Pre-Analysis Plan
Tackling Biased Beliefs to Foster Women's Entry into Economics: Experimental Evidence from Mexico

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This version: October 20, 2025
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Abstract

This pre-analysis plan describes the design and analysis strategy for a cluster-randomized controlled trial evaluating an *in-person female role-model* intervention aimed at increasing women's participation in *economics* in Mexico. The study leverages high schools affiliated with the Universidad Autónoma de Nuevo León (UANL) and the Tecnológico de Monterrey. Schools are randomly assigned to a treatment or a control group. The *primary outcome* is whether female students apply to an economics program during the 2026 admissions cycle (administrative data). *Secondary outcomes*, collected through surveys and school-based lab sessions, include beliefs about economics, confidence in quantitative skills, interest in economics, identity alignment, and academic performance. Guided by a motivated-beliefs framework adapted from Bénabou and Tirole (2002, 2016), the study examines how exposure to relatable female economists reshapes students' beliefs, self-efficacy, and aspirations. The PAP pre-specifies research questions, hypotheses, estimation strategies (including difference-in-differences with cluster-robust inference), heterogeneity analyses, and robustness checks to ensure transparency and credibility.

Keywords: Gender gaps; role models; motivated beliefs; economics education; randomized controlled trial; Mexico.

JEL Classification: C93, I23, J16, D90.

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1 Introduction and Motivation

Economics remains a predominantly male-dominated field, with men significantly more likely to pursue it as a course of study. Across most countries, women continue to represent a minority among economics students and faculty, and this underrepresentation extends to research output and academic leadership positions. The situation in Mexico mirrors these global patterns. Recent national evidence shows that women's participation in economics programs and research has remained virtually unchanged over the past decade, with persistent gaps across educational and professional stages (Arceo-Gómez, 2025). While women have made notable inroads in other social sciences and even in several STEM fields, progress within economics has stalled, suggesting that the discipline continues to reproduce structural and perceptual barriers that constrain female participation. This persistent gender gap underscores a broader global challenge and highlights the need for targeted initiatives to make economics more inclusive and appealing to women—a challenge that is particularly acute in Latin America, where traditional gender norms and *machismo* continue to limit women's opportunities to thrive in the field.

Several factors contribute to why women are less likely to view economics as a viable field of study (Avilova and Goldin, 2024). Structural barriers, such as limited exposure to economics in high school, certainly play a role. However, growing evidence points to a significant influence from misperceptions: many women hold inaccurate beliefs about the nature of economics and often underestimate their quantitative skills. On one hand, economics is typically associated with macroeconomic issues emphasized by the media, such as inflation and exchange rates, providing a narrow view of a discipline that also studies pressing socioeconomic problems like poverty, inequality, health, and education—topics that often align with women's interests. On the other hand, some women believe they lack the mathematical ability required to succeed in the field, yet there is no quantitative evidence supporting this perception. In fact, women are more frequently enrolled in STEM programs than in economics, which clearly contradicts this belief (Barrera et al., 2024). These misconceptions discourage women from considering economics, even when they have the potential to excel in it.

This lack of diversity is concerning, as it limits the range of perspectives within the field and reduces the inclusiveness of economic policies. Economists shape policies on crucial issues

like labor markets, education, and inequality—areas that affect diverse groups in unique ways. Greater female representation in economics can enrich the discipline with valuable insights into challenges disproportionately faced by women, such as wage gaps and barriers to labor force participation, ultimately fostering more equitable policy solutions. Furthermore, attracting women to economics supports broader social progress by establishing female role models, reducing gender biases, and enhancing the profession's relevance across diverse populations. Yet, as Arceo-Gómez (2025) emphasizes, progress in Mexico has been stagnant even as access to higher education has expanded, pointing to the persistence of cultural and institutional barriers that cannot be addressed by enrollment growth alone.

To confront this challenge, we propose an intervention aimed at correcting misperceptions about economics, focusing on reshaping beliefs about the field and improving students' self-assessment of their quantitative abilities. Specifically, we propose an **in-person role-model intervention** for high-school students in Nuevo León, Mexico, leveraging a network of schools affiliated with two of the state's leading universities: the Tecnológico de Monterrey and the Universidad Autónoma de Nuevo León. Building on previous efforts (Porter and Serra, 2020; Carpio and Guadalupe, 2022; Breda et al., 2023), the intervention will consist of trained female economists visiting high schools to share their experiences, provide accurate information about the field of economics, discuss career opportunities, and challenge common stereotypes about economists and gender biases in quantitative disciplines. By exposing students to relatable female role models and factual information, this program seeks to correct misperceptions about women's quantitative abilities and the relevance of economics to solving real-world social problems. The ultimate goal is to modify high school students' beliefs about women's capacity to succeed in economics and to promote economics as a viable and attractive career choice for young women in Mexico.

This research is particularly timely given the increasing recognition of economics' role in addressing global challenges and the need for diverse perspectives within the field. Moreover, the study targets a crucial stage in the career decision-making process—the high school years—when interventions are likely to have the greatest impact on both perceptions and academic choices. By understanding how role models shape beliefs and aspirations, we can design more effective strategies to promote gender diversity in economics, ultimately contributing to a more inclusive discipline and to the development of equitable and informed economic policymaking.

2 Conceptual framework

This project adopts the lens of *motivated beliefs* as a unifying theoretical framework to understand gender disparities in economics. Recent work in behavioral economics and psychology demonstrates that individuals' beliefs are not passive reflections of information, but active constructions shaped by psychological, social, and identity-related motivations (Bénabou and Tirole, 2016; Golman et al., 2016; Kunda, 1990; Lockwood and Kunda, 1997). Beliefs serve instrumental purposes beyond accuracy—they help individuals preserve self-esteem, manage emotions, and maintain coherence between their self-concept and their social environment. When beliefs perform these functions, they become resistant to contradictory evidence, leading to persistent biases and underinvestment in potentially rewarding domains.

In the context of educational and career choices, motivated beliefs can explain why gender gaps persist in economics despite objective equality in ability. Economics is often perceived as abstract, competitive, and detached from social relevance—stereotypes that may conflict with women's identity-based motivations or their perceptions of belonging. Consequently, many female students underestimate their quantitative abilities, doubt their fit in economics, or anticipate social disapproval, even when their objective performance is comparable to that of male peers. These misperceptions emerge not from lack of information, but from the psychological incentives to maintain beliefs that protect one's identity, minimize perceived risk, and align with prevailing norms.

Within this unified framework, constructs such as confidence, aspirations, and social norms can all be understood as distinct manifestations of belief formation and maintenance. **Confidence** reflects beliefs about one's own competence and expected performance in analytical domains. **Aspirations** represent beliefs about what outcomes are attainable and worth pursuing, constrained by one's perception of personal efficacy and social comparison. **Social norms** capture beliefs about others' behavior and expectations—what peers or family members value, approve, or model as feasible. Even **identity congruence**—the sense that studying economics aligns with one's self-concept—is a belief about the compatibility between personal and disciplinary identities. Each of these belief domains can be distorted, self-reinforcing, and sensitive to identity threats or stereotype exposure.

Motivated reasoning processes sustain these belief distortions. **Confirmation bias** leads individuals to seek or interpret evidence in ways that validate prior views about ability or belonging.

Identity protection drives selective avoidance of threatening information—for instance, discounting positive counter-stereotypical examples that might challenge one's self-perception. **Social conformity** further reinforces biased beliefs by signaling what behaviors or aspirations are socially acceptable. Together, these mechanisms produce stable, interdependent belief systems that can maintain inequality even in the absence of overt discrimination.

From this perspective, role-model interventions can be interpreted as belief-updating treatments that relax psychological constraints on information processing. Exposure to relatable and successful female economists introduces credible, identity-congruent information that challenges stereotypes and weakens the motivational costs of belief revision. By making the connection between economics and prosocial objectives salient, the intervention also redefines the perceived purpose and identity of the discipline, aligning it more closely with students' values. These processes can shift beliefs across multiple dimensions—improving confidence in quantitative ability, expanding aspirations, altering perceptions of social approval, and fostering a sense of belonging.

In sum, the conceptual framework treats confidence, aspirations, identity congruence, and social norms as interrelated dimensions of motivated belief systems. Gender disparities in economics are thus understood as arising from systematically biased beliefs about self and field, maintained through motivated reasoning and social signaling. Interventions that provide identity-consistent information and credible social proof—such as exposure to female role models—can shift these beliefs, altering both perceptions and aspirations. This unified framework integrates cognitive, motivational, and social processes under the broader concept of motivated beliefs, offering a coherent theoretical foundation for understanding and measuring the behavioral effects of the proposed intervention.

To formalize these behavioral mechanisms, the next section presents a stylized decision-theoretic model, adapted from Bénabou and Tirole (2002, 2016), illustrating how exposure to a relatable female role model can modify beliefs, identity alignment, and application choices in economics.

3 A simple model of motivated beliefs and role-model exposure

We develop a simple framework, adapted from Bénabou and Tirole (2002, 2016), to formalize how exposure to a female role model can shift students' beliefs, identity alignment, and application decisions. The model is intentionally stylized and maps directly into our measured mechanisms

(confidence, perceived fit, aspirations, and application behavior).

Consider a student i deciding whether to pursue economics as an academic path (e.g., apply to an economics program). Let $d_i \in \{0, 1\}$ denote this decision, where $d_i = 1$ corresponds to applying. The student has an underlying quantitative or analytical ability a_i, which determines her likelihood of succeeding in economics if she applies. She does not observe a_i perfectly ex ante. Instead, she holds a (possibly biased) belief b_i about her own ability and fit in economics. Following Bénabou and Tirole (2002), beliefs are *motivated*: they are chosen and updated not only to forecast performance, but also because they support self-image, identity, and persistence.

If the student applies ($d_i = 1$), her expected utility is given by

$$U_i(d_i = 1) = p(b_i) \cdot S(a_i) - C + \gamma\, b_i. \tag{1}$$

In this formulation, $p(b_i)$ represents the student's perceived probability of success in economics, which increases with her belief b_i about her own quantitative and analytical ability and her perceived fit within the field. The term $S(a_i)$ denotes the payoff from succeeding in economics—such as access to desirable career paths, expected financial returns, or the social value of contributing to public policy—and it is increasing in the student's true ability a_i. The parameter C captures the total (psychological, financial, or social) cost of applying, encompassing factors such as fear of failure, stereotype threat, or anticipated disapproval. Finally, γb_i reflects the direct motivational or identity-related utility derived from holding a positive belief about oneself in economics; a higher b_i yields ego utility and reduces perceived identity threat, consistent with the framework of Bénabou and Tirole (2016).

If the student does not apply ($d_i = 0$), we normalize utility to

$$U_i(d_i = 0) = 0. \tag{2}$$

The student will choose $d_i = 1$ if and only if

$$p(b_i) \cdot S(a_i) - C + \gamma\, b_i > 0. \tag{3}$$

Equation (3) highlights three distinct psychological channels through which our intervention

may operate:

(i) Belief updating about ability and fit. Before the intervention, the student observes noisy personal signals (grades, teacher feedback, stereotypes) and holds an initial belief b_i. After the role-model visit, she observes a new signal σ_i constructed from the talk: a successful female economist with similar background describes her trajectory, discusses what economists actually do, and frames economics as socially meaningful rather than narrowly financial. This signal is both informational and identity-relevant.

We denote the updated belief by

$$b_i' = f(b_i, \sigma_i), \tag{4}$$

where $f(\cdot)$ is an updating rule. In a purely Bayesian model, σ_i would be treated as an additional unbiased signal about a_i or about the mapping from effort to success in economics. In a motivated-beliefs model (Bénabou and Tirole, 2002), the student may *overweight* signals that preserve or enhance identity ("people like me can succeed here") and *underweight* signals that are identity-threatening. Because the role model is demographically and experientially proximate, σ_i is psychologically "cheap" to accept. As a result, $b_i' \geq b_i$ for many female students.

(ii) Perceived relevance and value of economics. The session emphasizes that economics is not only about money and finance, but also about inequality, education, health, labor markets, and social policy. Let $S(a_i)$ capture the perceived payoff from success in economics. If the student believes economics produces meaningful social impact, then the value of succeeding in economics, $S(a_i)$, rises. This increases the expected return $p(b_i') \cdot S(a_i)$ in (1).

(iii) Identity costs and perceived barriers. The term C reflects both practical and psychological costs, including stereotype threat ("people like me don't belong here"), anticipated discrimination, and fear of social disapproval. Exposure to a credible female economist can (a) demonstrate that women do succeed in economics, and (b) legitimize economics as an acceptable and respected path for women. Both reduce the identity cost component of C. In addition, the intervention may increase perceived social support (family encouragement, peer acceptance), which further lowers C.

Implication for application behavior. Combining (i)–(iii), after exposure to the role model the decision rule becomes

$$p(b_i') \cdot S(a_i)' - C' + \gamma\, b_i' > 0, \tag{5}$$

where $b_i' \geq b_i$, $S(a_i)' \geq S(a_i)$ (economics seen as more valuable and socially meaningful), and $C' \leq C$ (lower perceived exclusion cost and stigma). Each of these inequalities pushes in the direction of $d_i = 1$ being optimal for more female students.

This generates three empirically testable predictions that are directly aligned with our pre-specified outcomes:

1. **Belief and identity shift (short run):** Immediately after the session, treated students should report higher perceived fit with economics, higher confidence in their quantitative skills, and lower stereotype-based barriers.

2. **Persistence (medium run):** Eight to ten weeks later, these shifts should persist partially: treated students should retain improved beliefs about economics, recall the role model, and still express higher aspirations to study economics.

3. **Behavioral decision (primary outcome):** At the application stage, treated female students should be more likely to apply to economics programs.

Heterogeneity and motivated beliefs. A key feature of motivated-belief models is that students with lower initial beliefs b_i (e.g., lower self-confidence or stronger stereotype exposure) may update more, because the psychological value of the new identity-consistent signal is highest for them. This implies larger treatment effects for female students, students with initially low reported confidence in math and economics, students facing stronger ex ante identity threat or higher perceived barriers.

In summary, the role-model session operates not only as an information treatment but as an identity-compatible signal that increases self-belief, elevates the perceived social value of economics, and lowers the psychological cost of pursuing it. Within this framework, observed changes in aspirations, self-efficacy, and perceived fit are not ancillary; they are core mechanisms through which the intervention increases the probability that female students apply to study economics.

This simple model directly motivates the main and mechanism hypotheses presented in Section 5,

linking belief updating, identity alignment, and stereotype reduction to observable changes in confidence, aspirations, and application decisions.

4 Research Questions

Persistent gender disparities in economics education suggest that informational and psychological factors—rather than ability alone—shape students' educational choices. Despite substantial progress in other quantitative disciplines such as mathematics and engineering, economics continues to attract disproportionately fewer women. This project examines whether exposure to relatable female role models can alter beliefs, aspirations, and identity alignment in ways that increase female students' interest in studying economics.

The intervention targets multiple *belief domains*—including self-confidence, identity congruence, social norms, and aspirations—through a unified process of belief updating. Specifically, we ask whether providing identity-consistent information about economists can shift students' beliefs about their own abilities, the nature of economics as a discipline, and the social acceptability of pursuing economics, ultimately influencing their academic choices.

4.1 Pre-specified research questions

(1) Main question. *How effective are female role-model interventions in increasing female students' applications to economics programs in Mexico?*

This is the central question of the study. It tests whether brief, in-person interactions with female economists can increase students' interest in studying economics, affect their stated intentions to apply to economics programs, and ultimately raise the proportion of women who view economics as an accessible and socially valuable career.

(2) Mechanism questions. We test three pre-specified mechanisms consistent with our theoretical framework:

(a) **Belief updating:** Does exposure to female economists change students' understanding of economics and its social relevance?

(b) **Identity and self-efficacy:** Does it strengthen students' confidence and perceived fit between their identity and a career in economics?

(c) **Stereotype reduction and aspirations:** Does it weaken gender stereotypes and raise female students' aspirations to pursue economics?

These questions correspond to pre-specified outcome domains and are tested using the inverse-covariance-weighted (ICW) indices described in Section 10.

(3) Heterogeneity questions. We also pre-register tests of heterogeneous effects along theoretically motivated dimensions:

(a) Gender: Are effects larger for female students than for male peers?

(b) Baseline interest: Do students initially less interested in economics respond more strongly?

(c) Socioeconomic background: Are impacts stronger in schools with lower average parental education or income levels?

4.2 Exploratory questions

In addition to these confirmatory analyses, the study will explore secondary questions that are not part of the pre-specified hypothesis testing but are of potential theoretical and policy relevance:

(a) Do short-term changes in beliefs and identity alignment persist after two months?

(b) Are there cross-gender spillovers within classrooms, such that male students also update beliefs about women's quantitative abilities?

(c) Do changes in beliefs translate into greater interest in other quantitative or policy-related fields beyond economics?

Exploratory results will be clearly distinguished from confirmatory analyses in reporting and interpretation.

5 Hypotheses

Building on the behavioral and motivational mechanisms discussed above, this study examines the effectiveness of an in-person role-model intervention in addressing gender disparities in economics. The intervention operates through two primary channels: (i) correcting misperceptions about the field of economics and its societal relevance, and (ii) reshaping students' self-assessment of their quantitative abilities through exposure to relatable female role models. By targeting these belief-based mechanisms, we expect meaningful changes in both perceptions and behavioral intentions.

Main hypothesis. The in-person role-model intervention will **increase the likelihood that female students apply to economics programs** at the university level relative to students in control schools.

Mechanism hypotheses.

1. **Belief updating:** Exposure to female economists and students will lead to more accurate and inclusive beliefs about what economics involves and who can succeed in it.
2. **Self-beliefs:** Treated female students will report higher confidence in their analytical and quantitative abilities, reflecting updated beliefs about their own competence.
3. **Identity congruence:** Treated students will express stronger beliefs that studying economics aligns with their personal identity and social values.
4. **Normative beliefs and aspirations:** Students will revise beliefs about social approval and feasibility of pursuing economics, expanding their perceived opportunity set and career aspirations.

All mechanisms are interpreted as distinct but interrelated forms of belief change within the broader framework of motivated beliefs.

Heterogeneity hypotheses.

1. **Academic ability:** Effects will be stronger among high-achieving female students in mathematics and related subjects, consistent with the idea that confidence rather than competence constrains aspirations (Breda et al., 2023).

2. **Baseline stereotypes:** Classrooms with stronger initial gender stereotypes or lower female representation in quantitative tracks will experience larger treatment effects.

3. **Socioeconomic context:** Impacts will be larger in public schools and among lower-income students, where informational barriers and gender norms are more pervasive.

4. **Peer gender composition:** Female students in classrooms with higher proportions of male peers may experience stronger identity threat mitigation when exposed to successful female role models.

Exploratory hypothesis. Because male students also participate in the sessions, the intervention may generate indirect attitudinal effects among them. We hypothesize that:

- Male students exposed to female role models will report more egalitarian views about women's competence in economics and quantitative field.

These changes in male students' beliefs may further reinforce female students' aspirations through peer-norm feedback within classrooms. However, capturing such effects is difficult in practice without specialized survey instruments; therefore, we do not pursue this potential channel in our design.

Taken together, these hypotheses emphasize that belief updating and identity alignment are mutually reinforcing mechanisms through which exposure to female role models can reshape aspirations and reduce gender disparities in economics education.

6 Institutional Background and Setting

6.1 Institutional Background

Education in Mexico is structured across three broad stages: **basic education**, **upper-secondary (middle) education**, and **higher education**. This structure reflects the organization established by the *Secretaría de Educación Pública* (SEP) and has undergone important reforms aimed at expanding access, improving quality, and reducing inequality.

Basic education. Basic education spans twelve years and is compulsory for all children. It includes three years of pre-school (ages 3–5), six years of primary school (grades 1–6, ages 6–12),

and three years of secondary school (grades 7–9, ages 12–15). At this stage, all students follow a common national curriculum with mandatory courses in mathematics, natural sciences, Spanish language and literature, and social studies, along with civics and ethics education. By the end of secondary school, students are expected to acquire the foundational competencies needed to pursue upper-secondary studies.

Upper-secondary (middle) education. Following completion of basic education, students enroll in **upper-secondary education** (*educación media superior*), also known as *bachillerato* or *preparatoria*, which typically lasts three years (grades 10–12, ages 15–18). Since the 2012 constitutional reform, this stage has been mandatory nationwide. Upper-secondary education serves as a bridge between general schooling and higher education and is organized into three main tracks that differ in academic orientation and university access:

- **General baccalaureate** (*bachillerato general*): an academically oriented track that prepares students for university studies across disciplines, including economics and other social sciences.
- **Technological baccalaureate** (*bachillerato tecnológico*): combines academic and vocational components, providing pathways to higher education while offering applied training in technical fields.
- **Professional technical programs** (*profesional técnico*): offered mainly through the National College of Technical Professional Education (CONALEP), these programs are oriented toward immediate labor-market entry and provide limited access to university programs.

Within many large institutions, such as the UNAM or the *Instituto Politécnico Nacional* (IPN), students in the final years of upper-secondary education must also select an **area of specialization** (*área de conocimiento*)—typically physical-mathematical sciences, chemical-biological sciences, social sciences, or humanities. This specialization strongly determines access to specific university fields: for example, entry into STEM or economics programs generally requires completion of a general or technological baccalaureate with emphasis on the exact sciences.

This institutional structure plays a crucial role in shaping students' perceptions and academic aspirations. The specialization and track choices made during upper-secondary education—often

between ages 15 and 17—largely determine exposure to economics and other quantitative disciplines. Moreover, gender differences in track selection and self-assessed quantitative competence tend to emerge at this stage, making it a critical window for interventions that aim to correct misperceptions, provide female role models, and encourage greater participation of women in economics and related fields.

To facilitate understanding of the institutional context in which the study is implemented, Figure A1 in the Appendix provides a schematic overview of the Mexican educational system. It summarizes the main stages from pre-school to higher education and highlights where our target population—students enrolled in the final years of *preparatoria*—fits within this broader structure.

6.2 Female under-representation in economics in Mexico

The under-representation of women in economics is a well-documented phenomenon across the world, and Latin America is no exception. According to the first regional survey by the Women Economists in Latin America and the Caribbean (WELAC) network, which collected information from 84 institutions in ten countries, women accounted on average for 42% of economics graduates, 38.6% of master's graduates, and only 33% of PhD graduates in 2019 (Women Economists in Latin America and the Caribbean (WELAC), 2022). These numbers mirror those observed in the United States, where women represent roughly one-third of economics majors. Yet, behind these regional averages lie substantial cross-country differences that help contextualize the Mexican case.

In Mexico, female representation in economics education remains below the regional mean. The WELAC survey finds that women made up 41% of undergraduate graduates and only 31% of master's graduates in 2019—figures that place Mexico closer to the lower end of the Latin American distribution, alongside Brazil (37% at the undergraduate level) and Peru (34%). By contrast, countries such as Uruguay (47%) and Argentina (45%) exhibit nearly gender-balanced undergraduate cohorts. Moreover, in the top five Mexican universities ranked by research output in RePEc, women accounted for just 31% of bachelor's and 28% of master's graduates, suggesting that gender disparities are more acute in the most prestigious programs. These results align with the national trends documented by Arceo-Gómez (2025), who reports a persistent plateau in female enrollment at roughly 38–42% over the past decade.

The academic profession reflects an even sharper gender imbalance. Across the region, WELAC

reports that women occupy 35% of assistant professorships, 33.5% of associate positions, and only 24% of full professorships. Mexico again falls close to these averages, with 28% of assistant, 32% of associate, and 29% of full professors being women. Compared to other countries, these figures are lower than those in Uruguay—where women represent 57% of assistant professors—and Argentina (41%), but higher than those in Chile and Brazil, where female full professors represent barely 6% and 13%, respectively (Women Economists in Latin America and the Caribbean (WELAC), 2022). Moreover, only one in three heads of economics departments in Mexico is a woman, consistent with the regional pattern where female leadership remains the exception rather than the rule.

The stagnation observed in these indicators is corroborated by administrative data from the National System of Researchers (SNII). As Arceo-Gómez (2025) documents, women represent 34% of economists recognized by SNII—below the 40% average across all scientific fields—and their share declines steadily with seniority: 41% among *Candidates*, 28% at Level I, 27% at Level II, and only 20% at Level III. This progression reveals a clear glass ceiling within the profession. In terms of research productivity, women constitute 21% of registered economists in RePEc, author about 23% of journal articles and 30% of book chapters, and are less likely to occupy editorial positions. They also tend to work in smaller coauthor networks and receive fewer citations on average, consistent with evidence from other regions (Bayer and Rouse, 2016; Lundberg and Stearns, 2019).

Beyond academia, gender disparities persist—and in some cases intensify—in the broader professional market for economists. Data from the Mexican government's *Data México* platform, based on the National Employment and Occupation Survey (ENOE), shows that women account for only 17% of the total workforce classified as *Economistas, consultores e investigadores en política económica*. In the second quarter of 2021, female economists earned on average 5,080 Mexican pesos per month, compared with 8,350 pesos for their male counterparts, implying a gender wage gap of nearly 40%. Women in this occupation also faced higher informality rates and were disproportionately concentrated in lower-paid sectors and smaller firms. These figures indicate that the disadvantages women face in academic economics extend into the professional labor market, where barriers to advancement, occupational segregation, and pay inequities remain entrenched (Secretaría de Economía, Gobierno de México, 2021).

Taken together, these findings show that Mexico reproduces the broader Latin American pattern: modest female participation at entry, a decline across academic ranks, and a marked concentration

of women in less visible or less rewarded roles. Although some neighboring countries—such as Uruguay, Argentina, and Venezuela—display higher representation at early career stages, none has achieved parity at the top. Beyond academia, the labor market outcomes of female economists reveal similar or even wider gaps, with women earning substantially less than men and facing higher rates of informality and occupational segregation. These patterns suggest that gender disparities in economics are not confined to the educational pipeline but extend throughout the professional trajectory, reflecting structural barriers that constrain women's career progression, recognition, and economic rewards. Addressing these inequalities requires coordinated efforts across universities, research institutions, and labor market policies to ensure that women's participation in economics translates into equitable opportunities, influence, and outcomes across all stages of their professional lives.

6.3 Setting

Nuevo León, Mexico, provides an ideal setting to examine research questions about gender disparities in economics education. As one of the most economically dynamic states in the country and a major hub for higher education, Nuevo León offers unique advantages for studying beliefs and career choices related to economics. The state's educational landscape is anchored by two prestigious institutions: the *Universidad Autónoma de Nuevo León* (UANL), the third-largest public university in Mexico with a long-standing tradition in economics education, and the *Tecnológico de Monterrey* (Tec), a leading private institution renowned for its business and economics programs.

Our study leverages an extensive network of affiliated high schools encompassing both systems: fifty-five UANL-affiliated schools serving approximately 78,397 students, and eight TEC-affiliated schools with roughly 13,673 students. Together, these institutions provide access to a large and diverse student population exceeding 92,000 individuals. Notably, both universities display a striking parallel with American institutions in terms of gender representation in economics: female students constitute only about 32% of economics majors at both UANL and Tec, closely mirroring the persistent gender imbalance observed in U.S. universities.

This similarity in gender distribution—despite the institutions' contrasting missions, resources, and student demographics—suggests that the mechanisms influencing women's participation in economics may transcend national and institutional boundaries. The affiliated high schools represent

a broad cross-section of the student population, encompassing diverse socioeconomic backgrounds, educational tracks, and academic environments. This diversity enables the study to explore how beliefs and perceptions about economics vary across social contexts while holding constant regional and cultural factors.

Furthermore, working within the networks of UANL and Tec offers a unique opportunity to connect early perceptions of economics with subsequent academic choices. Because many students from these affiliated schools traditionally continue their higher education within these universities, we will be able to trace how changes in beliefs, aspirations, and gender norms at the high-school level translate into real university application and enrollment decisions. This feature makes Nuevo León an exceptional and policy-relevant context for understanding the mechanisms driving gender disparities in economics education.

7 Intervention

7.1 Intervention design

We propose an in-person role model intervention designed to address women's misperceptions and beliefs regarding economics and their quantitative abilities. By engaging students at a critical stage in their educational trajectory—just before university application decisions—the intervention aims to reshape beliefs about economics as a field and strengthen students' confidence in their own quantitative skills.

The intervention consists of a single, interactive classroom session led by trained female economists. During these in-person visits, role models will deliver a comprehensive 45–60 minute session that combines the sharing of personal narratives, the projection of informative videos, guided reflection exercises, and structured information delivery. Each session will take place during the *Proyecto de Vida* course, which focuses on students' personal development and career planning. This format ensures high participation rates and curricular relevance, while allowing discussions to unfold in a psychologically safe and familiar classroom environment.

7.2 Treatment content

Each session will follow a standardized structure that combines informational, motivational, and reflective components. Specifically, the content will include:

- **Information about economics as a field:** an overview of the breadth of economics as a profession and its applications to issues such as poverty, inequality, health, and education, highlighting the social impact of the discipline.
- **Labor market opportunities:** discussion of career paths available to economics graduates in public, private, and non-profit sectors, emphasizing their diversity and relevance.
- **Challenging stereotypes and gender biases:** sensitization exercises designed to confront common misconceptions about economics being overly technical or male-dominated, and to promote the view of economics as an inclusive and impactful field.
- **Role model narratives:** personal testimonies from the visiting economists about their motivations to study economics, the challenges they faced as women in the field, and the strategies they used to succeed.
- **Future perspectives:** a short discussion on how new technologies and data-driven approaches are expanding the scope of economics, underscoring its relevance in the era of artificial intelligence and digital transformation.

All materials used during the intervention—including slides, videos, activity guides, and communication templates—will be developed collaboratively by an interdisciplinary team of economists, educators, and psychologists from both universities. This team will also be responsible for training the role models, ensuring consistent delivery across schools, and maintaining the fidelity of the intervention to its pedagogical and behavioral objectives.

In addition, role models will participate in preparatory workshops focusing on communication, gender-sensitive facilitation, and classroom engagement strategies. These trainings will ensure that the sessions are not only informative but also emotionally resonant, promoting identification and belief updating among participating students.

The sequence of activities—from baseline data collection to the intervention and subsequent survey waves—is summarized in Figure A2 in the Appendix. This timeline provides a visual overview of the experimental schedule, indicating when each component of the study (surveys, classroom visits, and follow-ups) takes place relative to the academic calendar. It complements the design discussion in this section by clarifying the temporal alignment between treatment implementation and measurement of outcomes.

8 Experimental Design

8.1 Design overview

We will implement a clustered randomized controlled trial (RCT) to evaluate the causal impact of an in-person female role model intervention on the beliefs and aspirations of high-school students towards economics. The study will take place in 24 upper-secondary schools affiliated with UANL and 5 schools affiliated with Tec, covering a total of 29 schools. These schools were selected because they are located in the Monterrey metropolitan area and have at least 6 groups in the *Proyecto de Vida* course.

Schools will be the primary unit of randomization. Half of the schools will be assigned to the treatment condition and the other half to the control condition. Treated schools will implement the in-person role model intervention during one academic semester (February–April 2026), while control schools will continue with their regular curriculum without any additional activities. Within each treated school, six classroom groups enrolled in the compulsory *Proyecto de Vida* course will be selected, with three randomly assigned to receive the intervention and three left untreated to measure potential within-school spillovers. In control schools, the same six groups will be surveyed but will not receive any treatment.

This two-level randomization structure provides two complementary sources of variation: (i) a between-school comparison for the main treatment effect, and (ii) a within-treated-school comparison to study heterogeneity in exposure, peer influence, and spillover mechanisms.

8.2 Randomization procedure

Randomization will be implemented centrally using a blocked design (Imbens and Rubin, 2015; Gerber and Green, 2012). The first stage assigns schools to the treatment or control condition, stratifying by university network (UANL vs. Tec).

Within each treated school, the second stage of randomization assigns three of the six selected classroom groups to receive the role model session. This intra-school assignment will follow a simple randomization procedure with re-randomization to ensure covariate balance using the algorithm proposed by Morgan and Rubin (2012). The re-randomization criterion will ensure that across the three treated and three untreated groups within each treated school, standardized mean differences in baseline variables remain below 0.25 standard deviations.

9 Outcomes of Interest

This section defines the outcomes used to evaluate the impact of the in-person role-model intervention, links them to the pre-specified survey instruments and timing, and describes the construction of composite indices. The design distinguishes a single *primary* outcome measured with administrative data and a set of *secondary* outcomes measured with student surveys collected at three moments: (i) baseline (pre-visit), (ii) short-term endline (end of the intervention day), and (iii) long-term endline (8–10 weeks later). The survey modules reproduced in the Appendix follow the final instruments agreed for this study ("Student Survey—Baseline," "Student Survey—Short-term Endline," and "Student Survey—Long-term Endline") and are aligned with the study timeline (Figure A2).

9.1 Primary Outcomes

Our primary outcome is the proportion of students who *apply to an undergraduate economics program* during the 2026 admissions cycle (April–June 2026). This outcome will be measured with university administrative records from UANL and Tec and complemented, where needed, with institutionally held application logs (e.g., file creation and submission flags). This definition ensures a behaviorally meaningful endpoint and dovetails with the Difference-in-Differences specification that uses the 2025 cohort as pre-intervention comparison.

9.2 Secondary Outcomes

Secondary outcomes capture the belief- and identity-based channels through which role models may affect applications. Following best practice in survey-based evaluations of role-model interventions, conceptually related items are combined into standardized z-score indices to improve power and mitigate concerns with multiple testing (e.g., Breda et al., 2023). We pre-specify the following domains and measurement:

A. Intentions and aspirations. This outcome captures students' academic and motivational intentions related to studying economics and pursuing fields aligned with it. It reflects the extent to which the intervention influences students' aspirations, perceived feasibility, and family support toward continuing education in economics or related disciplines. These dimension are captured with the following questions:

(i) Likelihood of applying to economics.

(ii) Preferred field after high school.

(iii) Perceived family support.

(iv) Perceived affordability.

The outcome will be summarized in an overall *Intentions and Aspirations Index*, representing the main behavioral intention targeted by the intervention.

B. Beliefs about economics (content and social value). This outcome captures students' conceptual and normative understanding of economics as a discipline. It reflects both the accuracy of their beliefs about what economists do and the perceived social importance and relevance of the field. These dimensions are captured with the following questions:

(i) Understanding of what economists do.

(ii) Perceived social relevance of economics.

(iii) Belief that economics is mainly about money or finance (reverse-coded).

The outcome will be summarized in an overall *Economics Beliefs Index*, representing the extent to which students hold informed and socially grounded views about the field.

C. Identity alignment and self-concept. This outcome captures the extent to which students perceive economics as consistent with their personal identity and sense of belonging. It reflects both self-assessments of ability and the degree to which students identify with the image of an economist or feel comfortable in economics-related contexts. These dimensions are captured with the following questions:

(i) Perception that studying economics fits with one's self-concept.

(ii) Identification with economists ("I imagine someone like me").

(iii) Nervousness about studying economics (reverse-coded).

(iv) Self-assessed ability in economics and mathematics.

(v) Comparative ability relative to same-gender and other-gender peers.

The outcome will be summarized in an overall *Identity and Self-Concept Index*, representing the strength of alignment between students' self-image and the field of economics.

D. Gender stereotypes and perceived barriers. This outcome captures students' gender-related beliefs and perceived obstacles to participation in economics. It reflects both the internalization of gender stereotypes about ability and the perception of external barriers or discrimination that may affect educational and career choices in the field. These dimensions are captured with the following questions:

(i) Belief that men are naturally better at economics than women.

(ii) Perceived discrimination in economics-related careers.

(iii) Perceived main barrier to studying economics.

(iv) Ability to name a female economist (recall proxy).

The outcome will be summarized in a *Gender Stereotypes and Barriers Index* based on scale items, with recall and barrier measures reported separately.

To ensure consistency between the conceptual framework and the empirical implementation, Table A1 in the Appendix presents the mapping between the theoretical mechanisms discussed in the conceptual framework and their corresponding constructs and survey measures. Each

mechanism—belief updating, self-efficacy, and identity alignment—is linked to specific items in the student questionnaires, clarifying how theoretical concepts are operationalized into measurable outcomes.

10 Data Collection and Measurement

10.1 Sample and implementation

Participating schools are relatively large, with an average of 612 students in the final year of high school, distributed across approximately 15 classroom groups. Only six groups per school will be included in the study sample to ensure comparability and logistical feasibility. The intervention will consist of a single, in-person, 45–60 minute session delivered by trained female economists during the *Proyecto de Vida* class period.

In control schools, the same data collection instruments will be applied without the intervention. In treated schools, both treated and untreated classrooms will complete the same baseline and follow-up surveys to allow for the identification of direct and indirect (spillover) effects.

10.2 Sample composition

This study's sampling strategy brings together students from two distinct socioeconomic contexts, enhancing the overall representativeness of the sample. On the one hand, high schools affiliated with the Tecnológico de Monterrey primarily enroll students from higher-income families, although there are growing efforts to attract more diverse students through scholarships. On the other hand, high schools affiliated with the UANL serve a more diverse and representative student body: 48% of these students are female, about 9% work an average of 27 hours per week, and 60% come from families with monthly incomes below US$1,000—indicating that many are from lower-middle-class or poor backgrounds. By combining these two groups, the study captures a broad spectrum of socioeconomic realities in Mexico, offering a richer perspective on gender disparities in economics education than would be possible by focusing on any single institution type.

10.3 Survey instruments

We designed three student survey instruments to measure outcomes across multiple time horizons: a *Baseline Survey* administered before treatment exposure, a *Short-term Endline* implemented immediately after the classroom visit, and a *Long-term Endline* conducted approximately 8–10 weeks later. Each instrument was administered in paper form during class under supervision by trained research assistants.

Baseline survey. The baseline captures pre-treatment information on demographic background, socioeconomic status, academic performance, and household proxies for educational resources. It also includes pre-treatment measures of the four main outcome domains: *Intentions and Aspirations*, *Beliefs about Economics*, *Identity and Self-Concept*, and *Gender Stereotypes and Perceived Barriers*. Optional short lab-style items elicit percentile and probability beliefs about academic performance, intended to proxy confidence and self-assessment accuracy.

Short-term endline. Administered immediately after the intervention, this survey measures exposure, recall, and immediate reactions to the classroom visit. It also captures short-term changes in beliefs, gender stereotypes, identity alignment, and academic intentions. These measures serve to identify immediate treatment effects and short-lived motivational or informational shifts.

Long-term endline. Conducted approximately two months later, this follow-up survey measures persistence of treatment effects and recall of the visit. It includes the same core domains as the baseline and short-term surveys, plus additional items on information requests, perceived barriers to studying economics, and interest in receiving program updates. This instrument provides a medium-run assessment of whether the intervention produced durable changes in aspirations, beliefs, and identity-related outcomes.

All instruments use harmonized 0–10 Likert-type scales where higher scores consistently indicate stronger agreement, higher confidence, or greater alignment with pro-equality attitudes. The surveys are fully parallel across waves to enable consistent index construction and longitudinal comparisons. All survey-based outcomes correspond to measures pre-specified in the student questionnaires to be administered at baseline, short-term endline, and long-term endline.

The complete instruments, including all items and scales, are provided in the Appendix.

10.4 Index construction and scoring for survey measures

Survey instruments capture a large set of dimensions to approach motivated beliefs and misperceptions. Within each domain, items are oriented so that higher values reflect more pro-equality attitudes or greater alignment with the target construct. All items are standardized using the control-group baseline mean and standard deviation. Domain indices—*Intentions/Aspirations*, *Economics Beliefs*, *Identity/Self-Concept*, and *Gender Stereotypes/Barriers*—are then aggregated following the inverse-covariance-weighted (ICW) procedure proposed by Anderson (2008). This approach assigns optimal weights that account for correlations among items, improving statistical efficiency and providing a summary measure of treatment effects across related outcomes. The resulting indices are re-standardized to facilitate interpretation and comparability across domains.[1]

10.5 Measurement, missing data, and multiplicity

All survey outcomes are on 0–10 scales unless otherwise noted and will be coded so higher values uniformly indicate greater inclusiveness, interest or fit (reverse-coding where specified in the instruments). Item non-response below 10% is handled via within-domain mean imputation; otherwise, we report domain indices on available items and include a missing-indicator flag in robustness checks. For families with multiple correlated endpoints, we report both domain-level indices (primary within-family endpoint) and key constituent items; p-values in the survey family are adjusted using the Benjamini–Hochberg procedure (Benjamini and Hochberg, 1995). Administrative primary outcomes are not subject to multiplicity. The finalized questionnaires and timing are reproduced in the Appendix.

11 Estimation Strategy

The study combines a randomized controlled trial (RCT) with a Differences-in-Differences (DiD) estimation framework to evaluate the effects of an in-person female role model intervention on students' beliefs, aspirations, and actual applications to economics programs. Because the *Proyecto*

[1] See Anderson (2008) for details.

de Vida course is only offered to final-year students, it is important to notice that no longitudinal individual data exist for belief or perception outcomes. Therefore, all attitudinal and psychological outcomes (beliefs, intentions, identity alignment, and quantitative self-efficacy) will be analyzed using a cross-sectional comparison across treatment arms within the experimental design, rather than through a DiD approach.

11.1 Estimation and inference for school-level outcomes

While the randomization of treatment across schools provides a credible source of exogenous variation, the relatively small number of clusters poses challenges for statistical balance and power. Therefore, we complement the randomized design with a DiD specification for our main administrative outcome—applications to economics programs—using data from consecutive cohorts (2025 and 2026). This design enables us to exploit both experimental and temporal variation to improve precision and internal validity.

Despite randomization, the relatively small number of participating schools may limit the extent to which treatment and control units are balanced on key pre-treatment characteristics. Moreover, students are not randomly assigned to schools or instructors; they may self-select based on preferences, commuting distance, or institutional reputation. Variations in grading standards, teaching quality, and student composition across schools could confound simple post-treatment comparisons. These factors, coupled with limited statistical power for purely cross-sectional estimation, motivate the use of a Differences-in-Differences (DiD) strategy for the primary outcome. The DiD framework leverages administrative data on consecutive student cohorts (2025 as pre-treatment and 2026 as post-treatment). It compares the change in the proportion of students applying to an economics program between treated and control schools, effectively differencing out time-invariant unobserved heterogeneity at the school level.

Let Y_i denote a binary outcome equal to one if student i applies for admission to an undergraduate economics program, and zero otherwise. The following model will be estimated:

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 D_i + \beta_3 (T_i \times D_i) + \delta \mathbf{X}_i + \varepsilon_i. \tag{6}$$

In this specification, T_i is a post-treatment indicator equal to one for students graduating in

2026—the first cohort exposed to the intervention—and zero for students graduating in 2025, the pre-treatment cohort. The variable D_i is a treatment indicator equal to one if the student's school was assigned to the in-person role model intervention and zero otherwise. The interaction term $(T_i \times D_i)$ captures the Differences-in-Differences estimator of interest, representing the differential change in outcomes between treated and control schools across cohorts. Finally, $\mathbf{X}_i$ denotes a vector of school-level covariates, which are included to account for residual pre-treatment imbalances.

The coefficient β_3 identifies the intention-to-treat (ITT) effect of the intervention, capturing the differential change in application rates between treated and control schools after the intervention. Because attendance at the intervention sessions may not be universal among final-year students, β_3 will be interpreted as the ITT effect rather than a treatment-on-treated (TOT) estimate.

11.2 Estimation and inference for classroom- and individual-level outcomes

Beliefs, aspirations, and quantitative self-concept will be measured for the 2026 cohort of students through three survey rounds: (i) a baseline survey immediately before the start of the role model session, (ii) a short post-intervention survey conducted immediately after the session, and (iii) a follow-up survey in April 2026, when students are expected to have selected their intended field of study or submitted university applications. Because the *Proyecto de Vida* course is exclusive to final-year students, repeated observations are available only for this cohort, allowing us to construct an individual-level panel for psychological and attitudinal outcomes. We will therefore implement an Analysis of Covariance (ANCOVA) framework to control for baseline outcomes and increase statistical power.

We begin by estimating the average school-level intention-to-treat (ITT) effect using the following ANCOVA specification:

$$Y_{sgi,1} = \alpha + \gamma_s + \beta\,\text{TreatSchool}_s + \rho\,Y_{sgi,0} + \mathbf{X}'_{sgi}\theta + \varepsilon_{sgi}, \tag{7}$$

where $Y_{sgi,1}$ denotes the post-treatment value of the outcome for student i in group g at school s, $Y_{sgi,0}$ is the corresponding baseline value, TreatSchool_s is an indicator equal to one if school s was assigned to the intervention, γ_s captures strata fixed effects, and $\mathbf{X}_{sgi}$ includes individual- and classroom-level covariates such as gender, math GPA, and socioeconomic status. The coefficient β

measures the average impact of assignment to a treated school on students' beliefs, aspirations, and self-concept, conditional on baseline outcomes.

To explore within-school mechanisms and potential spillovers, we extend this model by incorporating classroom-level variation in exposure:

$$Y_{sgi,1} = \alpha + \gamma_s + \beta_1 \,\text{TreatGroup}_{sg} + \beta_2 \,\text{TreatSchool}_s + \rho\, Y_{sgi,0} + \mathbf{X}'_{sgi}\theta + \varepsilon_{sgi}, \tag{8}$$

where TreatGroup_{sg} equals one if classroom g in school s received the role model session and zero otherwise. In this specification, β_1 captures the direct effect of being in a treated classroom within a treated school, while β_2 identifies spillover effects on students in untreated classrooms within treated schools. The inclusion of the baseline outcome $Y_{sgi,0}$ increases precision and corrects for residual imbalance (McKenzie, 2012).

All inference will employ cluster-robust standard errors at the school level following MacKinnon et al. (2023). For multiple correlated outcomes related to beliefs, aspirations, and self-concept, p-values will be adjusted using the Benjamini and Hochberg (1995) false discovery rate procedure. This two-stage ANCOVA approach preserves the hierarchical structure of the experimental design, allowing us to estimate both overall and within-school effects while maintaining efficiency and internal validity.

12 Heterogeneity and Subgroup Analyses

We will assess whether the role-model intervention produces heterogeneous impacts across student subgroups. Heterogeneity is examined using two complementary approaches. The first pre-specifies conventional triple-difference (DDD) models applied to the primary outcome and the main survey indices; the second adopts a model-agnostic, data-driven method based on the double/debiased machine-learning framework proposed by Chernozhukov et al. (2025) to explore effect heterogeneity without over-fitting.

12.1 Pre-specified triple-difference models

Although only one treatment arm is implemented, the Difference-in-Differences (DiD) specification can be extended to estimate heterogeneous effects by interacting the treatment indicator with pre-treatment characteristics. For the main outcome—applications to economics programs—and for the principal survey indices, we will estimate a triple-differences model of the form

$$Y_{ist} = \beta_0 + \beta_1 T_s + \beta_2 Post_t + \beta_3 (T_s \times Post_t) + \beta_4 Z_i + \beta_5 (T_s \times Post_t \times Z_i) + \delta' \mathbf{X}_i + \varepsilon_{ist}, \quad (9)$$

where Y_{ist} is the outcome for student i in school s and cohort t; T_s indicates treatment assignment; $Post_t$ identifies the post-intervention cohort (2026); and Z_i represents the subgroup characteristic of interest. The coefficient β_5 captures the differential DiD effect for the subgroup defined by Z_i.

We pre-specify four heterogeneity dimensions:

- **Gender.** Female (F_i) vs. male students, following Porter and Serra (2020). This captures whether the intervention benefits female students disproportionately.
- **Baseline beliefs about economics and quantitative skills.** Using the standardized baseline index of economics understanding and self-assessed math ability; above- vs. below-median values define high- and low-belief subgroups.
- **Socioeconomic background.** Derived from household proxies (ownership of computer, internet, books, private bedroom) aggregated into a standardized SES index; high- vs. low-SES students are contrasted.
- **Academic achievement prior to intervention.** Based on self-reported GPA or the class-level academic terciles; interaction terms test whether higher-achieving students respond differently.

For survey-based mechanisms (beliefs, identity, stereotypes, aspirations), heterogeneity will be estimated using standard DiD models with subgroup interactions only within the treated cohort, given that no pre-intervention measurements exist for earlier cohorts. All models include covariates $\mathbf{X}_i$ (age, class fixed effects) and cluster-robust standard errors at the school level.

12.2 Machine-learning–based heterogeneity analysis

In addition to the pre-specified parametric models, we will explore heterogeneous treatment effects using the double/debiased machine-learning (DML) approach of Chernozhukov et al. (2025). This framework estimates the conditional average treatment effect (CATE) function

$$\tau(x) = \mathbb{E}[Y(1) - Y(0) \mid X = x],$$

by combining cross-fitting with flexible nuisance estimation of outcome and treatment models. The estimator solves orthogonal score equations that render the estimated treatment effects robust to first-stage over-fitting and model misspecification.

Practically, we will proceed as follows:

1. Use student-level covariates X_i (gender, baseline indices, SES, GPA, and class identifiers) to predict both treatment assignment and outcomes under cross-validation folds.
2. Implement DML using random forests and LASSO learners to estimate CATEs $\hat{\tau}(X_i)$.
3. Summarize heterogeneity patterns via Partial Dependence Plots (PDPs) and by reporting average treatment effects within deciles of predicted CATEs.
4. Conduct inference using the asymptotically normal score-based standard errors described in Chernozhukov et al. (2025).

This machine-learning analysis complements the DDD estimates by uncovering potentially nonlinear or multidimensional sources of heterogeneity not captured by simple interaction terms. Results from both approaches will be interpreted jointly: the DDD models provide interpretable subgroup contrasts, whereas the DML estimates offer exploratory evidence on which baseline features most strongly predict treatment responsiveness.

13 Robustness and Sensitivity Checks

13.1 Attrition, non-response, and missing data

Attrition may occur at different levels of the study design—schools, classrooms, or individual students—potentially affecting the internal validity of the estimates if correlated with treatment assignment or potential outcomes. We will explicitly model attrition at each level and assess its implications for inference using complementary approaches.

First, we will estimate inverse-probability weights (IPW) to adjust for differential response probabilities. Attrition models will be estimated separately at the school, classroom, and student levels, using baseline covariates that are predictive of follow-up participation and pre-treatment outcomes. The resulting weights will be applied in the main estimation equations to recover treatment effects that are representative of the original sample under the assumption of selection on observables.

Second, we will compute Lee (2009) bounds to estimate the range of plausible treatment effects under monotonic selection, which provides partial identification when attrition is potentially endogenous. These bounds will be estimated at the appropriate level of aggregation (e.g., school or student) depending on the outcome of interest. The comparison between the unadjusted estimates, the IPW-adjusted results, and the Lee bounds will provide a transparent assessment of the robustness of the findings to different attrition mechanisms.

Finally, sensitivity analyses will be reported to illustrate how results vary under alternative assumptions about attrition, including scenarios where entire clusters are lost or where individual-level attrition differs across treatment arms. All main outcomes will thus be re-estimated across these specifications to ensure that conclusions are not driven by selective follow-up at any level of the experimental hierarchy.

13.2 Alternative outcome definitions and measurement robustness

For the primary outcome—applications to economics programs—we will test robustness to alternative codings: (i) including related majors such as finance, public policy, or data analysis; (ii) restricting to applications submitted to public universities only; and (iii) using either binary individual outcomes or school-level application shares. For survey-based indices, we will verify

that results are consistent across index construction methods, comparing (a) standardized mean indices, (b) Anderson inverse-covariance-weighted (ICW) indices (Anderson, 2008), and (c) principal-component (PCA) scores. This triangulation ensures that conclusions do not depend on any single aggregation method.

13.3 Placebo and falsification tests

We will conduct placebo tests to verify that estimated effects are not driven by spurious correlations or unobserved shocks. Specifically, we will estimate treatment effects on outcomes that should not plausibly be affected by the intervention, such as: (i) self-reported interest in non-economics fields (e.g., medicine, law, engineering); (ii) self-assessed reading or language ability; and (iii) belief items unrelated to economics (e.g., "I enjoy literature classes").

13.4 Balance and baseline comparability

We will assess the baseline comparability of treatment and control groups using both conventional hypothesis tests and standardized mean differences. For each baseline covariate, we will report the difference in means between treated and control units, as well as its standardized version (the difference divided by the pooled standard deviation). Following the guidelines proposed by Imbens and Rubin (2015), we will interpret absolute standardized differences below 0.2–0.3 standard deviations as evidence of adequate balance, rather than relying solely on p-values that depend on sample size. These diagnostics will be computed at both the school and classroom levels for key pre-treatment variables, including baseline beliefs, academic indicators, and demographic characteristics. Aggregate balance tables and summary indices will be presented for each treatment arm to document the effectiveness of the random assignment and to ensure that subsequent estimates are not driven by pre-existing differences across groups.

13.5 Inference robustness

Given the limited number of clusters, we will complement cluster-robust inference with wild-cluster bootstrap p-values following Cameron et al. (2008). We will also compute randomization-inference (Fisher exact) p-values at the school level to ensure that significance results are not driven

by asymptotic approximations. Sensitivity to alternative clustering levels (school vs. classroom) will also be reported.

13.6 Specification and spillover robustness

Main results will be re-estimated under alternative model specifications, including: (i) simple difference-in-means, (ii) ANCOVA with baseline controls, and (iii) DiD with cohort fixed effects for administrative outcomes. We will also test robustness to inclusion and/or exclusion of baseline covariates and strata fixed effects. To evaluate potential within-school spillovers, we will compare untreated classrooms in treated schools with classrooms in control schools, estimating indirect effects on non-exposed peers. This analysis will clarify whether observed treatment effects reflect direct exposure, peer influence, or broader informational diffusion.

Together, these robustness and sensitivity checks ensure that estimated treatment effects are not artifacts of specific modeling choices, attrition patterns, or measurement conventions, but reflect consistent causal patterns across specifications and samples.

14 Mechanisms

Understanding the behavioral channels through which the intervention operates is essential to interpret its overall impact on female students' educational choices. The intervention is expected to influence key psychological constructs—such as beliefs about quantitative ability, self-confidence, and identity congruence—which in turn shape students' aspirations and application decisions. This section focuses on the measurement and empirical identification of these mediating mechanisms using survey-based data collected in the field, while the subsequent section describes complementary laboratory measures designed to capture additional behavioral dimensions that cannot be elicited reliably through surveys.

14.1 Measuring mediators

To investigate the behavioral mechanisms through which the intervention affects students' aspirations and career choices, we will complement the analysis of administrative records on college applications and academic outcomes with survey-based data on beliefs and perceptions. These data

will constitute the main mediators for the causal analysis developed in the following subsection.

The survey instrument, implemented using existing data platforms at our partner institutions, will measure students' perceptions about economics as a field, stereotypes regarding women's quantitative skills, perceived discrimination against women in economics, self-reported confidence in quantitative abilities, the importance attached to quantitative skills for academic success, and students' interest in pursuing a career in economics. These constructs are consistent with the mediating variables examined in previous research on gender gaps in economics and STEM disciplines (González-Pérez et al., 2020; Breda et al., 2023), ensuring comparability and external validity.

These survey-based mediators capture core psychological and attitudinal mechanisms through which exposure to female role models may influence students' beliefs, aspirations, and self-concept. Complementary laboratory-based measures of belief updating, competitiveness, and preference-related mechanisms are described in detail in Section 15.

14.2 Causal mediation analysis

To quantify the contribution of belief-related mechanisms, we will employ the causal mediation framework proposed by Imai et al. (2010, 2011). Let T_i denote the treatment assignment for student i, equal to one if her classroom received the in-person role model session and zero otherwise. Let M_i represent a vector of post-treatment mediators capturing beliefs and perceptions, and let Y_i denote the main outcome, such as whether the student applied to study economics.

The potential values of the mediator and outcome are denoted $M_i(t)$ and $Y_i(t, m)$, representing the mediator that would be realized under treatment status $t \in \{0, 1\}$ and the outcome that would occur if treatment were t and the mediator set to m. The *average causal mediation effect* (ACME), or indirect effect, is defined as

$$\delta(t) = \mathbb{E}\left[Y_i(t, M_i(1)) - Y_i(t, M_i(0))\right], \tag{10}$$

while the *average direct effect* (ADE), net of mediation, is

$$\zeta(t) = \mathbb{E}\left[Y_i(1, M_i(t)) - Y_i(0, M_i(t))\right]. \tag{11}$$

The total treatment effect can thus be decomposed as

$$\tau = \delta(t) + \zeta(t). \tag{12}$$

Under the standard *sequential ignorability* assumption—that is, conditional on pre-treatment covariates $\mathbf{X}_i$, treatment assignment is as good as random, and mediators are independent of potential outcomes given the treatment and covariates—these parameters can be estimated using observed data.

Empirically, the ACME and ADE will be estimated via the following system:

$$M_i = \alpha_M + \beta_M T_i + \mathbf{X}_i'\theta_M + \varepsilon_{Mi}, \tag{13}$$

$$Y_i = \alpha_Y + \tau_Y T_i + \gamma M_i + \mathbf{X}_i'\theta_Y + \varepsilon_{Yi}, \tag{14}$$

where β_M measures the causal effect of treatment on the mediator, γ reflects the association between the mediator and the outcome, and τ_Y represents the direct treatment effect. Under linearity and no-interaction assumptions, the product $\beta_M\gamma$ provides an estimate of the indirect effect.

Given the nested design of the experiment (students within classrooms and schools), standard errors will be clustered at the school level, and multilevel mediation models will be explored to account for within-school correlation. Sensitivity analyses following Imai et al. (2011) will be conducted to assess the robustness of results to potential violations of sequential ignorability. This analysis will identify which belief-related constructs—such as quantitative self-efficacy, stereotype endorsement, or perceived discrimination—explain the largest share of the total treatment effect.

While the mediators described above are measured using survey instruments, a complementary laboratory component will further examine the behavioral mechanisms underlying these belief changes. This additional component is presented in Section 15.

15 Laboratory elicitation of behavioral mechanisms

To complement the field experiment and deepen our understanding of the psychological mechanisms underlying the intervention, we will conduct laboratory sessions with a randomly selected subsample of students from both treated and control schools. These sessions will take place at

the *Tec Behavioral and Experimental Economics Research Lab* (BEER) on the main campus of the Tecnológico de Monterrey. Students will be invited for a campus visit shortly after the role model intervention but before the college application process begins. During this visit, participants will learn more about economics as a field and complete a structured series of incentivized experimental tasks designed to measure behavioral constructs that cannot be reliably captured in surveys.

Each session will last approximately **1 hour and 30 minutes** and will consist of six components: (1) introduction and instructions, (2) belief elicitation and motivated cognition, (3) preferences over risk, time, and social behavior, (4) willingness to compete and identity threat, (5) aspirations and goal setting, and (6) debriefing and reflection.

15.1 Introduction and instructions (10 minutes)

Participants will receive standardized instructions explaining that the study aims to understand how students make academic and career-related decisions. Incentives will be provided for selected tasks using small monetary payments or vouchers to ensure engagement and incentive compatibility. Students will provide informed consent and complete comprehension checks before beginning the exercises.

15.2 Belief elicitation and motivated cognition (20 minutes)

We will first elicit participants' beliefs about their own and others' quantitative abilities using incentivized belief-elicitation tasks. Students will complete a short quantitative reasoning exercise (e.g., logical or arithmetic problems) and subsequently estimate their percentile rank within the group and their probability of scoring above the median. Belief accuracy will be rewarded using a proper scoring rule, such as a quadratic scoring function.

To measure motivated reasoning, participants will then receive either stereotype-consistent or stereotype-neutral information (e.g., data showing no gender gap in math performance) and will re-elicitate their beliefs. This design, inspired by Golman et al. (2016) and Sharot et al. (2011), allows us to detect asymmetric belief updating consistent with motivated cognition or information avoidance.

15.3 Preferences over risk, time, and social behavior (20 minutes)

To capture structural behavioral parameters often associated with gender differences in decision-making, we will elicit risk, time, and social preferences using well-established experimental paradigms. Risk attitudes will be measured using the Holt and Laury (2002) or Eckel and Grossman (2008) lottery tasks. Time preferences will be elicited through a multiple price list design (Coller and Williams, 1999), and social preferences will be measured via a dictator game or social value orientation task capturing altruism and inequality aversion. These measures will serve as behavioral controls in the mediation analysis and help account for heterogeneity in economic preferences.

15.4 Willingness to compete and identity threat (20 minutes)

We will assess willingness to compete using the tournament-entry design by Niederle and Vesterlund (2007). In the first stage, participants perform a simple arithmetic task under piece-rate payment; in the second, they can choose between a competitive payment scheme and a fixed rate. This task measures confidence and competitiveness, traits often linked to gender gaps in academic and career outcomes. To explore identity effects, we will introduce a gender-salience manipulation prior to the competition stage to examine whether exposure to gender identity cues affects willingness to compete.

15.5 Aspirations and goal-setting (10 minutes)

Finally, to capture changes in students' educational and career aspirations, participants will complete a structured and incentivized goal-setting task. Following experimental approaches in Bernard et al. (2023) and Beaman et al. (2012), each student will first indicate her desired and expected educational outcomes, such as the degree she most wishes to pursue and the field she expects to study. Participants will then allocate a limited number of tokens across potential academic fields (e.g., economics, business, health, engineering, education) to indicate the relative strength of their aspirations. After stating their preferred field, students may voluntarily allocate a small share of their participation earnings to receive additional information or reminders related to that field, thereby providing an incentivized measure of the intensity of their aspirations.

This task complements survey-based aspiration measures collected in the main study by offering

incentive-compatible indicators of desired versus expected outcomes and the willingness to invest in one's goals. Together with belief- and preference-based measures, these data will allow us to examine whether exposure to female role models affects not only self-confidence and perceptions but also the formation and commitment to higher educational aspirations.

15.6 Debriefing and reflection (10 minutes)

Students will conclude the session with a short reflection survey about their perceptions of economics, learning experience, and interest in pursuing the field. Participants will then be fully debriefed to ensure understanding and ethical compliance. This closing stage reinforces self-efficacy and prevents any unintended negative effects of the experimental manipulation.

15.7 Integration with field experiment

The laboratory data will provide fine-grained, incentive-compatible measures of belief distortions, competitiveness, and individual preferences that complement survey and administrative outcomes from the field. These measures will serve as potential mediators in the causal pathway between exposure to female role models and educational aspirations. Integrating these data into the mediation framework of Imai et al. (2011) will allow us to identify the extent to which changes in beliefs, competitiveness, and preferences account for the observed treatment effects.

Table A2 in the Appendix summarizes how each of these lab measures corresponds to the theoretical mechanisms introduced in the conceptual framework. These tasks provide complementary evidence on the same psychological channels—belief updating, self-efficacy, and identity alignment—by observing how students process feedback, respond to uncertainty, and express willingness to engage in competitive or analytical activities.

16 Power Calculations

16.1 Power calculations for school-level outcomes

Power calculations follow the design-based variance of a cluster-level difference-in-differences (DiD) estimator, explicitly incorporating autocorrelation across both schools and classrooms as recommended by Burlig et al. (2020) and Teerenstra et al. (2012). Let Y_{st} denote the school-level

outcome (e.g., the proportion of students applying to economics) for school s and cohort $t \in \{0, 1\}$, and define $\Delta_s = Y_{s1} - Y_{s0}$. The estimator of interest is the difference in average changes between treated and control schools:

$$\widehat{\tau}_{DiD} = \overline{\Delta}_T - \overline{\Delta}_C.$$

Assuming equal numbers of treated and control schools ($J_T = J_C = 14$), the variance of $\widehat{\tau}_{DiD}$ is given by the serial-correlation-robust (SCR) expression:

$$Var(\widehat{\tau}_{DiD}) = 2(1 - \rho_{\text{school}})\sigma_s^2 \left(\frac{1}{J_T} + \frac{1}{J_C} \right),$$

where σ_s^2 is the variance of the school-level mean outcome and ρ_{school} denotes the correlation of school means across cohorts.

Following the hierarchical extension of Teerenstra et al. (2012), the correlation of school-level means ρ_{school} is a weighted average of the autocorrelation at the cluster (school) level and at the classroom level:

$$\rho_{\text{school}} = \frac{n^* \text{ICC}}{1 + (n^* - 1)\text{ICC}} \rho_{\text{cluster}} + \frac{1 - \text{ICC}}{1 + (n^* - 1)\text{ICC}} \rho_{\text{class}},$$

where n^* is the number of classrooms per school, ICC denotes the within-school intraclass correlation, ρ_{cluster} represents the autocorrelation of school-level means across cohorts, and ρ_{class} the autocorrelation of classroom-level means across cohorts within schools.

In this experiment, the school is the randomization cluster, and classrooms are the units within each cluster. Based on parameters commonly observed in educational RCTs, we assume a within-school intraclass correlation of ICC = 0.05, a school-level autocorrelation $\rho_{\text{cluster}} = 0.60$, and a classroom-level autocorrelation $\rho_{\text{class}} = 0.30$. Given six classrooms per school ($n^* = 6$), the resulting pre–post correlation of school means is $\rho_{\text{school}} \approx 0.37$.

We take $\sigma_s = 0.015$ (1.5 percentage points) as a conservative estimate of the standard deviation of the school-level proportion of students applying to economics, consistent with cross-school variation in comparable educational settings reported by Breda et al. (2023). Using standard normal critical values $z_{1-\alpha/2} = 1.96$ and $z_{1-\beta} = 0.84$ for a two-sided 5% test with 80% power, the minimum

detectable effect (MDE) is given by

$$\text{MDE} = (z_{1-\alpha/2} + z_{1-\beta})\sqrt{2(1-\rho_{\text{school}})\sigma_s^2\left(\frac{1}{J_T}+\frac{1}{J_C}\right)} \approx 0.017.$$

Thus, the experimental design has 80% power to detect a change of approximately **1.7 percentage points** in the proportion of students applying to economics. This MDE is smaller than the 3–3.5 percentage point effects reported by Breda et al. (2023), suggesting that the proposed experiment will have ample power (well above 90%) to detect effects of similar magnitude, even under conservative assumptions about school- and classroom-level autocorrelation.

16.2 Power for classroom- and student-level outcomes

The intervention design combines school-level treatment assignment with random allocation of treated and untreated classrooms within treated schools. Consequently, precision and power for short-run psychological outcomes (beliefs, aspirations, quantitative self-concept) can be assessed using two complementary ANCOVA contrasts: (i) a within-school contrast between treated and untreated classrooms in treated schools, and (ii) a between-school contrast comparing treated classrooms in treated schools with control classrooms in untreated schools.

Let $Y_{sgic}^{(1)}$ and $Y_{sgic}^{(0)}$ denote post- and baseline outcomes for student i in classroom g at school s. The ANCOVA model is

$$Y_{sgic}^{(1)} = \alpha + \tau\,\text{TreatGroup}_{sg} + \gamma\,Y_{sgic}^{(0)} + \lambda_s + \mathbf{X}_{sgic}'\theta + \varepsilon_{sgic},$$

where TreatGroup_{sg} is a classroom-level treatment indicator, λ_s are school fixed effects (included when exploiting within-school variation), and $\mathbf{X}_{sgic}$ are predetermined covariates. Outcomes will be standardized to unit variance at baseline so that all effect sizes are expressed in standard deviation (SD) units. Standard errors will be clustered at the school level, consistent with the randomization structure.

16.2.1 Within treated schools: direct classroom contrast.

In treated schools, $G_T = 3$ classrooms receive the role-model session and $G_C = 3$ remain untreated. Each classroom includes $n = 30$ students. Let J_T denote the number of treated schools ($J_T = 14$). Following Teerenstra et al. (2012), the residual variance under ANCOVA adjustment is $(1 - \rho_I^2)\sigma_Y^2$, where ρ_I is the pre–post correlation at the individual level. The variance of the within-school classroom-treatment contrast is:

$$\mathrm{Var}(\widehat{\tau}_{\text{within}}) \approx \frac{2}{G_T} \frac{(1 - \rho_I^2)\,[1 + (n-1)\mathrm{ICC}_{\text{class}}]}{n\,J_T}.$$

The corresponding minimum detectable effect (MDE) is

$$\mathrm{MDE}_{\text{within}} = (z_{1-\alpha/2} + z_{1-\beta})\sqrt{\frac{2}{G_T} \frac{(1 - \rho_I^2)\,[1 + (n-1)\mathrm{ICC}_{\text{class}}]}{n\,J_T}}.$$

Plugging moderately conservative parameters ($\rho_I = 0.6$, $\mathrm{ICC}_{\text{class}} = 0.10$, $G_T = 3$, $n = 30$, $J_T = 14$, $\alpha = 0.05$, $1 - \beta = 0.80$) gives:

$$\mathrm{MDE}_{\text{within}} \approx 0.16 \text{ SD}.$$

If $\rho_I = 0.7$, the MDE improves to 0.14 SD, whereas with $\mathrm{ICC}_{\text{class}} = 0.15$, it increases to 0.19 SD.

16.2.2 Across schools: pooled classroom contrast.

Including untreated schools ($J_C = 15$) allows an additional comparison between treated classrooms in treated schools and all untreated classrooms in control schools. This captures the overall intent-to-treat (ITT) effect across the experimental population. The variance of the ANCOVA-adjusted classroom-mean contrast (pooled across schools) is:

$$\mathrm{Var}(\widehat{\tau}_{\text{between}}) \approx (1 - \rho_I^2)\,[1 + (n-1)\mathrm{ICC}_{\text{class}} + n(G_T - 1)\mathrm{ICC}_{\text{school}}] \left(\frac{1}{J_T G_T n} + \frac{1}{J_C G_C n}\right),$$

where $\mathrm{ICC}_{\text{school}}$ captures the correlation of outcomes across classrooms within the same school due to shared school-level factors. The corresponding MDE is:

$$\mathrm{MDE}_{\text{between}} = (z_{1-\alpha/2} + z_{1-\beta})\sqrt{(1 - \rho_I^2)\,[1 + (n-1)\mathrm{ICC}_{\text{class}} + n(G_T - 1)\mathrm{ICC}_{\text{school}}] \left(\frac{1}{J_T G_T n} + \frac{1}{J_C G_C n}\right)}.$$

Using the same parameters as above and adding $\text{ICC}_{\text{school}} = 0.03$ yields:

$$\text{MDE}_{\text{between}} \approx 0.18 \text{ SD}.$$

This pooled estimate is slightly less precise than the within-school contrast, as it incorporates between-school heterogeneity.

The within-school contrast measures the *direct causal effect* of classroom exposure among treated schools, exploiting randomization within institutions. The across-school contrast estimates the *average treatment effect* for the experimental population, including both treated and untreated schools. Together, these two sources of variation provide complementary evidence: the first isolates mechanisms under tightly controlled conditions, while the second generalizes treatment effects to the full experimental sample. Following the conventions in Cohen (1978), an effect of 0.2 SD is considered *small*, 0.5 SD *medium*, and 0.8 SD *large*. Therefore, detectable effects in the range of 0.14–0.18 SD indicate that the design is powered to capture small but meaningful behavioral and cognitive changes—making these MDEs both realistic and moderately conservative.

The ANCOVA adjustment with baseline measures ensures that both designs are well powered to detect treatment effects in the range of 0.15–0.20 SD, which is also consistent with the magnitude of effects observed in classroom-based interventions affecting beliefs, aspirations, and identity alignment.

16.3 Power calculations for the laboratory experiment

The laboratory sessions will include a subsample of students randomly invited from both treated and control schools to participate in a 1-hour and 30-minute elicitation exercise. Each session will host approximately 20 participants, and we plan to conduct a total of $J = 10$ sessions (five per treatment arm), yielding an anticipated sample size of $N \approx 200$ students. Participation will be voluntary but stratified to maintain balanced representation across treatment status and gender.

The primary goal of this component is to measure treatment-induced differences in psychological and behavioral mechanisms—such as competitiveness, aspirations, belief updating, and social preferences—between students exposed to the role model intervention and those in the control condition. Because these are continuous, standardized measures collected at the individual level,

the experiment is powered to detect mean differences in standard deviation (SD) units.

Let Y_i denote a standardized outcome for student i and T_i a treatment indicator equal to one if the student attended a treated school. The estimated treatment effect is:

$$\widehat{\tau} = \overline{Y}_T - \overline{Y}_C,$$

with sampling variance

$$\text{Var}(\widehat{\tau}) = \frac{\sigma^2}{n_T} + \frac{\sigma^2}{n_C}.$$

Assuming equal cell sizes $n_T = n_C = N/2$, the minimum detectable effect (MDE) at significance level α and power $1 - \beta$ is:

$$\text{MDE} = (z_{1-\alpha/2} + z_{1-\beta})\sqrt{\frac{2\sigma^2(1 - R^2)}{N}},$$

where R^2 represents the proportion of outcome variance explained by pre-treatment covariates.

To improve precision, we will exploit baseline data collected during the school visits prior to the lab sessions, including measures of beliefs, aspirations, academic performance, and demographics. Empirical evidence from similar interventions suggests that these covariates can explain between 30% and 50% of the variation in post-intervention psychological measures ($R^2 = 0.3$–0.5).

Substituting $z_{1-\alpha/2} = 1.96$, $z_{1-\beta} = 0.84$, $\sigma = 1$, $N = 200$, and $R^2 = 0.4$ yields:

$$\text{MDE} = (1.96 + 0.84)\sqrt{\frac{2(1 - 0.4)}{200}} \approx 0.21 \text{ SD}.$$

If the explained variance is as high as $R^2 = 0.5$, the MDE falls further to 0.18 SD. For a larger sample of $N = 300$, these values would decrease to approximately 0.17 SD and 0.15 SD, respectively.

Thus, the laboratory experiment has 80% power to detect treatment effects in the range of 0.18–0.21 SD, depending on the predictive strength of baseline covariates. Following Cohen (1978), such effects correspond to small but meaningful changes in psychological and behavioral mechanisms—well within the magnitude observed in laboratory and field studies of identity, competitiveness, and motivated beliefs. Standard errors will be clustered at the school level to adjust for potential intra-school correlation among participants.

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Appendix

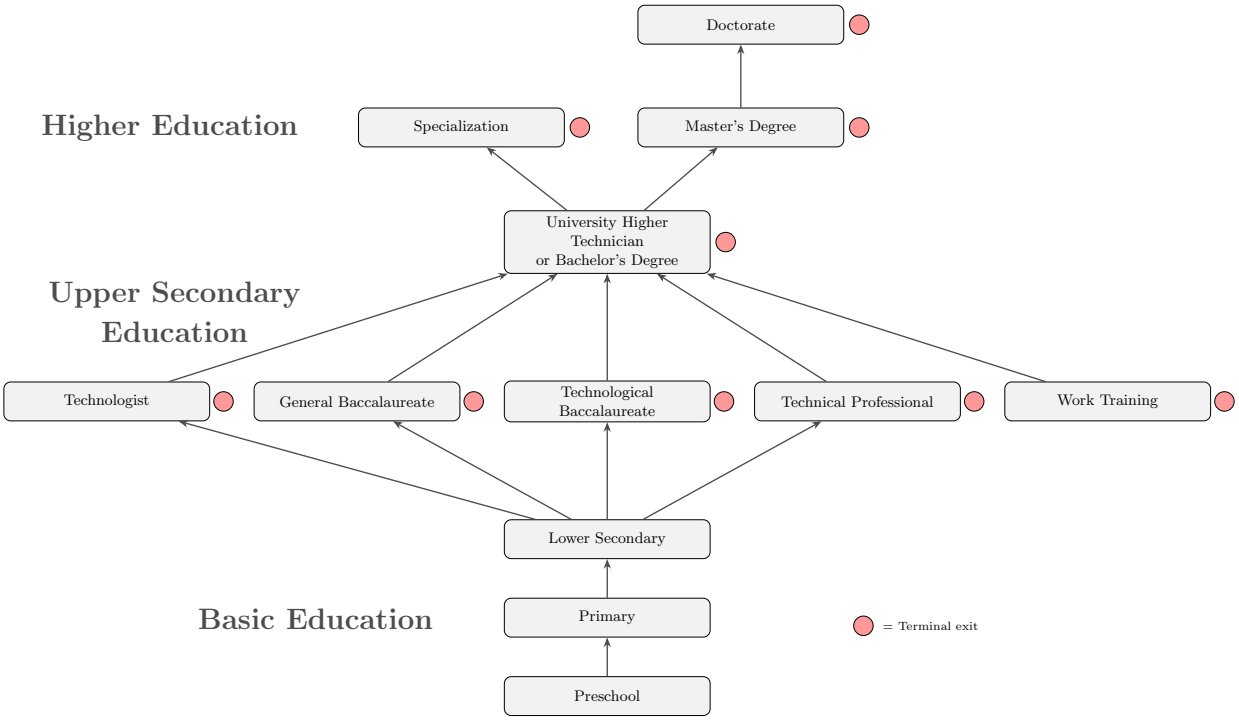


Figure A1: National Education System

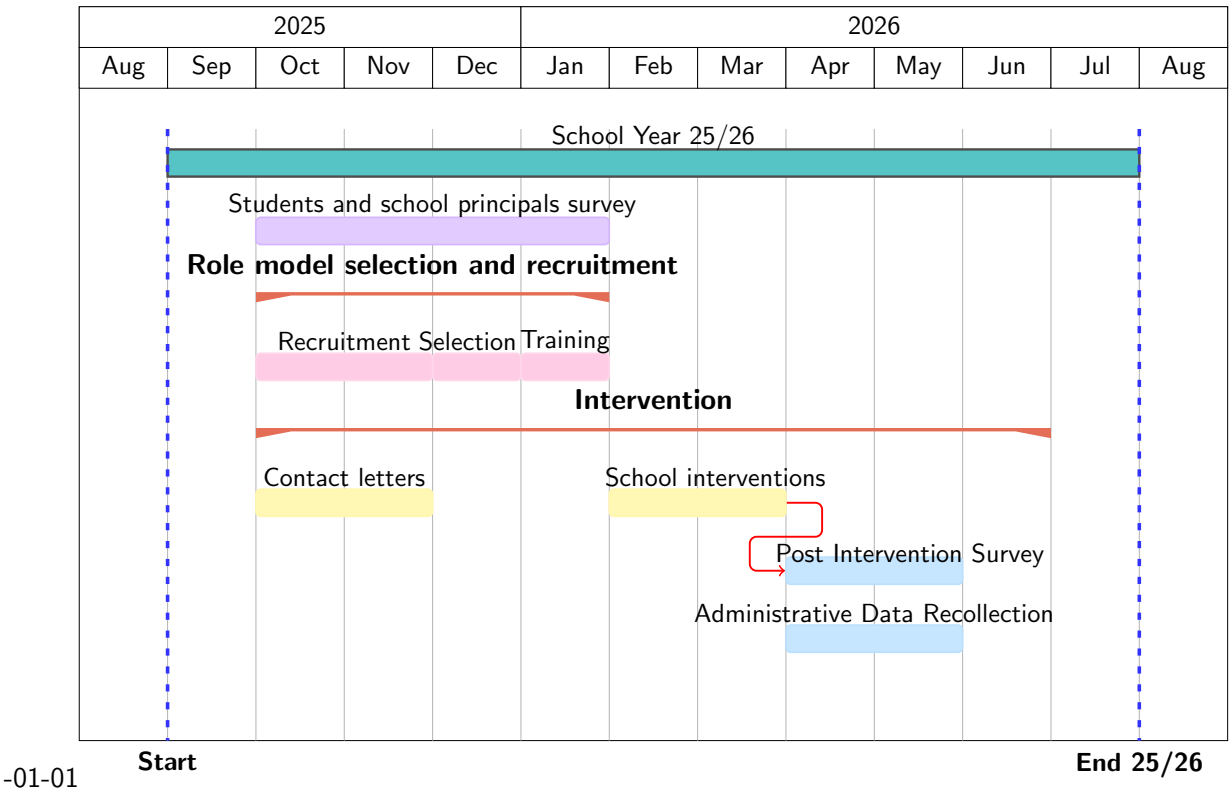


Figure A2: Program evaluation Timeline

Table A1: Mapping of survey constructs to theoretical mechanisms

Mechanism	Operational Measure (Survey Items)	Instrument Section(s)
Motivated beliefs	Self-assessed ability in economics and mathematics; comparative self-evaluation vs. same/opposite gender (B2–B4). Belief updating via percentile and probability beliefs (E1–E2, P1). Post-intervention belief revision (S7, T1–T5).	Baseline (B, E), Short-term (S, T), Long-term (P)
Identity congruence and protection	"Studying economics fits with who I am" (C8, T5, N5). "Thinking about studying economics makes me nervous or uncertain" (C7, reverse coded). "I can imagine myself as an economist" (S6).	Baseline (C), Short-term (S, T), Long-term (N)
Social conformity and perceived norms	"Most students of my gender think economics is a suitable field for women" (C6). "Family or friend support if you study economics" (D3, U2). "Since the visit, I have talked about economics with family or friends" (L3).	Baseline (C, D), Short-term (U), Long-term (L)
Prosocial value alignment	"Economics helps improve people's lives and reduce social problems" (C2, T2, N2). Wording retained across waves: "Economics helps solve real social problems."	Baseline (C), Short-term (T), Long-term (N)
Gender stereotypes	"Men are naturally better at economics than women" (C4, T4, N4). "Women face discrimination in economics-related careers" (C5).	Baseline (C), Short-term (T), Long-term (N)
Field beliefs and understanding	"I understand what economists do in real jobs" (C1, T1, N1). "Economics is mainly about money and finance" (C3, T3, N3, reverse coded).	Baseline (C), Short-term (T), Long-term (N)
Aspirations and intentions	Likelihood of applying to economics (D2, U1, O1). Field of interest (D1). Revealed aspiration proxy: willingness to receive updates/reminders (O5).	Baseline (D), Short-term (U), Long-term (O)
Information retention and persistence	"Do you remember the female economist who visited your class?" (L1). "I can describe at least one topic she discussed" (L2). "Can name any female economists" (N6).	Long-term (L, N)
Belief calibration and overconfidence	Percentile and probability beliefs about performance (E1–E2, P1). Optional delayed-choice task (P2) for time preferences.	Baseline (E), Long-term (P)

Table A2: Mapping of laboratory measures to theoretical mechanisms

Mechanism	Behavioral task / constructed variable (lab)	Session module
Belief updating (motivated cognition)	Short quantitative quiz (baseline performance); incentivized beliefs: perceived percentile and probability of scoring above median (pre and post information). Compute: (i) belief update = post−pre; (ii) absolute miscalibration = |belief − realized|; (iii) *asymmetric updating* after stereotype-consistent vs. stereotype-neutral signals.	Belief & info module
Overconfidence / miscalibration	Difference between believed rank and realized rank; Brier or quadratic scoring accuracy; fraction overconfident ($\mathbb{1}\{\text{belief} > \text{real}\}$).	Belief & info module
Information avoidance (identity protection)	Choice to view/delay/forgo feedback about own score or comparative rank (small cost/latency). Measure: take-up of performance feedback; WTP to avoid/obtain feedback.	Belief & info module
Competitiveness (willingness to compete)	Two-stage arithmetic task: Stage 1 piece-rate; Stage 2 choice between piece-rate vs. tournament (Niederle–Vesterlund). Outcomes: tournament entry; performance under competition; pay sensitivity. Variant: belief report about winning probability.	Competitiveness module
Identity threat sensitivity	Gender-salience prime before competition/belief re-elicitation. Outcome: change in (i) tournament entry, (ii) accuracy and confidence, (iii) task performance relative to neutral prime.	Competitiveness module
Risk preferences	Lottery-choice task (Holt–Laury *or* Eckel–Grossman). Construct CRRA bins or risk-class index; switching point; implied risk aversion.	Preferences module
Time preferences	Multiple price list for near-term vs. delayed payoffs (e.g., 7 vs. 30 days). Outcomes: switching point; implied discount rate; present-bias indicator (if 2-horizon variant used).	Preferences module
Social preferences (altruism / inequality aversion)	Dictator game (or Social Value Orientation slider). Outcomes: share sent; SVO angle/type. Optional: disadvantageous vs. advantageous inequality choices.	Preferences module
Aspirational commitment (revealed)	Low-stakes commitment choices tied to economics: (i) opt-in to receive program deadlines/scholarship info; (ii) allocate small share of earnings for tailored info/reminders; (iii) sign-up for a short follow-up mentoring slot. Construct: commitment index / WTP for aspiration support.	Aspirations module
Norm salience / perceived peer norms (optional)	Brief elicitation of beliefs about peers' intentions (e.g., % of classmates who think econ is suitable for women) and a non-binding pledge cue. Outcomes: norm belief; change in stated intention post-cue.	Optional add-on

Student Survey — Baseline

Instructions. Please answer honestly. For items with numbers, circle a value from 0 to 10, where 0 = Not at all / Strongly disagree and 10 = Very much / Strongly agree. For checkboxes, mark with ☐.

Identifiers (RA use only): School: _____ Class: _____ Student ID: _____

A. Background and academic information

A1. Gender: ☐ Female ☐ Male ☐ Prefer to self-describe: _____

A2. Age: ____ Grade/Year: ____

A3. Do you work for pay during the school week? ☐ No ☐ Yes, hours/week: _____

A4. Parent or guardian highest education: ☐ Primary ☐ Secondary ☐ High school ☐ Technical ☐ University ☐ Postgraduate

A5. Parent or guardian occupation related to economics, business, public policy, finance, or data analysis: ☐ No ☐ Yes ☐ Don't know

A6. Approximate GPA or average grade (0–100): _____

A7. Household proxies (mark all that apply): ☐ Own computer ☐ Internet at home ☐ More than 25 books at home ☐ Own bedroom

B. Interests and self-perception (0–10)

Circle a number from 0 to 10.

B8. Interest in subjects:
Economics 0 1 2 3 4 5 6 7 8 9 10
Mathematics 0 1 2 3 4 5 6 7 8 9 10
History/Social sciences 0 1 2 3 4 5 6 7 8 9 10
Spanish 0 1 2 3 4 5 6 7 8 9 10
English 0 1 2 3 4 5 6 7 8 9 10

B9. Self-assessed ability:
Economics (concepts, graphs, data) 0 1 2 3 4 5 6 7 8 9 10
Mathematics (algebra, problem solving) 0 1 2 3 4 5 6 7 8 9 10

B10. Compared with students of your gender, your level in economics 0 1 2 3 4 5 6 7 8 9 10

B11. Compared with students of the other gender, your level in economics 0 1 2 3 4 5 6 7 8 9 10

C. Beliefs about economics, identity, and gender stereotypes (0–10)

Circle a number: 0 = Strongly disagree / Not at all true, 10 = Strongly agree / Completely true.

C12. I understand what economists do in real jobs. 0 1 2 3 4 5 6 7 8 9 10

C13. Economics helps improve people's lives and reduce social problems (for example, inequality, health, education). 0 1 2 3 4 5 6 7 8 9 10

C14. Economics is mainly about money and finance (reverse coded). 0 1 2 3 4 5 6 7 8 9 10

C15. Men are naturally better at economics than women. 0 1 2 3 4 5 6 7 8 9 10

C16. Women face discrimination in economics-related careers. 0 1 2 3 4 5 6 7 8 9 10

C17. Most students of my gender think economics is a suitable field for women. 0 1 2 3 4 5 6 7 8 9 10

C18. Thinking about studying economics makes me nervous or uncertain (reverse coded). 0 1 2 3 4 5 6 7 8 9 10

C19. Studying economics fits with who I am (identity alignment). 0 1 2 3 4 5 6 7 8 9 10

C20. When I think of an economist, I imagine someone like me. 0 1 2 3 4 5 6 7 8 9 10

D. Aspirations and career intentions

D21. Field most interesting after high school (choose one):
☐ Economics/Finance/Data analysis ☐ Business/Management ☐ Engineering ☐ Health ☐ Education ☐ Law ☐ Other: _____

D22. Likelihood of applying to an economics program (0–10) 0 1 2 3 4 5 6 7 8 9 10

D23. Family or friend support if you study economics (0–10) 0 1 2 3 4 5 6 7 8 9 10

D24. I could afford to study economics if I wanted (0–10) 0 1 2 3 4 5 6 7 8 9 10

E. Optional short lab items (classroom-friendly)

E25. Percentile belief: if the class took a short math/economics quiz, what percentile would you be in? (0–100) _____

E26. Probability belief: probability that your score would be above the class median (0–100%) _____%

Thank you for your participation.

Student Survey — Short-term Endline

Instructions. Applied at the end of the day after the visit. Circle numbers from 0 to 10. Mark checkboxes with ☐.

Identifiers (RA use only): School: _____ Class: _____ Student ID: _____

S. Exposure and immediate perceptions

S1. Did you attend the visit by a female economist? ☐ No ☐ Yes

S2. I remember her name or affiliation (university, organization). 0 1 2 3 4 5 6 7 8 9 10

S3. I enjoyed the session. 0 1 2 3 4 5 6 7 8 9 10

S4. The visit increased my interest in studying economics. 0 1 2 3 4 5 6 7 8 9 10

S5. The visit increased my confidence in my quantitative skills. 0 1 2 3 4 5 6 7 8 9 10

S6. After the visit, I can imagine myself as an economist. 0 1 2 3 4 5 6 7 8 9 10

S7. My view of what economists do has changed after the session. 0 1 2 3 4 5 6 7 8 9 10

T. Beliefs and stereotypes (0–10)

T8. I understand what economists do in real jobs. 0 1 2 3 4 5 6 7 8 9 10

T9. Economics helps improve people's lives and reduce social problems. 0 1 2 3 4 5 6 7 8 9 10

T10. Economics is mainly about money and finance (reverse coded). 0 1 2 3 4 5 6 7 8 9 10

T11. Men are naturally better at economics than women. 0 1 2 3 4 5 6 7 8 9 10

T12. Studying economics fits with who I am. 0 1 2 3 4 5 6 7 8 9 10

U. Intentions and social support

U13. Likelihood of applying to an economics program (0–10) 0 1 2 3 4 5 6 7 8 9 10

U14. My family would support me if I study economics (0–10) 0 1 2 3 4 5 6 7 8 9 10

Thank you for your participation.

Student Survey — Long-term Endline (8–10 weeks later)

Instructions. Circle numbers from 0 to 10. Mark checkboxes with ☐.
Identifiers (RA use only): School: _____ Class: _____ Student ID: _____

L. Recall of the intervention and information retention

L1. Do you remember the female economist who visited your class? ☐ No ☐ Yes ☐ Partially

L2. I can describe at least one topic she discussed (for example, a policy problem or a career path). 0 1 2 3 4 5 6 7 8 9 10

L3. Since the visit, I have talked about economics with family or friends. 0 1 2 3 4 5 6 7 8 9 10

M. Interests and self-perception (persistence, 0–10)

M4. Interest in economics 0 1 2 3 4 5 6 7 8 9 10 Interest in mathematics 0 1 2 3 4 5 6 7 8 9 10

M5. Self-assessed ability:
Economics (concepts, graphs, data) 0 1 2 3 4 5 6 7 8 9 10
Mathematics (algebra, problem solving) 0 1 2 3 4 5 6 7 8 9 10

N. Beliefs about economics and gender stereotypes (persistence, 0–10)

N6. I understand what economists do in real jobs. 0 1 2 3 4 5 6 7 8 9 10

N7. Economics helps improve people's lives and reduce social problems. 0 1 2 3 4 5 6 7 8 9 10

N8. Economics is mainly about money and finance (reverse coded). 0 1 2 3 4 5 6 7 8 9 10

N9. Men are naturally better at economics than women. 0 1 2 3 4 5 6 7 8 9 10

N10. Studying economics fits with who I am. 0 1 2 3 4 5 6 7 8 9 10

N11. Can you name any female economists? ☐ No ☐ Yes (write one): _____

O. Aspirations, intentions, and perceived feasibility

O12. Likelihood of applying to an economics program (0–10) 0 1 2 3 4 5 6 7 8 9 10

O13. I could afford to study economics if I wanted (0–10) 0 1 2 3 4 5 6 7 8 9 10

O14. I would like to receive information about economics programs, deadlines, or scholarships (mark all that apply):
☐ Program brochures ☐ Admissions deadlines ☐ Financial aid/scholarships ☐ Career talks

O15. Main barrier that might stop you from studying economics (choose one):
☐ Cost ☐ Distance ☐ Family expectations ☐ Low confidence in math ☐ Prefer another field
☐ Other: _____

O16. Would you like to receive reminders or updates about economics programs? ☐ No ☐ Yes

Thank you for your participation.