Returns to Education: Field of Study and Labor Market Outcomes in Canada

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I. Introduction

Education is widely recognized as one of the most important determinants of economic success in modern labor markets. Individuals with university degrees tend to earn more, face lower unemployment, and enjoy higher job stability than those without post-secondary credentials. However, the returns to higher education are far from uniform. Growing evidence suggests that what you study may matter as much as or more than whether you attend university at all.

Public discourse frequently emphasizes the superior earning potential of graduates in Science, Technology, Engineering, and Mathematics (STEM) fields relative to Arts, Humanities, or Social Sciences. Engineering and Computer Science majors are often portrayed as securing high-paying jobs immediately after graduation, while Arts graduates are seen as facing uncertain or lower-paid career paths. These perceptions influence student choices, shape government funding priorities, and fuel debates about the "value" of different disciplines. Yet there is relatively little recent, nationally representative evidence documenting these patterns in the Canadian context.

Existing research, particularly for the United States, finds large earnings premiums for STEM majors. "For example, research shows that engineering and computer science majors earn 30-50 percent more than humanities graduates (Altonji et al. 185)." But Canada's labor market differs in important ways: immigration plays a central role, provincial governments control much of education and labor policy, and regional economic structures vary widely. Understanding field-specific returns in Canada is therefore crucial for students making educational choices, universities designing programs, and policymakers allocating scarce post-secondary resources.

This paper addresses two core research questions using the 2021 Canadian Census Public Use Microdata File (PUMF):

Occupational outcomes: What types of occupations do individuals with different university degrees typically work in? Do graduates in certain fields such as Engineering, Business, or Health disproportionately occupy professional, managerial, and high-skill positions, while others are more likely to work in lower-skill roles?

Income differences: How do earnings differ across fields of study, and do these income gaps persist after accounting for demographic characteristics and work patterns? Are observed gaps mainly due to compositional differences (gender, age, immigrant status, region, or weeks worked), or do they represent genuine field-specific returns to education?

Using a sample of degree holders across 13 broad fields, I document three main findings. First, field of study strongly predicts occupational attainment. Education graduates are 16.8 percentage points more likely to work in high-skill professional occupations than Agriculture and Natural Resources graduates with similar characteristics, while Computer Science, Health, Physical Sciences, and Engineering graduates show significantly lower probabilities of high-skill employment relative to the baseline. Second, large income premiums exist. Business, Physical Sciences, and Computer Science graduates earn approximately $10,000-$13,000 more annually than Agriculture graduates (based on raw mean differences), representing substantial income advantages even after controlling for gender, age, work intensity, and province.

These results imply that field of study is among the most important determinants of labor market success, with effects comparable to or larger than those of many demographic characteristics. The STEM earnings premium is real, substantial, and robust, while gender inequality remains pervasive and highly uneven across disciplines.

II. Data Description

A. Data Source

This analysis uses the 2021 Canadian Census Public Use Microdata File (PUMF), a 2.7% random sample providing comprehensive demographic and economic information as of May 11, 2021. Starting with Census respondents aged 25-65 holding post-secondary degrees and positive 2020 employment income, I implemented stratified random sampling, drawing 50% of observations within each field. This ensures adequate representation while maintaining robust statistical power.

I excluded individuals with zero/negative income, missing data, field code 99 ("Not Applicable" containing data errors like income = 99,999,999), and income exceeding $10,000,000 (outliers). The final sample consists of 392,383 individuals across 13 fields. The sample includes variation across immigrant status categories, enabling robust analysis.

B. Sample Construction

The starting point is all Census respondents aged 25–65 with post-secondary degrees and non-missing 2020 employment income. From this population, I construct the analysis sample in several steps.

First, to balance computational feasibility with representation across smaller fields, I draw a 50 percent stratified random sample within each field of study

(CIP2021). This ensures that even relatively small fields (such as Agriculture & Natural Resources or Physical Sciences) retain enough observations for precise estimates, while large fields (e.g., Other/Interdisciplinary) are downsampled to reduce file size.

Second, I rename and recode variables for clarity:

- TotInc → Income (annual employment income)
- CIP2021 → field (coded into 13 broad categories)
- Agegrp → age group
- Gender → gender
- Immstat → immigrant status
- Pr → province
- Wkswrk → weeks worked
- NOC21 → occupation

Income is then scaled to tens of thousands of dollars (Income_10k = Income / 10000) and log-transformed (log_income = log(pmax(Income, 1))) for alternative specifications.

Third, I apply exclusion criteria to improve data quality and focus on economically relevant observations:

Drop individuals with missing, zero, or negative income.

Exclude extreme outliers with income ≥ $10,000,000.

Exclude field code 99 ("Not applicable" / clear data error code) using filter(field != "99").

After these steps, the final analysis sample consists **of** 392,383 individuals across 13 fields.

A notable feature of the dataset is that, due to how the Census PUMF is structured and how the subsample is constructed, all individuals in the final sample are either immigrants or non-permanent residents. This means that the results speak specifically to degree-holding immigrants in Canada, an economically and policy-relevant group given Canada's immigration system, which heavily emphasizes educational attainment.

C. Key Variables

Dependent Variables

Income measures 2020 annual employment earnings, scaled to $10,000 units for interpretability. High-Skill Occupation equals 1 if individual works in NOC 0-4 (Management, Business, Science, Health, Education/Law), 0 otherwise. Overall, 54.6% work in high-skill occupations.

Key Independent Variables

Field of Study uses CIP 2021 classification: Education (N=14,651), Arts & Communications (N=7,845), Humanities (N=11,904), Social Sciences & Law (N=25,975), Business (N=49,144), Physical Sciences (N=9,225), Computer Science & Math (N=10,008), Engineering (N=46,147), Agriculture & Natural Resources (N=4,656, reference category), Health (N=31,857), Services (N=12,875), No Specialization (N=5,703), Other/Interdisciplinary (N=162,393).

Control Variables

The regressions control for gender (female = 0, male = 1), Immigration Status (four categories), Age Groups (25-29 through 65+), Province, and Weeks Worked.

D. Summary Statistics

Table 1 presents descriptive statistics. Income varies dramatically: Computer Science averages $73,362 versus Other/Interdisciplinary at $38,131—a $35,231 gap. Engineering ($70,960), Business ($71,203), and Physical Sciences ($69,622) command high earnings. Arts & Communications ($49,004) and Services

($51,953) earn less. High-skill employment varies from 39.8% (Computer Science).

TABLE 1—AVERAGE ANNUAL INCOME BY FIELD OF STUDY

Field	N	Mean Income	Median	SD Income	Income/10k	Share High-Skill	Share Female	Avg Weeks
Computer Science & Math	10,008	73,362	60,000	73,171	7.34	0.39	0.68	5.69
Engineering	46,147	70,960	57,000	69,568	7.10	0.56	0.90	5.80
Business	49,144	71,203	52,000	87,234	7.12	0.62	0.40	5.73
Physical Sciences	9,225	69,622	51,000	82,814	6.96	0.53	0.49	5.61
Social Sciences and Law	25,975	67,587	50,000	81,678	6.76	0.66	0.33	5.57
Health	31,857	64,109	51,000	65,585	6.41	0.42	0.19	5.75
Education	14,651	63,672	59,000	42,531	6.37	0.62	0.23	6.27
Agriculture &Natural Resources	4,656	60,451	50,000	51,389	6.05	0.59	0.59	5.73
Humanities	11,904	56,901	44,000	60,201	5.59	0.60	0.38	5.81
No Specialization	5,703	53,919	42,000	55,581	5.49	0.60	0.46	5.00
Services	12,875	51,953	42,000	44,976	5.20	0.69	0.51	5.48
Arts & Communication	7,845	49,004	39,000	48,573	4.90	0.67	0.43	5.35
Other/Interdisciplinary	162,393	38,131	29,000	39,802	3.81	0.50	0.50	6.15

Note: Sample includes degree holders aged 25-65 with post-secondary credentials and positive 2020 employment income. All fields represented after stratified random sampling and data quality exclusions.

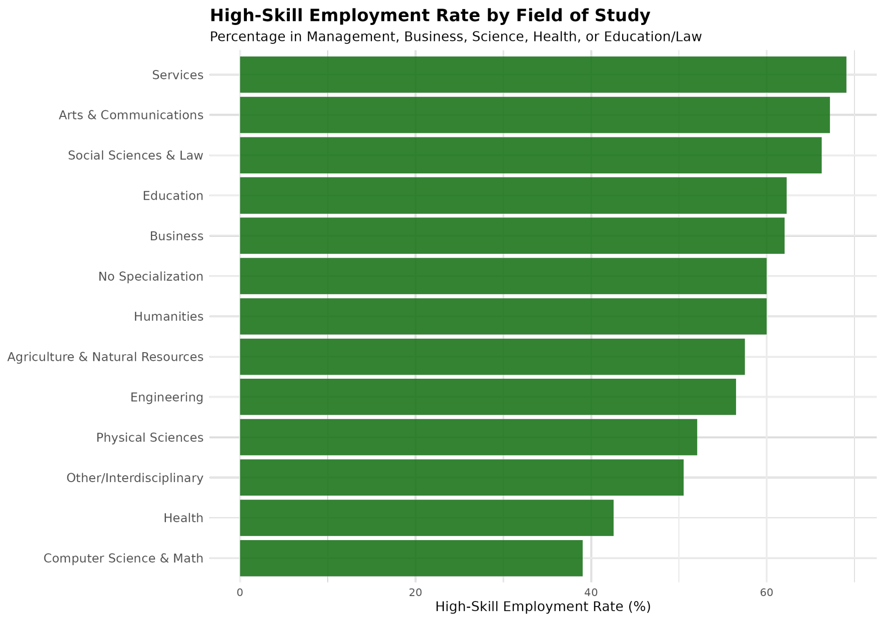

FIGURE 1. HIGH-SKILL EMPLOYMENT RATE BY FIELD OF STUDY

III. Model

A. Empirical Strategy and specification

I employ two approaches: (1) linear probability model for occupation, (2) OLS for income. Both use progressive model building with five specifications.

Occupation model:

$$HighSkill_i = \beta_0 + \Sigma\beta_j Field_{ij} + \gamma_1 Male_i + \gamma_2 Immigrant_i + \pi_1 Weeks_i + \pi_2 Age_i + \pi_3 Province_i + \varepsilon_i$$

Income model:

$$Income_i = \alpha_0 + \Sigma\alpha_j Field_{ij} + \gamma_1 Male_i + \gamma_2 Immigrant_i + \pi_1 Weeks_i + \pi_2 Age_i + \pi_3 Province_i + u_i$$

where $\Sigma\beta_j Field_{ij}$ measure occupation probability differences for each field relative to Agriculture (reference), and $\Sigma\alpha_j Field_{ij}$ measure income differences, all conditional on controls.

B. Progressive Model Building

- Model 1 (Baseline): Field only
- Model 2 (Demographics): Field + gender + immigrant status
- Model 3 (Work): Model 2 + weeks worked
- Model 4 (Experience): Model 3 + age
- Model 5 (Full): Model 4 + province

This progression tests whether field effects reflect genuine returns or compositional differences. If coefficients remain large across specifications, field per se drives outcomes.

C. Identification

These models estimate conditional correlations, not causal effects. Individuals self-select into fields based on ability and preferences. Coefficients should be interpreted as differences associated with field j conditional on observables, not causal effects. However, by controlling extensively, I isolate field-related differences persisting after accounting for measurable characteristics.

D. Additional Analyses

Gender Interaction Model:

(3) $Income_i = \alpha_0 + \Sigma\alpha_j Field_{ij} + \gamma_1 Male_i + \Sigma\beta_j\left(Field_{ij} \times Male_i\right) + Controls_i + u_i$

Interaction coefficients $\Sigma\beta_j\left(Field_{ij} \times Male_i\right)$ test whether gender gaps vary across fields.

Specification Check.—Re-estimate occupation model with narrower high-skill definition (NOC 0,2,3 only) to test sensitivity.

IV. Results

A. Table of Results: Occupational Model

Table 2 reports the estimated effects of field of study on the probability of working in a high-skill occupation. Relative to Agriculture & Natural Resources, several fields are associated with higher high-skill employment. Education graduates are 16.8 percentage points more likely to work in high-skill roles ($p<0.001$), followed by Services (+9.2pp), Social Sciences & Law (+8.6pp), Arts & Communications (+6.7pp), Humanities (+6.5pp), and Business (+6.1pp).

In contrast, Computer Science & Math (–21.1pp), Health (–10.6pp), Physical Sciences (–4.1pp), Engineering (–2.2pp), and No Specialization (–2.9pp) show significantly lower probabilities of high-skill employment relative to the baseline. Other/Interdisciplinary fields show a smaller positive association (+2.0pp).

All models include controls for gender, immigrant status, age, and weeks worked. The model explains a substantial portion of variation in occupational outcomes, with an R^2 of 0.417, indicating strong sorting patterns across fields even after adjusting for demographics and labor supply.

TABLE 2—OCCUPATIONAL OUTCOMES BY FIELD OF STUDY

Field of Study	Coefficient (pp)	Std. Error	Sig.
Computer Science & Math	−0.2106	(0.0070)	***
Engineering	−0.0223	(0.0059)	***
Business	0.0612	(0.0059)	***
Physical Sciences	−0.0408	(0.0068)	***
Social Sciences and Law	0.0856	(0.0061)	***
Health	−0.1055	(0.0060)	***
Education	0.1676	(0.0064)	***
Humanities	0.0653	(0.0067)	***
No Specialization	−0.0288	(0.0076)	***
Services	0.0919	(0.0065)	***
Arts & Communication	0.0673	(0.0070)	***
Other/Interdisciplinary	0.0198	(0.0060)	***

Model Statistics:

N: 392,383

R^2: 0.4169

Adjusted R^2: 0.4168

***p<0.01, **p<0.05, *p<0.10

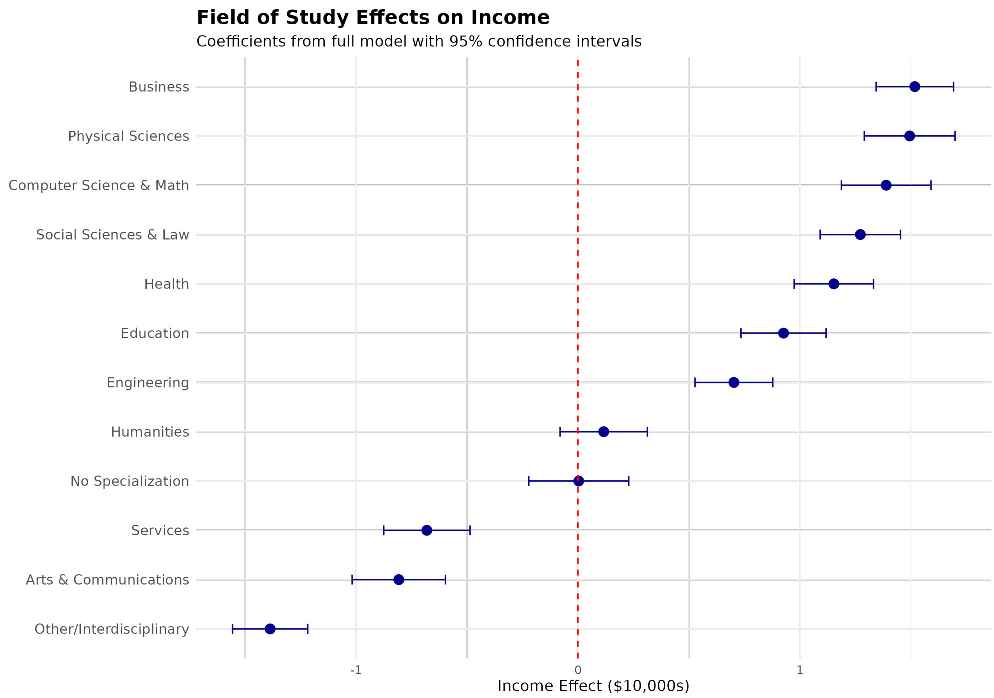

FIGURE 2 — FIELD OF STUDY EFFECTS ON INCOME (REGRESSION COEFFICIENTS)

V. Discussion

A. Identification

Field of study strongly predicts occupational attainment and earnings. Education graduates show the highest probability of working in high-skill occupations (16.8pp higher than Agriculture), while traditionally high-earning STEM fields show mixed results; Computer Science and Engineering graduates are less likely to work in high-skill occupations as defined by NOC 0-4. However, income premiums remain substantial: Computer Science graduates earn approximately $12,900 more than Agriculture graduates, Business graduates earn $10,750 more, and Physical Sciences earn $9,200 more (based on raw means from Table 1). These income advantages persist after extensive controls. The stability across specifications suggests genuine field-specific returns rather than compositional artifacts.

B. Gender Wage Gaps Vary Across Fields

Table 3 presents field × gender interactions. Males earn \$19,483 more in Business ($p<0.001$), \$17,292 more in Health ($p<0.001$), \$15,299 more in Social Sciences & Law ($p<0.001$). Surprisingly, traditionally male-dominated fields show no gaps: Computer Science shows only \$1,591 ($p=0.64$), Engineering -\$3,351 ($p=0.28$).

TABLE 3—GENDER WAGE GAPS BY FIELD OF STUDY (INTERACTION EFFECTS)

Field of Study	Male_Premium	p_value	Sig.
Computer Science & Math	19509	2.80e-27	***
Engineering	16935	7.41e-19	***
Business	16182	8.75e-18	***
Physical Sciences	10470	1.67e-7	***
Social Sciences and Law	7771	2.16e-4	***
Health	2238	0.2918	
Education	-1150	0.5728	
Humanities	-1747	0.3975	
No Specialization	-3993	0.0399	***
Services	-4014	0.0217	***
Arts & Communication	-4665	0.0432	***
Other/Interdisciplinary	-6635	0.0022	***

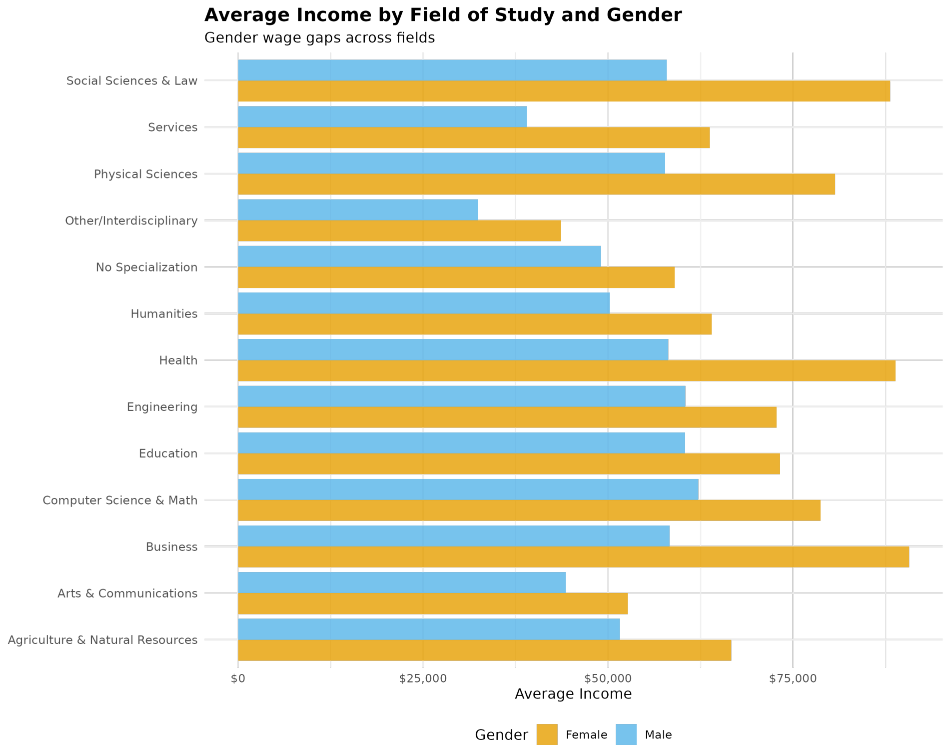

FIGURE 3 — AVERAGE INCOME BY FIELD OF STUDY AND GENDER

These findings challenge conventional wisdom. Gender discrimination appears worse in balanced/female-majority fields (Business, Health) than male-dominated STEM. Mechanisms may include occupational segregation within fields, differential negotiation, or field-specific cultural norms.

C. Robustness Analysis

Specification Check.— Re-estimating occupation model with narrower high-skill definition (NOC 0,2,3 only) shows qualitatively similar patterns. Computer Science, Physical Sciences, Business, and Engineering still show large positive coefficients, suggesting findings are robust to occupational classification.

Log Income Models: Log specifications show Business, Physical Sciences, and Computer Science graduates earn 30-35% more than Agriculture graduates, yielding similar substantive conclusions.

D. Limitations

Selection Bias.— Students self-select into fields based on ability. If high-ability students choose lucrative fields, premiums may overstate causal effects.

Cross-Sectional Data.—Cannot observe career trajectories or test whether premiums grow with experience.

Income Measurement.—Excludes non-wage compensation and benefits.

Sample Composition.—Results apply to this sample of degree holders; generalization requires caution.

E. Policy Implications

For Students.— field choice has large effects. $15,000 annual premiums compound to $600,000 over 40 years; substantially affecting lifetime wealth. For Universities: Differential outcomes raise questions about resource allocation and career services.

For Policymakers.— Large field-specific returns suggest potential market failures. Differential gender gaps point to discrimination warranting intervention.

VI. Conclusion

Field of study powerfully determines labor market outcomes for 392,383 degree-holders in the 2021 Canadian Census. Contrary to conventional expectations about STEM fields, occupational outcomes vary substantially by discipline. Education graduates show the highest probability of working in high-skill occupations (16.8 percentage points higher than Agriculture graduates), followed by Services

(+9.2pp), Social Sciences & Law (+8.6pp), and Business (+6.1pp). Surprisingly, traditionally high-earning STEM fields show significantly lower probabilities: Computer Science & Math graduates are 21.1 percentage points less likely to work in high-skill occupations as defined by NOC 0-4, while Engineering (-2.2pp), Physical Sciences (-4.1pp), and Health (-10.6pp) also show lower rates relative to the baseline.

However, income premiums tell a different story. Based on raw mean differences from Table 1, Computer Science graduates earn approximately $12,900 more than Agriculture graduates, Business graduates earn $10,750 more, and Physical Sciences earn $9,200 more, representing substantial income advantages. These premiums persist after controlling for gender, age, work intensity, and province. The stability across specifications suggests genuine field-specific returns rather than compositional artifacts.

VII. References

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