Bachelor Thesis

Wage Premiums Among Young Graduates in Latvia: Is Higher Education Losing Its Value at Labour Market Entry?

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Elīza Zariņa Annija Rulle-Titava

Date

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Abstract

This thesis examines wage premiums among young graduates in Latvia and evaluates whether higher education is losing its value at labour market entry. The study focuses on employed individuals aged 20–29 and uses harmonized microdata from the Latvian Labour Force Survey covering the period 2014–2024. The analysis investigates overall wage premiums associated with tertiary education and explores heterogeneity by degree level, field of study, field of work, gender, and field-of-study match.

The empirical approach is based on Mincer-type earnings regressions estimated by ordinary least squares with heteroskedasticity-robust standard errors. Monthly wages are harmonized across survey years, and gross wages in 2021–2024 are converted into estimated net wages to ensure comparability. The baseline specification controls for labour market experience, its squared term, and year fixed effects, while extended models include interactions between education and field of study, field of work, and job match.

The results show that higher education continues to generate a substantial wage premium in Latvia. Compared with young workers without tertiary education, Bachelor's degree holders earn on average about 23% higher wages, while individuals with a Master's degree or PhD earn about 45% higher wages. The analysis also reveals strong heterogeneity across fields of study, with the highest premiums observed in information and communication technologies, natural sciences, engineering, and health, and lower premiums in education and arts and humanities. In addition, working in an occupation that matches one's field of study is associated with higher wages, especially among Master's and PhD graduates.

Overall, the findings suggest that higher education does not lose its value in Latvia during labour market entry, although its economic payoff differs substantially across degrees and fields.

1. Introduction

The economic value of higher education is a central concern in contemporary labour economics and policy. Many European countries, including Latvia, have seen rapid tertiary expansion alongside technological change, sectoral restructuring, and wage-setting reforms. This leads to the following research question: What are the wage premiums associated with higher education among young adults (aged 20–29) in Latvia? Based on existing theoretical and empirical insights from other European countries, this study hypothesizes that the wage premium for tertiary education among young workers in Latvia could have declined over the period 2014–2024. To address this, the sub-research questions focus on identifying wage premiums by field of study, field of work, gender, and education–job match status.

Wage premiums- the average percentage earnings advantage associated with particular qualifications- offer a direct way to address this by comparing tertiary-educated workers to less educated peers, but can hide important differences by field, gender, and period, especially in small open economies such as Latvia.

The literature distinguishes between wage premiums and education premiums. A wage premium is the earnings advantage linked to a given characteristic, such as holding a tertiary degree or graduating from a particular field, relative to a comparison group (Autor, 2014), while education premiums (returns to schooling) measure the percentage wage increase from an additional year or level of education, typically estimated with Mincer-type equations (Vilerts et al., 2015). In higher education, this corresponds to vertical stratification (between education levels) and horizontal stratification (between fields at the same level) (Gerber & Cheung, 2008; OECD, 2021). The combination of the two frameworks as explanatory variables in Mincer regression is used in the thesis to analyse wage differences in Latvia between tertiary and non-tertiary young people, and among tertiary graduates across fields and gender.

Empirical evidence for Europe indicates that tertiary education continues to yield sizeable private returns. Harmonised microdata and internal-rate-of-return estimates show substantial wage advantages for tertiary graduates, especially in long-cycle and STEM programmes (Anghel & Lacuesta, 2025). Policy reports also find that each additional year of education raises earnings, with particularly large wage premiums for university graduates in Eastern Europe, including Latvia, compared with Nordic countries, reflecting differences in wage dispersion and labour-market institutions (European Commission, 2025; OECD, 2025a).

At the same time, international evidence shows that the wage premium is not constant over time. European panel data and OECD comparisons document high and heterogeneous tertiary returns in the 1990s and early 2000s, followed in several countries by stagnation or decline (Strauss & Christine, 2007; Crivellaro, 2014). This pattern fits a supply–demand framework: rapid growth in the supply of graduates compresses wage premiums unless matched by strong demand for high-skill labour. Recent U.S. decomposition work links the post-2000 flattening mainly to slower skill-biased technological change and greater substitutability between college and non-college workers (Bengali, Valletta, & Zhao, 2025).

A further key insight is that returns to tertiary education are strongly heterogeneous by field of study. Across European economies, long-cycle academic degrees (ISCED 6–8) consistently deliver higher returns than short-cycle vocational programmes, and STEM disciplines systematically outperform humanities and many social sciences (Anghel & Lacuesta, 2025). Such differentials are particularly important for Latvia, because the economic value of tertiary education depends not only on having a degree, but also on the field in which it was obtained. Therefore, average tertiary wage premiums can mask large differences across young graduates.

The literature also shows that wage premiums are gendered. Although women now match or exceed men in tertiary attainment, sizeable earnings gaps persist among university-educated workers, driven by gender segregation in fields of study, differences in employment continuity and hours, and sorting into lower-paying occupations and firms (Bar-Haim et al., 2018; OECD, 2025b). As a result, the realised tertiary wage premium is systematically lower for women than for men, a pattern that is especially relevant for Latvia, where gender pay gaps remain above the EU average (Eurostat, 2025).

However, to our knowledge, there is a notable gap in up-to-date, field-of-study–specific estimates for young graduates in Latvia that track wage premiums over time and across demographic groups. Most available European analyses either treat Latvia as part of a broader regional aggregate or focus on overall education levels, without disentangling heterogeneity by discipline, gender, and early-career stage. This thesis addresses this gap by combining the conceptual tools of wage and education premiums with detailed microdata from the Latvian Labour Force Survey for 2014–2024.

To answer the research question, this thesis applies a quantitative empirical approach based on Mincer-type earnings regressions estimated using ordinary least squares (OLS). This framework is widely used in labour economics to analyse returns to education, as it allows wage differences to be expressed as percentage premiums while controlling for key factors such as labour market experience and time effects. Using harmonized microdata from the Latvian Labour Force Survey for the period 2014–2024, the analysis estimates both average wage premiums and their variation across fields of study, fields of work, gender, and job-education match. This approach is particularly suitable for the Latvian context, as it enables consistent comparison over time and provides a detailed decomposition of heterogeneity in early-career wage outcomes.

2. Literature review

2.1. Wage and Education Premiums

Wage premiums and education premiums are fundamental concepts in labor economics and form the groundwork for understanding earnings differentials among workers. A wage premium refers to the percentage earnings advantage that certain groups of workers receive relative to a baseline group, typically without the featured skill or qualification (Autor, 2014). In the context of higher education, wage premiums capture differences in earnings associated with both the level and field of education. Wage premiums by field of study show that graduates from different disciplines can earn very different wages even when they hold the same level of qualification, a pattern often described as horizontal stratification in higher education (Gerber & Cheung, 2008; OECD, 2021).

The concept of the education premium, or returns to schooling, measures the percentage increase in wages gained from each additional year of education or from completing a higher level of schooling. This idea is commonly estimated using empirical models such as the Mincer earnings equation, which relates wages to years of schooling and work experience. The key parameter of this model, the Mincer coefficient, indicates the percentage by which wages increase with each extra year of education (Vilerts et al., 2015). More importantly, according to the most recent OECD publication, in Latvia, adults aged 25–34 with tertiary qualifications earn, on average, 35% higher wages than those whose highest level of education is upper secondary, a figure slightly below the OECD average of 38%. Across OECD countries more generally, wage differentials by education level are relatively moderate. Workers aged 25–64 who have completed upper secondary education earn about 17% more than those who have not, while tertiary-educated workers earn roughly 54% more than upper secondary graduates. Latvia shows a similar pattern: the wage gap between those with and without upper secondary education stands at 16%, and the earnings advantage of tertiary graduates over upper secondary graduates is identical to the OECD average at 54% (OECD, 2025a).

It is important to distinguish these concepts: the education premium reflects the vertical aspect of education, showing how moving to higher levels of education leads to higher wages., whereas wage premiums by field of study capture horizontal variation among graduates with the same degree level, reflecting differences in discipline-specific skills, labor market demand, and signaling effects. This distinction is critical since declining wage premiums by field may indicate weakening economic value of specific disciplines or challenges in labor market absorption of graduates. However, such trends must be interpreted within broader changes in the education premium and labor market dynamics (Autor, 2014; Leuven & Oosterbeek, 2011).

In sum, wage premiums and education premiums provide complementary perspectives on how education translates into returns in earnings. The former focuses on differences across fields of study among graduates, while the latter emphasizes the advantage of longer or higher educational attainment. Understanding both is essential to analyze whether, and how, higher education maintains or loses its value in today's economy.

2.2. Returns of Education in Europe

Anghel and Lacuesta (2025) in Economic Bulletin published by Banco de España (Eurosistema) analyze private returns to schooling in Germany, France, Italy, and Spain by computing internal rates of return (IRRs) across attainment levels using pooled HFCS microdata from 2010–2021. They construct lifecycle earnings profiles from a squared experience–wage specification and compare income streams across education groups, treating schooling as an investment with forgone earnings during study. The estimates show that the wage premium for tertiary education over upper secondary education corresponds to IRRs of 14% in Germany, 16% in France, 7% in Italy, and 14% in Spain. Within tertiary education, long-cycle degrees (ISCED 6–8) outperform higher vocational programs (ISCED 5), and STEM fields systematically exceed humanities, with Germany again showing the highest STEM returns. The authors note widening wage gaps over the career and acknowledge data constraints and potential cohort-quality shifts, alongside standard endogeneity concerns. (Anghel & Lacuesta, 2025).

In contrast, the 2025 European Commission report “Investing in Education” provides a broad EU-level overview of education investment, returns, and challenges. Covering all EU member states, it emphasizes that education spending is beginning a moderate recovery after pandemic disruptions with an average of 4.7% of GDP allocated to education in 2023. The report highlights the critical role of education in enhancing economic resilience, productivity, and social mobility across Europe. It confirms that each additional year of education in Europe translates roughly into a 7 percent increase in earnings. Persistent inequalities in education access and quality challenge economic fairness and growth potential, with socio-economic background strongly influencing learning outcomes. The report stresses the importance of STEM and digital competencies for future labor market needs and demographic resilience. It also highlights sizeable disparities in wage and education premiums across countries and calls for targeted policy measures to improve the education system quality and align skills with evolving demands. Notably, this report highlights substantial regional variation in wage premiums, with university graduates in Eastern Europe earning between 40% and 178% more than workers with medium education levels, such as approximately 57% more in Lithuania, 54% in Albania, 51% in Romania, 48% in Bulgaria, 44% in Latvia, and 40% in Serbia. This contrasts starkly with Nordic countries, where wage premiums for university graduates are significantly smaller, ranging from 6% in Iceland to 19% in Denmark, reflecting differences in labor market structures, stronger social protections, and more egalitarian wage distributions (European Commission, 2025).

Synthesizing evidence from these studies, wage premiums for higher education in Europe appear stable or moderately increasing over time, particularly in countries with established and diversified education systems such as Germany and France. Nonetheless, clear regional disparities are apparent, with Southern European countries exhibiting lower returns and persistent inequalities that dampen overall gains. Field-of-study differences are prominent across Europe; STEM fields reliably generate higher premiums compared to social sciences or humanities, while vocational education returns depend largely on institutional factors and labor market structures specific to each country. Wage gaps tend to widen as workers gain experience, reinforcing the lifetime economic advantage of tertiary education, especially in specialized academic tracks. The notably higher wage premiums in Eastern Europe compared to Nordic countries underscore the significant role of regional context, reflecting differences in baseline income levels, labor market regulation, transitional economic phases, and social policy frameworks.

Human capital theory remains the main theoretical underpinning in the literature, with education understood as an investment that improves productivity and employability. They also recognize signaling mechanisms, where educational credentials act as signals to employers, influencing wage determination alongside actual productivity gains. Institutional variation plays a crucial role, with the interaction between vocational and academic education paths and labor market regulations shaping the magnitude and stability of wage premiums. Additionally, demographic pressures such as aging populations and shrinking youth cohorts highlight the urgency of improving education quality and labor market alignment, especially concerning the development of STEM skills vital for technological and economic progress. The expansion of higher education raises the supply of graduates and may increase the risk of credential inflation when labour-market demand grows more slowly.

Overall, the literature shows that tertiary education still brings economic benefits in Europe, but these benefits are not equally shared across all groups. This is important for understanding wage and education premium trends in Latvia in a broader European context.

2.3. The Evolution and Stagnation of the College Wage Premium

Across Europe since the mid-1990s, the college wage premium has been large but uneven, and in many places it has stopped rising. Using harmonised household surveys and the same Mincer-style method across countries, the OECD Economics Department Working Papers No. 589 finds that completing tertiary education was associated with an average gross hourly premium of about 11% per year of study in the early 2000s, with big cross-country gaps: roughly 5.5–6% at the low end (e.g., Greece, Spain; women in Austria and Italy) and 16–18% at the high end (Hungary, Portugal, several Anglo-Saxon countries). Adjusting for study length matters: systems with shorter degrees tend to show higher per-annum payoffs, while long programs often do not translate into proportionally higher wages. These patterns point to both demand conditions and institutions as drivers of differences and help set the baseline for judging later stagnation. (Strauss & Christine, 2007).

Focusing on Europe, Crivellaro (2014) uses panel evidence from ECHP and EU-SILC microdata (1994–2009) shows that the premium rose in some countries (e.g., Portugal, Denmark, Italy), was broadly flat in others (e.g., the United Kingdom, Germany), and fell in a few (e.g., Sweden, Austria). A simple "race" story fits the data: when the *relative supply* of graduates grows faster, the premium tends to fall; when *relative demand* for high-skill hours rises, the premium tends to increase. Crivellaro (2014) constructs supply and demand indexes from OECD and EUKLEMS and, crucially, uses changes in university autonomy as an instrument for graduate supply. The IV results strengthen the negative link between rising graduate supply and the premium, suggesting that rapid higher-education expansion can compress returns unless matched by stronger skill demand or weaker wage-compression institutions. (Crivellaro, 2014).

Why has the premium flattened in many places since the 2000s? Recent work (U.S. data but mechanism-focused) helps interpret Europe's experience. Bengali, Valletta, and Zhao (2025) extend the canonical supply–demand model and decompose movements in the premium through 2023. They find that the *stagnation* is driven mainly by a demand slowdown, a cooler pace of skill-biased technological change and greater substitutability between college and non-college labor, rather than by supply alone. Together with the EU results, this suggests that Europe's uneven pattern after 2000 was shaped by differences in high-skill job creation and wage-setting institutions. Where economies created fewer high-skill jobs and adopted new technologies more slowly, wage premiums tended to stagnate despite rising numbers of graduates (Bengali et al., 2025).

Putting the evidence together, Europe's evolution looks like this: the 1990s–early 2000s delivered high and very diverse tertiary premium, as higher education expanded further, countries that combined fast growth in graduate supply with only modest growth in high-skill demand saw flat or declining premium, while those with strong demand continued to post gains. Together, these studies provide a layered explanation of returns to higher education: the OECD cross-sectional evidence identifies the level and dispersion of returns, the EU panel evidence clarifies the underlying mechanisms, and the recent demand-slowdown findings help explain why wage premiums may no longer increase despite continued growth in higher-education enrolment (Strauss & Christine, 2007; Crivellaro, 2014; Bengali et al., 2025). This pattern highlights a clear research gap for Latvia: we lack up-to-date, field-of-study–specific estimates for young graduates that can show whether Latvia's tertiary premiums have similarly stagnated or changed differently across fields as the number of graduates and demand in different sectors changed.

2.4. Gender Disparities in Returns to Wage Premiums in Europe

Although gender is not a central focus of this thesis, the literature suggests that it can affect the realised wage premium from higher education through field-of-study choices and early labour-market sorting. European evidence shows that tertiary education continues to generate positive private returns, especially in STEM and long-cycle programmes, but women remain underrepresented in many of these higher-paying fields and overrepresented in lower-paying disciplines such as education, health, and humanities (Anghel & Lacuesta, 2025; Viarengo, 2021). As a result, part of the observed difference in graduate earnings reflects field composition rather than education level alone.

The literature also shows that gender earnings gaps persist even among tertiary-educated workers because labour-market outcomes are shaped not only by qualifications, but also by occupational sorting, working time, and career progression (Bar-Haim et al., 2018; OECD, 2025b). This is relevant mainly as background, since it indicates that wage premiums by field of study may partly reflect broader labour-market structures. In the Latvian context, this is worth noting because the unadjusted gender pay gap remains comparatively high within the EU (Eurostat, 2025). However, since the present thesis focuses on field-of-study wage premiums among young graduates in Latvia, gender is going to be treated as a secondary contextual factor rather than a separate line of analysis.

2.5. Effect of Field of Study Mismatch on Earnings of Individuals

Field-of-study mismatch refers to situations where people work in jobs that are not related to what they studied, and a substantial share of workers are employed outside their field of education. In Latvia, for example, about 41% of workers are mismatched by field of study (OECD, 2024). While the size of the wage effect varies across countries, the OECD evidence shows that mismatched workers tend to earn less. In Latvia, the wage penalty is around 8%, compared to an OECD average of about 5% (OECD, 2023). This suggests that working in a job that matches one's field of study can be an important factor in explaining wage differences.

3. Methodology

The main objective of our research is to estimate the graduate wage premium in Latvia over the last decade (2014-2024) and examine whether higher education continues to offer a meaningful financial advantage in the Latvian labor market. In addition to estimating the overall wage premium, our study also analyzes how this advantage varies across gender, fields of study, fields of work and match status throughout the examined period.

3.1. Research Design

Given that our research seeks to identify trends, compare population groups, and quantify differences in earnings, a quantitative research design is the most suitable methodological approach to answer our research question.

We use Latvian Labour Force Survey (LFS) microdata, obtained from the Central Statistical Bureau of Latvia. The LFS is carried out quarterly and provides a comprehensive overview of the labour market situation of individuals aged 15 and above. It is one of the most widely used datasets in labour economics research due to its large sample size, national representativeness, and internationally harmonized methodology following Eurostat standards. This ensures high data quality and full-time comparability across years, making the dataset particularly suitable for analyzing long-term wage patterns in Latvia. In addition, the survey contains detailed information on respondents' labour market status, occupation, economic activity, demographic characteristics, and highest completed education, all of which are crucial for estimating graduate wage premiums. A list of the LFS variables used in the analysis, including their coding and definitions, is provided in Appendix A.

The research design defines educational level using the LFS measure of the highest completed level of education the person has successfully obtained so far. This allows us to classify individuals clearly into two groups: those with higher education and those without. Wage outcomes are measured using monthly net earnings from the respondent's main job, providing a consistent and widely used indicator of labour-market returns. Additionally, relevant demographic and employment-related variables, such as gender, age, occupation, and sector, are incorporated to better explain differences in earnings and improve the interpretation of our results.

3.2. Data Harmonization

To enable consistent econometric analysis across time, microdata from the Latvian Labour Force Survey (LFS) for the years 2014 to 2024 were harmonized into a single, structurally unified dataset. Although each yearly file followed similar logic, changes in variable names, coding schemes, and survey design, especially around 2021, required systematic alignment. Harmonization was done by manual cross-checking, based on a year-by-year review of all LFS variables relevant to the analysis.

The harmonization process was implemented fully in R, using a modular, rule-based approach. For each yearly dataset, variables were first standardized to consistent labels using mutate() and rename() functions based on documented differences. Recoding schemes were then applied only where explicitly defined, including harmonized mappings for education levels, fields of study, work sectors, occupation codes, etc.

Special attention was paid to wage harmonization. For years 2021–2024, where only gross wages were available, an income-dependent tax model was constructed using average wage data and effective marginal tax rates to estimate net income. All wages were then converted to a standardized monthly equivalent based on a 168-hour work month, ensuring comparability across different work schedules.

The final output is a cleaned, person-level dataset spanning ten years, with consistent variable names and values, suitable for pooled regression analysis.

3.3. Empirical Methods

This thesis applies Mincer earnings function to examine the relationship between wages, education, and experience, estimated using Ordinary Least Squares (OLS) regression on harmonized Latvian Labour Force Survey microdata from 2014 to 2024. The main objective is to quantify how educational attainment, field of study, and field of work relate to differences in earnings, while controlling for labor market experience and broader macroeconomic trends.

3.3.1. Canonical Mincer Regression

The starting point is the canonical Mincer specification, widely used in labor economics to estimate returns to human capital:

Equation (1):

$$\ln(wage_i) = \beta_0 + \beta_1 Bachelor_i + \beta_2 Master/PhD_i + \beta_3 Experience_i + \beta_4 Experience_i^2 + \delta_t + \varepsilon_i$$

In Equation (1), the dependent variable is the natural logarithm of monthly net earnings. This transformation allows the coefficients to be interpreted approximately as percentage differences in wages.

The coefficients β1 and β2 capture the returns to education. Specifically, β1 measures the average percentage difference in wages between individuals with a bachelor's degree and those in the reference group (individuals with lower levels of education), holding other factors constant. Similarly, β2 represents the wage premium associated with holding a master's or PhD degree relative to the same reference group.

The coefficients β3 and β4 describe the relationship between labor market experience and wages. β3 reflects the initial return to an additional year of experience, while β4 captures the curvature of this relationship. The intercept β0 represents the expected log wage for an individual in the reference category (i.e., with lower education, zero experience, and in the omitted time period).

Finally, δt denotes year fixed effects, which control for time-specific factors affecting wages uniformly across individuals, such as macroeconomic conditions, inflation, or shocks like the COVID-19 pandemic. The error term εi captures unobserved individual-level determinants of wages.

This baseline regression provides average wage premiums by education level, controlling for individual experience and macroeconomic context. The coefficients on the education dummies represent the estimated log-wage differences relative to the reference group and reflect approximate percentage wage differentials attributable to educational attainment.

3.3.2. Extended Mincer Specifications

To investigate heterogeneity in wage returns across different segments of the labor market, two extended versions of the Mincer model are estimated. These specifications introduce interaction terms between education and contextual variables, allowing the wage premium associated with a degree to vary depending on field of study or field of employment.

1. Wage Premiums by Field of Study

The first extended model interacts educational attainment with the individual's field of study:

Equation (2):

$$\ln(wage_i) = \beta_0 + \sum\beta_1 edu\_level_i + \sum\beta_2 studyfield_i + \sum\beta_3(edu\_level_i \times studyfield_i) + \beta_4 Experience_i + \beta_5 Experience_i^2 + \sum\delta_t + \varepsilon_i$$

This Equation (2) estimates field-specific wage premiums among individuals with different levels of education. The dependent variable is the log of full-time monthly net earnings, so coefficients can be interpreted as approximate percentage differences.

The summation terms (∑) indicate sets of dummy variables, with one category omitted as the reference group.

$\sum\beta_1 edu\_level_i$ captures wage differences across education levels relative to lower education.

$\sum\beta_2 studyfield_i$ measures baseline wage differences across fields of study relative to a reference field (Agriculture, forestry, fisheries & veterinary)

$\sum\beta_3(edu\_level_i \times studyfield_i)$ captures how returns to education vary across fields.

β_4 and β_5 model the (concave) relationship between experience and wages.

$\sum\delta_t$ controls for year-specific effects relative to a base year.

β_0 is the baseline log wage for the reference year, and εi captures unobserved factors.

2. Wage Premiums by Field of Work

The second model focuses on the interaction between educational attainment and the field in which the individual is employed:

Equation (3):

$$\ln(wage_i) = \beta_0 + \sum\beta_1 edu\_level_i + \sum\beta_2 workfield_i + \sum\beta_3(edu\_level_i \times workfield_i) + \beta_4 Experience_i + \beta_5 Experience_i^2 + \sum\delta_t + \varepsilon_i$$

This Equation (3) explores whether returns to education differ across sectors, such as the public sector, services, or industry. It reflects the idea that the deployment of human capital in different labor market contexts may shape how education translates into earnings. By including interaction term between educational attainment and field of work, it captures how the returns to a bachelor's or master's degree vary across work fields.

3.3.3. Wage Difference of Working in Matched Field

As discussed in Section 2.5, working outside one's field of study may be associated with lower wages. Therefore, we include a measure of match to examine whether being employed in a job related to one's field of education is linked to a wage premium. Additionally, we analyse how this relationship varies for young adults by gender and education level, as the effects of mismatch may differ across these groups.

Equation (4):

$$\ln(wage_i) = \beta_0 + \sum\beta_1 match_i + \sum\beta_2 edu\_level_i + \sum\beta_3(match_i \times edu\_level_i) + \beta_4 Experience_i + \beta_5 Experience_i^2 + \sum\delta_t + \varepsilon_i$$

The coefficient β_0 represents the baseline log wage of an individual who is mismatched, has low education, zero experience, and is observed in the reference year. The coefficient β_1 captures the effect of working in a job that matches one's field of education. The coefficient β_2 measures the wage difference associated with higher education levels relative to low education. The interaction term β_3 shows how the effect of working in a job which matches with the field of study. The total match effect of field match for higher degree of education is given by $\beta_1+\beta_3$. The coefficient β4 reflects the return to an additional year of work experience, while β_5 captures the nonlinear effect of experience, allowing for diminishing returns as experience increases. Finally, δ_t represents year fixed effects that control for time-specific factors such as inflation and overall wage growth, and ε_i is the error term capturing unobserved influences on wages.

3.3.4. Estimation Strategy

All regressions are estimated using OLS with heteroskedasticity-robust standard errors (HC1). Year fixed effects are included in every specification to net out macroeconomic shifts over time. The analysis is restricted to individuals aged 20–29 in order to capture wage differentials at early career stages, where educational attainment plays a particularly prominent role. To ensure comparability, wages are adjusted for working hours and harmonized across years. A detailed explanation of the conversion of gross wages to estimated net wages is described in Section 3.4. In addition, the natural logarithm of adjusted monthly net wages is used in the regression analysis to improve distributional properties and reduce skewness in the wage variable.

Together, the canonical and extended Mincer regressions offer a comprehensive empirical framework to assess returns to education in Latvia, both on average and across relevant dimensions such as field of study and field of employment.

3.4. Sample Description

For the analysis, we restrict the sample to individuals aged 20 to 29, to exclude those who are still likely to be in education and to most accurately represent recent graduates entering the labour market. The sample includes only employed individuals who report positive monthly net earnings from their main job, as wage premiums can only be estimated among active earners. To ensure consistency across years, the dataset is harmonized using common variable definitions.

Wage definitions differ across periods, with monthly net earnings available for 2014–2020 and gross earnings for 2021–2024. To ensure comparability, net earnings for these years were constructed from gross wages by applying specific tax rates, producing a unified wage measure suitable for analyzing wage differences throughout the 2014–2024 period. Rather than using a flat percentage, these tax rates were determined on a case-specific basis, calculated according to each respondent’s before-tax earning bracket. As shown in Table 1, the tax rates increase progressively with income level.

Table 1. Applied Tax Rates for Gross-to-Net Wage Conversion by Earnings Category and Year.

Earnings category	2021 (%)	2022 (%)	2023 (%)	2024 (%)
Up to 50% of average earning	19.96	17.82	18.03	19.62
50-67% of average earning	23.27	22.16	22.61	23.80
67-80% of average earning	24.86	24.24	24.80	25.80
80-100% of average earning	26.49	26.38	27.06	27.88
100-120% of average earning	27.79	28.18	28.79	29.02
More than 120% of average earning	29.05	29.22	29.45	29.62

Note. This table is created by the authors using data from Eurostat (n.d.-b), "Tax rate" (dataset code: earn_nt_taxrate), accessed via the Eurostat Data Browser.

In addition, for the fields of education, the LFS uses the International Standard Classification of Education (ISCED), however, the level of detail differs across years. Years 2014 and 2015 use broader 2-digit ISCED 1997 categories (e.g., 22 for Humanities), whereas since 2016 surveys use a more detailed 3-digit ISCED-F 2013 classification (e.g., 022), replacing the former ISCED 1997 codes. To ensure consistency across the full period, all three-digit codes are collapsed into their corresponding two-digit ISCED 1997 categories. This results in a harmonized field-of-study classification that is consistent across the research period.

The final sample is therefore representative of Latvia's young, employed workforce and is well-suited for analyzing wage differences between recent graduates with higher education and their peers without a tertiary degree.

3.5. Limitations

Despite careful data preparation, several limitations must be acknowledged. First, differences in wage definitions across years create potential measurement error. Although gross earnings for 2021–2024 were converted to net earnings to maintain consistency, these conversions rely on simplified assumptions about tax liabilities and may not fully capture individual-specific deductions or allowances.

Second, the field-of-study variable is not fully consistent across years. While harmonization of 3-digit ISCED-F 2013 codes into broader 2-digit categories allows for comparability, this aggregation inevitably leads to a loss of detail and may obscure differences between more specific study programs. The detailed correspondence between ISCED-F 2013 and ISCED 1997 categories is provided in Appendix B.

Third, the analysis focuses on individuals aged 20-29 and includes only those who are employed and report positive earnings. While this improves comparability across recent graduates, it excludes unemployed or inactive individuals, which may introduce sample-selection bias if higher education affects the probability of employment. A possible way to address this issue would be to use a Heckman selection model, where the probability of employment is first estimated and subsequently accounted for in the wage equation. However, this is beyond the scope of the present study.

A key limitation of the analysis is the potential presence of omitted variable bias. While the models control for experience and time effects, the data do not include information on important factors such as individual ability or motivation. If these are related to both education and wages, the estimated wage premiums may be biased. In addition, individuals may self-select into higher education, so the results should be interpreted as conditional associations rather than causal effects. Furthermore, the smaller number of observations in later years may also reduce the precision of the estimates. Finally, the use of a log-linear Mincer model and interaction terms increases model complexity, which with limited sample size reduces degrees of freedom for estimation and might affect significance of estimated coefficients.

Finally, the analysis is constrained by data availability, as the most recent LFS data for 2025 are not yet available. As a result, the analysis is limited to the period up to 2024 and may not fully capture the most recent developments in the labour market.

4. Results

4.1. Descriptive Statistics

The descriptive analysis summarise the main characteristics of the dataset and key variables used in the empirical analysis of young graduate wage premiums in Latvia over the period 2014–2024. The descriptive statistics aim to illustrate the composition of the analytical sample, the distribution of wages, and raw differences across education levels, fields of study, gender, and time. These patterns provide important context for the subsequent econometric analysis.

In total, 443'162 Labor Force Survey observations were recorded over the period 2014-2024. After restricting the sample to individuals aged 20-29 and excluding respondents with zero net wages, the analytical sample initially consists of 10'120 individuals. It was reduced to 10'114 after excluding 6 outliers. We excluded these observations because the respondents reported working 8 hours or less in the reference week, and our wage normalisation method - scaling reported earnings to a full-time (168-hour) workmonth - would translate this to an implausibly high monthly wages (above 10'000Eur) for our chosen age group. Keeping these values would distort the average wages and significantly influence the regression results.

Table 2. Number of Respondents in the Sample Aged 20-29 by Years.

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
n	1387	1375	1367	1419	1178	1077	924	363	360	324	340

Note. This table is created by authors using data from the Labour Force Survey.

Table 2 illustrates that the participation level of 20-29-year-old individuals with non-zero earnings is declining over the ten-year period. The sample remained relatively stable between 2014 and 2017, peaking at 1,419 respondents, but a significant decrease occurred in the latter half of the decade, dropping from 924 respondents in 2020 to just 340 by 2024. As a result, the analysis in the last years of the sample- especially from 2021 onwards - is based on fewer observations and should therefore be interpreted with greater caution than the earlier years.

Table 3. Sample Size by Age, Gender, and Level of Education.

Age	n	%	Gender	n	%	Education	n	%
20-24	3711	36.7%	**Men**	5638	55.7%	**Lower education**	6787	67.8%
25-29	6403	63.3%	**Women**	4476	44.3%	**Bachelor's degree**	2558	25.6%
Total	10114	100%	**Total**	10114	100%	**Master's/PhD**	664	6.6%
						Total	10009	100%

Note. This table is created by the authors using data from the Labour Force Survey by filtering the sample to individuals aged 20-29 and retaining only respondents with non-zero net wages.

Table 3 presents the composition of the analytical sample by age, gender, and highest level of education completed. Of 10,114 individuals in the sample, the majority were in the 25–29 age group (63.3%), while individuals aged 20–24 made up 36.7% of the observations. Men represent 55.7% of the sample, and women 44.3%, indicating a moderately balanced gender distribution. In terms of educational attainment, the majority of young workers have not completed tertiary education (67.8% have lower education as their highest completed level), with a substantial minority holding a bachelor's degree (25.6%) or a master's/PhD (6.6%).

Table 4. Distributional Patterns in Mean Wages Across Demographic Groups.

Mean Net Wage							
		Men			Women		
Year	**Overall**	**Lower**	**Bachelor**	**Master/PhD**	**Lower**	**Bachelor**	**Master/PhD**
2014	488.1	460.9	618.5	836.0	367.3	524.8	619.6
2015	513.3	508.3	602.0	878.1	419.0	541.1	627.5
2016	572.3	552.6	711.4	1,069.7	432.3	619.9	685.8
2017	601.3	606.9	772.4	874.5	464.2	637.5	678.9

2018	651.8	606.2	792.1	1,049.4	538.4	706.6	844.3
2019	693.2	680.0	788.5	1,021.3	545.4	770.0	877.9
2020	712.6	693.2	999.5	1,071.1	590.9	751.8	877.1
2021	924.4	864.3	1,180.9	1,370.4	712.1	930.2	1,133.7
2022	965.9	903.1	1,198.0	1,448.9	790.1	1,002.6	1,232.2
2023	1,073.9	1,010.3	1,300.9	1,907.7	843.5	1,181.8	1,309.3
2024	1,121.9	1,124.9	1,334.3	1,338.1	863.8	1,156.5	1,541.9

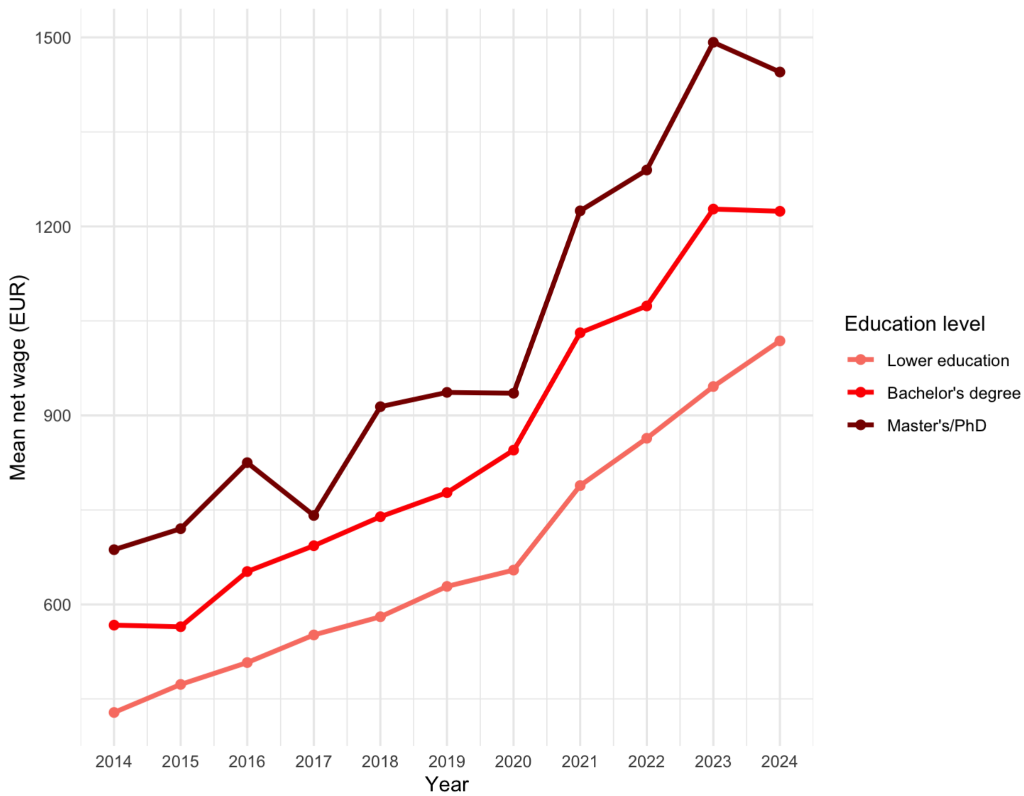
Note. This table is created by the authors using data from the Labour Force Survey using weights to estimate mean values.

Table 4 presents the evolution of mean net wages in Latvia over the period 2014-2024, disaggregated by gender and education level. First, there is a strong upward trend in wages over time across all demographic groups. The overall mean net wage more than doubled, increasing from EUR 488.1 in 2014 to EUR 1,121.9 in 2024. This growth is particularly pronounced after 2020, suggesting either structural changes in the labour market, wage inflation, or compositional shifts in employment. Importantly, this upward trajectory is consistent across all subgroups, indicating that wage growth is not driven by changes in any single segment.

Second, educational attainment serves as a primary driver of wage growth, as individuals with tertiary education (Bachelor and especially Master/PhD degrees) consistently earn significantly more than those with lower education. For instance, in 2024, men with lower education earn on average EUR 1,124.9, compared to EUR 1,334.3 for Bachelor graduates and EUR 1,338.1 for those with a Master/PhD. The education wage premium is even more pronounced when considering earlier years, where the relative wage gap between lower and tertiary education levels appears larger in proportional terms. This suggests that while wages have increased across the board, returns to education remain a key driver of wage inequality.

Third, gender differences are also evident throughout the period. Men generally earn higher wages than women at comparable education levels in nearly all years. Only in the most recent year does this pattern change at the highest education level, where women with a Master/PhD degree outperform men (EUR 1,541.9 versus EUR 1,338.1). However, this appears to be an exception rather than a trend, as in all previous years the gender wage gap remains persistent and women earned less than men with the same level of education.

Figure 1. Mean Monthly Net Wage by Education Level Among Young Workers.



Note. This figure is created by the authors using data from the Labour Force Survey.

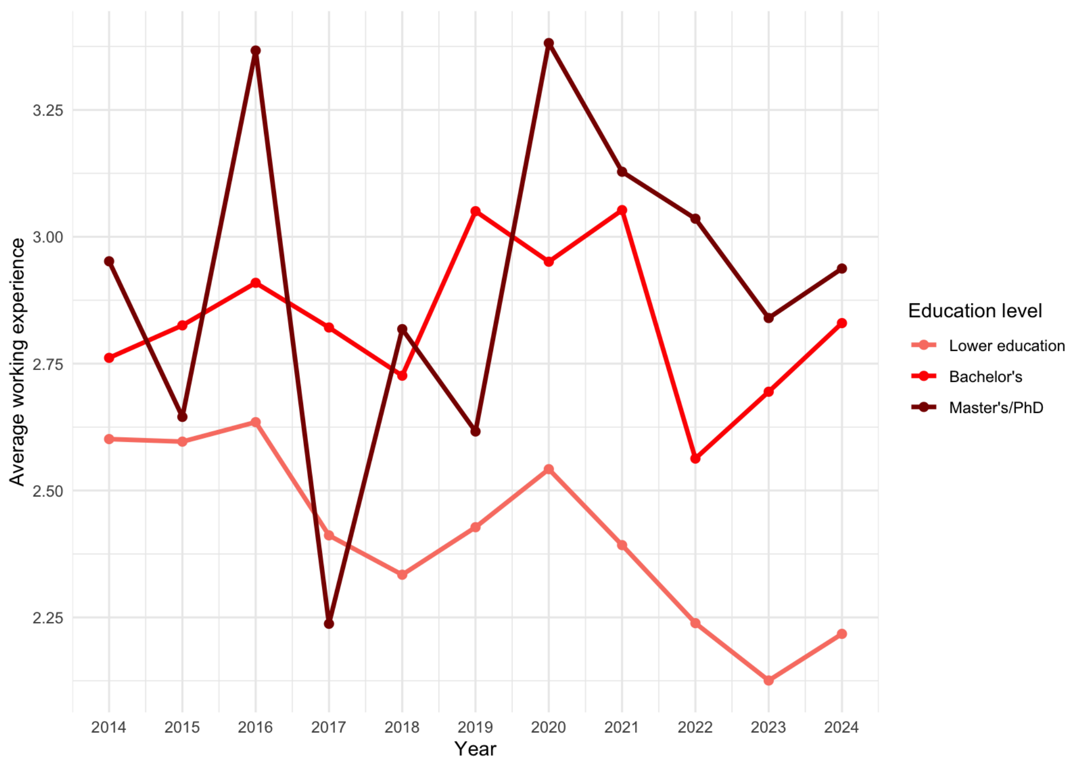
Figure 1 complements these cross-sectional patterns by showing how mean wages by education level differ over the period 2014-2024. Mean wages increase across all education levels throughout the entire period, although the pattern is not monotonic. While the overall trend is upward, the most pronounced increase for all education groups occurs between 2020 and 2021. In addition, Bachelor’s degree holders and Master’s/PhD holders experience another notable rise in mean wages between 2022 and 2023, followed by a slight decline in 2024.

The ranking of mean wages remains the same throughout the period. Individuals with a Master’s/PhD consistently earn the highest mean wages, followed by Bachelor’s degree holders, while individuals with lower education have the lowest mean wages in every year. By

2023, mean monthly net wages for individuals with a Master's or PhD reach nearly EUR 1,500 and just above EUR 1,200 for Bachelor's degree holders, while remaining below EUR 1,000 for those with lower education. In 2024, wages for the higher-educated groups decreased slightly but remained well above levels observed in earlier years.

Overall, the figure suggests that the wage gap by educational attainment persists over the entire sample period and appears to widen in the later years, particularly after 2020, when wage growth accelerates for all groups.

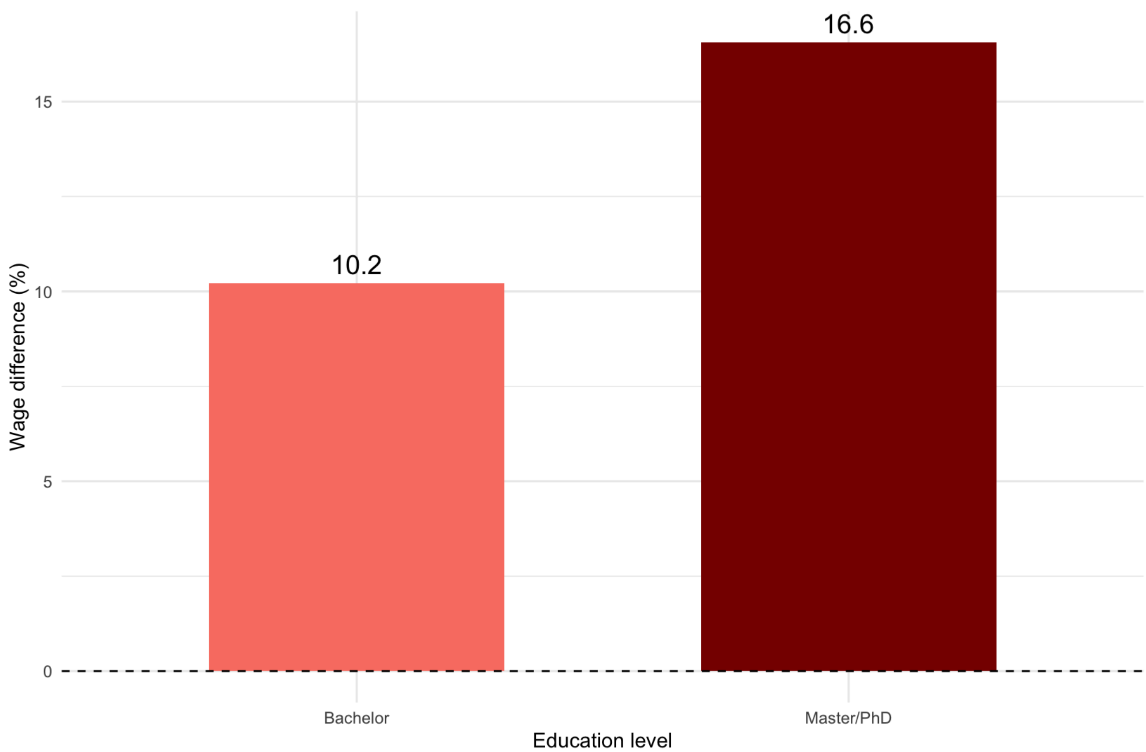
Figure 2. Average Working Years by Education Level Among Young Workers



Note. This figure is created by the authors using data from the Labour Force Survey by calculating the average working years using WORKING_SINCE and survey year variables.

Figure 2 shows that the average professional experience of the sample remained relatively stable over the decade, ranging from 2.1 to 3.4 years. While the graphical representation shows frequent directional changes - particularly for the Master's and PhD groups - these represent minor variations within a narrow two-year window rather than fundamental shifts in the sample's length of work experience. For workers with primary or secondary education, average working years remain the lowest throughout the period and show a gradual downward trend. Bachelor's degree holders display relatively stable work experience over time, remaining just below three years on average. In contrast, the Master's and PhD group exhibits the highest volatility. Average working years for this group fluctuate noticeably across the period, with peaks around 2016 and 2020. This volatility can be justified with a smaller sample size and more heterogeneous patterns, which makes the average more sensitive to the entry or exit of just a few individuals. Furthermore, because advanced degrees require varying lengths of time to complete, the age at which these individuals enter the labor market is less uniform than those with lower levels of education.

Figure 3. Wage Difference Between Matched and Mismatched Workers among 20-29 year olds in Latvia, (%)



Note. This figure is created by the authors using data from the Labour Force Survey by calculating weighted mean wages for matched and mismatched workers expressing the difference as a percentage relative to mismatched workers.

Figure 3 compares the average wages of matched and mismatched young workers with tertiary education using the following formula:

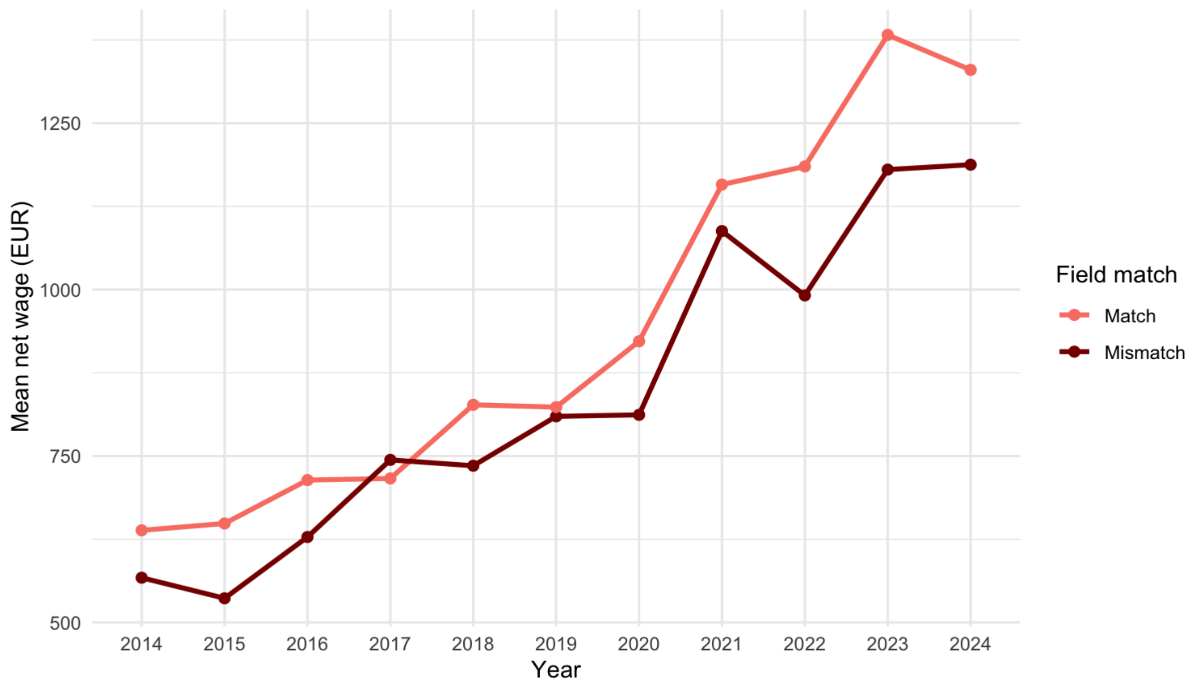
$$Wage\ difference\ (\%) = \frac{Mean\ net\ wage\ for\ matched\ workers - Mean\ net\ wage\ for\ mismatched\ workers}{Mean\ net\ wage\ for\ mismatched\ workers} x100,$$

Where the wage difference is calculated as the percentage difference between the mean wage of matched and mismatched workers, expressed relative to mismatched workers. In this context, a matched job is defined as employment in an occupation that corresponds to the individual's field of study, while a mismatched job refers to employment in an occupation outside that field (Appendix H).

The results show on average a positive wage advantage for workers employed in jobs that match their field of study in both education levels. Among workers with a Bachelor's degree, matched workers earn on average 10.2% more than mismatched workers. Among workers with a Master's degree or PhD, the difference is larger: matched workers earn on average 16.6% more than mismatched workers. This suggests that field-of-study match is associated with higher wages.

It is important to note that this figure presents raw descriptive differences, not causal effects. The estimates are weighted group averages and do not yet control for differences in work experience, year effects, gender, occupation, or other factors. Therefore, the figure should be interpreted as an initial summary of the data.

Figure 4. Mean Net Wage by Study-Field Match Status



Note. This figure is created by the authors using data from the Labour Force Survey by calculating weighted mean wages for matched and mismatched workers, combining individuals with Bachelor’s and Master’s/PhD degrees.

Figure 4 presents a comparison of weighted mean net wages from 2014 to 2024 for young workers aged 20-29 with tertiary education, distinguished by whether their occupation corresponds to their field of study.

There is a clear upward trend for both series, indicating that overall wage levels increased over time for young tertiary-educated workers regardless of the match status. However, individuals employed in the jobs corresponding to their field of study consistently earn higher wages on average than mismatched workers in nearly all years. The only exception occurs in 2017, where mismatched workers appear to earn slightly more. This deviation is likely driven by compositional factors - for example, the presence of relatively higher-earning individuals in the mismatched group - and is not persistent over time.

The wage gap becomes more pronounced in the later years, particularly from 2022 onward, when matched workers earn on average approximately EUR 130-200 more per month than mismatched workers. Overall, these findings suggest that study-field match is associated with higher wages among young workers with Bachelor's and Master's/PhD degrees.

4.2. Wage Premiums from Canonical Mincer Regression

Table 5 reports the results of the Equation (1) canonical Mincer regression estimated by OLS with heteroskedasticity-robust standard errors. The coefficients on the education variables indicate positive and statistically significant returns to higher education.

Table 5. Results from the Canonical Mincer Regression of Log Monthly Net Wages

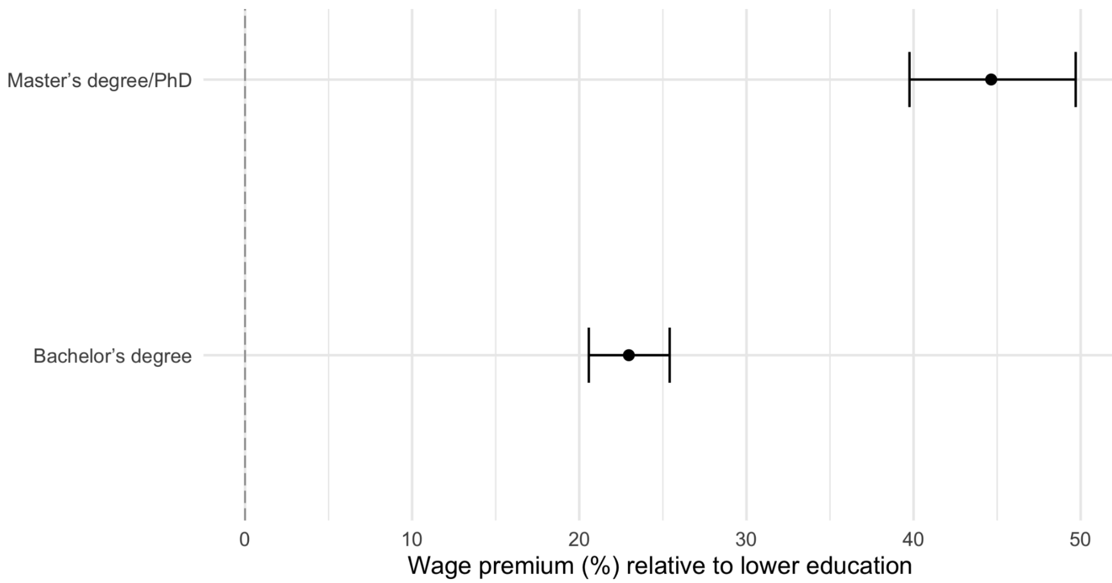
	Log(wage)	**Std. Error**
Bachelor's	0.207***	0.010
Master's/PhD	0.369***	0.018
Experience	0.045***	0.005
Experience²	-0.003***	0.001
Num.Obs.	10008	
R2	0.291	
R2 Adj.	0.290	
AIC	11462.5	
BIC	11577.9	
Log.Lik.	-5715.262	
RMSE	0.43	

*Note. This table is created by the authors using data from the Latvian Labour Force Survey. The results are based on a Mincer log-wage regression estimated by ordinary least squares (OLS) with robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

In particular, the estimated coefficient for individuals with a Bachelor's degree is 0.207, while for those with a Master's degree or PhD it is 0.369. Since the dependent variable is in logarithms, these coefficients represent log wage differences relative to individuals with lower levels of education.

To facilitate interpretation, these estimates are transformed into percentage wage premiums using the exponential transformation $100 \times (e^{\beta} - 1)$. This implies that individuals with a Bachelor's degree earn approximately 23% higher wages, while those with a Master's degree or PhD earn approximately 45% higher wages, holding experience and year effects constant shown in Figure 6.

Figure 6. Education Wage Premiums among Young Adults in Latvia (%)



Note. This graph is created by the authors using data from the Labour Force Survey by applying Mincer log-wage model controlling for experience, experience squared, and year fixed effects; reported as percentage differences relative to individuals without tertiary education; point estimates with 95% confidence intervals.

Figure 6 presents the estimated returns to education, expressed as percentage wage premiums relative to the baseline category of lower education. The coefficients on education indicators are transformed using the exponential function, allowing for interpretation in percentage terms.

The results indicate a clear and economically meaningful gradient in wages by educational attainment. Individuals with a Bachelor’s degree earn, on average, approximately 23% higher wages compared to individuals with lower levels of education, holding experience and time effects constant. The estimated premium for individuals with a Master’s degree or PhD is substantially larger, at approximately 45%.

The precision of these estimates is reflected in the relatively narrow 95% confidence intervals. Importantly, the effects for Master's degree is statistically significantly higher than for Bachelor degree stressing the importance in wage return from higher education degree.

These findings are consistent with the human capital framework, which predicts that individuals with higher levels of educational attainment exhibit greater productivity and, consequently, earn higher wages. The increasing magnitude of returns across education levels further suggests that advanced degrees are particularly valued in the Latvian labor market.

It is important to emphasize that the estimates presented in Figure 6 represent conditional associations rather than causal effects. While the baseline specification controls for observable factors such as experience and time effects, it does not account for potentially important unobserved characteristics, including individual ability or motivation. As a result, the estimated returns to education may partially capture selection effects. A detailed year-by-year decomposition of the estimated wage premiums, based on a Mincer specification with interactions between education and year indicators, is provided in Appendix C. An alternative specification of wage premiums by gender, based on a Mincer model with interactions between education, gender, and year indicators, is presented in Appendix D.

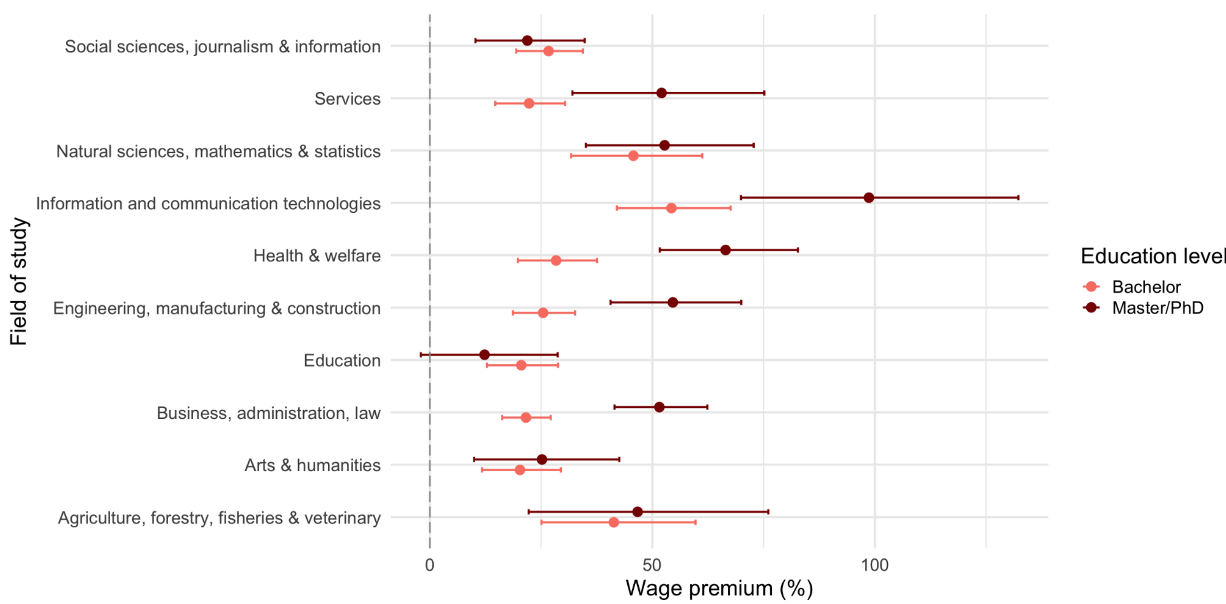
Figure 7 extends this analysis by incorporating field of study and its interaction with education level within the Mincer framework. This allows the estimated wage premiums to vary across fields, capturing an important dimension of heterogeneity in returns to education.

4.3. Wage Premiums by Field of Study

The full set of regression results from the Mincer-type model with interactions between education level and field of study, as specified in Equation (2), is reported in Appendix E. The reported coefficients represent differences in log wages associated with educational attainment, field of study, and their interactions. In particular, the coefficients on the education variables capture log wage differences between individuals with a Bachelor's or Master's/PhD degree and those with lower education within the reference field of study. The field-of-study coefficients reflect baseline differences in log wages across fields for individuals with lower education, relative to the omitted field. The interaction terms indicate how the returns to education vary across fields, showing whether the log wage premium associated with a given degree is higher or lower compared to the reference field.

Because the specification includes interaction terms, individual coefficients cannot be interpreted directly as field-specific wage premiums. Instead, field-specific effects are obtained by combining the relevant main and interaction effects and transforming them into percentage terms using the exponential function. To present these results more clearly, Figure 7 reports the model-implied wage premiums by field of study and education level, based on predicted wages evaluated at mean experience and averaged across years.

Figure 7. Wage Premiums by Field of Study and Education Level among 20-29 year olds in Latvia, (%)



Note. This graph is created by authors using data from the Labour Force Survey by applying Mincer log-wage model controlling for experience, experience squared, and year fixed effects; reported as percentage differences relative to individuals without tertiary education.

Figure 7 presents estimated wage premiums by field of study and education level for individuals aged 20–29 in Latvia. The results are derived from an extended Mincer-type earnings equation that includes interactions between education level and field of study, allowing returns to education to vary across fields. The reported estimates are based on model-predicted wages evaluated at mean experience and averaged across years using sampling weights. Wage premiums are expressed relative to individuals with lower education.

This figure presents wage premiums estimated from a regression model, meaning the results reflect differences after controlling for factors such as experience and time, rather than raw averages. The results reveal substantial heterogeneity in returns to education across fields of study. For individuals with a Bachelor's degree, wage premiums vary considerably, ranging from relatively modest returns in fields such as education and arts and humanities (approximately 15–25%), to higher returns in fields such as information and communication technologies (ICT) and natural sciences (around 40–55%). Intermediate returns are observed in fields such as business, engineering, and health.

For individuals with a Master's degree or PhD, wage premiums are consistently higher across all fields, but the magnitude of returns differs significantly. The highest premiums are observed in ICT, where returns approach or exceed 100%, indicating that individuals with advanced degrees in this field earn more than double the wages of those with lower education, conditional on experience and time effects. High returns are also observed in health, engineering, and natural sciences (approximately 60–80%). In contrast, fields such as education and arts and humanities exhibit substantially lower premiums, generally below 30%.

The comparison between education levels within fields highlights that the additional return to postgraduate education is particularly large in technical and high-demand fields, especially ICT. In contrast, the incremental return from a Bachelor's to a Master's degree is more limited in fields such as education and social sciences. In the field of education, the estimated wage premium for individuals with a Master's degree or PhD is lower than that for individuals with only a Bachelor's degree. This suggests that the additional return to postgraduate education in this field is limited. A likely explanation is the occupational structure: individuals with a Bachelor's degree are more likely to work as school teachers, who tend to have relatively stable and comparatively higher earnings, whereas those with advanced degrees are more likely to be employed in academic positions, such as university lecturers, where wages may be lower on average in Latvia. This composition effect reduces the observed returns to postgraduate education in the field of education.

The confidence intervals shown in Figure Y indicate that most estimated wage premiums are statistically significant, as they lie well above zero. However, intervals are wider in some fields, particularly for Master's/PhD estimates, reflecting greater uncertainty, likely due to smaller sample sizes within specific field-degree combinations.

Overall, the results demonstrate that returns to education are not uniform but depend strongly on the field of study. This highlights the importance of accounting for field-specific heterogeneity when analyzing wage differentials and suggests that aggregate estimates of returns to education may mask substantial variation across disciplines.

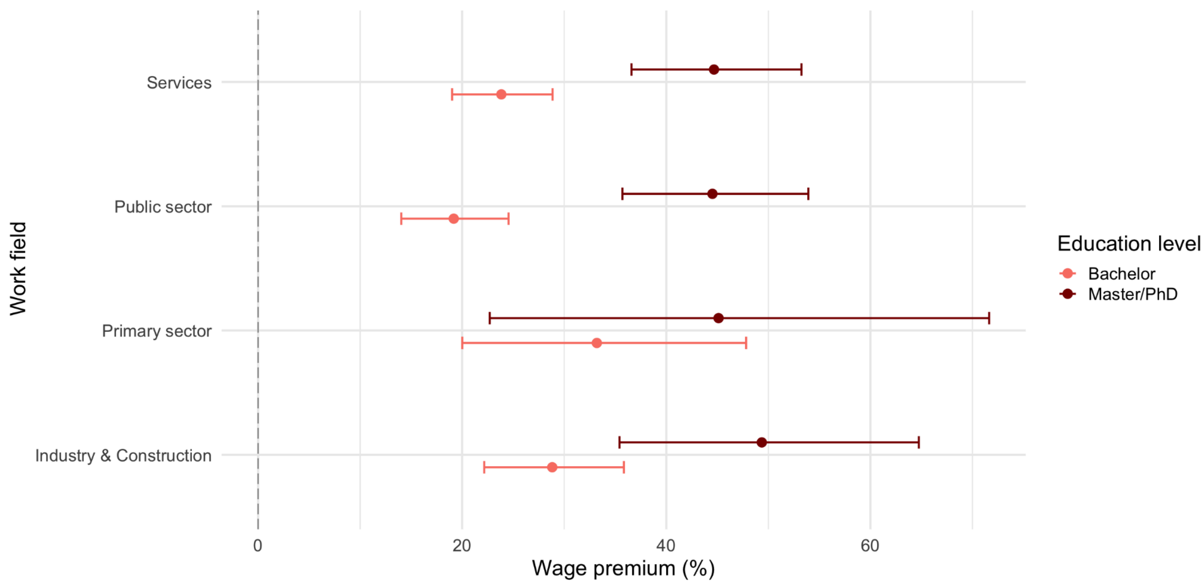
Despite the richer specification, these estimates should be interpreted as conditional associations rather than causal effects. While the model controls for experience, time effects, and field of study (including heterogeneous returns through interaction terms), unobserved factors such as ability, preferences, or selection into specific fields may still bias the estimates.

To further explore heterogeneity in wage outcomes, Figure 8 extends the analysis by presenting wage premiums by field of work and education level among young adults.

4.4. Wage Premiums by Field of Work

The results of the Mincer-type model with interactions between education level and field of work, as specified in Equation (3), are reported in a table in Appendix F. The estimated coefficients represent differences in log wages associated with education, field of work, and their interaction, with Industry & Construction as the reference category. Because the model includes interaction terms, coefficients cannot be interpreted directly as sector-specific wage premiums. Therefore, Figure 8 presents the model-implied wage premiums by field of work and education level, expressed relative to individuals with lower education.

Figure 8. Wage Premiums by Field of Work and Education Level among 20-29 year olds in Latvia, (%)



Note. This graph is created by the authors using data from the Labour Force Survey by applying Mincer log-wage model controlling for experience, experience squared, and year fixed effects; reported as percentage differences relative to individuals without tertiary education. The work-field variable is grouped into four broad sectors. The Primary sector includes agriculture, forestry and fishing, and mining and quarrying. Industry and Construction includes manufacturing, electricity, gas, steam and air conditioning supply, water supply and waste management, and construction. The Services sector includes wholesale and retail trade, transportation and storage, accommodation and food service activities, information and communication services, financial and insurance activities, real estate activities, professional, scientific and technical services, administrative and support service activities, arts, entertainment and recreation, and other service activities. The Public sector includes public administration and defence, education, and human health and social work activities.

Figure 8 presents estimated wage premiums by field of work and education level for individuals aged 20–29 in Latvia. The results are derived from an extended Mincer-type earnings equation that includes interactions between education level and field of work, allowing returns to education to differ across sectors of employment. Predicted wages are evaluated at mean experience and averaged across years, and wage premiums are expressed relative to individuals with lower education.

This figure is based on regression results and shows estimated wage premiums, rather than simple descriptive differences. The results indicate substantial variation in returns to education across fields of work. For individuals with a Bachelor's degree, wage premiums are relatively moderate across most sectors, ranging from approximately 20% in the public sector to around 30% in the primary sector. Slightly higher returns are observed in industry and construction, as well as services, where premiums reach roughly 25–30%.

For individuals with a Master's degree or PhD, wage premiums are consistently higher across all work fields, but the magnitude varies. The highest returns are observed in industry and construction and in services, where premiums approach 50–60%. Similarly high returns are found in the public sector, suggesting strong rewards to advanced education in these areas. In contrast, while the primary sector also shows substantial returns (around 45–50%), the associated confidence intervals are wide, indicating greater uncertainty in these estimates.

Comparing education levels within each sector reveals that the additional return to postgraduate education is positive across all work fields, but relatively similar in magnitude compared to the variation observed across fields of study in Figure 7.

The confidence intervals indicate that most estimated premiums are statistically significant, as they lie above zero. However, wider intervals in the primary sector, particularly for Mater's/ PhD education, suggest more limited precision, likely reflecting smaller sample sizes in this category.

Overall, the results show that returns to education vary across sectors of employment, but the differences are less pronounced than those observed across fields of study. This highlights that both study field and labor market allocation contribute to wage differentials.

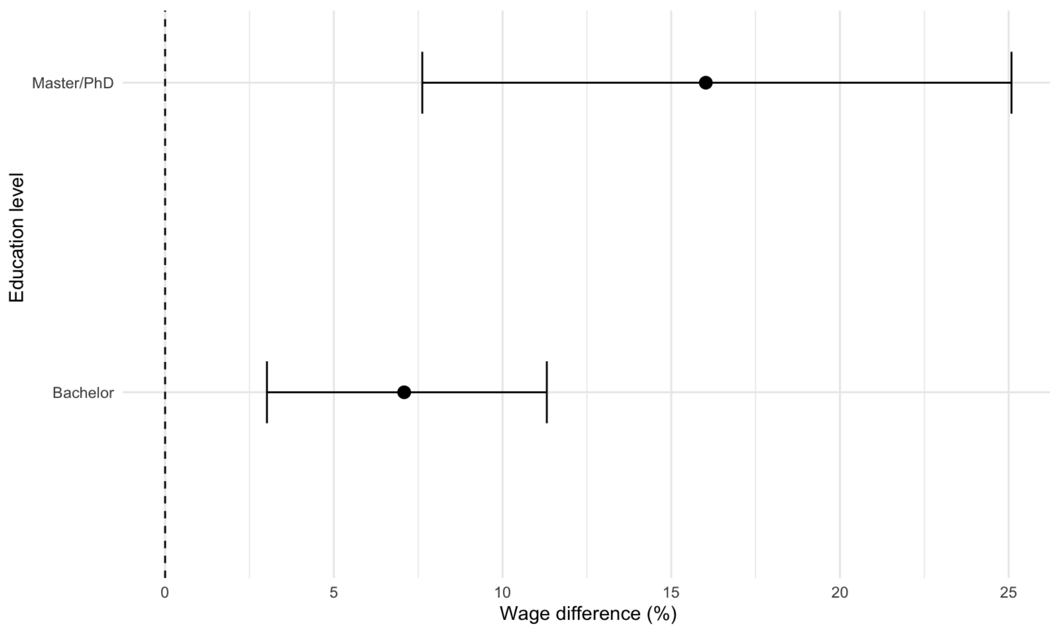
As with previous specifications, these estimates should be interpreted as conditional associations rather than causal effects. While the model controls for experience, time effects, and field of work (including heterogeneous returns through interaction terms), unobserved factors, such as individual ability or selection into sectors, may still influence the results.

4.5. Wage Difference of Working in Matched Field

To complement the descriptive evidence presented in Figure 3, which compares average wages of matched and mismatched young workers with tertiary education, the table in the Appendix G reports the results of Equation (4). This specification employs a regression-based approach that controls for experience and time effects and estimates a log wage model with an interaction between field-of-study–occupation match and education level, using OLS with heteroskedasticity-robust standard errors. The coefficient on the match indicator is positive and statistically significant, indicating that working in a matched field is associated with higher wages for the reference education group (Bachelor level). In particular, the estimated coefficient for matched employment is 0.068, while the interaction term between match and Master/PhD education is 0.080, suggesting that the match effect is larger for higher-educated individuals, although the interaction is only weakly significant, this likely reflects lower statistical precision due to the substantially smaller sample size of Master/PhD graduates compared to Bachelor graduates.

Since the dependent variable is expressed in logarithms, these coefficients represent log wage differences. To facilitate interpretation, the estimates are transformed into percentage wage effects using the exponential transformation $100\times(e^{\beta}-1)$. For Bachelor graduates, the relevant coefficient is the main match effect, $\beta=0.068$. For individuals with a Master's degree or PhD, the relevant coefficient is the sum of the main match effect and the interaction term, $\beta=0.068+0.080$. This implies that Bachelor graduates working in matched fields earn approximately 7% higher wages compared to their mismatched counterparts, while individuals with a Master's degree or PhD earn approximately 16% higher wages when working in a matched field, holding experience and year effects constant. These results are visualized in Figure 9.

Figure 9. Wage Difference of Working in a Matched Field among 20-29 year olds in Latvia, (%).



Note. This figure is created by the authors using data from the Labour Force Survey by applying a Mincer log-wage model with an interaction between field-of-study–occupation match and education level, controlling for experience, experience squared, and year fixed effects. Reported values represent percentage wage differences between matched and mismatched workers within each education group. Point estimates are shown with 95% confidence intervals.

Figure 9 presents the estimated wage premium associated with working in a field that matches an individual's education (Appendix H), based on a regression framework. The definitions of matched and mismatched jobs follow those introduced earlier (see Section 4.1). The estimates are obtained from a log-wage model that includes an interaction between field-of-study match and education level, while controlling for labor market experience (and its square) as well as year fixed effects. The reported coefficients are transformed into percentage terms and interpreted as average marginal effects.

The results indicate that working in a matched field is associated with a statistically significant wage premium for both education groups. For individuals with a Bachelor's degree, the estimated premium is approximately 7%, implying that, holding experience and time effects constant, matched workers earn about 7% higher wages than their mismatched counterparts.

For those with a Master's or PhD degree, the effect is substantially larger, at around 16%. The confidence intervals shown in the figure do not cross zero, indicating that these effects are statistically different from zero at conventional significance levels.

These findings suggest that the economic returns to job-education match increase with the level of education. In particular, the substantially larger premium for Master's and PhD holders is consistent with stronger specialization at higher levels of education, where skills are more field-specific and less transferable across occupations.

Conclusions

This thesis examines whether higher education continues to provide an economic advantage for young people entering the Latvian labour market. Using harmonized Latvian Labour Force Survey microdata for 2014–2024 and applying Mincer-type wage regressions, the analysis estimates wage premiums for tertiary education among employed individuals aged 20–29. The results show that higher education remains economically valuable in Latvia at labour market entry.

The baseline estimates indicate a clear positive relationship between educational attainment and wages. Compared with young workers without tertiary education, individuals with a Bachelor's degree earn on average around 23% higher wages, while those with a Master's degree or PhD earn around 45% higher wages, after controlling for labour market experience and year effects. These findings suggest that tertiary education still provides a substantial earnings advantage in Latvia and does not appear to be losing its value overall.

At the same time, the results show that the value of higher education is not uniform. Wage premiums differ significantly across fields of study. The highest returns are observed in information and communication technologies, natural sciences, engineering, and health, while lower returns are found in education and arts and humanities. This means that the labour-market value of higher education depends not only on whether an individual attains a tertiary degree, but also on the type of knowledge and skills acquired. The results by field of work show some variation as well, although sectoral differences are less pronounced than differences across study fields.

The thesis also finds that job match matters. Young graduates working in occupations related to their field of study earn more than mismatched graduates. The estimated wage premium for working in a matched field is around 7% for Bachelor graduates and around 16% for Master's and PhD graduates. This suggests that the economic return to education is strengthened when graduates are able to use their field-specific skills in relevant occupations.

Although the initial hypothesis expected a decline in the tertiary wage premium over time, the year-specific estimates do not show a persistent downward trend. Instead, wage premiums remain positive and broadly stable, with some year-to-year fluctuation. Overall, the evidence does not support the view that higher education is losing its value in Latvia. Instead, higher education continues to generate meaningful wage advantages for young workers, although these returns are highly uneven across degrees, fields of study, and match quality. Therefore, the main conclusion of this thesis is that higher education still pays in Latvia, but some degrees and fields pay considerably more than others.

These findings have several implications. For students, the results show that both the choice of field of study and finding a related job are important for higher wages. For policymakers, the results suggest that it is not enough to increase the number of graduates, education should also match labour market needs. For researchers, the results show that it is important to look at differences between fields, not only average returns to education.

In addition, the results should be interpreted as conditional associations rather than causal effects, since unobserved factors such as ability, motivation, or selection into study fields may influence the estimates. The conversion of gross to net wages for 2021–2024 may also introduce measurement error. Nevertheless, the consistent pattern of positive premiums across specifications provides robust evidence that tertiary education remains valuable in the Latvian labour market.

In sum, this thesis shows that for young people in Latvia, higher education continues to offer a meaningful wage premium at labour market entry. However, its value is increasingly differentiated, making the field of study, level of degree, and education-job match central to understanding who benefits most from tertiary education.

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Appendices

Appendix A

LFS variable mapping across years 2014-2024, used for variable harmonization and the construction of the analytical database.

Color coding explanation:

- (blue) LFS code and its answer options are consistent across years 2014-2020
- (pink) LFS code and its answer options are consistent across years 2021-2024
- (green) LFS code and its answer options remain unchanged the entire period 2014-2024
- (yellow) Cases where answer options were harmonized or recoded across years (e.g., merging or reassigning answer options)

CODE	ANSWER	MEANING	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
AGE	1	0 to 4 years	1	1	1	1	1	1	1	1	1	1	1
	2	5 to 9 years	2	2	2	2	2	2	2	2	2	2	2
	3	10 to 14 years	3	3	3	3	3	3	3	3	3	3	3
	4	15 to 19 years	4	4	4	4	4	4	4	4	4	4	4
	5	20 to 24 years	5	5	5	5	5	5	5	5	5	5	5
	6	25 to 29 years	6	6	6	6	6	6	6	6	6	6	6
	7	30 to 34 years	7	7	7	7	7	7	7	7	7	7	7
	8	35 to 39 years	8	8	8	8	8	8	8	8	8	8	8
	9	40 to 44 years	9	9	9	9	9	9	9	9	9	9	9
	10	45 to 49 years	10	10	10	10	10	10	10	10	10	10	10
	11	50 to 54 years	11	11	11	11	11	11	11	11	11	11	11
	12	55 to 59 years	12	12	12	12	12	12	12	12	12	12	12
	13	60 to 64 years	13	13	13	13	13	13	13	13	13	13	13
	14	65 to 69 years	14	14	14	14	14	14	14	14	14	14	14
	15	70 to 74 years	15	15	15	15	15	15	15	15	15	15	15
	16	75 years and over	16	16	16	16	16	16	16	16-19	16-19	16-19	16-19
			vecums							Vecums2			
ED_COM_YEAR	1948-2023	Four digits of the relevant year	1948-2014	1951-2015	1952-2016	1959-2017	1954-2018	1956-2019	1957-2020	1944-2021	1945-2022	1945-2023	1949-2024
	9998	Refuses to answer	9998	9998	9998	9998	9998	9998	9998	9998	9998	9998	9998
	9999	Does not know	9999	9999	9999	9999	9999	9999	9999	9999	9999	9999	9999
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			L'105							L'126			
WORKING_SINCE	1960-2016	Four digits of the relevant year	1962-2014	1962-2015	1960-2016	1962-2017	1964-2018	1964-2019	1965-2020	1965-2021	1964-2022	1964-2023	1964-2024
	9998	Refuses to answer	9998	9998	9998	9998	9998	9998	9998	9998	9998	9998	9998
	9999	Does not know	9999	9999	9999	9999	9999	9999	9999	9999	9999	9999	9999
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			D'51g							D'52g			
FPrimary	14		14	14	14	14	14	14	14	14	14	14	14
			FPrimary										

CODE	ANSWER	MEANING	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
HOURS_WORKED	1-80	Usual number of hours worked per week in main job	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80
	81	81+	81	81	81	81	81	81	81	81	81	81	81
	98	Refuses to answer	98	98	98	98	98	98	98	98	98	98	98
	99	Does not know	99	99	99	99	99	99	99	99	99	99	99
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			E'59							E'72			
ED_COMPLETED	1	No education or less than primary education	1-2	1-2	1-2	1	1	1	1	1	1	1	1
		Primary education	3	3	3	2	2	2	2	2	2	2	2
		Basic education	4	4	4	3	3	3	3	3	3	3	3
		Vocational basic education; 1-year vocational education after basic education or vocational education with pedagogical correction (after grade 8, duration – 3 years)	5-6	5-6	5-6	4	4	4	4	4	4	4	4
		Vocational education after basic education (duration – 3 years)	7	7	7	5	5	5	5	7	7	7	7
		General secondary education; general secondary education after vocational education	8-9	8-9	8-9	6	6	6	6	5-6	5-6	5-6	5-6
		Vocational secondary education after basic education or after vocational education	10-11	10-11	10-11	7	7	7	7	8	8	8	8
		Vocational education after general or vocational secondary education; vocational secondary education after general secondary education	12-13	12-13	12-13	8	8	8	8	9	9	9	9
		First-level professional higher education	14	14	14	9	9	9	9	10	10	10	10
	2	Bachelor's degree (including professional); second-level professional higher education with a study duration of 3–4 years	15	15	15	10	10	10	10	11	11	11	11
	3	Master's degree (including professional); second-level professional higher education with a study duration of 5 years	16-17	16-17	16-17	11-12	11	11	11	12	12	12	12
		Doctoral degree	18	18	18	13	12	12	12	13	13	13	13
	98	Refuses to answer	98	98	98	98	98	98	98	98	98	98	98
	99	Does not know	99	99	99	99	99	99	99	99	99	99	99
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			L'103							L'124			
HOURS_WORKED	1-80	Usual number of hours worked per week in main job	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80	1-80
	81	81+	81	81	81	81	81	81	81	81	81	81	81
	98	Refuses to answer	98	98	98	98	98	98	98	98	98	98	98
	99	Does not know	99	99	99	99	99	99	99	99	99	99	99
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			E'59							E'72			
ECON_ACTIVITY	1	Employed population	1	1	1	1	1	1	1	1	1	1	1
	2	Unemployed	2	2	2	2	2	2	2	2	2	2	2
	3	Economically inactive population	3	3	3	3	3	3	3	3	3	3	3
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			eka										
PSEIDOCODE	15		15	15	15	15	15	15	15	15	15	15	15
			PSEIDOKODS										
WEIGHT_YEAR	10		10	10	10	10	10	10	10	10	10	10	10
			Svars_1										

CODE	ANSWER	MEANING	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
ED_COM_CODE	1	General programmes	1	1	1	1	1	1	1	1	1	1	1
	2	Literacy and numeracy	-	-	2	2	2	2	2	2	2	2	2
	3	Personal development	9	9	3	3	3	3	3	3	3	3	3
	11	Education	14	14	11	11	11	11	11	11	11	11	11
	21	Arts	21	21	21	21	21	21	21	21	21	21	21
	22	Humanities (excluding languages)	22	22	22	22	22	22	22	22	22	22	22
	23	Languages	22	22	23	23	23	23	23	23	23	23	23
	31	Social and behavioural sciences	31	31	31	31	31	31	31	31	31	31	31
	32	Journalism and information	32	32	32	32	32	32	32	32	32	32	32
	41	Business and administration	34	34	41	41	41	41	41	41	41	41	41
	42	Law	38	38	42	42	42	42	42	42	42	42	42
	51	Biology and related sciences	42	42	51	51	51	51	51	51	51	51	51
	52	Environment	42	42	52	52	52	52	52	52	52	52	52
	53	Physical sciences	44	44	53	53	53	53	53	53	53	53	53
	54	Mathematics and statistics	46	46	54	54	54	54	54	54	54	54	54
	61	Information and communication technologies	48	48	61	61	61	61	61	61	61	61	61
	71	Engineering	52	52	71	71	71	71	71	71	71	71	71
	72	Manufacturing and processing	54	54	72	72	72	72	72	72	72	72	72
	73	Architecture and construction	58	58	73	73	73	73	73	73	73	73	73
	81	Agriculture	62	62	81	81	81	81	81	81	81	81	81
	82	Forestry	62	62	82	82	82	82	82	82	82	82	82
	83	Fisheries	62	62	83	83	83	83	83	83	83	83	83
	84	Veterinary	64	64	84	84	84	84	84	84	84	84	84
	91	Health care	70; 72	70; 72	91	91	91	91	91	91	91	91	91
	92	Welfare	76	76	92	92	92	92	92	92	92	92	92
	101	Personal services	81	81	101	101	101	101	101	101	101	101	101
	102	Hygiene and occupational health services	81	81	102	102	102	102	102	102	102	102	102
	103	Security services	86	86	103	103	103	103	103	103	103	103	103
	104	Transport services	84	84	104	104	104	104	104	104	104	104	104
	998	Refuses to answer	98	98	998	998	998	998	998	998	998	998	998
	999	No information	99	99	999	999	999	999	999	999	999	999	999
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			L'104k							L'125k			
GENDER	1	Male	1	1	1	1	1	1	1	1	1	1	1
	2	Female	2	2	2	2	2	2	2	2	2	2	2
			B'11										
WAGE_NET	1-2000	Net (after-tax) wages from main job in the last month	1-2000	1-2000	1-2000	1-2000	1-2000	1-2000	1-2000	1-4000	1-4000	1-4000	1-4000
	.	Refuses to answer, does not know, not applicable	.	.	.	.	.	.	.	.	.	.	.
			N'121							N'142			

CODE	ANSWER	MEANING	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
ED_4WEEKS	1	Primary education	1	1	1	1	1	1	1	1	1	1	1
	2	Basic education	2	2	2	2	2	2	2	2	2	2	2
	3	Vocational basic education	3	3	3	3	3	3	3	3	3	3	3
	4	General secondary education or general secondary education after vocational education	6-7	6-7	6-7	5	5	5	5	4	4	4	4
	5	Vocational education after basic education (duration – 3 years)	4-5	4-5	4-5	4	4	4	4	5	5	5	5
	6	Vocational secondary education after basic education or vocational education	8-9	8-9	8-9	6	6	6	6	6	6	6	6
	7	Vocational education after general or vocational secondary education; vocational secondary education after general secondary education	10-11	10-11	10-11	7	7	7	7	7	7	7	7
	8	First-level professional higher education (college)	12	13	14	8	8	8	8	8	8	8	8
	9	Bachelor's studies (including professional) or second-level professional higher education (study duration 1–2 years)	13	13	13	9	9	9	9	9	9	9	9
	10	Master's studies (including professional); second-level professional higher education with a study duration of 5 years (doctors, pharmacists, dentists, etc. long programmes leading to doctoral studies)	14-15	14-15	14-15	10-11	10-11	10-11	10-11	10-11	10	10	10
	11	Doctoral studies	16	16	16	12	12	12	12	12	11	11	11
	98	Refuses to answer	98	98	98	98	98	98	98	98	98	98	98
	99	Does not know	99	99	99	99	99	99	99	99	99	99	99
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			L'108							L'132			
RELATION	1	Respondent	1	1	1	1	1	1	1	1	1	1	1
	2	Respondent's partner	2-3	2-3	2-3	2-3	2-3	2-3	2-3	2	2	2	2
	3	Respondent's child	4	4	4	4	4	4	4	3	3	3	3
	4	Respondent's father/mother	5	5	5	5	5	5	5	6	6	6	6
	5	Other relative	6	6	6	6	6	6	6	4-5, 7-10	4-5, 7-10	4-5, 7-10	4-5, 7-10
	6	Other person (not a relative)	7	7	7	7	7	7	7	11	11	11	11
	99	Not specified	99	99	99	99	99	99	99	99	99	99	99
	.	Not applicable				.	.	.	.	.	.	.	.
			B'09										

CODE	ANSWER	MEANING	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
WORK_INDUSTRY	1	Agriculture, forestry and fishing	1	1	1	1	1	1	1	1	1	1	1
		Mining and quarrying	2	2	2	2	2	2	2	2	2	2	2
	2	Manufacturing	3	3	3	3	3	3	3	3	3	3	3
		Electricity, gas, steam and air conditioning supply	4	4	4	4	4	4	4	4	4	4	4
		Water supply; sewerage, waste management and remediation activities	5	5	5	5	5	5	5	5	5	5	5
		Construction	6	6	6	6	6	6	6	6	6	6	6
	3	Wholesale and retail trade; repair of motor vehicles and motorcycles	7	7	7	7	7	7	7	7	7	7	7
		Transportation and storage	8	8	8	8	8	8	8	8	8	8	8
		Accommodation and food service activities	9	9	9	9	9	9	9	9	9	9	9
		Information and communication services	10	10	10	10	10	10	10	10	10	10	10
		Financial and insurance activities	11	11	11	11	11	11	11	11	11	11	11
		Real estate activities	12	12	12	12	12	12	12	12	12	12	12
		Professional, scientific and technical services	13	13	13	13	13	13	13	13	13	13	13
		Administrative and support service activities	14	14	14	14	14	14	14	14	14	14	14
	4	Public administration and defence; compulsory social security	15	15	15	15	15	15	15	15	15	15	15
		Education	16	16	16	16	16	16	16	16	16	16	16
		Human health and social work activities	17	17	17	17	17	17	17	17	17	17	17
	3	Arts, entertainment and recreation	18	18	18	18	18	18	18	18	18	18	18
		Other service activities	19	19	19	19	19	19	19	19	19	19	19
	5	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	20	20	20	20	20	20	20	20	20	20	20
		Activities of extraterritorial organizations and bodies	21	21	21	21	21	21	21	21	21	21	21
	22	No information	22	22	22	22	22	22	22	22	22	22	22
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			D'39							D'47			
WORKING&PAID_REPORT_WEEK	1	Yes	1	1	1	1	1-3	1-4	1-4	1-4	1-4	1-4	1-4
	2	No	2	2	2	2	4	5	5	5	5	5	5
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			C'31										
ELATION&NOT_WORKING_REPOR	1	Yes	1	1	1	1	1	1	1	1	1	1	1
	2	No	2	2	2	2	2	2	2	2	2	2	2
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			C'32										

CODE	ANSWER	MEANING	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
WORK_CODE	11	Legislators, senior officials and managers	11	11	11	11	11	11	11	11	11	11	11
	12	Administrative and commercial managers	12	12	12	12	12	12	12	12	12	12	12
	13	Production and specialized services managers	13	13	13	13	13	13	13	13	13	13	13
	14	Hospitality, catering, trade and other services managers	14	14	14	14	14	14	14	14	14	14	14
	21	Science and engineering professionals	21	21	21	21	21	21	21	21	21	21	21
	22	Health professionals	22	22	22	22	22	22	22	22	22	22	22
	23	Teaching professionals	23	23	23	23	23	23	23	23	23	23	23
	24	Business and administration professionals	24	24	24	24	24	24	24	24	24	24	24
	25	Information and communication technology professionals	25	25	25	25	25	25	25	25	25	25	25
	26	Legal, social and cultural professionals	26	26	26	26	26	26	26	26	26	26	26
	31	Science and engineering associate professionals	31	31	31	31	31	31	31	31	31	31	31
	32	Health associate professionals	32	32	32	32	32	32	32	32	32	32	32
	33	Business and administration associate professionals	33	33	33	33	33	33	33	33	33	33	33
	34	Legal, social, cultural and related associate professionals	34	34	34	34	34	34	34	34	34	34	34
	35	Information technology technicians	35	35	35	35	35	35	35	35	35	35	35
	41	Clerical support workers and office machine operators	41	41	41	41	41	41	41	41	41	41	41
	42	Customer service workers	42	42	42	42	42	42	42	42	42	42	42
	43	Numerical and material recording clerks	43	43	43	43	43	43	43	43	43	43	43
	44	Other clerical support workers	44	44	44	44	44	44	44	44	44	44	44
	51	Personal service workers	51	51	51	51	51	51	51	51	51	51	51
	52	Sales workers	52	52	52	52	52	52	52	52	52	52	52
	53	Personal care workers	53	53	53	53	53	53	53	53	53	53	53
	54	Protective services workers	54	54	54	54	54	54	54	54	54	54	54
	61	Market-oriented skilled agricultural workers	61	61	61	61	61	61	61	61	61	61	61
	62	Market-oriented skilled forestry, fishery and hunting workers	62	62	62	62	62	62	62	62	62	62	62
	63	Subsistence farmers, fishers, hunters and gatherers	63	63	63	63	63	63	63	63	63	63	63
	71	Building and related trades workers (excluding electricians)	71	71	71	71	71	71	71	71	71	71	71
	72	Metal, machinery and related trades workers	72	72	72	72	72	72	72	72	72	72	72
	73	Handicraft and printing workers	73	73	73	73	73	73	73	73	73	73	73
	74	Electrical and electronic trades workers	74	74	74	74	74	74	74	74	74	74	74
	75	Food processing, wood processing, garment and other craft and related trades workers	75	75	75	75	75	75	75	75	75	75	75
	81	Plant and machine operators	81	81	81	81	81	81	81	81	81	81	81
	82	Assemblers	82	82	82	82	82	82	82	82	82	82	82
	83	Drivers and mobile plant operators	83	83	83	83	83	83	83	83	83	83	83
	91	Cleaners and helpers in households	91	91	91	91	91	91	91	91	91	91	91
	92	Agricultural, forestry and fishery labourers	92	92	92	92	92	92	92	92	92	92	92
	93	Mining, construction, manufacturing and transport labourers	93	93	93	93	93	93	93	93	93	93	93
	94	Food preparation assistants	94	94	94	94	94	94	94	94	94	94	94
	95	Street workers and street vendors	95	95	95	95	95	95	95	95	95	95	95
	96	Refuse workers and other elementary workers	96	96	96	96	96	96	96	96	96	96	96
	98	Refuses to answer	98	98	98	98	98	98	98	98	98	98	98
	99	Does not know	99	99	99	99	99	99	99	99	99	99	99
	.	Not applicable	.	.	.	.	.	.	.	.	.	.	.
			D'41							D'48			

Note. This table was created by the authors to map the Labour Force Survey (LFS) variables used in the analysis, including their coding and definitions.

Appendix B

Correspondence between ISCED Fields of Education and Training 2013 (ISCED-F 2013) and ISCED 1997 (fields).

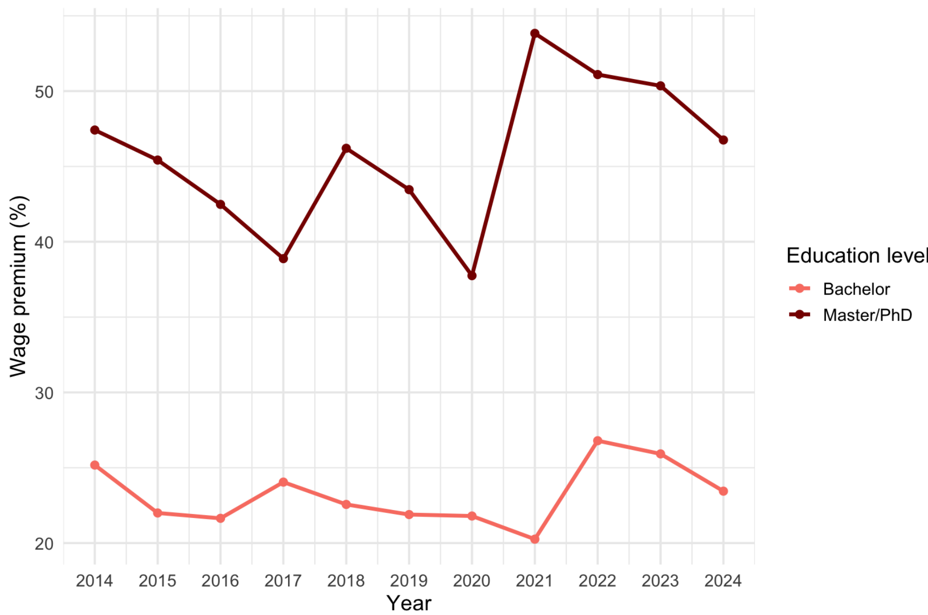
ISCED 1997 (fields) Title	ISCED 1997 (fields) Code (2014-2015)	ISCED-F 2013 Title	ISCED-F 2013 Code (2016-2024)	Harmonized Group (used in study)
Basic/broad general programmes	01	Basic programmes and qualifications	001	General education
		Literacy and numeracy	002	
Personal development	09	Personal skills and development	003	
Teacher training and education science	14	Education	011	Education
Arts	21	Arts	021	Arts & Humanities
Humanities	22	Humanities (except languages)	022	
		Languages	023	
Social and behavioural science	31	Social and behavioural science	031	Social sciences, Business & Law
Journalism and information	32	Journalism and information	032	
Business and administration	34	Business and administration	041	
Law	38	Law	042	
Life sciences	42	Biological and related sciences	051	STEM
Environmental protection	85	Natural environments and wildlife	052	
Physical science	44	Physical sciences	053	

Mathematics and statistics	46	Mathematics and statistics	054	
Computing	48	Information and Communication Technologies	061	
Engineering and engineering trades	52	Engineering and engineering trades	071	
Manufacturing and processing	54	Manufacturing and processing	072	
Architecture and building	58	Architecture and construction	073	
Agriculture, forestry and fishery	62	Agriculture	081	Agriculture & Veterinary
		Forestry	082	
		Fisheries	083	
Veterinary	64	Veterinary	084	
Health and welfare	70	Health	091	Health & Welfare
Health	72			
Social services	76	Welfare	092	
Personal services	81	Personal services	101	Services
		Community sanitation	102	
Security services	86	Security services	103	
Transport services	84	Transport services	104	

Note: Table is created by the authors based on Eurostat (n.d.-a), “International Standard Classification of Education (ISCED)”

Appendix C

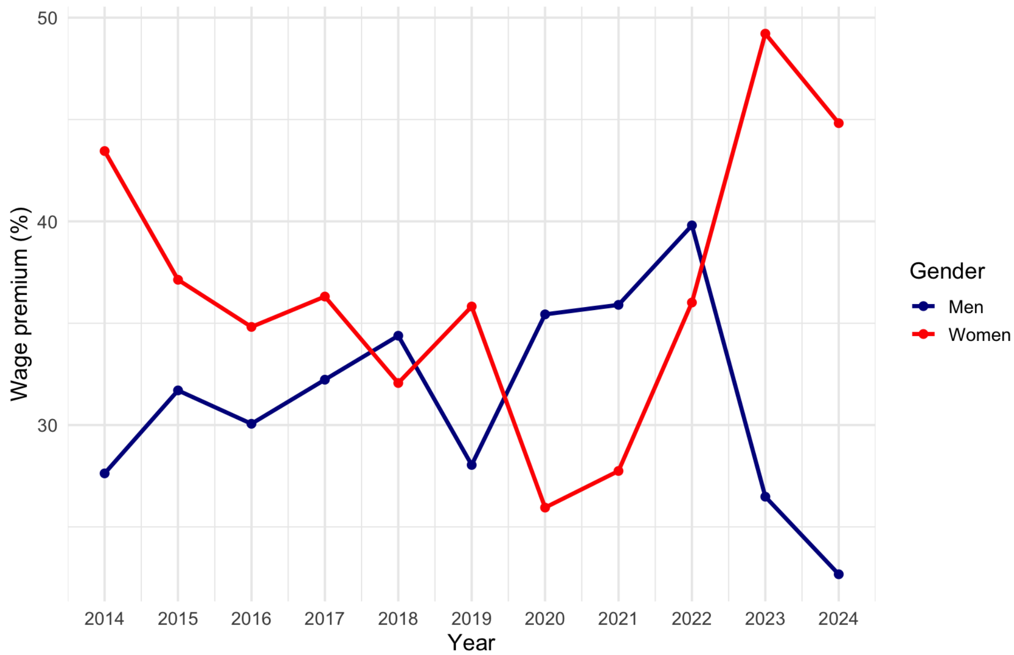
Wage premium by education level for young adults



Note. This graph is created by the authors using data from the Labour Force Survey by applying the Mincer log-wage model.

Appendix D

Wage premium by year and gender among young adults



Note. This graph is created by the authors using data from the Labour Force Survey by applying a Mincer log-wage model. Wage premiums are estimated for individuals aged 20–29 and expressed as percentage differences relative to lower education. The model includes interactions between education, gender, and year, allowing wage premiums to vary across both time and gender.

Regression results underlying gender-specific wage premiums

	Log(wage)	Std. Error
(Intercept)	5.963***	0.018
edu2Higher	0.244***	0.038
genderWomen	-0.228***	0.026
year2015	0.069***	0.025
year2016	0.149***	0.024
year2017	0.229***	0.024
year2018	0.300***	0.025
year2019	0.377***	0.026
year2020	0.399***	0.027
year2021	0.609***	0.048
year2022	0.673***	0.041
year2023	0.826***	0.043
year2024	0.896***	0.046

exp	0.039***	0.005
exp2	-0.003***	0.001
edu2Higher × genderWomen	0.117**	0.051
edu2Higher × year2015	0.031	0.056
edu2Higher × year2016	0.019	0.056
edu2Higher × year2017	0.035	0.052
edu2Higher × year2018	0.052	0.053
edu2Higher × year2019	0.003	0.055
edu2Higher × year2020	0.059	0.059
edu2Higher × year2021	0.063	0.085
edu2Higher × year2022	0.091	0.081
edu2Higher × year2023	-0.009	0.109
edu2Higher × year2024	-0.040	0.073
genderWomen × year2015	0.002	0.041
genderWomen × year2016	0.024	0.037
genderWomen × year2017	-0.003	0.037
genderWomen × year2018	0.063	0.040
genderWomen × year2019	0.034	0.040
genderWomen × year2020	0.106**	0.042
genderWomen × year2021	0.109	0.066
genderWomen × year2022	0.087	0.066
genderWomen × year2023	-0.014	0.074
genderWomen × year2024	-0.006	0.071
edu2Higher × genderWomen × year2015	-0.076	0.077
edu2Higher × genderWomen × year2016	-0.081	0.074
edu2Higher × genderWomen × year2017	-0.086	0.071
edu2Higher × genderWomen × year2018	-0.134*	0.073
edu2Higher × genderWomen × year2019	-0.058	0.074
edu2Higher × genderWomen × year2020	-0.190**	0.078
edu2Higher × genderWomen × year2021	-0.179	0.109
edu2Higher × genderWomen × year2022	-0.144	0.113
edu2Higher × genderWomen × year2023	0.048	0.134
edu2Higher × genderWomen × year2024	0.049	0.104
Num.Obs.	10008	
R2	0.318	
R2 Adj.	0.315	

AIC	11139.2
BIC	11478.1
Log.Lik.	-5522.581
RMSE	0.42
Std.Errors	Custom

Notes: This table is created by the authors using data from the Latvian Labour Force Survey. The dependent variable is the natural logarithm of monthly net wages. The reference categories are lower education, men, and the omitted base year. All regressions include experience and its square. Robust standard errors (HC1) are included. The model includes interactions between education, gender, and year. Wage premiums are computed from predicted values as percentage differences between higher- and lower-educated individuals within each year and gender.

Appendix E

Full Mincer-type regression with field-of-study interactions (dependent variable: log monthly net wage)

	Log(wage)	Std. Error
(Intercept)	5.793***	0.086
degreeBachelor	0.345***	0.096
degreeMaster/PhD	0.396***	0.112
fieldArts & humanities	0.035	0.091
fieldBusiness, administration, law	-0.004	0.087
fieldEducation	0.291**	0.121
fieldEngineering, manufacturing & construction	0.158*	0.084
fieldHealth & welfare	0.062	0.124
fieldInformation and communication technologies	0.173*	0.091
fieldNatural sciences, mathematics & statistics	-0.075	0.128
fieldServices	0.003	0.085
fieldSocial sciences, journalism & information	-0.109	0.085
exp	0.045***	0.007
exp2	-0.003***	0.001
factor(year)2015	0.054**	0.023
factor(year)2016	0.135***	0.022
factor(year)2017	0.210***	0.021
factor(year)2018	0.295***	0.022

factor(year)2019	0.381***	0.022
factor(year)2020	0.423***	0.023
factor(year)2021	0.637***	0.032
factor(year)2022	0.697***	0.033
factor(year)2023	0.824***	0.039
factor(year)2024	0.851***	0.031
degreeBachelor × fieldArts & humanities	-0.131	0.107
degreeMaster/PhD × fieldArts & humanities	-0.169	0.144
degreeBachelor × fieldBusiness, administration, law	-0.058	0.100
degreeMaster/PhD × fieldBusiness, administration, law	0.141	0.119
degreeBachelor × fieldEducation	-0.412***	0.132
degreeMaster/PhD × fieldEducation	-0.562***	0.149
degreeBachelor × fieldEngineering, manufacturing & construction	-0.173*	0.099
degreeMaster/PhD × fieldEngineering, manufacturing & construction	-0.046	0.122
degreeBachelor × fieldHealth & welfare	-0.139	0.135
degreeMaster/PhD × fieldHealth & welfare	0.036	0.152
degreeBachelor × fieldInformation and communication technologies	-0.070	0.113
degreeMaster/PhD × fieldInformation and communication technologies	0.221	0.143
degreeBachelor × fieldNatural sciences, mathematics & statistics	0.143	0.142
degreeMaster/PhD × fieldNatural sciences, mathematics & statistics	0.136	0.158
degreeBachelor × fieldServices	-0.056	0.101
degreeMaster/PhD × fieldServices	0.091	0.129
degreeBachelor × fieldSocial sciences, journalism & information	0.095	0.101
degreeMaster/PhD × fieldSocial sciences, journalism & information	0.060	0.125
Num.Obs.	5826	
R2	0.329	
R2 Adj.	0.325	
AIC	6429.8	
BIC	6716.6	
Log.Lik.	-3171.900	
RMSE	0.42	
Std.Errors	Custom	

- $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table is created by the authors using data from the Latvian Labour Force Survey. The dependent variable is the natural logarithm of monthly net wages. The reference category for education is individuals with lower education. The reference category for field of study is Agriculture, forestry, fisheries & veterinary. The reference year is 2014. All regressions include year fixed effects. Robust standard errors (HC1) are included.

Appendix F

Full Mincer-type regression with field-of-work interactions (dependent variable: log monthly net wage)

	Log(wage)	Std. Error
(Intercept)	5.926***	0.015
work_fieldPrimary sector	-0.092***	0.021
work_fieldPublic sector	-0.033**	0.016
work_fieldServices	-0.068***	0.012
eduBachelor	0.205***	0.024
eduMaster/PhD	0.353***	0.045
exp	0.044***	0.005
exp2	-0.003***	0.001
factor(year)2015	0.061***	0.017
factor(year)2016	0.143***	0.016
factor(year)2017	0.218***	0.016
factor(year)2018	0.311***	0.017
factor(year)2019	0.376***	0.017
factor(year)2020	0.420***	0.018
factor(year)2021	0.626***	0.026
factor(year)2022	0.711***	0.026
factor(year)2023	0.831***	0.029
factor(year)2024	0.884***	0.026
work_fieldPrimary sector × eduBachelor	0.126**	0.058
work_fieldPublic sector × eduBachelor	-0.044	0.031
work_fieldServices × eduBachelor	0.029	0.028
work_fieldPrimary sector × eduMaster/PhD	0.064	0.080

work_fieldPublic sector × eduMaster/PhD	0.001	0.053
work_fieldServices × eduMaster/PhD	0.037	0.053
Num.Obs.	9999	
R2	0.294	
R2 Adj.	0.293	

· p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table is created by the authors using data from the Latvian Labour Force Survey. The dependent variable is the natural logarithm of monthly net wages. The reference category for education is individuals with lower education. The reference category for the field and this graph of work is Industry & Construction. The reference year is 2014. All regressions include year fixed effects. Robust standard errors (HC1) are included.

Appendix G

Log wage regression results with field-of-study - occupation match and education interactions

	Interaction model	Std. Error
(Intercept)	6.490***	0.033
match_field_OECDMatch	0.068***	0.020
degreeMaster/PhD	0.114***	0.034
working_years	0.044***	0.011
I(working_years^2)	-0.004*	0.001
factor(year)2014	-0.413***	0.035
factor(year)2015	-0.377***	0.037
factor(year)2016	-0.303***	0.036
factor(year)2017	-0.186***	0.035
factor(year)2018	-0.116***	0.035
factor(year)2019	-0.047	0.036
factor(year)2021	0.227***	0.047
factor(year)2022	0.300***	0.050
factor(year)2023	0.420***	0.057
factor(year)2024	0.436***	0.044
match_field_OECDMatch × degreeMaster/PhD	0.080+	0.043
Num.Obs.	2630	
R2	0.283	

R2 Adj.	0.279
AIC	3147.9
BIC	3247.8
Log.Lik.	-1556.964
RMSE	0.44
Std.Errors	Custom

· p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: This table is created by the authors using data from the Latvian Labour Force Survey. The dependent variable is the natural logarithm of monthly net wages. The reference category for education is individuals with lower education. The reference category for the field-of-study–occupation match is mismatched employment. The reference year is 2014. All regressions include year fixed effects. Robust standard errors (HC1) are included.

Appendix H

ISCED broad field code (2-digit)	ISCED broad field	Matched ISCO-08 occupation groups
0	General education	91, 92, 93, 94, 95, 96
1	Arts & humanities	23, 24, 53
2	Social sciences, journalism & information	21, 23, 26, 34
3	Business, administration & law	11, 12, 13, 14, 22, 23, 24, 26, 32, 33, 34, 41, 42, 43, 44, 52, 95
4	Natural sciences, mathematics & statistics	21, 22, 23, 25, 31, 32, 33, 35
5	Information and communication technologies	21, 23, 25, 31, 33, 35, 51, 71, 72, 73, 74, 75, 81, 82, 83, 93
6	Engineering, manufacturing & construction	21, 22, 23, 31, 32, 61, 62, 63, 75, 83, 92
7	Agriculture, forestry, fisheries & veterinary	21, 22, 23, 26, 31, 32, 34, 51, 53, 54
8	Health & welfare	22, 32

Note: Table created by the authors based on (OECD, 2023) correspondence between fields of study and occupations. The reported ISCED broad field–ISCO-08 (2-digit) links are used to *classify whether a respondent works in a matched or mismatched occupation relative to their field of study; this match-status variable is then used for Figure 9.*

Weighted distribution of study-field match status

Match status	Weighted count	Percent
Mismatch	80,535.62	41.2%
Match	115,160.27	58.8%

Note: Table created by the authors. The table reports weighted estimates based on harmonized microdata from the Latvian Labour Force Survey (2014–2024). The variable match_field_OECD indicates whether an individual works in an occupation corresponding to their field of study. Weighted counts reflect population estimates using survey weights, rather than raw sample sizes. Percentages are calculated as shares of the weighted total. The table is restricted to individuals aged 20–29 with tertiary education.

Appendix I

Acknowledgement of AI use

We acknowledge the use of artificial intelligence tools in the preparation of this thesis. These tools were used primarily for paraphrasing and improving the clarity and academic quality of the language, as well as for identifying and correcting errors in R Studio code. Their role was limited to assisting in the enhancement of existing material rather than generating original textual content. All substantive content, data handling decisions, and empirical analysis remain our own work.