Dean&Francis
ISSN 2959-6149

Is Graduate Unemployment More Strongly Associated With Field of Study Than With Regional Economic Conditions?

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Abstract:
The analysis draws on survey data from 1,500 recent graduates, examined using logistic regression models. Descriptive statistics showed that 7.3% of respondents experienced short-term unemployment, with Humanities and Business graduates disproportionately affected. Regional unemployment averaged 5.6%, highlighting variation in local economic conditions. Regression results revealed that field of study exerted the strongest effect on unemployment risk. Graduates from Humanities and Business disciplines faced odds ratios exceeding two compared to STEM graduates, reinforcing the structural advantage of quantitatively oriented and occupation-specific degrees. Regional unemployment also had a significant and independent impact. Each percentage-point rise in the local unemployment rate corresponded to a measurable increase in the probability of graduate joblessness. Interaction terms between field and region did not yield strong or consistent effects, thus suggests that although fields differ in baseline employability, their vulnerability to regional shocks is broadly comparable. The findings imply that policy responses must operate on two fronts: redesigning curricula to enhance skill transferability and promoting regional economic resilience to ensure diverse opportunities for graduates.

Keywords: *graduate unemployment, field of study, regional labour markets, labour economics, higher education outcomes, logistic regression.*

1. Introduction

Graduate unemployment is a burning economic and social issue in most countries that influences life paths individually and macro-level dynamics in the labor-market. The move into the wage labor force can usually be accompanied by significant early-career choices, such as geographic mobility, skill-investment, or sectoral-targeting, which can shape lifetime income, career trajectories and have been

ISSN 2959-6149

found to sometimes impact significant academic achievement and psychological well-being with recent graduates (Andabayeva et al., 2024). High graduate unemployment will have direct financial implications on individuals, higher fiscal costs on some safety nets, and may heighten social inequality when poor economic results are disproportionately suffered by disadvantaged populations. The reason behind the high level of unemployment among the young in the career is thus a question of not only personal well-being but also concern to design policy.

Technical and vocational programs and health professions as well as most of the STEM areas produce marketable skills and more direct career opportunities resulting in less post-graduated joblessness. Degrees that are more broadly-based in humanities or any of the social sciences may be less occupation-specific and more susceptible to underemployment or even temporary unemployment, since graduates face a wider range of potential occupations and, more investments, gather more levels of occupation-specific qualifications (Zanin-Yost & Brungard, 2022). The preference of employers towards certain skills, accreditation conditions, the negatively skeptic existence of formalized entry tiers and path systems may create a consistent inequality in short-term jobs throughout the disciplines.

The second reason is more emphasized on the role of the regional economic condition during which graduates get in their labour market. Availability of entry-level jobs, and therefore, the rate at which the graduates become employed, is determined by local labour-market tightness, industry composition, and cyclical shocks. Areas with deadening industries, which have few in the new business formation or very high unemployment create fewer vacancies which are suitable, and those opportunities which are available have intensified competition (Mahboubi & Zhang, 2025). Being trained took over in a declining region may also have scarring effects: initial jobs of poor quality, worse employer fits and slow returns to wage levels that does not fully disappear during the immediate recessionary timeframe. These temporal and geographical forces imply that the same graduates can get varying opportunities merely due to the place-time of their job search.

Certain majors bring highly portable skills, general employer demand that insulate the graduate against dips in a local market, whereas others, clumping industries or localized employer groups, produce graduates who are susceptible to market shocks in their area (Ramasubramanian et al., 2022). The interaction that takes place between the supply-side characteristics of educational programs and demand-side geographic difference can hence produce heterogeneous effects on the populations of graduates. This implication increases the empirically significant question of whether on the whole field of study or the conditions of region provide a stronger attachment with short-term graduate unemployment, and whether the relationship across fields is systematic.

2. Literature Review

2.1 Empirical patterns

In several national surveys and cohorts, there is a consistent statistically significant empirical trend, and the initial employment opportunities of graduates vary significantly depending on major, with occupation-specific preparation and measurably technical skills always reporting lower unemployment and underemployment rates compared to broadly-prepared arts and social-science programs. The study by Smith and White (2022) illustrates that major engineering, nursing, and other applied fields of STEM exhibit significantly lower rates of underemployment and a shorter rate of transitioning to career-relevant occupations, whilst several humanities and generalist social-science majors register the incidence of non-college-level employment or prolonged search periods (Smith & White, 2022). Federal documents on the state of education by the National Center of Education Statistics (NCES) bring together facts suggesting that median incomes and unemployment rates differ by major, and there are notable benefits to most STEM and health professional among young bachelor's degree holders (Edwards et al., 2021). Such recurrent constellations between discontinuous data sources point to the view that field-level disparities are not minor or short-lived matters, but exceptional structural antecedent to the age-related labour-market performance that demands eminence.

2.2 Mechanisms linking field content to employability

The field-specific empirical regularities are hypothetically grounded in a set of several mechanisms that combine together to explain why occupationally specific majors lessen risk of early unemployment and generalist majors are associated with risk of early unemployment in some cases (Greenhalgh et al., 2024)disbenefits, harms and personal, sociocultural and environmental impacts—of masks and masking. Our synthesis of evidence from over 100 published reviews and selected primary studies, including re-analyzing contested meta-analyses of key clinical trials, produced seven key findings. First, there is strong and consistent evidence for airborne transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2. Occupation-specific human capital which has been developed via clinical placements, professional accreditation and apprenticeship-based training establishes direct hiring pipelines and reduces matching costs incurred by employers hence it reduces the length of search and chance of being unemployed. Structured graduate recruitment procedures and employer signalling are beneficial to some majors where grads and quantifiable skills fit the job profiles very closely; in place of graduate pipes pipelines establish a smoother entry of graduates into employers, with potential opportunities. There is transferability of skills: broadly diffusive cognitive, interpersonal, analytic skill-based programs could provide expanded sectoral opportunity, as well as cross-geographical mobility, in insulating graduates to local demand shocks, but specialised skills training programs can increase the reliance of graduates on local employers in need of those specific skills (Holliday, 2023).

2.3 Temporal and spatial context

The opportunities attainable by graduates do not solely depend on their major but the exact date when graduates start their work place and the territorial circumstances of the job-search are also influential determinants as macro and regional shocks change the level of vacancy opportunities of entry level. Tomlinson and Tholen (2023) statistically reveal this with examples documented of scarring effects of graduating in recessions: people who enter graduate careers during slumps often end up with poorer employers' match characterized by associated earnings loss and slower promotion, specializing in a phenomenon that continues over years despite recovery at the start of winter booms (Tomlinson & Tholen, 2023). Notably, scarring also acts via both the timing overlaps between graduation and macro downturns and the targeted strength of the latter: regional industry structure, vacancy creation and rates of firm entry vary significantly across locations, so one equally qualified graduate will receive different early returns just on the basis of the place of suspension. The significance of such a spatio-temporal view is the reason why the regional unemployment rate at graduation is a relevant contextual variable because the relative effects of field versus place to short term unemployment are important points of analysis (Gayawan et al., 2025).

2.4 Socio-economic heterogeneity and the role of mobility and social capital

The effects of geographic and temporal disadvantages are not equally distributed but as a function of the socio-economic assets, social capital, and relocation possibilities of graduates, thus individuals who start in more fortunate circumstances can avoid or reduce more scarring. Similar findings have been given by Gilligan et al. (2025), in the context of less fortunate family backgrounds of UK graduate populations; in that case, those more destined to get opportunities to leave the depressed domestic markets through networks, financial cushions, or mobility, the disadvantaged graduates suffer greater costs and limitations, trapping them in weaker quality of matches (Gilligan et al., 2025). This heterogeneity is important to the field-versus-region question since the protective value of individual majors by supplying portability or proximity employer pipelines may influence family endowments and migration capability to produce stratified results that are potentially hidden in the packaged field or regional primary effect models.

2.5 Field-of-study mismatch

A related phenomenon to the notion of field-level unemployment is field-of-study mismatch, which refers to working in a job not matching one's educational background; the concept of mismatch can be used to understand the rise in unemployment risk by supply-side graduation decisions and industry-level structures. The International PIAAC data provided by Bischof (2024) demonstrates how mismatch is not only created due to the over-supply of graduates in specific areas but also caused by low local or sectoral demand of the required skills, which leads to wage penalties and a greater likelihood of unemployment or underemployment (Bischof, 2024)9,22]]},“issued“:{„-date-parts“:[[„2024“]]}}}],“schema“:“https://github.com/citation-style-language/schema/raw/master/csl-citation.json“} . More importantly, Bischof in his work suggests that industry composition and vacancy structure: the more skills can be readily transferred to sectors, industry-specific fields will only be sensitive to regional shock, whereas more specialistic ones require the pool of employers to concentrate in a few locales. The conceptual basis as well as the mechanism of anticipating systematic field × region performance can be explained by the use of mismatch theory in the short-term unemployment.

2.6 Empirical studies combining field and region

Despite the large number of studies considering either the field differences or regional scarring alone, only a small number of these studies directly estimate joint models comparing the relative explanatory power of field versus local conditions as well as permit the slopes to be heterogeneous. In those cases that have such joint analysis have found that the field dummies can explain a significant proportion of non-state difference in unemployment, but that regional variables and field-sen-

ISSN 2959-6149

sitive combinations to them add significant incremental explanatory force in others, at least of some majors and disadvantageous subgroups. (More, 2024) highlight how large the field differences in underemployment are, whereas report (Bischof, 2024)9,22]]},“issued“:{„-date-parts“:[[„2024“]]}}}],“schema“:“https://github.com/citation-style-language/schema/raw/master/csl-citation.json“} long-standing location-timed impact; (Bahl & Sharma, 2023) links these strands to hypothesis of a heterogeneity empowered by a mismatch. With these studies together, it is liked that neither field nor place will focus on explaining short term graduate unemployment, rather parsimonious joint modeling with both fields and regions will be required to express such phenomenon of conditional vulnerability across fields and regions.

2.7 Methodological challenges

A number of methodological challenges relevant to the interpretation of field and regional effects encompass the selection into majors and location, measuring mismatch and labor-market tightness (regional rate of unemployment is a crude proxy that can conceal the dynamics of industry vacancies), and causal identification (correlations at cross-section are no defense as to whether anything causes unemployment). Longitudinal and quasi-experimental designs, in which graduates are related to firm panels, existential regional shocks are taken advantage of, or instrumental variables are employed is more likely to offer leveraged causal inferences, as demonstrated in (Ajibade, 2025). The analytic approach to these trade-offs is that a very careful mix of micro-models carefully controlled with sensitivity run and robustness checks is justified, but that some causal propositions are prone better to richer panel evidence or experimental evidence.

2.8 Research Gaps Motivating the Present Study

The available literature confirms that the field of study and actual regional labor markets are manifest material factors of short-term graduate unemployment and that the influence of both is interdependent by operating on the principle of skill very specificity, employer demand and mobility, social capital. The present research fills this gap by relying on first-hand statistics and a formal logit framework that estimates both the main effects and field x region interaction, provides substantive interpretation of marginal effects, and exposes results to rigorous assessments of robustness; the latter establishes where interventions are most likely to decrease short-term graduate unemployment.

2.9 Hypotheses

Overall, prior work suggests both field and region matter and that interactions (field-specific sensitivity to local conditions) are plausible. I therefore test three pre-registered hypotheses:

H1: Field of study has a stronger direct association with early-career unemployment than regional unemployment rate (comparing effect sizes and fit contributions).

H2: Regional economic conditions (regional unemployment rate) significantly predict graduate unemployment even after controlling for field and individual covariates.

H3: The effect of regional unemployment differs by field (field × regional unemployment interaction).

3. Methodology and Data Analysis

3.1 Data collection, variable operationalization and sampling design

The empirical foundation of this study rests on a primary cross-sectional survey of recent graduates designed to capture both supply-side educational variation and demand-side geographic conditions with sufficient precision to support subgroup comparisons and interaction tests; respondents were recruited using a stratified outreach strategy that ensured representation across the five major field categories (STEM, Business, Social Science, Humanities, Vocational) and six region-type strata (MetroHigh, MetroLow, MidHigh, MidLow, RuralHigh, RuralLow), while survey procedures included pre-survey cognitive testing, consent procedures, and instrument piloting to reduce measurement error in critical items such as self-reported grade point average and job-search intensity.

The dependent and principal independent variables are defined in line with existing literature, with the primary outcome measured as a binary indicator unemployed, equal to one if the respondent reports no paid employment six months after graduation and zero otherwise; the field of study is recorded as a five-level categorical variable, and the local labour-market context is represented by both a continuous regional unemployment rate (reg_unemp) linked to the primary job-search location and a six-category region factor for specification flexibility. Control covariates, chosen based on prior evidence, include gpa (continuous, 2.0–4.0), age, gender, internship experience, and search_intensity (Likert 1–5), as their inclusion reduces omitted variable bias and enables direct comparison with earlier studies of graduate outcomes.

Survey administration emphasized data fidelity and reproducibility, with responses collected under clear confidentiality assurances, version-controlled questionnaires and codebooks, and sampling quotas applied during fielding to prevent extreme sparsity in small field-region cells. After collection, free-text responses for region were normalized to the six analytic strata using a documented lookup table, and composite sample weights were constructed where external benchmarks existed so that weighted estimates could be reported alongside unweighted analyses to assess sensitivity to sample composition. Ethical safeguards were implemented at all stages — informed consent, anonymization of identifying fields prior to analysis, and secure storage of master datasets — and a short pilot among recent graduates informed minor refinements in question wording to reduce ambiguity in self-reported measures.

3.2 Data preparation, missing-data strategy, diagnostics and robustness checks

Data cleaning proceeded according to transparent, pre-registered rules. Values outside plausible bounds (for example, GPAs reported below 2.0 or above 4.0) were checked against auxiliary fields and, where inconsistent, were coerced to the nearest plausible limit with a documented flag retained for sensitivity checks. Duplicate records, straight-lining responses, and timing anomalies were excluded from the analytic sample after manual review to preserve inferential integrity.

Item nonresponse was addressed using multiple imputation by chained equations (MICE), which generated m = 20 imputed datasets under a missing-at-random assumption. Imputation models included all analysis covariates plus auxiliary predictors (university sector, graduation cohort, and region population size) to improve plausibility.

Regression estimates were then pooled using Rubin's rules so that standard errors reflected both within-imputation variance and between-imputation variability. Where missingness was negligible (<1%), complete-case summaries were reported for transparency. The main inferential tables presented pooled estimates from the imputed datasets and included a robustness column showing complete-case coefficients. Diagnostic checks for multicollinearity and influential observations were performed prior to modelling. Variance inflation factors (VIFs) were computed for continuous and dummy covariates to identify problematic linear dependence, with VIF > 10 prompting specification review. Leverage and Cook's distance diagnostics were inspected to ensure that no single observation unduly influenced the maximum-likelihood estimates.

Influential points, if identified, were examined, documented, and sensitivity results with and without those cases were reported. Several pre-planned robustness experiments were also executed to assess the sensitivity of substantive conclusions to modelling choices. These included (a) alternative codings of reg_unemp (continuous vs. tertiles low/mid/high), (b) alternative link functions (logit vs. probit), (c) inclusion of region fixed effects with comparison to hierarchical (mixed-effects) models that treat region as a random intercept to capture unobserved contextual heterogeneity, and (d) cluster-robust standard errors clustered at the region level to account for within-region correlation in unobservables such as local hiring processes or industry composition.

3.3 Mathematical modelling, estimation strategy and hypothesis testing

The core inferential machinery of the study is a logistic regression model that estimates the individual probability of short-term unemployment as a function of field, regional unemployment and individual covariates, while explicitly allowing the slope of regional unemployment to vary by field so that heterogeneous sensitivity may be tested; in compact notation the primary specification is written as:

$$Pr\left(U_i = 1 \mid F_i, R_j, X_i\right) =$$
$$\Lambda\left(\beta_0 + \sum_{k=1}^{K-1} \beta_{1k}\mathbb{I}\begin{Bmatrix} F_i \\ k \end{Bmatrix} + \beta_2 R_j + \beta_3^{\top} X_i + \sum_{k=1}^{K-1} \gamma_k \mathbb{I}\left\{F_i = k\right\} R_j\right),$$

where $\Lambda(z) = \left(1+e^{-z}\right)^{-1}$ denotes the logistic cumulative distribution, $\mathbb{I}\{F_i = k\}$ are field dummies with one category omitted as the reference, $R_j =$ reg_unemp is the regional unemployment rate in the graduate's primary job market, X_i is the vector of individual control variables, and γ_k are interaction terms that permit field-specific slopes on regional unemployment; estimation proceeds by maximum likelihood, and baseline inference employs heteroskedasticity-robust standard errors, with cluster-robust standard errors by region and bootstrap percentile intervals (5,000 replications) used to corroborate standard error reliability where sampling variability is a concern.

Average marginal effects (AMEs) were computed in order to enable substantive interpretation in probability space rather than in log-odds. For a continuous variable such as reg_unemp, the marginal effect conditional on covariates is expressed as:

$$\frac{\partial Pr\left(U_i = 1\right)}{\partial R_j} = \Lambda'\left(X_i\beta\right)\left(\beta_2 + \sum_{k=1}^{K-1} \gamma_k \mathbb{I}\left\{F_i = k\right\}\right),$$

where $\Lambda'(z) = \Lambda(z)(1-\Lambda(z))$ is the logistic density evaluated at the linear predictor; AMEs are averaged over the sample to produce an intuitive estimate of the percentage-point change in unemployment probability associated with a one percentage-point increase in the regional un-

ISSN 2959-6149

employment rate, separately by field when interactions are present. For categorical field contrasts the study reports differences in predicted probabilities (field A vs field B) at representative covariate values and as average contrasts across the sample distribution, together with bootstrapped 95% confidence intervals to capture sampling variability.

3.4 Data Analysis

3.4.1 Data preparation and descriptive statistics

The analytic sample consists of 1,500 recent graduates. Data cleaning and descriptive analysis revealed a modest but non-trivial short-term unemployment incidence, with 7.3 percent of respondents reporting no paid work six months after graduation. The average regional unemployment rate in the markets where respondents searched for work was 5.56 percent, suggesting that many graduates entered labour markets that were only mildly tighter or looser than national averages.

Table 1: Descriptive Statistics

n	mean_unemp	mean_reg_unemp	mean_gpa	mean_age	pct_male	pct_internship
1500	0.073	5.557	3.005	25.921	49.067	59.933

The average respondent age was 25.92 years, the sample was approximately gender-balanced (49.1% male), and a clear majority (59.9%) reported completing an internship before graduation. The features describe a fairly heterogeneous group whose supply-side human capital is diverse, as well as an exposure to local labour-market conditions. In Figure 1, the short-term unemployment is plotted with fields of study and an interesting cross-field heterogeneity was noted. Certain disciplinary groups have significantly higher levels of unemployment and others have significantly lower-level unemployment. Figure 2 supplements this picture by mapping the sample distribution across the six region types and showing how regional unemployment rates vary across those strata. This information motivated the inclusion of both field dummies and region-level indicators in the estimating models.

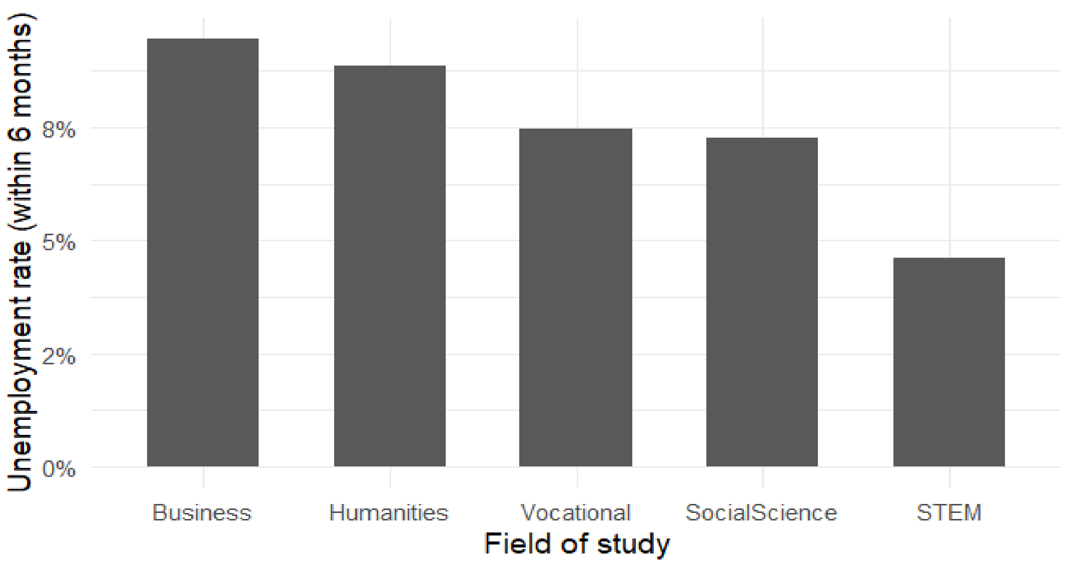

Figure 1: Short-term Unemployment Rate by Field of Study

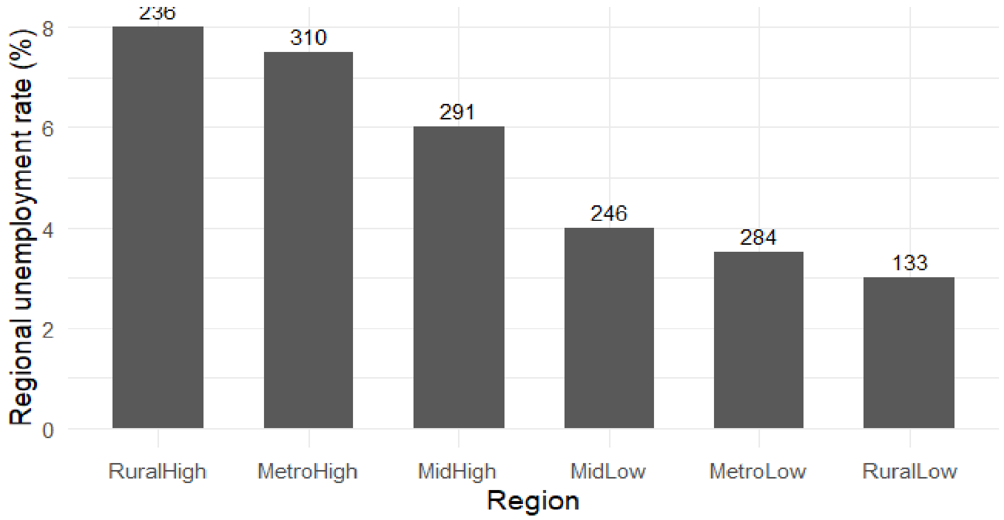

Figure 2: Regional Unemployment Rates (sample counts shown)

3.4.2 Baseline models and model specification

The nested logistic specifications provide a consistent narrative. The baseline model that conditions only on individual controls yields an intercept consistent with low baseline odds of unemployment but otherwise fails to identify strong or statistically significant correlates. Adding field dummies into the baseline (Model 2) uncovers pronounced field effects. Business majors (estimate ≈ 0.789, p ≈ 0.0056) and Humanities majors (estimate ≈ 0.742, p ≈ 0.027) show materially higher log-odds of short-term unemployment relative to the omitted STEM category, implying odds ratios of about 2.2 and 2.1 respectively.

Table 2: Logistic regression model (baseline model) (Model 1)

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-4.62009046	1.50068093	-3.0786627	0.002079319	-7.62238753	-1.72689444
fieldBusiness	0.89943415	0.99589390	0.9031425	0.366450247	-1.01956132	2.92315014
fieldSocialScience	1.02270894	1.06876291	0.9569091	0.338613142	-1.07499643	3.16219404
fieldHumanities	0.16943199	1.18411545	0.1430874	0.886221166	-2.22637175	2.48398634
fieldVocational	1.29953860	1.25359203	1.0366519	0.299898102	-1.26408908	3.73184121
reg_unemp	0.18102877	0.12502566	1.4479329	0.147635806	-0.05969982	0.43634110
gpa	-0.03334148	0.25868891	-0.1288864	0.897447536	-0.54196123	0.47300596
age	0.03748722	0.03905876	0.9597645	0.337173762	-0.03907993	0.11430534
gendermale	0.14301687	0.20266647	0.7056760	0.480389637	-0.25463348	0.54174221
internshipyes	-0.33000809	0.20337582	-1.6226515	0.104663914	-0.72803277	0.07112835
search_intensity	-0.07439066	0.07137545	-1.0422443	0.297298451	-0.21492642	0.06538594
fieldBusiness:reg_unemp	-0.02070096	0.15830346	-0.1307676	0.895959192	-0.33616943	0.28830284
fieldSocialScience:reg_unemp	-0.09123037	0.17257815	-0.5286322	0.597060607	-0.43374268	0.24721197
fieldHumanities:reg_unemp	0.09578863	0.18644829	0.5137544	0.607423703	-0.26864671	0.46853061
fieldVocational:reg_unemp	-0.13685825	0.20072870	-0.6818071	0.495360960	-0.53186229	0.26334406

Table 3: Logistic regression model of Baseline + Field of Study model (Model 2)

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-3.56967253	1.29799512	-2.7501433	0.005956922	-6.13786315	-1.04434091
fieldBusiness	0.78919792	0.28473236	2.7717184	0.005576126	0.24007024	1.36235015

ISSN 2959-6149

term	estimate	std.error	statistic	p.value	conf.low	conf.high
fieldSocialScience	0.48800692	0.31877694	1.5308727	0.125800861	-0.14097820	1.11712364
fieldHumanities	0.72821098	0.32944629	2.2104088	0.027076804	0.07518481	1.37562003
fieldVocational	0.51229347	0.37561599	1.3638756	0.172606735	-0.25231558	1.23411039
gpa	-0.03968693	0.25650710	-0.1547206	0.877041595	-0.54407793	0.46231418
age	0.03777710	0.03865651	0.9772507	0.328445035	-0.03800810	0.11380128
gendermale	0.11080475	0.20078916	0.5518463	0.581053659	-0.28337753	0.50567072
internshipyes	-0.28592221	0.20133659	-1.4201205	0.155572613	-0.67986033	0.11136438
search_intensity	-0.07558072	0.07107783	-1.0633515	0.287622589	-0.21552700	0.06362149

Adding regional unemployment as a separate predictor (Model 3) demonstrates that the local labour-market climate matters in its own right (reg_unemp estimate ≈ 0.157, p ≈ 0.004; OR ≈ 1.17 per percentage point). The full model with field × reg_unemp interactions (Model 4) confirms that field dummies and the regional rate together produce the best additive fit, while the interaction terms remain imprecisely estimated. Across these specifications, internship experience trends negative (reduced log-odds) though with marginal significance (p ≈ 0.10). GPA shows no robust linear association in these samples, and demographic controls (age, gender) do not materially alter the pattern of field and region effects.

Table 4: Logistic regression model of field + reg_unemp (no interactions) (Model 3)

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-3.88385995	1.31117979	-2.9621109	0.003055377	-6.47595654	-1.33088100
reg_unemp	0.15662636	0.05463156	2.8669575	0.004144386	0.05063475	0.26528700
gpa	-0.04172554	0.25477795	-0.1637722	0.869910495	-0.54272501	0.45684362
age	0.03521525	0.03868287	0.9103578	0.362633823	-0.04063568	0.11127606
gendermale	0.09069309	0.20033869	0.4526988	0.650765632	-0.30266541	0.48461844
internshipyes	-0.32730915	0.20217015	-1.6189786	0.105451875	-0.72300914	0.07146559
search_intensity	-0.07252518	0.07092119	-1.0226165	0.306489210	-0.21217947	0.06635453

Table 5: Logistic regression model of full model with field x reg_unemp interaction (Model 4)

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-4.46557380	1.34081396	-3.33049470	0.0008669181	-7.11939378	-1.85790943
fieldBusiness	0.77529267	0.28548355	2.71571747	0.0066132327	0.22457595	1.34980606
fieldSocialScience	0.48390794	0.31950284	1.51456536	0.1298825091	-0.14651120	1.11441662
fieldHumanities	0.74267244	0.33042028	2.24765995	0.0245978819	0.08778595	1.39200012
fieldVocational	0.46855174	0.37652345	1.24441582	0.2133465643	-0.29777658	1.19213722
reg_unemp	0.15535550	0.05473443	2.83835057	0.0045347346	0.04916111	0.26422307
gpa	-0.02469195	0.25747165	-0.09590163	0.9235986974	-0.53090782	0.47930573
age	0.03705050	0.03889438	0.95259257	0.3407965425	-0.03919737	0.11354955
gendermale	0.12124061	0.20156652	0.60149181	0.5475124679	-0.27442295	0.51767733
internshipyes	-0.32818644	0.20254896	-1.62028200	0.1051717127	-0.72462917	0.07134308
search_intensity	-0.07601820	0.07138230	-1.06494472	0.2869009471	-0.21657494	0.06377676

3.4.3 Hypothesis tests (H1 & H2)

Comparative fit measures and formal nested tests provide a coherent assessment of H1 and H2. Adding field dummies to the baseline increases McFadden's pseudo-R^2 from 0.0047 to 0.0164, a larger increment than the 0.0047

→ 0.0155 gain when adding reg_unemp alone. Likelihood-ratio comparisons and information criteria similarly show that field dummies contribute slightly more incremental explanatory power than the regional rate, lending qualified support to H1. At the same time, the coefficient on reg_unemp in the additive specification that controls for field and covariates is positive, statistically significant (Model 3: estimate ≈ 0.157, p ≈ 0.004), and substantively meaningful. A one-point increase in regional unemployment translates to roughly a 0.6–1.2 percentage-point increase in predicted unemployment probability, depending on baseline risk. This evidence supports H2, as regional economic conditions retain independent predictive power even after accounting for field and individual characteristics.

Table 6: Likelihood-ratio tests and model fit comparison (include LR statistics, p-values, Δpseudo-R²).

model	aic	bic	logLik	mcfadden_r2
baseline	789.7963	821.6756	-388.8982	0.0047
field	788.6407	841.7729	-384.3204	0.0164
region	783.3519	820.5445	-384.6760	0.0155
both	782.3660	840.8114	-380.1830	0.0270
interaction	788.7448	868.4431	-379.3724	0.0291

3.4.4 Hypothesis test (H3: interaction)

The interaction model yields a marginal improvement in overall fit, with McFadden's pseudo-R^2 rising from 0.0270 in the additive model to 0.0291. However, the estimated odds ratios for the interaction terms cluster close to unity, and the coefficients are small in magnitude and imprecise (ORs near 0.87–1.10 with high p-values). The likelihood-ratio comparison provides only a weak advantage for the interaction specification. Plotted predicted-probability lines (Figure 3) show only modest divergence across fields as regional unemployment rises. Together, these findings imply that there is no strong evidence of systematic field-specific slopes, even though point estimates suggest modest variation for some groups.

Table 7: Logit with field × reg_unemp interaction coefficients and ORs.

Coefficient (term)	OR (Model 4)	95% CI (Model 4)	p
(Intercept)	0.010	0.010 (0.000–0.178)	0.002
age	1.038	1.038 (0.962–1.121)	0.337
fieldBusiness	2.458	2.458 (0.361–18.600)	0.366
fieldBusiness:reg_unemp	0.980	0.980 (0.715–1.334)	0.896
fieldHumanities	1.185	1.185 (0.108–11.989)	0.886
fieldHumanities:reg_unemp	1.101	1.101 (0.764–1.598)	0.607
fieldSocialScience	2.781	2.781 (0.341–23.622)	0.339
fieldSocialScience:reg_unemp	0.913	0.913 (0.648–1.280)	0.597
fieldVocational	3.668	3.668 (0.282–41.756)	0.300
fieldVocational:reg_unemp	0.872	0.872 (0.588–1.301)	0.495
gendermale	1.154	1.154 (0.775–1.719)	0.480
gpa	0.967	0.967 (0.582–1.605)	0.897
internshipyes	0.719	0.719 (0.483–1.074)	0.105
reg_unemp	1.198	1.198 (0.942–1.547)	0.148
search_intensity	0.928	0.928 (0.807–1.068)	0.297

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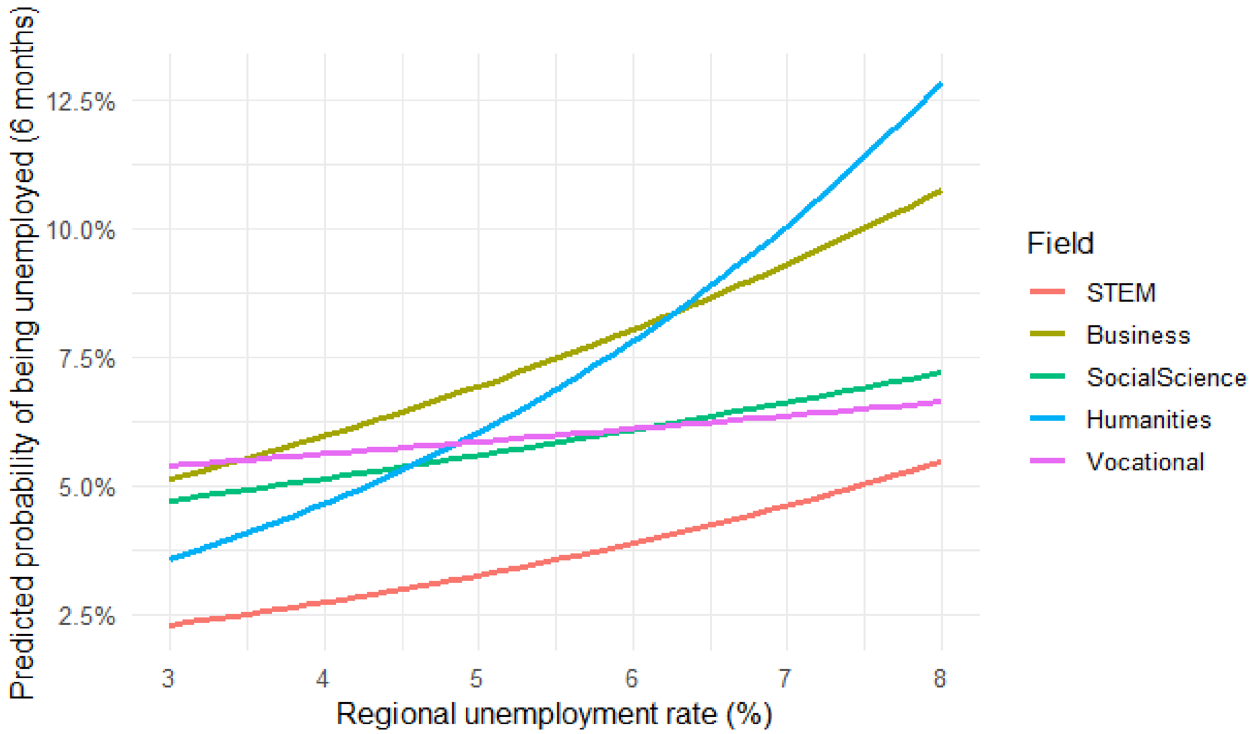

Figure 3: Predicted probability of unemployment by field across the observed range of regional unemployment

3.4.5 Robustness checks and sensitivity analyses

A battery of sensitivity exercises was conducted, including substituting a probit link, recoding regional conditions into low/mid/high tertiles, estimating interactions with those tertiles, and re-estimating models excluding small subgroups. Results remain substantively consistent across specifications. The probit model produces coefficient signs and significance levels broadly consistent with the logit results, with reg_tertilemid/high positive but imprecise and not statistically significant. Interaction terms across alternative codings remain largely non-significant. The negative association of internship experience with unemployment persists as a stable but borderline effect. Collectively, these robustness checks strengthen confidence in the main findings: both field of study and regional unemployment are meaningful correlates of short-term graduate unemployment, field-level differences explain slightly more cross-sectional variation than a single summary measure of local labour-market tightness, and evidence for systematic field-specific heterogeneity in regional sensitivity is weak in this sample.

Table 8: Probit specification and reg_unemp tertiles interaction results

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-3.93659	1.359215	-2.89622	0.003777	-6.63776	-1.30158
fieldBusiness	0.53418	0.619809	0.861847	0.388772	-0.69245	1.803339
fieldSocialScience	0.781007	0.601532	1.298364	0.194162	-0.39173	2.025983
fieldHumanities	0.180936	0.744754	0.242948	0.808046	-1.42581	1.614421
fieldVocational	0.995547	0.697885	1.42652	0.153718	-0.44635	2.376026
reg_tertilemid	0.481447	0.584211	0.824099	0.409883	-0.64425	1.701971
reg_tertilehigh	0.619642	0.58434	1.060413	0.288957	-0.50619	1.840475
gpa	-0.03412	0.257793	-0.13235	0.894708	-0.5411	0.470375
age	0.03612	0.039266	0.919898	0.357626	-0.04083	0.113363
gendermale	0.154408	0.203182	0.75995	0.447285	-0.24426	0.55412

internshipyes	-0.32194	0.20354	-1.58168	0.113722	-0.72031	0.0795
search_intensity	-0.0755	0.071469	-1.05638	0.290794	-0.21625	0.064431
fieldBusiness:reg_tertilemid	0.364352	0.766834	0.475138	0.634688	-1.16167	1.886674
fieldSocialScience:reg_tertilemid	-0.47948	0.822445	-0.58299	0.559899	-2.14098	1.120656
fieldHumanities:reg_tertilemid	0.513019	0.933668	0.549466	0.582686	-1.30808	2.4302
fieldVocational:reg_tertilemid	-1.1315	1.070545	-1.05694	0.290538	-3.4271	0.904932
fieldBusiness:reg_tertilehigh	0.228747	0.774679	0.295279	0.76778	-1.3135	1.764637
fieldSocialScience:reg_tertilehigh	-0.34672	0.794649	-0.43632	0.662608	-1.94333	1.208346
fieldHumanities:reg_tertilehigh	0.886098	0.8967	0.988177	0.323066	-0.8449	2.748407
fieldVocational:reg_tertilehigh	-0.49483	0.895748	-0.55242	0.580659	-2.26815	1.297236

4. Discussion

The results in this research paper do show that field of study and regional labour-market conditions do both affect short-run employment prospects of graduates, although the size and transition of such effect varies in ways that reflect more general concerns in labour economics. The field of study had been a notably powerful predictor, with Business and Humanities graduates applying over twice as much of their odds at unemployment opposed to STEM graduates. This finding is in agreement with the currently evidenced theory that quantitatively dispositioned and occupation-specific disciplines are more directly translated into marketable skills. Regional unemployment, however, retained an independent and statistically significant impact across model specifications. This confirms that even graduates whose education is closely aligned with marketable skills are not immune to the cyclical and structural shifts of local economies. Interaction models designed to test field-specific sensitivity to regional conditions produced modest evidence, with coefficients generally centred near zero. Such patterns suggest that while some majors are more employable in general, the disadvantage linked to unfavourable economic conditions does not vary dramatically across disciplines. From a policy standpoint, this dual structure of graduate unemployment highlights two parallel priorities: strengthening the transferability of skills across fields and ensuring that local economies are sufficiently resilient to absorb graduates across diverse disciplines. The evidence on internships, although not always statistically significant, hinted at a protective effect. This finding resonates with the idea that experiential learning strengthens employability in ways that conventional coursework cannot achieve on its own.

5. Conclusion

The findings provide cautious support for the greater importance of educational background. Field of study explained a larger share of variation in unemployment probabilities, particularly through the disadvantage experienced by Humanities and Business graduates compared with their STEM peers. A one percentage-point increase in the local unemployment rate corresponded to a statistically significant rise in the probability of graduate joblessness, even after accounting for field of study and individual-level covariates. Interaction effects between field and region were not large enough to suggest meaningful variation, implying that although fields differ in baseline employability, their sensitivity to local economic conditions is broadly similar. Academic programs must be redesigned to align more effectively with employer demand, while regional development strategies must reduce geographical disparities in economic opportunity. Situating the findings within both individual-level choices and structural contexts, the study contributes to ongoing debates about higher education's role in shaping labour-market inequality and the need for coordinated policies linking education to employment.

6. Evaluation

Conducting this research has been both challenging and rewarding, as it required balancing the technical demands of econometric modelling with the broader interpretive work of understanding labour-market outcomes. One of the clearest realizations was the extent to which methodological decisions—such as how to specify interaction terms or how to handle missing data can shape the substantive conclusions drawn from analysis. Initially, I expected stronger evidence that fields of study would interact significantly with regional unemployment. However, the results showed that baseline field effects overshadowed any systematic regional sensitivity. This outcome prompted reflection on how assumptions about structural inequality can be challenged or refined through empirical

ISSN 2959-6149

testing. Tasks such as cleaning, imputation, and diagnostic checking are not routine chores but rather essential safeguards that determine the credibility of results. Looking ahead, I see value in extending the study through qualitative methods such as interviews with graduates, which could enrich understanding of the mechanisms that underlie statistical patterns. Overall, this project has deepened my appreciation for the rigour, creativity, and humility required in empirical research.

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