Earning Differences by Domicile, Sex, and Years Since Graduation: Evidence from Master's Graduates in the UK

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Abstract

This study investigates the employment and earnings outcomes of Master's postgraduates from English Higher Education providers, utilizing the Longitudinal Education Outcomes (LEO) dataset for the 2014/15 to 2020/21 tax years. The research focuses on analyzing earnings differentials across domicile groups (UK, EU, and Non-EU) and genders, at one, three, five, and ten years after graduation. Preliminary analysis reveals persistent gender pay gaps across all domicile groups. To address potential biases arising from suppressed and missing data, particularly among international graduates, Inverse Probability Weighting (IPW) and Entropy Balancing are employed. The methodology incorporates a Weighted Least Squares regression model, utilizing entropy balancing weights to ensure covariate balance across treatment groups. This approach allows for a robust analysis of earnings differences, accounting for domicile status, gender, years after graduation, and subject of study. The model also includes interaction terms to capture the nuanced relationships between these variables. This research aims to provide valuable insights into the long-term labour market outcomes of Master's graduates in the UK. The findings have important implications for higher education policy, international student recruitment, and efforts to address gender disparities in postgraduate labour markets.

Contents

Introduction

The United Kingdom's higher education landscape has undergone a significant transformation in recent years, with international students now comprising approximately 24% of the student population (HESA, 2023). This surge in international enrolment presents both opportunities and challenges for the UK's labour market and the economy as a whole. As these graduates transition into the workforce, they encounter a complex interplay of factors that shape their career trajectories and economic outcomes.

The integration of international graduates into the UK labour market is a multifaceted issue that intersects with critical economic and social dynamics. It touches upon themes of skill composition, productivity gains, wage structures, and the persistent challenges of gender and nationality-based disparities (Peri, 2016). Moreover, this phenomenon unfolds against the backdrop of a rapidly evolving global labour market, characterized by technological advancements and increasing international mobility (Acemoglu & Autor, 2011).

Despite the growing importance of international graduates to the UK economy, significant barriers impede their seamless integration into the workforce. Information asymmetries, job search frictions, and the complex transferability of skills across national boundaries often result in suboptimal job matching and wage disparities (Mortensen & Pissarides, 1999; Chiswick & Miller, 2009). These challenges are particularly pronounced for master's graduates, a cohort that has been relatively understudied despite their increasing relevance in the knowledge-based economy.

The focus on master's graduates is crucial for several reasons. First, the specialized skills and research capabilities cultivated in these programs are increasingly valued by employers in high-skill sectors (Agarwal & Ohyama, 2013). Second, the substantial financial investment required for a master's degree creates heightened expectations for positive career outcomes. Finally, recent changes in UK immigration policy, such as the Graduate Route visa, aim to retain international talent, yet their long-term impact remains under-examined (UK Government, 2020). This study adopts a longitudinal approach to investigate the earnings trajectories of master's graduates at one, three, five, and ten years post-graduation. By utilizing the Longitudinal Education Outcomes (LEO) dataset and employing advanced econometric techniques such as Inverse Probability Weighting and Entropy Balancing, we address methodological challenges that have hindered previous research in this area (Imbens & Wooldridge, 2009).

This study contributes to the broader literature on human capital accumulation and its international transferability, providing insights into the role of country-specific skills in shaping labour market outcomes (Friedberg, 2000). Moreover, by focusing on the intersection of domicile, gender, and career progression over time, this study offers a comprehensive analysis of the factors influencing the success of master's graduates in the

UK labour market.

The findings of this research hold significant implications for a wide range of stakeholders, including higher education institutions, employers, and policymakers. As the global competition for high-skilled talent intensifies, understanding the drivers of post-graduation success becomes crucial for shaping effective immigration and education policies (Czaika & Parsons, 2017).

This paper seeks to provide robust evidence on earnings differentials and their determinants, contributing to the optimization of human capital in the UK's evolving knowledge-based economy. By clarifying the intricate factors influencing the labor market outcomes of international master's graduates, it seeks to inform strategies for their effective integration and retention, ultimately strengthening the UK's competitive edge in the global talent market.

Literature Review

The United Kingdom's higher education landscape has undergone significant transformation in recent decades, characterized by a surge in both domestic and international students pursuing master's degrees. This trend, driven by government policies promoting internationalisation, increasing demand for advanced qualifications in a competitive labour market, and financial incentives for universities, has positioned the UK as a prime destination for global talent (Sawir, 2013; Brooks et al., 2012;

Marginson, 2018). The perceived benefits of obtaining a degree from an English-speaking country have further enhanced the UK's appeal, promising improved employment prospects both domestically and internationally (Verbik & Lasanowski, 2007). As the higher education sector evolves, so too does the imperative to understand the complex dynamics of graduate outcomes, particularly concerning earnings disparities. This literature review aims to synthesize and critically evaluate the existing research on earnings differences among master's graduates in the UK, with a focus on the intersections of domicile, sex, and time since graduation. By examining these factors, we seek to uncover the nuanced realities faced by graduates in an increasingly globalised and competitive job market.

The foundation of graduate earnings research in the UK was laid by studies focusing on educational mismatch, particularly among ethnic groups. Battu and Sloane (2004) pioneered this field with their analysis of the Fourth National Survey of Ethnic Minorities, revealing significant over-education rates among ethnic minorities, especially Indian and African-Asian populations. Their work underscored the critical interplay between ethnicity and place of birth in shaping labour market outcomes. Green and Zhu (2010) later corroborated these findings, using UK Skills Surveys data to confirm persistent ethnic disparities and a growing trend of over-education among certain minority groups. A paradigm shift in graduate earnings research occurred with the introduction of administrative datasets, offering unprecedented accuracy in tracking graduate outcomes. Britton et al. (2016) made significant strides by linking HMRC earnings data with Student Loan Company records, enabling longitudinal analysis of earnings trajectories. Their findings revealed substantial variations in earnings based on the institution attended and subject studied, alongside persistent gender gaps. Building on this methodological innovation, Belfields et al. (2018) employed instrumental variables and matching methods to address selection biases, further confirming the heterogeneity in returns across academic disciplines and institutions.

As research expanded to encompass postgraduate education, Lindley and Machin (2016) provided a comprehensive analysis of returns to postgraduate degrees. Utilizing data from the Labour Force Survey and British Household Panel Survey, they documented increasing wage premiums for postgraduate qualifications, albeit with notable variations across subjects and institutions. Conlon and Patrignani (2011) corroborated these findings, highlighting significant returns to postgraduate qualifications, particularly for women and in fields such as economics, business, and STEM. The internationalisation of higher education has prompted investigations into the effects of international student mobility (ISM) on labour market outcomes. Kratz and Netz (2018) and Parey and Waldinger (2011) found positive impacts of ISM on wages and career mobility, with internationally mobile graduates experiencing steeper wage growth compared to their non-mobile counterparts. These studies employed robust methodological approaches, including growth curve models and instrumental variables, to address selection biases inherent in studying abroad decisions. Complementing these findings, Di Pietro (2015) and Oosterbeek and Webbink (2011) utilised propensity score matching and regression discontinuity designs, respectively, to strengthen the causal evidence on the impact of international education experiences. Their work collectively suggests that international exposure during higher education can confer significant advantages in the global labour market.

The study by Costas-Fernández et al. (2023) provides a nuanced perspective on the impact of foreign students on the outcomes of native students in English higher education. Employing fixed effects models and exploiting variation in foreign student numbers across university-degree programs, their research found little evidence of significant effects on the early labour market outcomes or educational performance of native students. This finding contrasts with earlier studies, such as Shih (2017), which suggested that exposure to foreign peers could enhance domestic students' critical thinking and global awareness. The mixed results underscore the complexity of assessing the full impact of international student presence on both native students' academic and labour market trajectories. Gender disparities in graduate earnings remain a critical focus of research. Chevalier (2007) found that approximately 70% of the gender wage gap could be attributed to differences in characteristics such as subject choice and job expectations. Longitudinal studies, such as Purcell et al. (1999), have revealed persistent gender disparities in earnings and career progression. Blundell et al. (2020) employed dynamic structural models to demonstrate that career interruptions and occupational choices significantly contribute to the persistence of gender wage gaps among graduates.

Ethnicity has emerged as a key factor in graduate earnings disparities. Zwysen and Longhi (2018) uncovered substantial ethnic penalties in the labour market, even after controlling for socio-economic background and educational attainment. These penalties were further elucidated by Lessard-Phillips et al. (2018), who revealed significant heterogeneity in outcomes among ethnic groups, particularly among Russell Group university graduates. Their findings highlight the complex interplay between ethnicity, institutional prestige, and labour market outcomes. Recent advancements in data availability, such as the Longitudinal Education Outcomes (LEO) dataset, offer new opportunities to explore gaps in our understanding, particularly concerning the intersectionality of domicile, gender, and time since graduation. Methodological techniques such as Inverse Probability Weighting (IPW) and Entropy Balancing are increasingly being employed to address selection biases and improve comparisons across different groups (Jenkins & Rios-Avila, 2023). While the literature has advanced significantly in terms of data quality and methodological sophistication, important gaps remain, particularly in understanding the distinct experiences of master's graduates. The intersection of domicile, gender, ethnicity, and career progression warrants further investigation, especially in the context of global competition for highly skilled workers.

This literature review has traced the evolution of research on graduate earnings disparities in the UK, from early studies on educational mismatch to sophisticated analyses of longitudinal administrative data. The interactions of factors such as domicile, gender, ethnicity, and time since graduation in shaping graduate outcomes underscores the need for nuanced, intersectional approaches to future research. As the higher education landscape continues to evolve, rigorous, data-driven research remains essential for informing policy and practice. By focusing on master's graduates, who occupy a unique position between undergraduate cohorts and doctoral candidates, future studies can deepen the understanding of earnings inequality in the UK higher education system. This will not only contribute to the broader academic discourse on human capital development but also provide valuable insights for policymakers and practitioners striving to create more equitable outcomes in higher education and the labour market.

Data Description

Data Source and Characteristics

This study utilizes the Longitudinal Education Outcomes (LEO) dataset, a comprehensive cross-sectional resource that amalgamates administrative data from Her Majesty's Revenue and Customs (HMRC), the Department for Work and Pensions (DWP), and the Higher Education Statistics Agency (HESA). The LEO dataset enables the analysis of graduate employment and earnings at one, three, five, and ten years after graduation (YAG), providing valuable insights into long-term labour market trends and the economic impact of higher education (Britton et al., 2016).

The focus of this analysis is on employment and earnings outcomes for Master's postgraduates from English Higher Education (HE) providers, covering the 2014/15 to 2020/21 tax years. The dataset classifies earnings outcomes into categories such as 'Activity not captured,' 'No sustained destination,' and 'Sustained employment, further study, or both.' It is important to note that this broad classification includes graduates employed for at least five of the six months between October and March, as well as those reporting self-employment income, potentially inflating employment figures by including minimal work activity.

Data Preprocessing and Limitations

The earnings data in the LEO dataset are rounded to the nearest £100, introducing minor imprecision. However, this rounding is negligible relative to the overall variance in earnings and is unlikely to significantly affect the reliability of the regression results. To address potential distortions and better capture central income tendencies, this analysis focuses on median earnings, which offer a more accurate representation of typical income by minimizing the influence of extreme values (Katz & Murphy, 1992).

The dataset contains instances of suppressed ("c") and missing ("z") data, particularly among EU and Non-EU graduates. Suppressed data indicates withheld information due to small numbers, while missing data often results from graduates leaving the UK, leading to the absence of recorded earnings data. The final sample, after filtering and cleaning, consists of 21,713 observations. Table 1 presents the frequency of suppressed and missing data by domicile.

Domicile	**Suppressed (”c”)**	**No Result (”z”)**
EU	991	142
Non-EU	745	161
UK	12,008	3,650
Total	13,744	3,953

Table 1: Suppressed and Missing Earnings Data by Domicile

Preliminary Data Analysis

Before delving into the detailed methodology, it is instructive to examine the earnings distribution across different groups. Figure 1 presents the mean earnings of Master’s graduates across three domicile groups (EU, Non-EU, and UK), disaggregated by sex.

As evident from Figure 1, male graduates consistently earn more than their female counterparts across all domicile groups. EU male graduates exhibit the highest mean earnings (£39,085.3), while EU female graduates earn £31,639.7, depicting a gender gap of approximately £7,400. Among Non-EU graduates, males earn £33,529.5 compared to £29,237.6 for females, with a smaller gender gap of around £4,300. For UK graduates, males earn £35,676.6 versus £29,066.2 for females, indicating a gender gap of about £6,600.

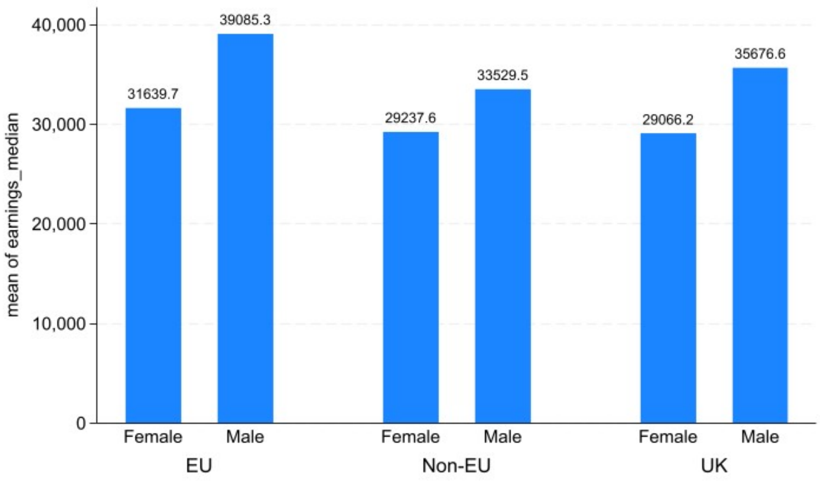

Figure 1: Earnings of Masters graduates by Gender and Domicile

These earnings disparities highlight potential differences in labour market outcomes by sex and domicile status for UK Master's graduates. It is crucial to note that some data points in the dataset are either suppressed or unavailable, which affects the interpretation of these results.

Methodology

To address the potential biases introduced by the presence of suppressed and missing data, especially among international graduates, this study employs 2 econometric techniques: Inverse Probability Weighting (IPW) and Entropy Balancing.

Inverse Probability Weighting (IPW)

Initially, IPW was considered to address selection bias and ensure covariate balance across treatment groups. IPW is particularly suited for studies involving multinomial treatments, as it uses the inverse of the propensity score to reweight the sample, creating a synthetic population where covariates are balanced across the treatment groups (Austin, 2011; Mansournia & Altman, 2016).

The treatment variable in this analysis is domicile status ($domicile_i$), categorized into three groups: 0 for UK, 1 for EU, and 2 for Non-EU. The propensity score model is estimated as a function of key covariates such as sex (sex_i) and years after graduation (YAG_i). The treatment assignment model is represented by a multinomial logistic regression:

$$\log\left(\frac{P(domicile_i = j|X_i)}{P(domicile_i = 0|X_i)}\right) = \beta_{j0} + \beta_{j1} sex_i + \beta_{j2} YAG_i \tag{1}$$

for $j = 1$ (EU) or $j = 2$ (Non-EU), where β_{j0} is the intercept for domicile category j, and β_{j1} and β_{j2} are the coefficients for sex and years after graduation, respectively, for domicile category j.

The outcome variable, $\ln(earnings_i)$, is modelled as a function of domicile and covariates:

$$\ln(earnings_i) = \alpha + \beta_1 domicile_j + \beta_2 sex_s + \beta_3 YAG_t + \epsilon_t \tag{2}$$

Where ϵ_t is the error term, accounting for within-group correlation at the cohort level (based on YAG).

However, the inclusion of subjects in the model resulted in perfect prediction for 97 cases, causing the model to become unidentified for these observations. Additionally, the introduction of interaction terms between domicile status, sex, and YAG led to severe multicollinearity, inflating the standard errors and reducing model stability.

Entropy Balancing

To address the limitations encountered with IPW, this study employs Entropy Balancing as an alternative method. Introduced by Hainmueller (2012), Entropy Balancing addresses selection bias when comparing employment outcomes between UK-domiciled and international (EU and Non-EU) master's graduates. This method minimises the Kullback-Leibler divergence between the original and adjusted weights while enforcing constraints to achieve covariate balance.

Entropy Balancing solves the following optimization problem:

$$\min_{w_i} \sum_{i \in \mathcal{UK}} w_i \log(w_i) \tag{3}$$

where w_i are the weights assigned to each observation in the UK-domiciled group. Subject to the following constraints:

$$\sum_{i \in \mathcal{UK}} w_i x_{ik} = \frac{1}{|\mathcal{INT}|} \sum_{j \in \mathcal{INT}} x_{jk}, \quad \text{for } k \in \{\text{Sex}, \text{Subject}, \text{YAG}\} \tag{4}$$

This constraint ensures that the weighted mean of each covariate k in the UK-domiciled group equals the unweighted mean in the international group.

$$\sum_{i \in \mathcal{UK}} w_i = 1, \quad w_i \geq 0 \quad \text{for all } i \in \mathcal{UK} \tag{5}$$

This constraint ensures that the weights sum to 1 and are non-negative.

Where:

- $\mathcal{UK}$ is the set of UK-domiciled master's graduates (control group)
- $\mathcal{INT}$ is the set of international master's graduates (treatment group)
- x_{ik} is the k-th covariate for graduate i in the UK-domiciled group
- x_{jk} is the k-th covariate for graduate j in the international group
- Covariates k include Sex, Subject of Study, and Years After Graduation (YAG)
- w_i are the weights assigned to each observation in the UK-domiciled group
- $|\mathcal{INT}|$ represents the number of observations in the international group

The covariates included in the balancing process are Sex, Subject of Study, and Years After Graduation (YAG). Entropy Balancing generates a set of weights, w_i, which adjust the control group (UK-domiciled graduates) to have a covariate distribution similar to that of the treatment group (international graduates). These weights minimise the entropy distance from uniform weights while satisfying the balance and normalization constraints.

Weighted Least Squares Regression

Using the entropy balancing weights, a Weighted Least Squares model is employed to analyze the differences in earnings for master's graduates in the UK. This approach allows for interactions between domicile, gender, and YAG. The dependent variable is the logarithm of the earnings median, allowing for the interpretation of coefficients as approximate percentage changes in salary for a unit change in the independent variables (Mincer, 1974; Heckman et al., 1997). The model specification is as follows:

$$
\begin{aligned}
\ln(\mathrm{e}_i) = &\beta_0 + \beta_1 EU_i + \beta_2 NonEU_i + \beta_3 Female_i + \beta_4 YAG1_{it} \\
&+ \beta_5 YAG3_{it} + \beta_6 YAG5_{it} + \beta_{6+j} Subject_j \\
&+ \beta_{42}(EU_i \times Female_i) + \sum_{j=1}^{35} \beta_j Subject_j \\
&+ \beta_{43}(NonEU_i \times Female_i) + \beta_{44}(EU_i \times YAG1_{it}) + \\
&+ \beta_{45}(EU_i \times YAG3_{it}) + \beta_{46}(EU_i \times YAG5_{it}) \\
&+ \beta_{47}(NonEU_i \times YAG1_{it}) + \beta_{48}(NonEU_i \times YAG3_{it}) \\
&+ \beta_{49}(NonEU_i \times YAG5_{it}) + \epsilon_{it}
\end{aligned}
\tag{6}
$$

Where, i indexes individual graduates, EU_i and $NonEU_i$ are dummy variables for domicile (with UK as the base category), $Female_i$ is a dummy variable for sex (with male as the base category), $YAG1_{it}$, $YAG3_{it}$, and $YAG5_{it}$ are dummy variables for years after graduation (with 10 years after graduation as the base category), $Subject_j$ represents dummy variables for each subject (with MBA as the base category), and ϵ_{it} is the error term, clustered by years after graduation. This comprehensive methodological approach, combining Entropy Balancing with Weighted Least Squares regression, allows robust analysis of earnings differences among master's graduates, accounting for domicile status, gender, years after graduation, and subject of study, while addressing potential biases in the dataset.

Results

Employing both Inverse Probability Weighting (IPW) and entropy balancing reveals significant earnings disparities among graduates based on domicile, gender, years since graduation, and field of study. We present our findings in three main subsections: domicile differences, gender disparities, and subject-specific earnings.

	EU vs UK	Non-EU vs UK
ATE	0.081**	-0.022
	(0.03)	(0.03)
Pomean UK	10.337***	
	(0.04)	
1 YAG	0.157**	-0.082
	(0.06)	(0.05)
3 YAG	0.112**	-0.039
	(0.04)	(0.03)
5 YAG	0.126**	0.015
	(0.04)	(0.03)

Table 2: IPW Results for Domicile Differences

IPW analysis (Table 2) reveals that EU students experience a statistically significant 8.1% increase in earnings relative to UK students. This aligns with previous studies highlighting the positive impact of international student mobility on wages and career prospects (Kratz & Netz, 2018; Parey & Waldinger, 2011). Conversely, Non-EU students show, non-significant 2.2% decreases in earnings compared to UK students, echoing findings from Costas-Fernández et al. (2023). The entropy balancing results shown in Table 3 further support these findings: EU graduates earn approximately 15.7% more than UK graduates 10 years after graduation (coefficient: 0.146, $e^{0.146} - 1 = 0.157$), while Non-EU graduates earn about 5.0% less than UK graduates over the same period. These results underscore the importance of controlling for selection biases in such analyses (Britton et al., 2016; Belfields et al., 2018).

Time since graduation significantly impacts earnings, particularly for EU students. IPW analysis shows statistically significant increases for EU students at 1, 3, and 5 years post-graduation (15.7%, 11.2%, and 12.6% respectively). Non-EU graduates show no statistically significant earnings changes across the same periods, with decreases of 8.2% at 1 year and 3.9% at 3 years, and a slight 1.5% increase at 5 years. These findings support d'Hombres and Schnepf (2021) on the long-term benefits of mobility for EU students while suggesting that these benefits may not extend equally to Non-EU students (Scott & Mhunpiew, 2021). The entropy balancing results provide additional insights on earnings trajectories: EU graduates 1 year after graduation face an additional earnings penalty of 12.7% compared to UK graduates at the same stage. By 3 years post-graduation, EU graduates earn 6.9% less than UK graduates 10 years after graduation. At 5 years post-graduation, EU graduates see a slight increase of 1.2% in earnings relative to UK graduates 10 years after graduation. For Non-EU graduates, earnings 1 year post-graduation shows negligible difference compared to UK graduates. By 3 years post-graduation, Non-EU graduates experience an overall earnings reduction of 18.0% compared to UK graduates 10 years after graduation. At 5 years post-graduation, Non-EU graduates face a total earnings decrease of 12.4% relative to UK graduates 10 years after graduation.

Gender wage gaps persist across all domiciles, though they vary in magnitude. IPW analysis shows EU females exhibit a statistically significant 12.1% higher earnings compared to their male peers. For Non-EU students, this gap is less pronounced, with females showing only a 4.8% increase in earnings compared to males. Entropy balancing results indicate that female graduates overall earn approximately 15.5% less than male graduates. This discrepancy highlights the complexity of gender wage gaps and aligns with earlier studies attributing these gaps to differences in subject choice and job expectations (Chevalier, 2007). The interaction between domicile and gender reveals further nuances: The coefficient for EU female graduates is 0.006, suggesting that the gender wage gap is 0.6 percentage points lesser for EU graduates compared to UK graduates. EU female graduates still earn approximately 15.0% less than their male EU counterparts. For Non-EU female graduates, the interaction term indicates that the gender gap is 5.5% lesser than for UK graduates. Non-EU female graduates earn about 10.7% less than Non-EU males. These findings are consistent with Blundell et al. (2020), emphasizing the role of occupational choices and career interruptions in shaping gender wage disparities.

There is significant variation in earnings among master's graduates from different fields of study, with MBA graduates consistently outperforming those from other disciplines. Medicine and Dentistry graduates earn approximately 15.1% less than MBA graduates. Economics graduates earn about 22.7% less than MBA graduates. STEM fields show varying gaps: Mathematical Sciences graduates earn 20.4% less, Computing graduates earn 32.7% less, and Engineering graduates earn 32.2% less. Creative Arts, Design, and Performing Arts graduates face the largest gap, earning 64.2% less than MBA graduates. English Studies graduates earn 55.1% less than MBA graduates. Additional subject-specific findings include: Within healthcare fields, Nursing and Midwifery graduates earn 35.6% less than MBAs, and Allied Health graduates face a 40.5% earnings gap. In social sciences, Sociology, Social Policy, and Anthropology graduates earn 41.9% less than MBAs, and Politics graduates earn 37.6% less than MBA graduates. Education and Teaching graduates earn 34.7% less than MBAs. Law graduates earn 35.9% less than MBA graduates. These findings align with previous research (Conlon & Patrignani, 2011; Lindley & Machin, 2016) on the high wage premiums associated with postgraduate degrees in business-related fields. The substantial variation in earnings across subjects underscores the critical role of subject choice in shaping long-term earning trajectories, with important implications for students, universities, and policymakers.

In conclusion, significant earning differences are based on domicile, gender, years since graduation, and subject of study. These findings contribute to the growing body of literature on graduate outcomes and provide valuable insights for understanding the complex interplay of factors influencing earnings in the graduate labour market.

Discussion

This study contributes to the existing body of literature on graduate earnings by providing a comprehensive analysis of the earnings trajectories of Master's graduates in the UK. Through the examination of key variables including domicile, gender, time since graduation, and field of study, this research has elucidated significant disparities in labour market outcomes among diverse graduate cohorts. The findings reveal a complex landscape of earnings differentials that both corroborate and extend previous research in the field.

The analysis demonstrates that EU graduates enjoy a statistically significant earnings advantage, a finding that aligns with previous research on the benefits of international student mobility (Kratz & Netz, 2018; Parey & Waldinger, 2011). This advantage may be attributed to factors such as enhanced cultural capital, communication skills, and networking that EU graduates bring to the UK labour market. In contrast, Non-EU graduates exhibit more heterogeneous outcomes, often facing earnings penalties. These results are consistent with the challenges in international labour market integration documented by Costas-Fernández et al. (2023), suggesting that Non-EU graduates may encounter more significant barriers in translating their educational qualifications into commensurate earnings within the UK context.

A persistent gender wage gap is evident across all domicile groups, with female graduates earning approximately 15.5% less than their male counterparts. This disparity aligns with prior studies that attribute such gaps to differences in subject choice, job expectations, and potentially, labour market discrimination (Chevalier, 2007). The consistency of this gap across domicile groups suggests that gender-based earnings inequalities transcend national boundaries and persist even among highly educated cohorts.

The longitudinal aspect of our analysis reveals patterns of gradual improvement in earnings over time since graduation. This trend is consistent with theories of labour market assimilation (Borjas, 2015), suggesting that graduates generally experience positive returns to labour market experience. However, the rate and extent of this improvement vary across different graduate groups, indicating that initial disparities may have long-lasting effects on career trajectories.

Our findings also highlight substantial variation in earnings potential associated with subject choice, particularly the premium commanded by STEM and business-related fields. This corroborates existing literature on field-specific earnings gaps (Zwysen & Longhi, 2018) and underscores the importance of subject selection in determining future economic outcomes. The persistence of these differentials raises questions about the relative valuation of different skill sets in the labour market and the potential for targeted educational policies to address skill shortages in high-demand fields.

The methodological approach employed in this study, utilizing Inverse Probability Weighting (IPW) and entropy balancing, provides robust insights within the constraints of cross-sectional data. These techniques allow for a more rigorous treatment of selection bias and confounding factors compared to traditional regression approaches. However, it is important to acknowledge the limitations inherent in this approach, particularly the potential for omitted variable bias and the inability to control for unobserved time-invariant factors (Imbens & Wooldridge, 2009; Wooldridge, 2003). Future research could address these limitations by incorporating longitudinal data to enable more sophisticated econometric approaches, such as fixed effects models or dynamic panel analysis, potentially offering deeper insights into the causal mechanisms underlying the observed patterns.

These findings have significant implications for policy formulation and institutional practices in higher education. They underscore the necessity for targeted interventions to address the challenges faced by international graduates, particularly those from Non-EU countries, in integrating into the UK labour market. Moreover, the persistent gender-based disparities highlight the need for comprehensive strategies to promote equity in career development and workplace practices. Policymakers and educational institutions should consider implementing programs that facilitate smoother transitions into the labour market for international students, address potential biases in recruitment and promotion processes, and provide targeted support for graduates in fields with lower earnings potential.

Conclusion

This study advances our understanding of the interplay between higher education and labour market outcomes in an increasingly globalised context. Highlighting the master's graduate earnings disparities lays the groundwork for evidence-based policymaking designed to create more equitable and efficient transitions from education to employment. The research highlights several key findings: the earnings advantage of EU graduates, the varied outcomes for Non-EU graduates, the persistent gender wage gap, the gradual improvement in earnings over time since graduation, and the significant impact of subject choice on earnings potential.

These findings underscore the need for nuanced and targeted interventions in higher education policy and practices. Policymakers should consider developing strategies that capitalize on the advantages demonstrated by EU graduates while simultaneously addressing the challenges faced by Non-EU graduates. Efforts to mitigate the gender wage gap should be intensified, potentially through initiatives that encourage women to enter high-paying fields and address structural biases in the workplace. Furthermore, the strong influence of subject choice on earnings outcomes suggests that there may be value in providing students with more comprehensive information about the long-term economic implications of their educational decisions.

As the landscape of global higher education continues to evolve, ongoing research in this vein will be crucial in informing strategies to maximise the economic and social returns of advanced education for diverse graduate populations. Future studies should focus on longitudinal data analysis to provide a more comprehensive understanding of how earnings trajectories evolve over extended periods. Additionally, investigating the long-term career trajectories of international graduates who remain in the UK versus those who return to their home countries or migrate elsewhere could provide valuable insights into the global dynamics of skilled labour mobility.

In conclusion, this study not only contributes to the academic discourse on graduate earnings but also provides actionable insights for policymakers, educational institutions, and students themselves. By deepening our understanding of the factors that influence post-graduation economic outcomes, we can work towards creating a more equitable and efficient system of higher education that truly serves the diverse needs of all students in an increasingly interconnected global economy.

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Appendix

Graphs

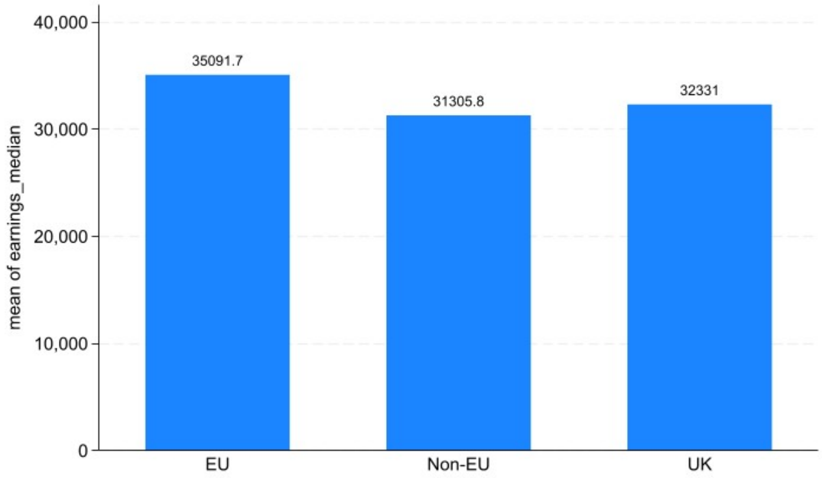

Figure 2: Domicile Earnings

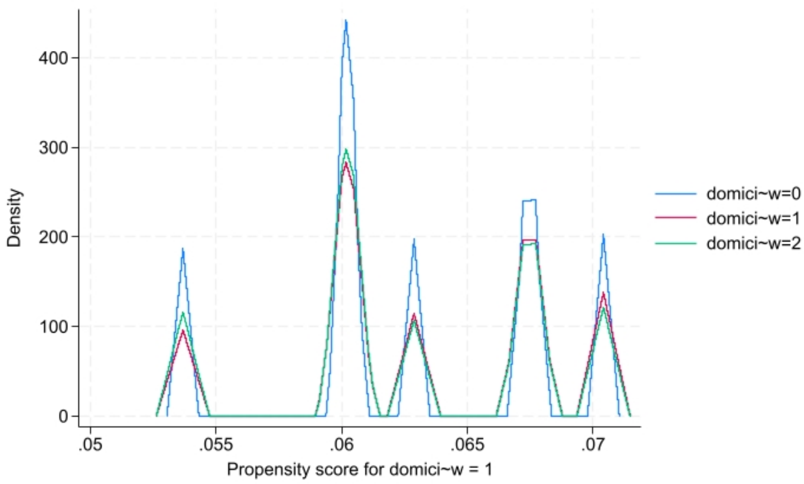

Figure 3: IPW overlap

Tables

Table 3: Regression Results

Variables	Weighted ordinary least squares (OLS)				
	Model 1	Model 2	Model 3	Model 4	Model 5
EU	0.075	0.075	0.075	0.072	0.146^{***}
	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)
Non-EU	-0.032^{**}	-0.032^{**}	-0.029^{**}	-0.058^{*}	-0.051^{*}
	(0)	(0)	(0)	(0.01)	(0.01)
Female	-0.168^{*}	-0.168^{*}	-0.152^{*}	-0.168^{*}	-0.168^{*}
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
1 YAG	-0.251^{***}	-0.251^{***}	-0.283^{***}	-0.283^{***}	-0.252^{***}
	(0)	(0)	(0)	(0)	(0)
3 YAG	-0.133^{***}	-0.133^{***}	-0.153^{***}	-0.153^{***}	-0.128^{***}
	(0)	(0)	(0)	(0)	(0)
5 YAG	-0.076^{***}	-0.076^{***}	-0.088^{***}	-0.088^{***}	-0.073^{***}
	(0)	(0)	(0)	(0)	(0)
Agriculture, food and related studies	-0.722^{***}	-0.722^{***}	-0.685^{***}	-0.683^{***}	-0.680^{***}
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Allied health	-0.537^{***}	-0.537^{***}	-0.520^{***}	-0.520^{***}	-0.519^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Architecture, building and planning	-0.528^{***}	-0.528^{***}	-0.483^{***}	-0.483^{***}	-0.483^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Biosciences	-0.675^{**}	-0.675^{**}	-0.634^{**}	-0.634^{**}	-0.635^{**}
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Business and management	-0.364^{**}	-0.364^{**}	-0.364^{**}	-0.364^{**}	-0.364^{**}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Chemistry	-0.617^{**}	-0.617^{**}	-0.629^{***}	-0.623^{***}	-0.619^{***}
	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)
Combined and general studies	-0.639^{***}	-0.639^{***}	-0.553^{***}	-0.542^{**}	-0.539^{**}

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Table 3: (continued)

Variables	Weighted ordinary least squares (OLS)				
	Model 1	Model 2	Model 3	Model 4	Model 5
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)
Computing	-0.478^{***}	-0.478^{***}	-0.396^{***}	-0.396^{***}	-0.396^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Creative arts and design	-0.976^{***}	-0.976^{***}	-0.878^{***}	-0.878^{***}	-0.878^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Economics	-0.321^{*}	-0.321^{*}	-0.256^{*}	-0.257^{*}	-0.258^{*}
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Education and teaching	-0.435^{***}	-0.435^{***}	-0.426^{***}	-0.426^{***}	-0.426^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Engineering	-0.411^{***}	-0.411^{***}	-0.388^{***}	-0.388^{***}	-0.389^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
English studies	-0.879^{***}	-0.879^{***}	-0.802^{***}	-0.801^{***}	-0.801^{***}
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
General, applied and forensic sciences	-0.746^{***}	-0.746^{***}	-0.706^{***}	-0.708^{***}	-0.705^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Geography, earth and environmental studies	-0.612^{***}	-0.612^{***}	-0.550^{***}	-0.550^{***}	-0.551^{***}
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Health and social care	-0.574^{***}	-0.574^{***}	-0.548^{***}	-0.552^{***}	-0.549^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
History and archaeology	-0.822^{***}	-0.822^{***}	-0.730^{***}	-0.729^{***}	-0.730^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Languages and area studies	-0.780^{***}	-0.780^{***}	-0.718^{***}	-0.718^{***}	-0.718^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Law	-0.520^{**}	-0.520^{**}	-0.444^{**}	-0.443^{**}	-0.444^{**}
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)

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Table 3: (continued)

Variables	Weighted ordinary least squares (OLS)				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Materials and technology	-0.487^{***}	-0.487^{***}	-0.477^{***}	-0.478^{***}	-0.474^{***}
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Mathematical sciences	-0.334^{**}	-0.334^{**}	-0.227^{*}	-0.228^{*}	-0.228^{*}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Media, journalism and communications	-0.781^{***}	-0.781^{***}	-0.690^{***}	-0.690^{***}	-0.690^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Medical sciences	-0.417^{***}	-0.417^{***}	-0.404^{***}	-0.404^{***}	-0.400^{***}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Medicine and dentistry	-0.160^{*}	-0.160^{*}	-0.164^{*}	-0.164^{*}	-0.164^{*}
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Nursing and midwifery	-0.434^{***}	-0.434^{***}	-0.442^{***}	-0.443^{***}	-0.440^{***}
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
PGCE	-0.695^{**}	-0.695^{**}	-0.638^{***}	-0.638^{***}	-0.638^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Performing arts	-1.033^{***}	-1.033^{***}	-1.028^{***}	-1.028^{***}	-1.028^{***}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Pharmacology, toxicology and pharmacy	-0.377^{***}	-0.377^{***}	-0.399^{***}	-0.398^{***}	-0.395^{***}
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Philosophy and religious studies	-0.800^{***}	-0.800^{***}	-0.711^{***}	-0.709^{***}	-0.708^{***}
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Physics and astronomy	-0.488^{***}	-0.488^{***}	-0.499^{***}	-0.496^{***}	-0.494^{***}
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Politics	-0.522^{**}	-0.522^{**}	-0.470^{**}	-0.470^{**}	-0.471^{**}

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Table 3: (continued)

Variables	Weighted ordinary least squares (OLS)				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Psychology	-0.688^{**}	-0.688^{**}	-0.639^{**}	-0.640^{**}	-0.639^{**}
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Sociology, social policy and anthropology	-0.590^{***}	-0.590^{***}	-0.544^{***}	-0.544^{***}	-0.544^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sport and exercise sciences	-0.736^{**}	-0.736^{**}	-0.734^{**}	-0.733^{**}	-0.720^{**}
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
Veterinary sciences	-0.434^{***}	-0.434^{***}	-0.389^{***}	-0.386^{***}	-0.389^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
EU # Female				0.005	0.006
				(0.01)	(0.01)
Non-EU # Female				0.056	0.055
				(0.02)	(0.02)
EU # 1 YAG					-0.136^{***}
					(0)
EU # 3 YAG					-0.089^{***}
					(0)
EU # 5 YAG					-0.061^{***}
					(0)
Non-EU # 1 YAG					0.002
					(0)
Non-EU # 3 YAG					-0.019^{***}
					(0)
Non-EU # 5 YAG					-0.008^{**}
					(0)
Constant	11.112^{***}	11.112^{***}	11.073^{***}	11.082^{***}	11.064^{***}
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
R-squared	0.713	0.713	0.695	0.696	0.701

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Table 3: (continued)

Variables	Weighted ordinary least squares (OLS)				
	Model 1	Model 2	Model 3	Model 4	Model 5

[*] $p < 0.05$, [**] $p < 0.01$, [***] $p < 0.001$

Standard errors in parentheses

Detailed Calculations for Results

This appendix provides detailed calculations for the key results presented in the main text. These calculations offer additional transparency and allow for a deeper understanding of the methodology employed in our analysis.

The percentage difference in earnings was calculated using the coefficient (β) from the entropy balanced regression:

$$\text{Percentage Difference} = (e^{\beta} - 1) \times 100\% \tag{7}$$

For example, for EU graduates:

$$(e^{0.146} - 1) \times 100\% = 15.7\% \tag{8}$$

Gender Wage Gap Calculations

The gender wage gap was calculated as the difference between male and female earnings, expressed as a percentage of male earnings:

$$\text{Gender Wage Gap} = \frac{\text{Male Earnings} - \text{Female Earnings}}{\text{Male Earnings}} \times 100\% \tag{9}$$

Subject-Specific Earnings Calculations

The earnings differences for each subject relative to MBA graduates were calculated as:

$$\text{Earnings Difference}_{\text{Subject}} = (e^{\beta_{\text{Subject}}} - 1) \times 100\% \tag{10}$$

where β_{Subject} is the coefficient for each subject in the regression model.

Time Since Graduation Effect

The effect of time since graduation on earnings was calculated using the following formula:

$$\text{Earnings Effect}_{\text{YAG}} = (e^{\beta_{\text{YAG}}} - 1) \times 100\% \tag{11}$$

where β_{YAG} is the coefficient for each "Years After Graduation" (YAG) category in the regression model.