income students can be generalized for the population of low-income students since the null hypothesis was not rejected for this subgroup. However, this is not true for mid-low- and mid-high-income students who exhibit attrition issues (see Appendix C – Table 10).

With regard to covariates, I introduced the Missing Indicator Approach when data were missing at the baseline (see suggestions in Groenwold et al. 2012 or Michael J. Puma et al. 2009). I tested whether the imputation affects the random allocation by running a balanced test that included 90 baseline variables (see E-Appendix 1). I could not capture evidence that the treatment group differs from the placebo group (F-test: 1.15; p-value = 0.16).

Sample description. About 28% of the sample do not plan to pursue college education. Thus, these students plan to enter the job market immediately after high school. Students exhibit a clear understanding of labor returns. On average, they believe the Ecuadorian monthly salary is about 400 US$. It is six dollars higher than the actual basic salary in 2019 (396 US$). They expect to earn 2.5 times more than the minimum salary in five years (1,072 US$) and 4.5 times more than the minimum salary in 10 years (2,850 US$). Due to the labor market characteristics, getting a college education degree in a high-rewarding program is the best option to reach an income closer than expected.

Concerning the differences by income level, the share of high-income girls is significantly lower than non-high-income groups. On the contrary, the study or risk preferences are higher among high-income individuals (see E-Appendix 2). A joint significance test suggests that high-income students' characteristics are not equal to non-high-income students (low, mid-low, and mid-high-income). Thus, I control for imbalances in the empirical strategy.

4.3. Empirical strategy

Pre-treatment specification. I estimate how academic aspirations, earning expectations, and test scores differ by income level by computing a linear model where $Y_0^{i,j}$ is the outcome variable for student i, in class j, at the time 0 (baseline).

(1) $$Y_0^{i,j} = \alpha + \beta_L LowI^i + \beta_{ML} MLowI^i + \beta_{MH} MHighI^i + \mu_A Ability^i + u_1^k + \varepsilon_1^{i,j}$$

$LowI^i$ is a dummy variable that takes the value of 1 if student i is at the bottom of the income distribution. $MLowI^i$ takes the value of 1 if student i is at the second quartile of the income distribution, and $MHighI^i$ takes the value of 1 if student i is at the third quartile of the income distribution. The omitted (comparison) group is high-income students. The coefficients β_L, β_{ML}, and β_{MH} capture the association between poverty and outcome variables

In addition, $Ability^i$ accounts for a set of personal characteristics and external factors. The former condensed the cognitive and non-cognitive skills described in the last section. It accounts for cognitive skills in the form of dummies for the standardized exam test scores deciles and dummies for the results from the Cognitive Reflection Test. In turn, the model accounts for non-cognitive skills in the form of deciles for the perseverance task (Grit), the Growth Mentality, Self-Construal, and Self-Efficacy assessments. Finally, it accounts for external factors by introducing dummies of parents and siblings with post-secondary education or higher. The estimation also introduced class-fixed effects to account for differences in peers, teachers, and the school environment (u_1^k). I clustered standard errors at the level of randomization (class) ($\varepsilon_1^{i,j}$).

I examine the relationship between academic aspirations and earning expectations with a strategy similar to Equation 1 but adding a control term for earning expectations. Furthermore, I added "conscientiousness" since it is correlated with intelligence (see Guyon and Huillery 2020)

Post-treatment specification. I measured the effect of watching a video-based intervention featuring role models on mitigating the academic aspirations gaps between high and non-high-income groups using the following ANCOVA specification:

$$(2)\ Y_t^{i,j} = \beta_0 + \beta_{RM} RM^{i,j} + \beta_{RM} RM^{i,j}(LowI^i + MLowI^i + MHighI^i) + \pi Y_0^{i,j} + \theta_1 Controls_0^{i,j} + M_0^{i,j} + u_t^j + \varepsilon_t^{i,j}$$

Where $Y_t^{i,j}$ is the academic aspirations for student i, in class j, at time t (t_1: midline, t_2: endline). RM is a binary variable that takes the value of 1 if the student *i* watched treatment videos and 0 if the student watched placebo videos. The coefficient β_{RM} captures the Intention-to-Treat on students' ambitions. It indicates whether the treatment reshaped the aspirational gap between non-high and high-income students.

I introduced the outcome variable at the baseline ($Y_0^{i,j}$) to increase efficiency. $Controls_0^{i,j}$ is a vector of control variables. I used the post-double Lasso selection for all regressions to choose baseline variables that strongly predict outcomes (Belloni et al., 2014). The $M_1^{i,j}$ is a vector of binary variables that equals 1 when the variable is missing at the baseline, and u_t^j represents class fixed effects. Finally, $\varepsilon_t^{i,j}$ is the error term clustered at the class level.

As a robustness check, I explored the effectiveness of the intervention for the average treated student against the placebo peer. The following specification captures the treatment effect:

$$(2a) \qquad Y_t^{i,j} = \beta_0 + \beta_{RM} RM^{i,j} + \pi Y_0^{i,j} + \theta_1 Controls_0^{i,j} + M_1^{i,j} + u_1^j + \varepsilon_1^{i,j}$$

Heterogeneous effects specification. I estimated heterogeneous effects using a Generic Machine Learning approach proposed by Chernozhukov et al. (2020). It relies on data partitioning[23] to estimate three components of the conditional average treatment effect (CATE): the Best Linear Predictor (BLP), the Sorted Group Average Treatment Effects (GATES), and the Classification Analysis (CLAN). The BLP indicates whether the baseline variables produce heterogeneity. The GATES splits the sample into comparable bins and shows the impact associated with each bin. The CLAN features the covariates associated with the heterogeneous effects.

One starts by examining the BLP. If the BLP is statistically non-significant from zero (BLP = 0), it suggests that the CATE has no predictive power or that the baseline characteristics do not produce heterogeneous effects. I adapted the specification proposed by Chernozhukov et al. (2020) to estimate the BLP for the video treatment as follows:

$$(3.1) \qquad Y_{t,InQ}^{i,j} = \beta_0 * B(Z_i) + \beta_{RM} RM^{i,j} + \beta_H RM^i * S(Z_i) + \varepsilon_{i,j}$$

Where β_H tests the null hypothesis of the presence of heterogeneity ($\beta_H = 0$). $B(Z_i)$ estimates the treatment effects if student i had been assigned to the placebo group in the simulation. $S(Z_i)$

[23] The process simulates a counterfactual scenario where one can observe a proxy of treatment (placebo) scenarios if the student had been allocated to the placebo (treatment) group. I replicated the partition process over 250 times and checked the consistency of results with alternative partitions (50, 100, 150, 200, 300) (see Appendix C).

estimates the effects if student i had been assigned to the treatment group in the simulation. RM^i takes the value of 1 if the student is assigned to the treatment group in the simulation. β_{RM} is the Average Treatment Effect (ATE) of the simulation. The closer the ATE is to the Intention-to-Treat estimate (ITT), the higher the reliability of the simulation.

When the BLP is non-significant, the GATES and CLAN become non-informative (Breda et al., 2021). Otherwise, the GATES indicate how effective the intervention is for the most and least affected groups. I computed the GATES using the following specification:

(3.2) $$Y_t^{i,j} = \alpha_0 * B(Z_i) + \sum_{j=1}^{4} \gamma^j * RM^i * 1(S^i \epsilon G^j) + \eta_i$$

Where, γ^j shows the treatment effects per quartile. Moreover, G^j defines the set of students in quartile *j*.[24]

5. Results

5.1. Pre-Treatment findings

Aspirations by income levels. Figure 1 reports the gaps in academic aspirations and earnings expectations between high and non-high-income students (low. mid-low, and mid-high-income). Panel A (red dots) shows the results of a raw estimation. Low-income students exhibit an academic aspiration of 0.67 points (p.) lower than high-income students (3.58) (omitted group). In other words, compared to high-income students, most low-income students either target a non-high-rewarding major or do not even consider entering college education.[25] The aspirations gap for mid-low income (-031 p.) and mid-high-income students (-0.18 p.) is shorter but significantly different from zero.

Although informative, this is a naïve approach since differences could be associated with features other than income level. Hence, I add personal characteristics (green dots) and external factors (blue dots) to the models. Panel A (green dots) shows that cognitive and non-cognitive skills account for only one-sixth of the gap between non-high and high-income students. It suggests that even when exhibiting equal skills, non-high-income students set lower aspirations than their high-income peers. The situation substantially improves after accounting for external factors (blue dots). For instance, the gap in aspirations between high and mid-low and mid-high-income students completely disappears. Moreover, the gap between high and low-income students is reduced to one-third of the original size, but it remains significantly different from zero.

[24] I computed the heterogeneous effects in R, using the "General ML" package (Welz et al. 2021). For the data partition, I worked with five machine learning algorithms, K-nearest neighbor (KKNN), Support Vector Machine (SVM), Random Forest (RF), Boosted Trees (BT), and LASSO (L) with the package "mlr3" (Lang, 2022).

[25] About half of the low-income students prefer a low-rewarding academic path. It means no college education (38.9%), Services (4.85%), and Education and Arts (6%). In contrast, less than 20% of high-income students exhibit no plans to enter college education. Most prefer to study Health (22.2%), Engineering (17%), or Business and Law (12.33%) (see Appendix D).

Panel B illustrates the differences in earning expectations between high and non-high-income students. Findings follow the same path as academic aspirations. In other words, the monthly salary expectation for high-income students (1,409.85 US$) is higher and statistically different than non-high-income ones (red-dots). Moreover, the difference is greater when the student is further down the income distribution. Panel B (blue dots) shows that after accounting for personal characteristics and external factors, the gap is about two-thirds shorter for low-income students (- 132.23 US$) and mid-low-income students (- 87.17 US$) and one-half shorter for mid-high-income students (- 86.84 US$). Even though the gap shrinks substantially, the differences in earning expectations between high and non-high-income students remain significant.

Consistency between academic aspirations and earning expectations. Figure 1 shows a similar trend when assessing academic aspirations and earnings expectations by income level. In both cases, the difference compared to high-income students is larger when the student is further down the income distribution. Despite that, the data reveals an inconsistency between what students aspire to study and their earning expectations. For instance, low-income students might earn 50% or less of their expected wage due to their college education preferences (Appendix A). On the contrary, high-income students would get at least 80% of the earning expectation due to their plans to study Life Science or Health-related majors.

I formally capture this inconsistency by introducing earning expectations to the regression in academic aspirations. Table 1 shows that the gap in academic aspirations between rich and poor students remains statistically significant even after accounting for high earning expectations. Altogether, findings suggest that students, particularly low-income ones, fail to realize the link between post-secondary preferences (and choices) and future earnings.

Academic aspirations and school performance. Theoretical propositions predict that capable students work harder when setting high ambitions. I test this hypothesis by examining the association between high aspirations and school performance as a proxy of effort. Table 6 in Appendix B reports results for the average students and the set of non-high-income students.

The data shows that setting high academic aspirations is associated with test scores 0.04 SD higher than setting low academic aspirations. The result remains significant among non-high-income students (0.03 SD), suggesting that increasing aspirations could boost school performance. The finding is even more relevant when one observes that setting middle aspirations is associated with null or negative test scores (-0.04 SD).

5.2. Post-treatment results

I begin the analysis by exploring the effectiveness of the treatment videos in mitigating the aspirations gap between low and high-income students. Figure 2 shows treatment effects on academic aspirations at the midline (red dots) and endline (blue dots). The results suggest that the intervention produces null effects on reshaping the aspirations gap between high-income and non-high-income students. Despite that, there is still the possibility that the treatment affects students within income groups. Table 2 – Panel B accounts for this hypothesis. It tests whether the subgroup net effect of the intervention is significantly different from zero.[26]

Findings show that treated low-income students substantially benefit from the videos. For low-income students, it increases academic aspirations by 0.23 points at the midline and 0.37 points at the endline. In other words, the aspiration level is 7% and 11.6% higher for treatment than placebo students (mean low-income placebo group 2.72 midline and 2.69 endline). This suggests that the intervention steers students from low-rewarding majors like Arts and Humanities and Services to high-rewarding options like Engineering and Health. Due to this difference, treated students could earn about 270.33 US$ more than their placebo peers each month. The increase accounts for 68% of the Ecuadorian basic salary (395 US$).

Likewise, mid-low- and mid-high-income students exhibit promising results. For example, the intervention increases mid-low-income students' academic aspirations by 0.23 points at the midline and 0.40 points at the endline. Furthermore, the treatment boost mid-high-income students' aspirations by 0.19 points at the midline and 0.28 at the endline. The increase in aspirations could also reflect advantages in monthly earnings as seen for low-income students. However, one should consider the possibility of attrition bias affecting these results, which might have led to an overestimation of the actual benefits. Therefore, these findings should be taken as suggestive rather than conclusive.

Heterogeneous effects. This section examines treatment heterogeneity using the Generic Machine Learning inference proposed by Chernozhukov et al. (2020). I report results for the average student and within the income group (low, mid-low, mid-high) at midline and endline. Each specification tests heterogeneous effects for pre-registered covariates, such as perseverance (Grit), risk preference, sex, ethnic minority, school performance (test scores), and self-efficacy. Following recent evidence, I also introduce the following variables, expected grade, expected earnings, and growth mentality (for instance, see Flechtner 2016; Fruttero, Muller, and Calvo-González 2021; Huillery et al. 2021).

Table 3 summarizes the results for the Best Linear Predictor (BLP) of the CATE. Findings report suggestive evidence of heterogeneous treatment effects only for mid-high-income students. Thus, I focus on this income group.

[26] The analysis reports the results of a null hypothesis test that compare if the treatment (T.RM) plus interaction (T.RM*Income Group = 0).

The Grouped Average Treatment Effect (GATES) divides students into comparable bins. For mid-high-income students, the most affected bin (G1) increased the midline aspiration index by 39 points. The effect is significant at the 10% level and two times higher than the subgroup ITT effect (Table 2). However, the result is not robust to multiple inference testing (q-value = 0.35). Thus, the result might suffer from a Type I error. To avoid confusion, I refrain from reporting the rest of the results.

5.3. Robustness checks

5.3.1. Treatment effects

I test the robustness of treatment effects by running Equation 2a. Findings are consistent with the subgroup's positive results (Appendix C). In other words, academic aspirations increase by 0.19 points at the midline and 0.30 points at the endline. Thus, the aspiration level is 6.2% and 10% higher for treatment than placebo students (mean placebo group = 3.06 midline and 3.00 endline).

Furthermore, I aim to study the primary effect of the treatment. To do so, I create two dummy variables accounting for i) plans to pursue college education and ii) preferences for a high-rewarding major. Findings suggest that the treatment mainly motivates students to target a more high-rewarding educative program rather than planning to enter college education (Appendix C). The result aligns with Breda et al. (2021), who report that in-person female role models steer students into high-rewarding majors.

5.3.2. Interaction analysis

I test the robustness of the heterogeneous effects by running an interaction analysis (Table 11). It can contribute to the academic debate on reshaping academic aspirations through video-based content, despite the criticism (see issues with overfitting bias Abadie, Chingos, and West 2018; or statistical power David Baranger 2021; Blake and Gangestad 2020).

Low-income students. I captured significant effects primarily for the endline aspiration index. The treatment increases academic aspirations by 0.31 and 0.24 points for students with a growth mindset and those from an ethnic minority. However, the joint test could not reject the null hypothesis, suggesting that estimates might appear by chance.

Mid-low-income students. The table indicates that the treatment effect increases academic aspirations by 0.27 points among students with a growth mindset. However, the joint test could not reject the null hypothesis, suggesting that estimates might appear by chance.

Mid-high-income students. Similar to the machine learning results, I capture significant interaction effects only for mid-high-income students at the midline (joint test = 0.07). The table shows that students with high perseverance (Grit) reduce their academic aspirations by 0.41

points. However, I capture null results when estimating the same effect using an incentivized game to elicit Grit.

Besides Grit, the analysis shows that cognitive ability positively affects the intervention. When treated students exhibit a high cognitive ability, they increase their midline aspiration index by 0.29 points. These students exhibit academic aspirations 9% higher than their placebo peers. On the other hand, I report a decrease in academic aspirations by 0.51 points when students belong to an ethnic minority. One could speculate that ethnic minorities from a mid-high-income level might be more severe when judging the role models' diversity. Since they might feel a low representation of their peers, they reject the content.

Finally, the estimation indicates that the treatment boosts academic aspirations by 0.34 points when students exhibit a growth mindset. Hence, findings align with theoretical propositions showing that agency is critical to boosting aspirations (see Fruttero, Muller, and Calvo-González 2021).

6. Policy recommendation

Findings show that a video-based intervention can reshape low-income students' preferences toward high-rewarding majors. Even though it does not close the gap, it raises aspirations among treated low-income students compared with placebo ones. Since the relationship between high aspirations and academic performance is positive, one could argue that raising aspirations could increase students' chances of achieving a better career path (i.e., better options to enter university). Furthermore, to the extent that academic aspirations translate into actual choices, the treatment effect could improve low-income students' economic returns in the long run by introducing a flexible, easy-to-scale, and low-cost intervention (less than US$ 1 per student).

Despite that, decision-makers should be careful when implementing similar interventions. As reported, the treatment primarily steers students into high-rewarding majors. However, evidence suggests that students who pursue high-rewarding programs experience low graduation rates (Hastings et al., 2016). Additional to the academic demands, one could argue that inequality in the college education system could exacerbate this association.[27] Since low-income students exhibit a lower margin for error (Bertrand et al., 2004), one should be careful when raising aspirations in the context of high inequality (see a discussion on frustrated aspirations in Ray 2006; McKenzie, Mohpal, and Yang 2021; Flechtner 2017). Matching similar media content with policies to reduce inequalities in college education retention could be a constructive strategy to attract and retain students (see a comprehensive set of options in Hoxby et al. 2004).

[27] Following the discussion in Hüther and Krücken (2018), I understand equality of opportunity when academic success does not depend on group membership (i.e., high socioeconomic status) or when success or failure cannot be predicted by the social background.

7. Concluding remarks

Poverty remains the biggest challenge in most political agendas worldwide (UN, 2015). Although much has been done to alleviate it, a key element, the state of mind, has been neglected (Vakis et al., 2016). The Scarcity Theory stresses the relevance of psychological constraints when fighting against poverty (Mullainathan & Shafir, 2014). For instance, living with less than the minimum to cover basic needs produces a state of hopelessness, curtailing the individual capacity to set forward-looking goals or aspirations (Appadurai, 2004; Duflo, 2012). It creates the perfect scenario to trap people into vicious cycles since low aspirations lead to welfare-dominated outcomes by preventing them from working hard (Genicot & Ray, 2020). Since low aspirations and detrimental outcomes constitute a feedback loop, the chances are high that the person cannot escape poverty even when getting external support (Dalton et al., 2014).

This article examines the influence of poverty on academic aspirations. A novel approach explores high school students' ambitions by linking their preferences for college education with economic returns in the labor market. In doing so, one could quantify the consequences of setting myopic goals. The index shows that theoretical propositions replicate in the sample. For instance, capable low-income students set less ambitious goals or aspirations than their high-income peers only because of their position in the income distribution (see Appadurai 2004; Nathan 2005).

One can see the consequences of these choices in three dimensions. First, by setting lower aspirations, students exert lower effort at school (i.e., lower test scores). Since academic and industrial organizations use grades as a sign of individuals' abilities, low test scores could resonate with their opportunities to pursue college education or secure a job (Leschnig et al., 2022; Schwerdt & Woessmann, 2017). Second, low aspirations perpetuate the gap between rich and poor. Setting lower aspirations means that students prefer to study majors that offer a low reward in the labor market. For instance, while most high-income students plan to study Health or Engineering, about 40% of low-income students plan to skip college education. This can explain part of the income gap among individuals with equal years of schooling and academic background (Hastings et al., 2016; Kirkeboen et al., 2016). Third, there is an inconsistency between academic aspirations and earning expectations. Although it affects the entire sample, low-income students are more susceptible to experiencing frustrated aspirations due to the large inconsistency (i.e., they could earn less than 50% of what is expected due to their academic preferences).

A flexible, low-cost video-based intervention featuring role models cannot mitigate the gap between the rich and the poor. However, it seems effective in improving the situation within income groups. Indeed, low-income students who watched the treatment instead of the placebo content changed their preferences for more high-rewarding majors. One can translate this impact into a monthly premium of about 270.33 US$. The bonus accounts for 68% of the Ecuadorian basic salary, suggesting that watching the treatment content could be beneficial for low-income students. Although results could be similar for mid-low- and mid-high-income students, the evidence is non-conclusive due to attrition bias.

Despite that, caution is needed when introducing this type of content. The efforts to attract students to high-rewarding majors assume that the college education system would guarantee equal opportunities for academic success. Due to their prevailing circumstances, low-income students exhibit a low tolerance for failure (Bertrand et al., 2004). Thus, nudging them into high-rewarding majors, knowing that the chances of success are low, can accelerate the feelings of despair or frustration, particularly when they perceive that the reason for failure is unrelated to their academic ability. Ray (2006), McKenzie, Mohpal, and Yang (2022), and Flechtner (2017) review some of the consequences of frustrated aspirations that go from spiritualism to violence.

An extension of this study could analyze the usability and validity of the current approach to measuring aspiration. Moreover, testing students' enjoyment and identification with role models would be ideal to understand better the channels that produce the treatment effects. Finally, testing the intervention in other contexts (i.e., different zones within Ecuador or other countries) could support additional elements to examine the generalizability of effects.

8. **Bibliography**

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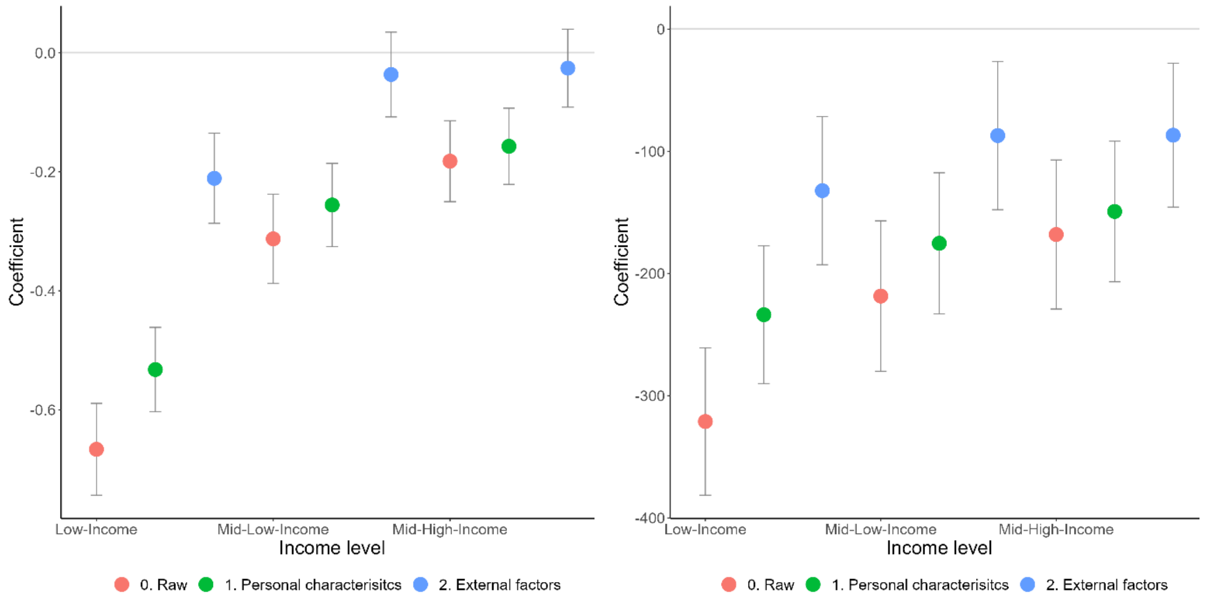
9. Figures

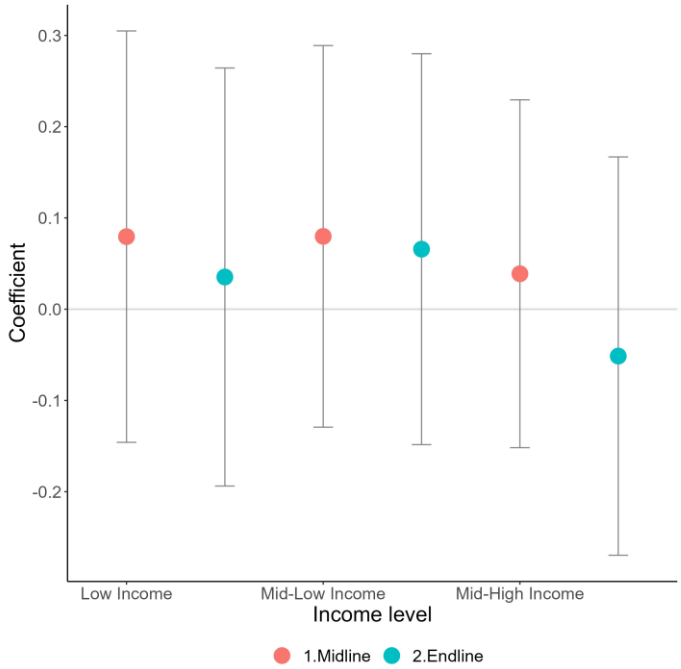
Figure 1: Academic aspirations and earning expectations by income level

Panel A: Academic Aspirations Panel B: Earning expectations



Note: The figure illustrates the academic aspirations at the baseline by income levels in Panel A and earning expectations in Panel B. Academic aspirations measure how rewarding the students' preferred major is according to the Ecuadorian labor market. Earning expectations show students' expected monthly wage 10 years after the intervention. Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The comparison group is students at the top of the income distribution (solid grey line). The red dots show the results of a raw estimation measuring the gap between high and non-high-income students. The green dots illustrate the estimation accounting for personal characteristics (cognitive and non-cognitive skills). They include the results of a standardized exam and the Cognitive Reflection Test as a proxy of cognitive ability. They also account for perceived behavior and self-esteem by introducing perseverance (Grit), growth mindset, Self-concept, and Self-efficacy. The blue dots add external factors to the estimation. They account for highly educated parents and siblings and class (fixed) effects. I clustered standard errors at the class level.

Figure 2: Intention-to-Treat effects on reducing the aspirational gaps between non-high and high-income students



Note: The figure illustrates the effectiveness of treatment videos in mitigating aspirational gaps between non-high and high-income students (solid grey line). Academic aspirations measure how rewarding the students' preferred major is according to the Ecuadorian labor market. Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The blue dots exhibit the treatment effect approximately two months after watching the treatment videos (mid-term); meanwhile, the blue dots introduce treatment effects four months (long-term) after the program. The estimations report clustered standard errors at the class level.

10. Tables

Table 1: Association between academic aspirations and earning expectations

	Academic aspirations	
	(1)	**(2)**
Mean academic aspirations: High-income students	3.58	3.58
Low-Income	-0.21***	-0.19***
	(0.04)	(0.04)
	[-0.29, -0.14]	[-0.26, -0.11]
Mid-low-Income	-0.04	-0.03
	(0.04)	(0.04)
	[-0.11, 0.03]	[-0.10, 0.04]
Mid-high-Income	-0.03	-0.02
	(0.03)	(0.03)
	[-0.09, 0.04]	[-0.08, 0.05]
High-earning expectations		0.23***
		(0.03)
		[0.18, 0.29]
Num.Obs.	16451	16286
R2 Adj.	0.133	0.137
N. clusters	610	610
Clustered SE	Yes	Yes
Personal characteristics	Yes	Yes
External factors	Yes	Yes

Note: The table reports the relationship between academic aspirations and high-earning expectations. Academic aspirations measure how rewarding the students' preferred major is according to the Ecuadorian labor market. I account for the high-earning expectation when the student exhibits an above-average expected wage. Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The comparison group is students at the top of the income distribution (omitted group). Column 1 introduces the gap between high and non-high-income students without accounting for earning expectations; meanwhile, Column 2 introduces high earning expectations to the estimation. The results correspond to an estimation accounting for personal characteristics and external factors. Personal characteristics include the results of the Cognitive Reflection Test as a proxy of cognitive ability. They also account for perceived behavior and self-esteem by introducing perseverance (Grit), growth mindset, Self-concept, and Self-efficacy. External factors account for highly educated parents and siblings and class effects. The table reports clustered standard errors in parenthesis and confidence intervals in brackets.

Table 2: Intention to Treat effect of role models on reducing the aspirational gaps on the midline and endline index

	Academic Aspirations	
	Midline	Endline
	(1)	(2)
Panel A: Main Treatment Effects		
Mean academic aspirations: High-income students	3.28	3.19
Treatment (T.RM)	0.15*	0.33***
	(0.09)	(0.10)
	[-0.02, 0.33]	[0.14, 0.52]
T.RM*Low-Income	0.08	0.04
	(0.11)	(0.12)
q-value	0.36	0.38
	[-0.15, 0.30]	[-0.19, 0.26]
T.RM*Mid-Low-Income	0.08	0.07
	(0.11)	(0.11)
q-value	0.36	0.36
	[-0.13, 0.29]	[-0.15, 0.28]
T.RM*Mid-high-Income	0.04	-0.05
	(0.10)	(0.11)
q-value	0.38	0.38
	[-0.15, 0.23]	[-0.27, 0.17]
Panel B: Subgroup Effects		
T.RM + T.RM*Low-Income = 0	0.23[0]	0.37[0]
T.RM + T.RM*Mid-Low-Income = 0	0.23[0]	0.4[0]
T.RM + T.RM*Mid-High-Income = 0	0.19[0]	0.28[0]
Baseline Aspiration index	Yes	Yes
Clustered SE	Yes	Yes
Controls	Yes	Yes
Class fixed effects	Yes	Yes
Num. clusters	273	273
Num.Obs.	6407	6365

Note: The table reports the impact of treatment videos on reducing the aspirational gaps associated with poverty. The outcome variable is academic aspirations. It measures how rewarding the students' preferred major is according to the Ecuadorian labor market. Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The midline outcome accounts for the treatment effect about two months after the intervention; meanwhile, the endline outcome examines the impact four months after watching the treatment videos. In Panel A, the table reports clustered standard errors at the class level (in parenthesis) and 95% confidence intervals in brackets. Moreover, it reports sharpened p-values (q-values) as Anderson (2008) suggested. Panel B reports the subgroup effects. In other words, it tests if the difference between the treatment plus interaction (subgroup net effect) is statistically different from zero. It features the net treatment effect and p-values in brackets. Following Equation 2, all estimations include class fixed effects and control variables selected with the post-Double Lasso approach.

Table 3: Results of the Best Linear Predictor (BLP)

	Midline			Endline		
	Estimate	p-values	Cbounds	Estimate	p-values	Cbounds
Panel 1: Average students						
ATE	0.10	0.08	[-0.01;0.22]	0.06	0.34	[-0.06;0.18]
BLP	-0.12	0.43	[-0.39;0.17]	-0.04	0.63	[-0.17;0.11]
Panel 2: Low-Income students						
ATE	0.27	0.04	[0.02;0.52]	0.17	0.21	[-0.1;0.43]
BLP	-0.13	0.75	[-0.88;0.62]	0.00	0.99	[-0.76;0.7]
Panel 3: Mid-Low-Income students						
ATE	0.10	0.38	[-0.14;0.34]	0.07	0.58	[-0.17;0.3]
BLP	-0.05	0.91	[-0.86;0.73]	-0.15	0.23	[-0.41;0.1]
Panel 4: Mid-High-Income students						
ATE	0.13	0.21	[-0.08;0.36]	0.10	0.44	[-0.16;0.35]
BLP	-0.39	0.09	[-0.83;0.07]	-0.08	0.83	[-0.79;0.65]

Note: The table reports the Best Linear Predictor (BLP) of CATE using the method developed by Chernozhukov et al. (2020). The outcome variable is academic aspirations. It measures how rewarding the students' preferred major is according to the Ecuadorian labor market. Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The midline outcome accounts for the treatment effect two months after the intervention; meanwhile, the endline outcome examines the impact four months after watching the treatment videos. The ATE reports median results of the Intention-to-Treat effect from 250 simulations. The closest the results to the ITT, the higher the reliability of the simulation. The simulation reports the results from the best Machine Learning algorithm from the following options, K-nearest neighbor (KKNN), Support Vector Machine (SVM), Random Forest (RF), Boosted Trees (BT), and LASSO (L). It also reports the median confidence intervals in brackets and median p-values.

Table 4: Grouped Average Treatment Effect (GATES) for Mid-high-income students

	Midline Aspirations		
	25% most affected	25% least affected	least-most affected
	(G1)	(G4)	(G4 - G1)
	0.39	-0.08	-0.44
p-values	0.07	0.73	0.16
q-values	0.35	0.73	0.40
Cbounds	[-0.04;0.81]	[-0.5;0.35]	[-1.03;0.16]

Note: The table reports the results of Grouped Average Treatment Effect (GATES). It presents the heterogeneous treatment effects on midline academic aspirations for mid-high-income students. The outcome variable is academic aspirations. It measures how rewarding the students' preferred major is according to the Ecuadorian labor market. The table shows results for the most and least affected groups. Moreover, it tests if the differences between groups are statistically different from zero (G4-G1). The table introduces median estimates, p-values, and confidence bounds from a simulation with 250 iterations. It also reports sharpened p-values (q-values), as Anderson (2008) suggested.

11. Appendixes

11.1. Appendix A: Aspiration Index

After high school, individuals face a critical decision, namely, what to do next? The first choice is between college education or the job market. Most empirical work on aspirations focuses on this trade-off since it has a direct link with economic returns (see the survey by Fruttero, Muller, and Calvo-González 2021). More years of education are correlated with better income (Psacharopoulos & Patrinos, 2018), well-being (Cutler & Lleras-Muney, 2006), or cognitive ability (Lövdén et al., 2020). However, more education cannot always translate into adequate employment. Inequality between professions has positioned some programs ahead of others (Holmes, 2018; Xie et al., 2016). It makes relevant the second choice, which major one should choose. Indeed, recent literature highlights the influence of educational preferences on the choice of major and returns to education (for instance, see de Bruijn and Antonides 2022; Hastings et al. 2016; Kirkeboen, Leuven, and Mogstad 2016). In light of this revelation, I propose an outcome to measure academic aspirations that accounts how ambitious students' preferred majors are.

The outcome was nurtured by work from Guyon and Huillery (2020) and Beaman et al. (2012). I classified students' preferred major based on their answers to the question *name the three subjects you would choose to study at university.*[28] I focused on the first choice as it should be correlated with actual career decisions (for example, see Jerrim, Shure, and Wyness 2020; Guyon and Huillery 2020). I classified the answers following the International Standard Classification of Education (ISCED). It allocates the programs into ten categories (Table 5). Each of them requires the same completion time.

Since future earnings are a common motivation to choose a profession (see Akosah-Twumasi et al. 2018; Ryan and Deci 2000), I designed the index to assimilate this information. Thus, I matched students' preferred educative programs with their returns from the labor market.[29] The most ambitious choice is the most rewarding in terms of monthly income. I rank the educative programs

28 Note that I could only collect information about educative programs from students who plan to enter university. For instance, they answered *yes* to the question, *do you plan to go to university*? Since this decision could introduce self-selection, I designed an unconditional index. It implies that I allocate all students who say no to a new category (zero) and rank them based on the market salary of an individual without college education. I assigned the same earnings category to the students who stated they planned to attend university but did not state any specific educative program. They represent 1.4% of the baseline observations, 6.7% of the midline observations, and 7.3% of endline students.

29 I introduced a novel approach since I could not adjust my data to prior experiences. For instance, Guyon and Huillery (2020) differentiated the study programs according to their completion time, which implies that answers exhibit heterogeneity in levels of education, a feature that is not part of my data. Jerrim, Shure, and Wyness (2020) introduced an alternative by evaluating ambitions according to the preferred university. The authors argue that the most ambitious students would wish to enter Oxford or Cambridge. However, I did not collect school information to replicate the idea. Beaman et al. (2012) identify certain occupations, such as doctor, engineer, scientist, teacher, or legal career, as more ambitious than others. However, it was unclear the reasoning behind choosing these professions over others.

using the 2019 National Employment Survey from the Ecuadorian Statistics Office (INEC, 2019). It features a unique opportunity to identify earnings by ISCED field (Table 5).

One should notice that I could only collect information about educative programs from students who plan to enter university. For instance, they answered *yes* to a question, *do you plan to go to university*? Since this decision could introduce self-selection, I designed an unconditional outcome. It implies that I allocate all students who say "no" to a new category (zero) and rank them based on the market salary of an individual without college education. I assigned the same earnings category to the students who planned to attend university but did not state any specific educative program or were undecided. The second group represents 1.4% of the baseline observations, 6.7% of the midline observations, and 7.3% of endline students.

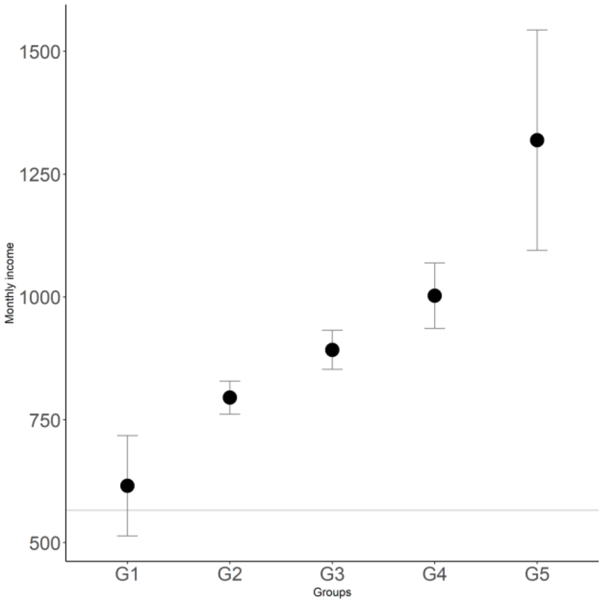
Table 5: Educative programs according to the International Standard Classification of Education by monthly earnings

Rank	Group	ISCED	Monthly income per program	Expected income per program	Expected income per group	Difference per program (expected - real)	p-value (Difference per program)	Share of expected earning (real / expected
11	5	5	1,319.11	1,620.14	1,542.79	301.03	0.00	0.81
10	5	9	1,013.86	1,568.93	1,542.79	555.07	0.00	0.65
9	5	6	980.49	1,368.89	1,542.79	388.40	0.00	0.72
8	4	7	928.50	1,500.84	1,472.73	572.34	0.00	0.62
7	4	3	911.09	1,483.49	1,472.73	572.39	0.00	0.61
6	4	8	897.45	1,333.61	1,472.73	436.16	0.00	0.67
5	4	4	864.25	1,461.56	1,472.73	597.32	0.00	0.59
4	3	1	796.64	1,230.90	1,393.09	434.26	0.00	0.65
3	3	10	786.02	1,483.17	1,393.09	697.15	0.00	0.53
2	2	2	615.68	1,338.15	1,317.62	722.47	0.00	0.46
1	1	0	566.05	1,129.92	1,129.92	563.86	0.00	0.50

Note: The table lists the broad categories of the International Standard Classification of Education (ISCED) by economic returns on the Ecuadorian job market. ISCED refer to the identification codes assigned by the standard classification. Rank and group order the majors according to their monthly income. I extracted the monthly income information from the 2019 National Employment Survey (INEC, 2019). Following the National Statics Office (INEC) guidelines, I control for sample design and the two selection stages to compute the income information. I drop less than 1% of observations that earns substantially more of the average sample. The outliers were in the top 0.0001% of the population according to their income level. Expected income per program accounts for students earning expectations in ten years per major. The label real indicates the monthly income per program.

Life Sciences (ISCED 05), Health and welfare (ISCED 09), and Technology (ISCED 06) have the highest economic returns, while Education (ISCED 01), Services (ISCED 10), and Humanities and Arts (ISCED 02) are the less-rewarding options. Students who choose not to pursue college education are at the bottom of the distribution.

Figure 3: Broad fields grouped by monthly salary



Note: The figure illustrates the average salary of individuals in each income group. The solid horizontal line represents the monthly income of individuals without college education. G1 is the group with lower earnings and comprises Arts and Humanities. In contrast, G5 is the group with higher returns on education and comprises Life Science, Statistics, and Math, Health and Welfare, and Computer Science (IT). The solid vertical lines represent the confidence interval.

Despite the clear differences, some educative programs are less statistically significant than others. Thus, I grouped them into five bins according to their economic returns. Figure 7 illustrates the alternative composition. Following the alternative composition, I created a fourth variable. It takes values from one to five, where four and five accounts for high-rewarding programs.

Assumptions. By ranking programs according to their economic returns, the index assumes that income information is similar among subjects. I tested the assumption by examining students' knowledge about job market returns. First, I examined how well they knew their potential salary by asking *how much is the Ecuadorian minimum wage* (394 US$). The data show that the average student accurately knows the minimum wage. The median answer was 398 US$. Moreover, I found that low-income students (US$ 398) are statistically more accurate than high-income ones (US$ 405).

Second, I examined students' knowledge about earnings for STEM scientists and entrepreneurs. The average student believes a STEM scientist's median earning is twice as high as the entrepreneur's (US$ 600). The ratio and values are close to the returns from the labor market (INEC, 2019). Furthermore, I observed that beliefs are equal between low- and high-income students. Therefore, one could argue that earnings information is accurate and comparable across the sample.

11.2. Appendix B: Aspirations and school attainment

Table 6: Association between Aspirations and School Attainment for low- and mid-low-income students.

	Standardized Test Scores				
	Average student		Non-High-income student		
	(1)	(2)	(3)	(4)	(5)
Mean school performance: Low-aspiration students	1.5	1.5	1.38	1.49	1.52
High Aspirations	0.11***	0.04***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.10, 0.12]	[0.03, 0.05]	[0.01, 0.05]	[0.01, 0.06]	[0.01, 0.06]
Middle Aspirations	0.05***	0.00	0.01	0.02	-0.04*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
	[0.03, 0.07]	[-0.01, 0.02]	[-0.03, 0.05]	[-0.02, 0.06]	[-0.08, 0.00]
Num.Obs.	16451	16451	4064	4133	4165
R2 Adj.	0.024	0.229	0.202	0.195	0.231
N. clusters	610	610	610	610	610
Low-income students	No	No	Yes	No	No
Mid-Low-income students	No	No	No	Yes	No
Mid-High-income students	No	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Class fixed effects	No	Yes	Yes	Yes	Yes

Note: The table examines the association between aspirations and educational outcomes. The outcome variable is a standardized index for test scores. The data come from a mini-test that simulates the National standardized exam called "*Ser Bachiller*." It assesses performance in statistics, English, and Spanish. The variable "high aspirations" examines how different test scores are when the aspirations are four points or more. The variable "Middle Aspirations" examines the influence of aspirations when the students choose majors in the Group 3 (Education and Services). The table shows the association for the average student (columns 1 and 2) and for the entire non-high-income sample (low, mid-low, and mid-low-income groups). Columns 1 exhibits the results of a raw estimation of aspirations on test scores. Columns 2 to 5 introduce control variables. The control variables contain results of the Cognitive Reflection Test as a proxy for cognitive skills, results from an incentive task to elicit Grit as a proxy for effort, Self-Concept and Self-efficacy, and Growth Mentality index as a proxy for perceived behavior and self-esteem. Finally, I introduced parents' and siblings' education to control for having highly educated families and class fixed effects. The table shows standard errors in parenthesis and confidence intervals in brackets. I clustered standard errors at the class level.

11.3. Appendix C: Robustness checks

Table 7: Intention-to-Treat effects of role models on educational aspirations

	Academic Aspirations	
	Midline	**Endline**
	(1)	**(2)**
Mean academic aspirations: placebo students	3.06	3
Treatment (T.RM)	0.19***	0.30***
	(0.03)	(0.03)
	[0.13, 0.25]	[0.24, 0.36]
Num.Obs.	6407	6365
R2 Adj.	0.321	0.313
N. clusters	274	273
Baseline Aspiration index	Yes	Yes
Clustered SE	Yes	Yes
Controls	Yes	Yes
Class fixed effects	Yes	Yes

Note: The table reports the Intention-to-Treat (ITT) impact of role models on aspiration. It compares the effectiveness of the intervention against a placebo treatment. The outcome variable is academic aspirations. It measures how rewarding the students' preferred major is according to the Ecuadorian labor market. The midline outcome accounts for the treatment effect one month after the intervention; meanwhile, the endline outcome examines the impact two and a half months after watching the treatment videos. The table reports clustered standard errors at the class level (in parenthesis). To select the control variables, I computed the post-double lasso selection approach.

Table 8: Intention-to-Treat effects of role models on the probability of entering college education by income level

	Preference for entering Higher education	
	Midline	Endline
	(1)	(2)
Mean academic aspirations: High-income students	0.27	0.31
Treatment (T.RM)	-0.02	0.00
	(0.03)	(0.03)
	[-0.07, 0.03]	[-0.05, 0.05]
T.RM*Low-Income	-0.01	-0.01
	(0.03)	(0.03)
	[-0.08, 0.05]	[-0.07, 0.06]
T.RM*Mid-Low-Income	-0.04	-0.04
	(0.03)	(0.03)
	[-0.09, 0.02]	[-0.10, 0.02]
T.RM*Mid-high-Income	-0.03	0.00
	(0.03)	(0.03)
	[-0.09, 0.02]	[-0.07, 0.06]
Num.Obs.	6407	6365
R2 Adj.	0.299	0.298
N. clusters	274	273
T.RM + T.RM*Low-Income = 0; p-value(q-value)	0.15	0.73
T.RM + T.RM*Mid-Low-Income = 0; p-value(q-value)	0	0.05
T.RM + T.RM*Mid-High-Income = 0; p-value(q-value)	0.01	0.75
Baseline Aspiration index	Yes	Yes
Clustered SE	Yes	Yes
Controls	Yes	Yes
Class fixed effects	Yes	Yes

Note: The table reports the results of a Linear Probability Model (LPM). It shows the Intention-to-Treat (ITT) impact of role models on entering college education by income level. The outcome is a binary variable that takes the value of 1 if the students plan to enter college education and 0 otherwise. Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The midline outcome accounts for the treatment effect two months after the intervention; meanwhile, the endline outcome examines the impact four months after watching the treatment videos. The table reports clustered standard errors at the class level (in parenthesis). The bottom panel reports regular p-values, testing if the difference between the treatment plus interaction (subgroup net effect) is statistically different from zero. To select the control variables, I computed the post-double lasso selection approach.

Table 9: Intention-to-Treat effects of role models on the probability of choosing a high-rewarding program by income level

	Preference for high-rewarding program	
	Midline	**Endline**
	(1)	**(2)**
Mean academic aspirations: High-income students	0.6	0.58
Treatment (T.RM)	0.05*	0.06**
	(0.03)	(0.03)
	[-0.01, 0.10]	[0.01, 0.12]
T.RM*Low-Income	0.04	0.01
	(0.04)	(0.04)
	[-0.03, 0.11]	[-0.06, 0.08]
T.RM*Mid-Low-Income	0.01	0.00
	(0.03)	(0.03)
	[-0.06, 0.08]	[-0.07, 0.06]
T.RM*Mid-high-Income	0.03	-0.03
	(0.03)	(0.03)
	[-0.03, 0.09]	[-0.09, 0.04]
Num.Obs.	6407	6365
R2 Adj.	0.265	0.259
N. clusters	274	273
T.RM + T.RM*Low-Income = 0; p-value(q-value)	0	0
T.RM + T.RM*Mid-Low-Income = 0; p-value(q-value)	0	0
T.RM + T.RM*Mid-High-Income = 0; p-value(q-value)	0	0.05
Baseline Aspiration index	Yes	Yes
Clustered SE	Yes	Yes
Controls	Yes	Yes
Class fixed effects	Yes	Yes

Note: The table reports the results of a Linear Probability Model (LPM). It shows the Intention-to-Treat (ITT) impact of role models on planning to study a high-rewarding program by income level. The outcome is a binary variable that takes the value of 1 if the students plan to study a high-rewarding program at university and 0 otherwise. A high rewarding program is one of the majors in groups four and five (i.e., Business and Law, Agriculture, Social Science, Engineering, Health, and Life Science). Income level is the Principal Component of questions that explore students' living quality. I create the income subgroups by splitting the sample into four comparable bins based on income quartiles. The midline outcome accounts for the treatment effect two months after the intervention; meanwhile, the endline outcome examines the impact four months after watching the treatment videos. The table reports clustered standard errors at the class level (in parenthesis). The bottom panel reports regular p-values, testing if the difference between the treatment plus interaction (subgroup net effect) is statistically different from zero. To select the control variables, I computed the post-double lasso selection approach.

Table 10: Attrition tests

	Midline		Endline	
	IV-R	IV-P	IV-R	IV-P
	(1)	(2)	(3)	(4)
Low-income students p-values	0.85	0.76	0.65	0.82
Mid-low-income students p-values	0	0	0	0
Mid-high-income students p-values	0	0	0	0

Note: The table report results of an attrition test proposed by Ghanem, Hirshleifer, and Ortiz-Becerra (2021). It reports results of the internal validity of the respondent subsample (IV-R) and the internal validity of the respondent population (IV-P) for the three income levels, low, mind-low, and mid-high-income students, at the midline and endline. The table reports p-values of the sharp test at the respondent and population levels.

Table 11: Results of the Best Linear Predictor (BLP) for alternative simulations

	Average student			Low-Income student			Mid-Low-Income student			Mid-High-Income student		
	Estimate	p-values	Cbounds	Estimate	p-values	Cbounds	Estimate	p-values	Cbounds	Estimate	p-values	Cbounds
Panel 1: 50 iterations												
ATE	0.11	0.06	[0;0.22]	0.29	0.02	[0.04;0.54]	0.11	0.36	[-0.14;0.36]	0.15	0.16	[-0.06;0.36]
BLP	-0.15	0.28	[-0.42;0.12]	-0.12	0.43	[-0.4;0.17]	0.07	0.58	[-0.19;0.31]	-0.39	0.10	[-0.82;0.07]
Panel 2: 150 iterations												
ATE	0.11	0.07	[-0.01;0.22]	0.26	0.03	[0.02;0.5]	0.10	0.39	[-0.14;0.33]	0.15	0.16	[-0.06;0.36]
BLP	-0.13	0.34	[-0.4;0.15]	-0.02	0.97	[-0.83;0.74]	0.05	0.90	[-0.76;0.8]	-0.39	0.07	[-0.84;0.03]
Panel 3: 200 iterations												
ATE	0.11	0.07	[-0.01;0.22]	0.25	0.05	[-0.01;0.5]	0.09	0.44	[-0.15;0.33]	0.16	0.15	[-0.06;0.38]
BLP	-0.14	0.33	[-0.42;0.13]	-0.05	0.91	[-0.77;0.71]	-0.03	0.93	[-0.8;0.73]	-0.39	0.08	[-0.82;0.05]
Panel 4: 300 iterations												
ATE	0.11	0.06	[0;0.22]	0.27	0.04	[0.02;0.52]	0.11	0.37	[-0.13;0.34]	0.16	0.13	[-0.05;0.38]
BLP	-0.14	0.34	[-0.41;0.15]	-0.05	0.90	[-0.82;0.71]	0.01	0.93	[-0.77;0.78]	-0.37	0.10	[-0.8;0.07]

Note: The table reports the Best Linear Predictor (BLP) estimations using the method developed by Chernozhukov et al. (2020). The outcome variable is academic aspirations. It measures how rewarding the students' preferred major is according to the Ecuadorian labor market. The midline outcome accounts for the treatment effect two months after the intervention; meanwhile, the endline outcome examines the impact four months after watching the treatment videos. The table reports results for simulations after 50, 150, 200, and 300 iterations. It assesses the results for the subsample of low, mid-low-, and mid-high-income students. The ATE reports the results of the Intention-to-Treat effect from a simulation. The closer the results are to the ITT, the better the simulation. The BLP indicates whether the subsample exhibits heterogeneous effects. If that is the case, the coefficient should be statistically different from zero. The simulation uses the following algorithms, K-nearest neighbor (KKNN), Support Vector Machine (SVM), Random Forest (RF), Boosted Trees (BT), and LASSO (L). The table reports the median confidence bounds in brackets and median p-values.

Table 12: Results of the Interaction Analysis on Academic Aspirations

	Midline Aspiration Index			Endline Aspiration Index		
	Low income	Mid-low income	Mid-High Income	Low income	Mid-low income	Mid-High Income
	Pre-registered variables					
Placebo mean	2.7	3.01	3.1	2.69	3.05	3.1
Treatment (T.RM)	0.63**	0.55**	-0.26	-1.05***	-0.46**	0.85***
	(0.32)	(0.27)	(0.28)	(0.24)	(0.18)	(0.22)
	[0.01, 1.25]	[0.02, 1.08]	[-0.80, 0.29]	[-1.53, -0.57]	[-0.80, -0.11]	[0.41, 1.29]
	(0.05)	(0.04)	(0.36)	(0.00)	(0.01)	(0.00)
T.RM* Grit high level - Grit-S	-0.11	0.09	-0.41**	0.20	0.06	-0.07
	(0.20)	(0.16)	(0.18)	(0.15)	(0.13)	(0.12)
	[-0.51, 0.29]	[-0.22, 0.40]	[-0.76, -0.06]	[-0.09, 0.49]	[-0.20, 0.31]	[-0.30, 0.17]
	(0.58)	(0.58)	(0.02)	(0.17)	(0.66)	(0.57)
T.RM* Grit high level - game	0.07	-0.02	0.25	0.18	-0.12	0.02
	(0.24)	(0.19)	(0.19)	(0.19)	(0.16)	(0.15)
	[-0.40, 0.54]	[-0.41, 0.36]	[-0.13, 0.63]	[-0.19, 0.56]	[-0.44, 0.20]	[-0.27, 0.30]
	(0.77)	(0.90)	(0.20)	(0.33)	(0.46)	(0.91)
T.RM* Highly educated father	0.37	0.16	-0.01	0.36	0.12	-0.07
	(0.36)	(0.28)	(0.22)	(0.29)	(0.22)	(0.18)
	[-0.34, 1.08]	[-0.40, 0.71]	[-0.44, 0.43]	[-0.21, 0.92]	[-0.31, 0.56]	[-0.42, 0.27]
	(0.31)	(0.58)	(0.97)	(0.21)	(0.58)	(0.68)
T.RM* Highly educated mother	0.22	-0.25	0.01	-0.09	-0.12	-0.19
	(0.41)	(0.28)	(0.22)	(0.26)	(0.23)	(0.16)
	[-0.59, 1.02]	[-0.79, 0.30]	[-0.42, 0.45]	[-0.60, 0.43]	[-0.57, 0.32]	[-0.51, 0.13]
	(0.60)	(0.38)	(0.95)	(0.74)	(0.58)	(0.24)
T.RM* Highly educated siblings	-0.31	0.14	-0.17	-0.30	0.17	-0.08
	(0.28)	(0.24)	(0.18)	(0.24)	(0.17)	(0.14)
	[-0.87, 0.25]	[-0.32, 0.61]	[-0.53, 0.19]	[-0.77, 0.16]	[-0.17, 0.50]	[-0.36, 0.20]
	(0.28)	(0.55)	(0.35)	(0.20)	(0.33)	(0.58)
T.RM* High cognitive ability	-0.28	0.15	0.29*	-0.19	0.16	0.17
	(0.18)	(0.16)	(0.17)	(0.14)	(0.13)	(0.12)

	[-0.65, 0.08]	[-0.17, 0.48]	[-0.04, 0.62]	[-0.46, 0.08]	[-0.09, 0.42]	[-0.07, 0.41]
	(0.12)	(0.35)	(0.08)	(0.16)	(0.20)	(0.16)
T.RM* High risk preference	-0.17	0.15	0.15	-0.02	0.02	0.13
	(0.17)	(0.16)	(0.16)	(0.14)	(0.13)	(0.12)
	[-0.50, 0.16]	[-0.17, 0.47]	[-0.16, 0.46]	[-0.29, 0.25]	[-0.23, 0.27]	[-0.11, 0.37]
	(0.31)	(0.35)	(0.34)	(0.89)	(0.87)	(0.28)
T.RM* Female	-0.03	0.06	-0.01	0.01	-0.01	0.01
	(0.18)	(0.16)	(0.16)	(0.14)	(0.13)	(0.12)
	[-0.39, 0.33]	[-0.25, 0.37]	[-0.33, 0.31]	[-0.26, 0.28]	[-0.26, 0.24]	[-0.24, 0.25]
	(0.86)	(0.72)	(0.96)	(0.94)	(0.96)	(0.97)
T.RM* Ethnic minority	-0.44*	0.21	-0.51**	-0.31**	0.07	0.06
	(0.24)	(0.21)	(0.24)	(0.15)	(0.18)	(0.18)
	[-0.90, 0.03]	[-0.21, 0.62]	[-0.98, -0.04]	[-0.61, -0.02]	[-0.29, 0.43]	[-0.29, 0.40]
	(0.07)	(0.33)	(0.03)	(0.04)	(0.72)	(0.75)
T.RM* High self-efficacy	-0.11	-0.02	0.04	0.03	0.02	-0.17
	(0.17)	(0.15)	(0.16)	(0.13)	(0.13)	(0.12)
	[-0.44, 0.22]	[-0.31, 0.27]	[-0.28, 0.36]	[-0.23, 0.28]	[-0.22, 0.27]	[-0.40, 0.06]
	(0.50)	(0.90)	(0.79)	(0.84)	(0.85)	(0.15)
Non-Pre-registered variables						
T.RM* High expected grade	0.17	-0.03	0.09	-0.05	0.12	-0.02
	(0.17)	(0.15)	(0.18)	(0.13)	(0.12)	(0.12)
	[-0.16, 0.50]	[-0.32, 0.26]	[-0.27, 0.45]	[-0.30, 0.20]	[-0.12, 0.36]	[-0.27, 0.22]
	(0.32)	(0.85)	(0.61)	(0.71)	(0.33)	(0.85)
T.RM* High test scores	-0.12	-0.08	0.27	0.06	-0.02	0.13
	(0.19)	(0.18)	(0.17)	(0.13)	(0.12)	(0.12)
	[-0.49, 0.25]	[-0.42, 0.26]	[-0.07, 0.61]	[-0.20, 0.31]	[-0.27, 0.22]	[-0.11, 0.38]
	(0.53)	(0.65)	(0.12)	(0.67)	(0.85)	(0.28)
T.RM* High growth mentality	-0.25	0.27*	0.34*	-0.24*	-0.02	0.12
	(0.19)	(0.16)	(0.17)	(0.14)	(0.14)	(0.12)
	[-0.62, 0.12]	[-0.05, 0.59]	[0.00, 0.67]	[-0.50, 0.03]	[-0.29, 0.24]	[-0.12, 0.36]
	(0.19)	(0.09)	(0.05)	(0.08)	(0.87)	(0.31)

Num.Obs.	1573	1653	1665	2972	3221	3145
R2 Adj.	0.284	0.363	0.349	0.269	0.282	0.336
N. clusters	252	259	260	512	530	530
Joint orthogonality F-test(p-value)*	1.2(0.28)	0.75(0.72)	1.65(0.07)	0.95(0.5)	0.47(0.94)	0.89(0.57)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports an Interaction Analysis testing heterogeneous treatment effects from a pre-registered set of covariates. It computes the impact from a fully specified model that introduces all covariates and interacts with the treatment variable (T.RM). The outcome variable is academic aspirations. It measures how rewarding the students' preferred major is according to the Ecuadorian labor market. The midline outcome accounts for the treatment effect two montha after the intervention; meanwhile, the endline outcome examines the impact four months after watching the treatment videos. I captured the effect of students' income levels. In this regard, each column accounts for a different position in the income distribution. Columns 1 and 4 report the effects on low-income students, columns 2 and 5 show the results for mid-low-income students, and columns 3 and 6 feature the impacts for mid-high-income students. Grit measures students' perseverance to reach long-term outcomes. I report Grit from two sources, the Grit-S scale and an incentivized task (game). A student exhibits high Grit when the score is above the average. High educated father, mother, or sibling indicates that parents or siblings have a university degree or a higher level of education. High cognitive ability refers to students who answer at least one question correctly from the Cognitive Reflection Task (CRT). High-risk preference refers to students who unveil more than 50 boxes from the Bomb Risk Elicitation Task (BRET). Female takes the value of one when the student is a girl. Ethnic minority refers to non-mestizo students. I identified them based on their spoken language. The variable is equal to 1 when the student speaks a native language. High test score indicates that the student exhibits an above-average self-efficacy level, while high expected grades account for students who expect above-average grades for Spanish, English, statistics, entrepreneurship, biology, physics, chemistry, and math. High test scores account for students whose results in a standardized test are above the average. High growth mentality accounts for students who exhibit a growth mindset. I report results from a fully saturated model that introduces control variables selected by the post-double lasso approach. Moreover, it introduces class-fixed effects. I report clustered standard errors in parenthesis, confidence interval in brackets, and p-values. Finally, the table reports results from a Test of Joint orthogonality to identify whether the group effects are significantly different from zero.

11.4. Appendix D: Preference for majors

Table 13: Preferences for academic majors for high and low-income students (in %)

	No college	Education	Arts and Humanities	Social Sciences	Business and Law	Life sciences and Math	Computer science (IT)	Engineering	Agriculture	Health	Services
	00	01	02	03	04	05	06	07	08	09	10
High-income	18.68%	2.01%	4.70%	4.82%	12.33%	4.55%	4.40%	17.05%	3.33%	22.23%	5.92%
Low-income	38.95%	3.15%	2.73%	2.36%	8.46%	4.31%	3.86%	15.65%	2.34%	13.34%	4.85%

Note: The table reports students' preferences for academic majors at the baseline (pre-treatment). It shows the share of students planning to study each educational option, according to the International Standard Classification of Education (ISCED). Below each major one can see the related ISCED category. Since the estimation reports a meaningful gap between low and high-income students, I report data only for these two groups. One can see how choices varies by income level. The data come from an open question asking students to declare their preferred academic major to study in college education.

Table 14: Preferences for academic majors by income level and treatment allocation at the Midline (in %)

	No college	Education	Arts and Humanities	Social Sciences	Business and Law	Life sciences and Math	Computer science (IT)	Engineering	Agriculture	Health	Services
	00	01	02	03	04	05	06	07	08	09	10
Panel 1: Low-Income students											
Placebo	26.53%	1.93%	4.62%	4.48%	10.89%	3.58%	3.86%	13.65%	2.89%	20.33%	7.24%
Treatment	28.47%	1.51%	3.29%	4.11%	9.72%	3.22%	2.60%	16.77%	2.94%	21.15%	6.23%
Panel 2: Mid-low-income students											
Placebo	43.71%	2.81%	2.34%	2.88%	9.64%	3.48%	2.88%	12.52%	1.74%	11.71%	6.29%
Treatment	42.35%	2.81%	2.23%	2.23%	8.99%	2.93%	3.25%	14.22%	2.61%	13.90%	4.46%
Panel 3: Mid-high-income students											
Placebo	33.27%	2.64%	3.04%	3.37%	8.84%	2.84%	3.89%	13.66%	2.57%	19.47%	6.40%
Treatment	31.26%	2.38%	3.36%	3.72%	8.06%	2.26%	4.09%	18.19%	3.48%	17.34%	5.86%
Panel 4: High-income students											
Placebo	34.42%	2.82%	2.24%	3.21%	10.90%	2.88%	3.53%	15.06%	2.31%	17.18%	5.45%
Treatment	35.03%	3.15%	3.09%	3.99%	8.23%	3.21%	3.99%	14.40%	2.18%	15.61%	7.14%

Note: The table reports students' preferences for academic majors at the midline (about two months after watching the videos). It shows the share of students by treatment allocation planning to study each educational option, according to the International Standard Classification of Education (ISCED). Below each major one can see the related ISCED category. Each panel exhibit students' preferences by income level. The data come from an open question asking students to declare their preferred academic major to study in college education.

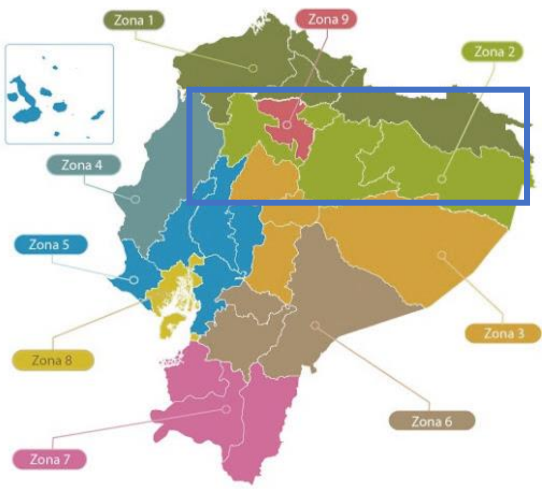
Table 15: Preferences for academic majors by income level and treatment allocation at the Endline (in %)

	No college	Education	Arts and Humanities	Social Sciences	Business and Law	Life sciences and Math	Computer science (IT)	Engineering	Agriculture	Health	Services
	00	01	02	03	04	05	06	07	08	09	10
Panel 1: Low-Income students											
Placebo	30.23%	1.92%	3.63%	4.99%	10.81%	3.63%	2.80%	12.79%	3.01%	19.29%	6.91%
Treatment	32.03%	1.59%	3.65%	4.97%	9.02%	2.85%	2.32%	15.12%	3.12%	20.23%	5.11%
Panel 2: Mid-low-income students											
Placebo	45.06%	3.17%	2.19%	2.19%	8.60%	2.40%	2.89%	10.93%	2.47%	13.40%	6.70%
Treatment	44.96%	2.12%	2.63%	2.05%	8.47%	3.40%	2.95%	13.66%	2.31%	13.09%	4.36%
Panel 3: Mid-high-income students											
Placebo	34.40%	2.93%	2.79%	3.86%	9.98%	2.99%	3.53%	12.44%	2.86%	19.69%	4.52%
Treatment	33.01%	2.31%	3.29%	4.38%	7.98%	3.05%	3.17%	15.96%	3.05%	17.97%	5.85%
Panel 4: High-income students											
Placebo	35.54%	2.57%	2.38%	3.21%	10.73%	2.76%	3.73%	14.27%	2.51%	17.61%	4.69%
Treatment	37.13%	2.28%	2.82%	3.48%	7.50%	3.54%	3.48%	14.70%	2.58%	15.96%	6.54%

Note: The table reports students' preferences for academic majors at the endline (about four months after watching the videos). It shows the share of students by treatment allocation planning to study each educational option, according to the International Standard Classification of Education (ISCED). Below each major one can see the related ISCED category. Each panel exhibit students' preferences by income level. The data come from an open question asking students to declare their preferred academic major to study in college education.

11.5. Appendix E: Intervention Design

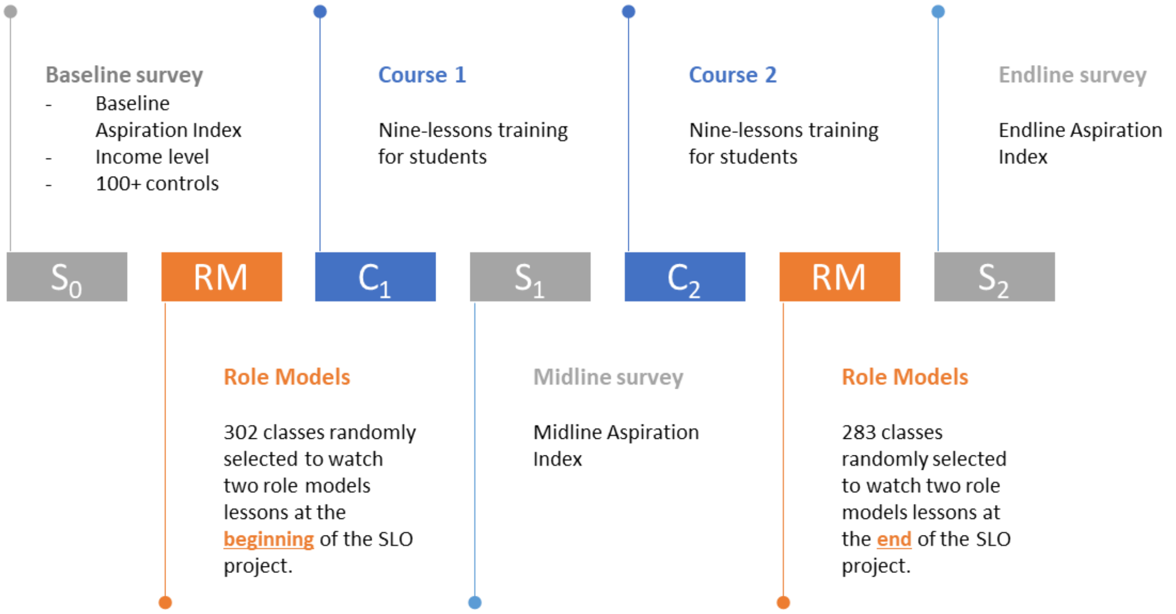
Figure 4: Experimental location – Zone 2 and Quito



Source: Panamerican Health Organization, 2017

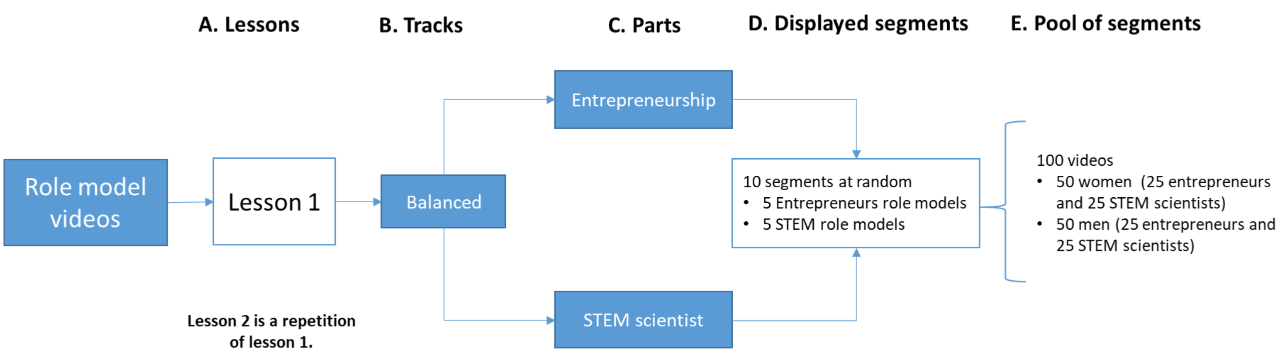
Note: The SLO project runs the study within the blue square, Zone 2 (light green), and Quito (pink).

Figure 5: Structure of the video-based component featuring role models within the SLO project.



Note: Students watched the experimental videos at the project's beginning (RM1) or end (RM2). This paper focuses on the cohort that watched the videos at the beginning of the SLO project (RM_1). C_1 and C_2 account for another component of the SLO project, training. The assessment of this training goes beyond the scope of this article.

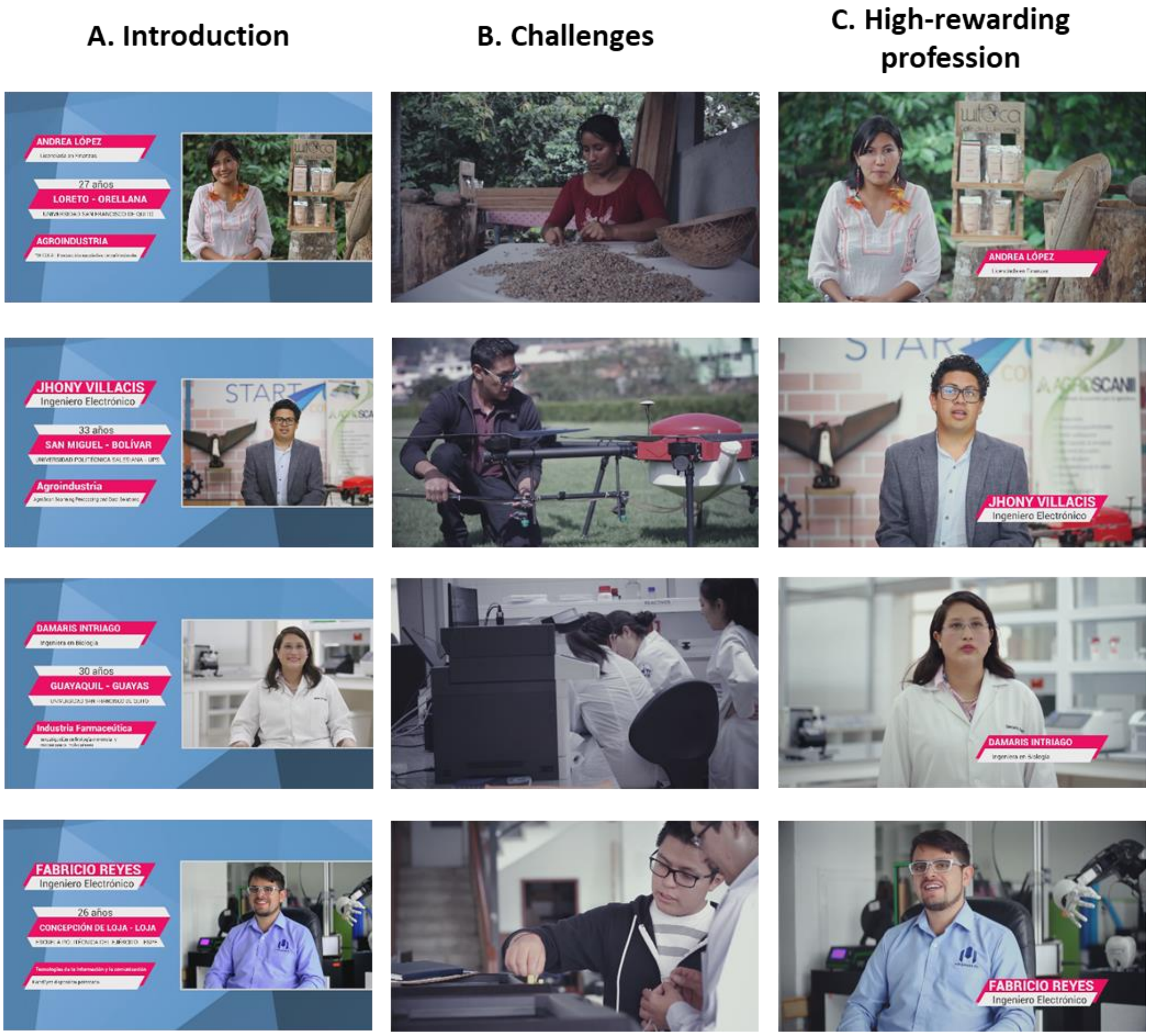
Figure 6: Experimental design of the intervention



Note: The lesson features two additional variations, i) pairing students and role models by sex and ii) increasing the share of entrepreneurs (STEM scientists). Assessing these variations exceeds the scope of the current paper.

Figure 7: Meeting the role models

Figure 8: Illustration of the messages to motivate students' aspirations



Note: Students watch an introduction screen at the beginning of each segment, emphasizing the role models' characteristics. The screen puts particular emphasis on the level of education (at least a university degree), the educational program, and the work activity. The video highlights the educational program during the interview (see Column C). Second, the narration highlights how important effort and teamwork are to succeed. Finally, the SLO project mainly selects individuals from high-rewarding fields. Thus, students could update their beliefs about the skills needed to navigate these options. Furthermore, all emphasize how critical it is to continue education to reach their current position.