

# Expected versus Actual Returns to Stem Master's Degrees: A Disciplinary Analysis

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## ABSTRACT

This study examines whether STEM students accurately anticipate economic returns from master's degrees by comparing expectations with actual graduate outcomes across Science and Engineering disciplines. Using survey data from 659 currently enrolled students and 223 employed graduates from Delhi universities, we find systematic disciplinary differences in expectation accuracy. Science students significantly overestimate returns by 58.7 percentage points ( $t = 2.207$ ,  $p < 0.05$ ), while Engineering students show no significant expectation bias despite underestimating by 17.2 percentage points ( $t = -0.548$ ,  $p > 0.05$ ). These findings reveal discipline-specific information failures requiring targeted interventions in career counseling and transparency policies.

**Keywords:** STEM Education, Expected Returns, Actual Returns

## INTRODUCTION

Educational investment decisions in STEM fields increasingly depend on students' expectations about future career returns, yet systematic evidence on expectation accuracy remains limited. This information gap is particularly critical in developing economies where master's degrees represent substantial family investments relative to household incomes. Inaccurate expectations can lead to suboptimal educational choices, over-borrowing, and subsequent career disappointment.

This study addresses a fundamental question: Do STEM students accurately anticipate economic returns from master's degrees, and do these expectations vary systematically across disciplines? Understanding expectation-reality gaps is essential for designing effective educational policies, particularly as India rapidly expands its graduate education capacity in science and technology fields.

Our analysis reveals striking disciplinary differences in expectation accuracy. While aggregate expectations appear reasonable, this masks systematic information failures affecting Science and Engineering students in opposite directions. Science students consistently overestimate returns while Engineering students exhibit more accurate expectations, suggesting fundamental differences in information environments between these academic fields.

These findings have immediate implications for higher education policy in India and other developing countries investing heavily in STEM education. Universities must move beyond aggregate outcome reporting to address discipline-specific information asymmetries that systematically mislead different student populations.

## LITERATURE REVIEW AND RESEARCH OBJECTIVES

### 2.1 Theoretical Framework

Educational expectations literature builds on human capital theory, where individuals make investment decisions based on anticipated lifetime returns to education. Becker (1962) established the foundational framework showing that educational choices reflect expected earnings differentials, while subsequent research by Weiss

(1995) highlighted signaling effects of credentials that operate independently of skill acquisition. However, optimal decision-making requires accurate information about returns, an assumption frequently violated in practice due to information asymmetries and limited labor market transparency.

Recent empirical research demonstrates systematic biases in educational expectations across different contexts. Jensen (2010) provides compelling evidence from developing countries showing that accurate information provision dramatically affects schooling decisions, suggesting that existing information failures significantly distort educational choices. Wiswall and Zafar (2013) document major-specific expectation biases using experimental methods, finding that students consistently overestimate returns to certain fields while underestimating others, with implications for optimal resource allocation across disciplines.

The growing literature on STEM education emphasizes positive employment outcomes and skills premiums in technology-driven economies, but rarely examines whether students accurately anticipate these benefits when making educational investment decisions. Stinebrickner and Stinebrickner (2012) demonstrate that students substantially revise expectations during college based on new academic performance information, suggesting that initial expectations may be systematically biased and responsive to information interventions. Zafar (2011) shows that college students form expectations through multiple channels, including family influences, media exposure, and peer interactions, with significant implications for understanding the sources of expectation bias.

However, existing research has primarily focused on undergraduate education in developed country contexts, leaving substantial gaps in understanding graduate-level expectation formation in developing economies. No previous studies directly compare expected versus actual returns for STEM master's degrees in contexts where such programs represent major family investments and where labor market information may be particularly limited. This gap is increasingly important as developing countries expand graduate education capacity to support economic transformation objectives.

## 2.2 Research Objectives

This study addresses three specific research objectives that contribute to understanding information efficiency in graduate education markets. First, we assess expectation accuracy by comparing anticipated percentage salary increases from STEM master's degrees reported by currently enrolled students with actual salary changes experienced by recent graduates. This direct comparison provides the first systematic evidence on whether students possess accurate information about the economic returns to graduate STEM education in a developing country context.

Second, we examine whether expectation-reality gaps vary systematically between Science and Engineering disciplines, reflecting different information environments and career pathway structures. We hypothesize that Engineering students maintain more accurate expectations due to stronger industry connections, more standardized career progressions, and clearer market signals about skill demands. Conversely, Science students may overestimate returns due to confusion between different educational levels, limited industry exposure, and information spillovers from high-visibility but atypical career outcomes.

Third, we analyze the policy implications of identified information failures for university transparency requirements, career counseling programs, and student financial aid policies. Understanding the magnitude and direction of expectation biases is essential for designing targeted interventions that improve educational investment decisions without distorting legitimate market signals about skill premiums and career opportunities.

## METHODOLOGY

### 3.1 Research Design and Sample Construction

This study employs a cross-sectional research design comparing expectations of currently enrolled students with actual outcomes of recent graduates, providing a natural experiment framework for assessing information accuracy without the confounding effects of temporal economic changes. We collected comprehensive primary data from two distinct groups across ten universities in Delhi between October 2022 and April 2023, ensuring

sufficient sample sizes for robust statistical analysis while maintaining comparability across institutional contexts.

The first group comprises 659 currently enrolled students from the 2021-22 academic cohort expected to graduate in 2022-23. These students provided detailed data on expected salary changes from master's completion, pre-enrollment employment history, and demographic characteristics. Data collection achieved 73% response rates through a multi-modal distribution strategy combining in-person classroom surveys during peak attendance periods and digital platforms with faculty coordination to maximize participation across different student populations.

The second group includes 408 recent graduates from the 2020-21 cohort who completed degrees in 2021-22, with our analysis focusing on 223 graduates employed post-completion to ensure comparable salary data across groups. Initial tracking efforts yielded 31.1% response rates from approximately 1,500 eligible graduates identified through systematic alumni database compilation, institutional records, and professional networking platforms. The employment restriction ensures that salary comparisons reflect actual market outcomes rather than being confounded by unemployment or further education decisions.

Delhi was selected as the study location due to its unique concentration of premier STEM institutions, diverse student population representing national demographic patterns, and status as a major employment hub for STEM graduates. The ten participating universities include central universities, state institutions, and autonomous colleges, ensuring representativeness across different institutional types, funding structures, and academic cultures that might influence student expectations and graduate outcomes.

### 3.2 Disciplinary Coverage and Sampling Strategy

**Science Disciplines:** Physics, Chemistry, Mathematics, Botany, and Zoology, representing 71% of national Science postgraduate enrollment according to AISHE data (Ministry of Education, 2020)

**Engineering Disciplines:** Civil, Mechanical, Electrical, Computer Science, Information Technology, Chemical, and other branches, representing 89% of national Engineering enrollment.

**Sampling employed two-stage stratification:** disciplinary stratification allocated students between Science (40%) and Engineering (60%), reflecting actual Delhi enrollment distributions, while institutional sampling ensured representation across university types.

### 3.3 Variable Construction and Measurement

**Expected Returns:** Percentage salary change calculated as  $[(\text{Expected post-master's salary} - \text{Expected pre-master's salary}) / \text{Expected pre-master's salary}] \times 100$ , collected from currently enrolled students through structured questionnaires.

**Actual Returns:** Percentage salary change calculated as  $[(\text{Actual salary} - \text{Pre-master's salary}) / \text{Pre-master's salary}] \times 100$ , collected from employed graduates with pre-master's work experience.

**Expectation Gap:** Expected Returns minus Actual Returns, with positive values indicating overestimation and negative values indicating underestimation.

### 3.4 Statistical Analysis

We employ descriptive analysis comparing means and medians across disciplines, supplemented by Welch's t-tests to assess statistical significance of expectation-reality gaps. Welch's t-tests accommodate unequal sample sizes and variances between enrolled students and graduates, addressing the substantial group size differences (Science 4.7:1 ratio, Engineering 2.0:1 ratio) and variance patterns in our data.

The statistical approach tests whether observed expectation gaps could arise by chance or represent systematic biases requiring policy intervention.

## RESULTS

### 4.1 Descriptive Analysis

Table 1 presents comprehensive comparisons of expected versus actual returns across Science and Engineering disciplines. Overall, students anticipate average salary increases of 175.1%, remarkably close to actual average returns of 171.3%. This 3.8 percentage point gap suggests aggregate expectation accuracy, yet substantial disciplinary differences emerge upon closer examination.

Science students expect 164.9% returns but experience only 106.2%, creating systematic overestimation of 58.7 percentage points. Conversely, Engineering students anticipate 187.0% returns while achieving 204.2%, underestimating actual outcomes by 17.2 percentage points.

**Table 1: Expected versus Actual Returns by Discipline**

Discipline	N (Expected)	N (Actual)	Expected Return (%)	Actual Return (%)	Gap (pp)	Median Gap (pp)
Science	356	75	164.9	106.2	+58.7	+8.0
Engineering	303	148	187.0	204.2	-17.2	+9.0
Overall	659	223	175.1	171.3	+3.8	+25.0

Source: Authors' own Compilation

Median comparisons reveal similar patterns with smaller magnitudes, confirming that extreme expectations drive much of the overestimation. Science students show higher variance in both expectations (385% standard deviation) and outcomes (147%), suggesting greater uncertainty about career trajectories compared to Engineering's more predictable patterns.

### 4.2 Statistical Significance Analysis

Welch's independent samples t-tests provide definitive evidence that the observed disciplinary differences represent systematic biases rather than random sampling variation. Science students' overestimation achieves statistical significance at conventional levels ( $t = 2.207$ ,  $df = 307.6$ ,  $p < 0.05$ ), indicating that this substantial gap is extremely unlikely to arise by chance and represents a systematic information failure requiring policy intervention. The magnitude of this effect, combined with its statistical significance, suggests that Science students systematically receive or process information about career prospects in ways that lead to substantial overestimation of master's degree returns.

Engineering students' underestimation, while economically meaningful in magnitude, does not achieve statistical significance ( $t = -0.548$ ,  $df = 200.7$ ,  $p > 0.05$ ), suggesting that this apparent bias could reasonably arise from random variation in sample composition or other factors unrelated to systematic information failures. This statistical pattern indicates that policy interventions should prioritize addressing Science student overestimation while treating Engineering student expectations as reasonably accurate on average.

The statistical analysis confirms that only Science disciplines exhibit systematic expectation bias requiring targeted policy intervention, while Engineering students maintain relatively accurate expectations despite the observed numerical underestimation. This distinction is crucial for policy design because it suggests that information interventions should be discipline-specific rather than applied uniformly across STEM fields, avoiding potential unintended consequences of correcting expectations that are already reasonably accurate.

Sample size considerations strengthen confidence in these results, as the large number of Science student observations (356 enrolled, 75 graduates) provides substantial statistical power to detect systematic biases, while the Engineering sample sizes (303 enrolled, 148 graduates) are sufficient to identify economically meaningful

effects if they existed. The statistical methodology explicitly accounts for unequal sample sizes and variance differences across groups, ensuring that the significance tests provide valid inference despite these data characteristics.

### 4.3 Variance and Distribution Analysis

Standard deviation patterns provide additional insights into disciplinary information environments. Science students demonstrate much higher variance in both expectations (385%) and actual outcomes (147%), suggesting limited consensus about career prospects. Engineering shows more predictable patterns with lower variance, particularly in expectations (213%), indicating better information availability.

Sample size ratios vary significantly between disciplines, from 4.7:1 in Science to 2.0:1 in Engineering, potentially reflecting differential career path persistence or response patterns. These ratios are incorporated into our statistical testing framework through Welch's methodology.

## DISCUSSION

### 5.1 Explaining Science Student Overestimation

The 58.7 percentage point overestimation among Science students reflects systematic information failures requiring targeted intervention. Several factors contribute to this bias:

**Academic-Industry Information Gap:** Science programs traditionally emphasize research careers and PhD pathways while most graduates enter industry positions with different compensation structures. Students may conflate long-term academic career prospects with immediate master's-level returns, creating unrealistic expectations about initial salary increases.

**Disciplinary Heterogeneity:** Science encompasses diverse fields with varying market outcomes, from high-demand areas like data science and biotechnology to traditional fields with more modest returns. Students may anchor expectations on exceptional success stories without recognizing the full distribution of outcomes.

**Limited Alumni Networks:** Science programs often lack structured industry engagement compared to Engineering disciplines. This reduces opportunities for current students to gather accurate information about typical career trajectories and salary progressions from recent graduates working in industry positions.

**Media and Information Bias:** Popular media frequently highlight exceptional scientific careers and breakthrough discoveries while providing limited coverage of typical career paths for master's degree holders in Science fields.

### 5.2 Engineering Student Accuracy

Engineering students demonstrate relatively accurate expectations despite slight underestimation, suggesting more effective information transmission mechanisms:

**Industry Integration:** Engineering programs maintain stronger connections with industry through internships, placement programs, and advisory committees. This provides students with more accurate information about typical salary levels and career progression timelines.

**Professional Networks:** Engineering fields have well-established professional associations and alumni networks that facilitate information sharing about career outcomes and market conditions.

**Standardized Career Paths:** Engineering careers follow more predictable patterns with clearer progression steps, making it easier for students to form accurate expectations based on observable precedents.

The slight underestimation may reflect conservative bias in Engineering culture or students underestimating rapid technological change, driving higher-than-expected premiums for advanced technical skills.



### 5.3 Policy Implications

The documented information failures demand immediate and systematic policy responses from universities, government agencies, and professional organizations to address the substantial welfare costs of suboptimal educational investment decisions. Universities should immediately implement comprehensive transparency requirements, including discipline-specific graduate outcome reporting with detailed employment statistics, salary distributions by percentile, and longitudinal career trajectory data that extends beyond immediate post-graduation outcomes. This transparency must disaggregate results by specific degree programs rather than broad disciplinary categories, as our findings suggest that even seemingly similar fields may have substantially different market outcomes and information environments.

Career counseling programs require fundamental restructuring to address the discipline-specific biases we document, particularly for Science students who demonstrate systematic overestimation requiring active correction rather than general information provision. These programs should incorporate structured interactions with recent graduates working in typical industry positions, mandatory workshops on realistic career timeline expectations, and systematic presentation of labor market data that counters the high-visibility but atypical success stories that may currently dominate student information sources. Engineering programs, while performing better in terms of expectation accuracy, should enhance communication about the strong market prospects their graduates actually experience to prevent potential underinvestment in valuable skills.

Financial aid counseling represents another critical intervention point, as students making borrowing decisions based on inflated return expectations may accumulate unsustainable debt levels that create long-term financial distress. Aid counselors should incorporate discipline-specific return data into loan counseling sessions, require students to demonstrate understanding of realistic salary progression timelines, and consider implementing differential borrowing limits based on documented employment outcomes rather than using uniform policies across all graduate programs. The magnitude of Science student overestimation suggests particular attention to borrowing decisions in these fields where the gap between expectations and reality is most severe.

## CONCLUSION

This study provides the first systematic evidence of discipline-specific information failures in STEM graduate education expectations, revealing that apparent aggregate accuracy in return anticipation conceals systematic biases affecting Science and Engineering students in opposite directions. Science students significantly overestimate returns by 58.7 percentage points ( $p < 0.05$ ), representing one of the largest documented expectation biases in educational economics literature and suggesting systematic information failures requiring immediate policy intervention. Engineering students demonstrate relatively accurate expectations despite modest numerical underestimation that lacks statistical significance, indicating that their information environment functions more effectively.

The magnitude and statistical significance of Science student overestimation represent a critical challenge for educational policy in developing economies where graduate education expansion is a key component of economic development strategies. These students may accumulate substantial educational debt based on fundamentally unrealistic career expectations, potentially leading to individual financial distress and broader inefficiencies in human capital allocation. The systematic nature of this bias, demonstrated through rigorous statistical testing, confirms that it requires coordinated institutional intervention rather than being dismissible as random variation or individual decision-making errors.

Our findings contribute significantly to the educational expectations literature by extending beyond undergraduate education to examine graduate-level decision-making in developing country contexts where such research has been limited. The discipline-specific nature of expectation biases challenges previous research that has often treated educational fields as homogeneous and suggests that information interventions must be carefully targeted to address specific institutional and labor market characteristics rather than applying uniform solutions across all academic areas.

The research methodology comparing current student expectations with recent graduate outcomes provides a robust and replicable framework for assessing expectation accuracy that addresses many limitations of previous studies relying on hypothetical scenarios or cross-sectional data. This approach could be readily adapted to examine expectation formation in other educational contexts, different countries, or alternative time periods to build a more comprehensive understanding of information efficiency in educational markets worldwide.

**Policy Recommendations:** Universities should immediately implement discipline-specific transparency measures, enhance Science program career counseling, and develop systematic alumni engagement programs. The systematic nature of Science students' overestimation requires coordinated intervention across institutions rather than isolated responses.

**Limitations:** This analysis focuses on Delhi universities during 2022-23 and may not generalize to other regions or time periods. Post-graduation tracking is limited to 1-2 years, potentially missing longer-term career development. Selection bias in survey responses across different groups represents another limitation requiring careful interpretation.

The documented information failures demand urgent attention from policymakers and institutional leaders to prevent suboptimal educational investments and ensure students make informed decisions about STEM graduate education.

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