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Louise Devos, François Rycx,
Thomas Senterre, Mélanie Volral

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Does Field of Study Shape the Gender Wage Gap?
The Role of Migration Background

Louise Devos
Ghent University (UGent@Work, CESSMIR)

François Rycx
ULB (CEBRIG, DULBEA), UMONS (Soci&ter), UCLouvain (IRES), GLO and IZA

Thomas Senterre*
ULB (CEBRIG, DULBEA), UMONS (Soci&ter),

Mélanie Volral
UMONS (Soci&ter) and ULB (CEBRIG, DULBEA)

Abstract

Using matched employer–employee data on more than 62,000 master's graduates, this paper examines how gender differences in wage returns to fields of study vary by migration background and how educational specialisation contributes to the gender wage gap. We estimate wage regressions and apply a decomposition approach to separate sorting across fields from differences in pay within fields. Returns vary widely, with law, economics and management, and science yielding the highest returns, and women earning less than men within all fields, especially in high-paying ones. First-generation immigrants from developing countries obtain the lowest returns regardless of field of study, while second-generation immigrants approach but do not fully match natives. Fields of study explain a substantial share of gender wage inequality among natives and second-generation immigrants, whereas among first-generation immigrants broader wage disadvantages dominate. Results further vary with the number of parents originating from developing countries and with age at arrival.

Keywords: gender wage gap, first- and second-generation immigrants, field of study, employer-employee data.

JEL classification: I24, I26, J16, J31.

* Corresponding author, thomas.senterre@ulb.be

Background

Despite substantial progress over recent decades, gender differences in earnings remain a persistent feature of contemporary labour markets. Although the gender wage gap has narrowed in most developed economies, sizeable disparities continue to characterise earnings distributions: among tertiary-educated full-time workers, women earn on average 23% less than their male peers (OECD, 2025), with gaps particularly pronounced at the upper end of the wage distribution — in the United States for example, the gender pay gap is 6–11 percentage points wider at the top than at the median (Blau & Kahn, 2017; England et al., 2020; Quadlin et al., 2023). At the same time, migration background constitutes another major axis of labour market stratification. Both first-generation (FG) and second-generation (SG) immigrants[1] often experience lower employment probabilities and wage returns compared with natives, even after controlling for observable characteristics (Dustmann et al., 2016; OECD, 2023). While both gender and origin shape labour market outcomes, much less is known about how these two dimensions of inequality interact among highly educated workers, such as university graduates.

One important mechanism linking education to wage inequality is educational specialisation. Fields of study differ substantially in their labour market returns, and gender segregation across fields contributes to overall gender wage disparities (Altonji et al., 2012; Charles & Bradley, 2009; Quadlin, 2020). Several studies show that field choice explains a non-negligible share of the gender wage gap among graduates (Francesconi & Parey, 2018; Machin & Puhani, 2003; Sloane et al., 2021). At the same time, immigrants often follow distinctive educational trajectories and continue to face labour market disadvantages linked to credential recognition,

[1] Unless stated otherwise, we use the following terminology: (i) 'natives' refers to individuals born in the host country with both parents also born in the host country; (ii) 'first-generation immigrants' or 'foreign-born individuals' refers to individuals born abroad; (iii) 'second-generation immigrants' refers to individuals born in the host country with at least one foreign-born parent; and (iv) 'immigrants' refers collectively to first- and second-generation immigrants.

language barriers, social networks, and discrimination (Abramitzky et al., 2021; Heath & Cheung, 2007; OECD, 2023). However, research on gender wage inequality and research on labour market inequalities by migration background have largely developed separately. Consequently, it remains unclear whether educational specialisation contributes to gender wage inequality in similar ways across natives and immigrants.

This paper addresses this gap by examining whether gender differences in wage returns to fields of study vary with workers' migration backgrounds. Using a large matched employer–employee dataset covering more than 62,000 university graduates observed in Belgium between 1999 and 2016, we estimate log-linear wage regressions by gender and origin and, using the Gelbach (2016) method, decompose the gender wage gap separately for natives, FG immigrants, and SG immigrants from developing countries. We thereby assess the extent to which group-specific gender wage gaps among highly educated workers reflect gender segregation across fields of study or gender differences in returns within the same field.

Our analysis contributes to the literature in three ways. First, we jointly examine gender and migration background as sources of wage inequality by estimating gender-specific returns to fields of study across natives and immigrant generations. Second, we quantify the contribution of fields of study to the gender wage gap within each origin group using a decomposition framework that separates composition effects, reflecting gender segregation across fields, from price effects, capturing gender differences in returns within the same field (Blinder, 1973; Gelbach, 2016; Oaxaca, 1973). Third, by comparing natives with FG and SG immigrants, we provide new evidence on whether the mechanisms linking educational specialisation to gender wage inequality differ across groups that face distinct labour market integration processes, in line with theories of segmented assimilation (Heath et al., 2008; Portes & Rumbaut, 2001).

Literature

Among highly educated workers, gender wage inequality is strongly shaped by educational specialisation. Although tertiary education yields substantial earnings premiums, returns vary considerably across fields of study (Altonji et al., 2012). Two mechanisms underpin this relationship. First, men and women tend to sort into different academic disciplines: men are overrepresented in higher-paying fields such as science, technology, engineering, and mathematics, as well as law, economics, and management, whereas women are more concentrated in fields such as education and social sciences with lower average labour market returns (Bayer & Wilcox, 2019; Charles & Bradley, 2009). This horizontal segregation contributes to gender wage disparities through composition effects, as the distribution of men and women across fields with different wage premia influences aggregate earnings differences (Quadlin, 2020). Second, gender differences in wage returns may arise within the same field of study. Women often earn less than men even when holding similar degrees in the same discipline (Francesconi & Parey, 2018; Sanchez-Mangas & Sanchez-Marcos, 2021).

Empirical studies further show that both sorting across fields and differential returns within fields are quantitatively important. For example, subject choice explains between 8 and 20 per cent of the gender wage gap in the United Kingdom and Germany (Machin & Puhani, 2003), around 28 per cent in the United States (Sloane et al., 2021), and up to 70 per cent among university graduates in their first job in Germany (Braakmann, 2013). Complementary evidence indicates that fields of study account for a substantial share of the raw wage gap among recent graduates (Francesconi & Parey, 2018), with both composition effects and within-field differences playing a key role, particularly at the upper end of the wage distribution (Quadlin et al., 2023; Choi et al., 2024).

While educational specialisation is therefore an important driver of gender wage inequality among highly educated workers, another strand of literature emphasises persistent labour market disparities related to migration background (Devos et al., 2024). Compared with natives, immigrants frequently experience lower employment probabilities and wage penalties even after controlling for observable characteristics (Dustmann et al., 2016; OECD, 2023). Several mechanisms may explain these disparities. FG immigrants may face difficulties transferring foreign educational credentials, limited host-country language proficiency and weaker access to labour market networks (Abramitzky et al., 2021; Algan et al., 2010; Devos et al., 2024). In addition, employers may rely on stereotypes about productivity or exhibit preferences for native workers, resulting in both statistical and taste-based discrimination (Becker, 1971; Phelps, 1972).

Although SG immigrants are generally educated in the host country, labour market disadvantages may persist across generations, as empirical evidence from the European context suggests (Heath et al., 2008; Pineda-Hernández et al., 2025b; Portes & Rumbaut, 2001). Individuals with immigrant backgrounds may continue to face barriers related to ethnic origin, limited access to social networks, and discrimination (Bratsberg et al., 2014; Devos et al., 2024; Heath & Cheung, 2007; Kanitsar, 2025). At the same time, evidence shows that controlling for observable worker characteristics substantially reduces wage gaps for FG immigrants and often eliminates them for the SG (Pineda-Hernández et al., 2025b). These findings are consistent with segmented assimilation theory, which posits that integration trajectories vary depending on the resources available to immigrant families and the structural barriers they encounter. In particular, individuals from minority backgrounds may experience difficulties accessing the primary segment of the labour market, characterised by higher wages and more stable employment (Heath et al., 2008; Portes & Rumbaut, 2001).

Compared with the literature on gender segregation in fields of study, relatively little research has examined educational specialisation among immigrants and their descendants. Existing studies nevertheless suggest that children of immigrants often follow distinctive educational trajectories. Evidence from several European countries indicates that SG immigrants are more likely than natives with similar socio-economic backgrounds to enrol in fields associated with higher economic returns (Borgen & Hermansen, 2023; Engzell, 2019; Feliciano & Lanuza, 2017; Ichou, 2014).

These patterns are commonly interpreted as reflecting strong educational aspirations among immigrant families and strategic choices aimed at improving labour market prospects (Støren, 2009). Several mechanisms may contribute to these choices, as described by Borgen and Hermansen (2023). Immigrant parents may anticipate labour market discrimination and encourage their children to pursue degrees in prestigious or economically secure fields. Individuals from immigrant backgrounds may also place greater emphasis on expected financial returns when choosing fields of study, particularly in contexts of greater economic uncertainty. In addition, the relatively disadvantaged socio-economic position of immigrants in host countries may mask positive selection prior to migration, motivating children of immigrants to pursue ambitious educational pathways. However, whether these educational strategies translate into comparable labour market rewards remains unclear. If immigrants face lower returns to education or barriers in high-paying occupations, selecting fields with high expected returns may not fully offset labour market disadvantages.

Despite extensive research on gender wage inequality and migration-related labour market disparities, relatively little attention has been paid to how these dimensions intersect. Most studies analyse gender differences in wages and origin-based inequalities separately, leaving open the question of whether the mechanisms linking educational specialization to wage inequality operate similarly across natives and immigrants. To our knowledge, only Black et al. (2008) and Budig et al. (2021) explicitly examine the three-way interaction between field of study, gender, and origin or ethnicity. Both studies focus on the United States and conceptualise origin in terms of race or ethnicity rather than migration background. Taken together, their findings show that the role of field of study in explaining gender wage gaps is not uniform across ethnic groups: both the distribution across fields and the wage returns to fields of study contribute differently to gender wage inequality across racial and ethnic groups. This suggests that the relationship between educational specialization and gender wage inequality is shaped by origin, highlighting the importance of analysing this three-way interaction. However, evidence regarding migration background—as opposed to race or ethnicity—remains scarce, particularly in the European context.

Data and methods

Data

Our empirical analysis relies on a matched employer–employee dataset provided by Statistics Belgium, covering the period 1999–2016. The data combine the Structure of Earnings Survey (SES), which contains detailed firm-reported information on workers and workplaces in Belgian establishments with at least ten employees operating in sectors B to S of the NACE-BEL 2008 classification[2], with Belgian National Register data, which provide information on workers' and parents' countries of birth. This linkage allows us to identify natives, FG immigrants, and SG immigrants.[3] Information on workers' field of study is drawn from the SES

[2] NACE-BEL 2008 denotes the Belgian adaptation of the EU statistical classification of economic activities.
[3] The origin of second-generation immigrants is defined following common practice in the literature (Corluy et al., 2015; FPS Employment & Unia, 2019; Pineda-Hernandez et al., 2025a, 2025b; Piton & Rycx, 2021), by prioritising the father's country of birth. If the father was born in Belgium and the mother abroad, the mother's country of birth is used instead. Second-generation immigrants from developing countries are therefore defined as individuals born in Belgium with at least one parent born in a developing country.

and grouped into three broad categories following Britton et al. (2022): science, technology, engineering and mathematics (STEM), law, economics and management/business (LEM), and Other fields, including arts, humanities, services, and other social sciences.

Belgium provides a relevant setting for this analysis because inequalities along both gender and migration-background lines remain substantial, particularly among the highly educated. While the overall gender wage gap is relatively modest—around 5 per cent per hour worked in 2022—it is considerably larger among highly educated workers, reaching 14.4 per cent in 2018 (STATBEL, 2021, 2022). At the same time, Belgium combines a sizeable population of immigrants from developing countries with comparatively weak labour market integration outcomes. Persistent employment and earnings gaps between natives and immigrants are well documented, although outcomes tend to improve from the first to the second generation (Corluy et al., 2015; De Cuyper et al., 2018; Fays et al., 2021; Jacobs et al., 2021; Pineda-Hernández et al., 2025b; Piton & Rycx, 2021).

We apply five sample restrictions. First, we retain only workers with a university master's degree and exclude those with a higher qualification, reducing the sample to 81,876 individuals. Second, we restrict the immigrant sample to individuals from developing countries, as this group faces the strongest and most persistent labour market disadvantages in the Belgian context; this removes 15,063 observations.[4] Third, we exclude workers younger than 25 to focus on individuals with more established labour market positions, resulting in a further loss of 3,146 observations. Fourth, we drop 937 observations with missing information on the field of study. Fifth, we exclude 67 zero-earnings observations. The final sample consists of 62,663 workers employed in 7,762 firms. Because the dataset covers wage earners employed in firms,

[4] To avoid misclassification by origin and generation, we first excluded workers with missing information on their own or at least one parent's country of birth.

our analysis excludes the self-employed. This is especially relevant for fields such as medicine and law, where self-employment is more common. Our estimates should therefore be interpreted as applying to the salaried segment of the labour market. That said, self-employment accounts for only around 15% of total employment in Belgium (STATBEL, 2022).

Descriptive Statistics

Table A.1. in the Appendix reports descriptive statistics by gender and origin. Women account for nearly 40% of the sample, providing a sufficiently balanced gender distribution for analysing gender wage differentials. A substantial gender wage gap is observed in real gross hourly wages: men earn, on average, €34.5 per hour, compared with €26.4 per hour for women. This difference of roughly €8 per hour indicates sizeable gender wage inequality among highly educated workers. Marked gender differences also appear in the distribution across fields of study. Among men, 48.1% hold a degree in STEM and 32.4% in LEM, while only 19.5% graduated in Other fields. Among women, the distribution is reversed: 46.1% graduated in Other fields, 29.9% in LEM, and 24.0% in STEM. Since STEM and LEM fields are associated with higher wages as demonstrated in *Table A.1.,* this gender segregation across fields of study represents an important potential source of the gender wage gap through composition effects.

Finally, differences are also observed in worker, job, and firm characteristics across gender and origin groups. SG immigrants are on average younger than natives and FG immigrants, while natives display longer tenure. Part-time employment is more frequent among women than men across all origin groups (8.1% versus 2.1% on average), with particularly high rates among FG immigrant women (13.1%). Occupational composition differs by both gender and origin: managerial positions are more common among men and natives, while FG immigrants are more often employed in lower-ranked occupations despite holding university degrees, and SG immigrants are strongly represented in professional occupations. Differences in firm size are relatively moderate across groups. The sectoral distribution is also broadly comparable, although some differences emerge, such as the underrepresentation of SG immigrant men in manufacturing and their overrepresentation in information and communication, and the relatively higher concentration of FG immigrant women in wholesale and retail trade.

Benchmark specifications

To examine gender differences in wage returns to fields of study and how these vary by migration background, we estimate log-linear wage equations by ordinary least squares. We first estimate the association between wages, gender, and field of study using the following specification:

$$log(wage_{it}) = \beta_0 + \sum_{s=1}^{5} \beta_s \, gender \times fos_{it} + z_{it}\,\vartheta + g_{it}\,\lambda + f_{it}\,\xi + \mu_t + \varepsilon_{it} \qquad (1)$$

where the dependent variable is the logarithm of the real gross hourly wage of worker i at time t. The main explanatory variable is the interaction between gender and field of study (fos), where field of study is grouped into STEM, LEM, and Other fields. In this specification, women with a degree in Other fields constitute the reference category. Accordingly, the coefficients β_s capture wage differentials associated with each of the 5 other gender–field combinations relative to this group, conditional on the included covariates. The specification includes a rich set of controls. z_{it} captures worker characteristics and includes age, measured through age-group dummies, as well as tenure and tenure squared to allow for a potentially non-linear relationship between tenure and wages. g_{it} includes employment characteristics, namely a dummy for part-time employment (defined as working fewer than 30 hours per week), contract type (permanent, temporary, or internship), and occupation at the one-digit ISCO level. f_{it} captures firm characteristics, including sector of activity at the one-digit NACE level and firm size, measured by the number of full-time equivalent employees. μ_t denotes year fixed effects over the period 1999–2016, and ε_{it} is the error term.

We then extend this model to assess whether wage returns to fields of study vary jointly by gender and origin, leading to 18 categories. In this specification, native women with a degree in Other fields constitute the reference category:

$$log(wage_{it}) = \beta_0 + \sum_{s=1}^{17} \beta_s \, origin \times gender \times fos_{it} + z_{it}\,\vartheta + g_{it}\,\lambda + f_{it}\,\xi + \mu_t + \varepsilon_{it} \quad (2)$$

Finally, as a sensitivity analysis, we further examine heterogeneity within immigrant generations. Specifically, among FG immigrants from developing countries, we distinguish between those who arrived before age 30 and those who arrived at age 30 or later, while among SG immigrants, we distinguish between individuals with one parent born in a developing country and those with two.[5] These distinctions are important as age at arrival is closely linked to the transferability of educational credentials and the likelihood of having obtained (part of) one's education in the host country, which is typically associated with better labour market outcomes (Bratsberg et al., 2014; Heath & Cheung, 2007). Similarly, having one native-born parent may facilitate access to country-specific social networks and institutional knowledge, thereby easing labour market integration and reducing potential disadvantages related to immigrant origin (Devos et al., 2024; Heath et al., 2008).

[5] When distinguishing second-generation immigrants by parental origin, we use the labels "one parent born in a developing country" and "both parents born in a developing country." Because classification is based on the father's country of birth, the latter group includes a small number of cases in which the father was born in a developing country and the mother in a developed country. These cases represent a minority of the group (12%, 78 observations out of 643 second-generation immigrants with both parents born abroad).

Wage decompositions

After estimating wage differentials by gender, field of study, and origin, we quantify the contribution of fields of study to the gender wage gap. We first perform the decomposition for the pooled sample and subsequently by origin group, thereby assessing both the overall contribution of fields of study and the extent to which this contribution varies across natives, FG immigrants, and SG immigrants. The same exercise is repeated for the subgroups considered in the sensitivity analysis.

To this end, we rely on the decomposition proposed by Gelbach (2016), which provides a unified extension of the Oaxaca–Blinder (1973) framework. A key advantage of this approach is that it is order-invariant: the estimated contribution of a given set of regressors does not depend on the sequence in which covariates are introduced into the model. This feature is particularly useful in our setting, as our aim is to isolate the contribution of fields of study while treating all remaining worker, job, and firm characteristics as controls.

Let D_i denote a gender indicator equal to 1 for women and 0 for men, and let μ_t denote year fixed effects. We begin by estimating the baseline specification.

$$\log(wage_{it}) = \alpha_0 + \alpha_D D_i + \mu_t + \varepsilon_{it} \qquad (3)$$

where $\log(wage_{it})$ is the logarithm of the real gross hourly wage of individual i observed in year t, and ε_{it} is an error term. The coefficient α_D captures the raw gender wage gap.

We then estimate the full specification:

$$\log(wage_{it}) = \beta_0 + \beta_D D_i + X_i'\beta_X + (D_i \times X_i')\beta_{DX} + \mu_t + \varepsilon_{it}, \qquad (4)$$

where X_i is a vector of observed characteristics, including field of study as well as the worker, employment, and firm characteristics introduced above. The vector β_X captures the wage returns associated with these characteristics for the reference group, while β_{DX} captures gender differences in these returns. The coefficient β_D measures the residual conditional gender wage gap, that is, the portion of the wage differential that remains after accounting for observed characteristics and their gender-specific returns.

The Gelbach decomposition partitions the raw gender wage gap α_D into a component attributable to gender differences in characteristics and a component attributable to gender differences in returns. Formally, the composition component is based on the term:

$$\widehat{H}_i^X \equiv X_i\hat{\beta}_X, \qquad (5)$$

which represents the portion of predicted wages attributable to observed characteristics. Regressing $\widehat{H}_i^X$ on the gender indicator and year fixed effects yields the share of the raw gender wage gap explained by gender differences in characteristics, referred to as the composition effect.

The second component captures gender differences in returns to observed characteristics. Following Gelbach (2016), the corresponding heterogeneity term for individual i is defined as:

$$\widehat{H}_i^{DX} \equiv \left(\hat{\beta}_D + \sum_k X_{ik}\hat{\beta}_{k,DX}\right) D_i \qquad (6)$$

where D_i is the gender dummy, X_{ik} denotes observed characteristic k, $\hat{\beta}_D$ captures the residual conditional gender gap, and $\hat{\beta}_{k,DX}$ captures gender differences in returns to characteristic k. Regressing $\widehat{H}_i^{DX}$ on the gender indicator and year fixed effects yields the contribution of gender differences in returns to the raw gender wage gap. In the Oaxaca–Blinder framework, this corresponds to the unexplained component, which is referred to as the price effect.

Our main interest lies in isolating the contribution of fields of study within each of these two components. Within the composition effect, this contribution captures the extent to which the gender wage gap is associated with the unequal distribution of men and women across STEM, LEM, and Other fields. Within the price effect, it captures the extent to which men and women receive different wage returns within the same field of study. All remaining covariates are treated as controls. Because field of study is measured using categorical indicators, the estimated price effects depend on the choice of reference category. We use Other fields as the omitted category throughout. This provides an economically meaningful benchmark against which wage premia in STEM and LEM can be interpreted, ensuring consistency across specifications.

Results

Main analysis

To assess how educational specialisation contributes to gender wage inequality, we first examine wage returns by field of study and gender. *Figure 1* reports the estimated wage premia, using women with a degree in Other fields as the reference category. All specifications include the full set of worker, job, firm, and year controls, and the full regression results are reported in *Table A.2.* in the Appendix. A clear hierarchy in wage returns emerges: degrees in LEM yield the highest premia, followed by STEM, while returns in Other fields are substantially lower.

<Figure 1 here>

Within each field, however, women systematically obtain significantly lower wage returns than men.[6] Among graduates in LEM, men earn 16.7% more than the reference group, compared

[6] Coefficient equality tests indicate that gender differences in wage returns are statistically significant across all fields of study (p<0.001).

with 10.5% for women, corresponding to a gender difference in returns of 6.2 percentage points.[7] The largest gender difference is observed in STEM, where the wage premium relative to women in Other fields amounts to 14.3% for men and 5.7% for women, a gap of 8.6 percentage points. In Other fields, the gender difference in returns is smaller (3.3%) but remains statistically significant. *Figure 1*, therefore, indicates that gender differences in returns are present in all fields, but are most pronounced in the highest-paying ones, such that even women with degrees in the most lucrative disciplines continue to earn less than their male counterparts with similar qualifications.

Next, we examine the extent to which fields of study contribute to the overall gender wage gap by decomposing the results based on the Gelbach (2016) method. In the pooled sample, the raw gender wage gap is 24.3% (SE = 0.003, $p<0.01$). Differences in the distribution of men and women across fields of study account for 2.9 percentage points (SE = 0.001, $p<0.01$) of this gap, indicating that men are more likely to graduate in higher-paying fields. Differences in wage returns within fields account for an additional 1.9 percentage points (SE = 0.002, $p<0.01$). Taken together, these estimates show that fields of study contribute to the gender wage gap both through gender segregation across fields and through unequal returns within fields, with composition effects playing a slightly larger role than differences in returns.

The analysis then turns to the interaction between gender, field of study, and origin, which addresses the second part of the research question. *Figure 2* reports the estimated wage premia by gender, field of study, and origin, again using native women with a degree in Other fields as the reference category (see Appendix *Table A.3.* for full regression results and alternative reference categories). Three main patterns emerge. First, the ranking of fields of study remains

[7] Coefficients reported are expressed in log points. Percentage effects associated with dummy variables can be obtained using the transformation $100 \times [\exp(\beta) - 1]$.

broadly similar across origin groups, with LEM and STEM associated with higher returns than Other fields. Second, within each field and origin group, men generally receive higher returns than women. Third, wage returns display a clear origin gradient: natives obtain the highest returns, followed by SG immigrants, while FG immigrants from developing countries receive substantially lower returns across all fields of study. This pattern is consistent with segmented assimilation theory (Portes & Zhou, 2014), which emphasises heterogeneous integration trajectories across generations rather than full convergence towards native outcomes.

<Figure 2 here>

In terms of magnitude, among natives, men earn 17.5% more than the reference group in LEM and 15.2% more in STEM, compared with 10.9% and 6.2% for women. Among SG immigrants, the same hierarchy holds, but at lower levels: returns amount to 13.6% in LEM and 10.9% in STEM for men, compared with 6.9% and 3.6% for women. Returns are substantially lower for FG immigrants, particularly in Other fields, where wage penalties reach −14.1% for men and −11.2% for women. Notably, SG immigrants with degrees in Other fields—both men and women—display returns broadly comparable to those of native women with similar degrees, while SG immigrant women in STEM reach near parity with native women in these fields. By contrast, returns are substantially lower for FG immigrants, with systematic penalties relative to native women with degrees in Other fields, except for women holding a degree in STEM. Overall, these results indicate that both gender and origin shape wage returns within fields of study, with particularly strong penalties for FG immigrants.

To further assess the role of educational specialisation in shaping gender wage inequality across origin groups, we decompose the gender wage gap separately for natives, SG immigrants, and FG immigrants, as presented in *Table 1*. The raw gender wage gap is largest among natives

(25.6%), smaller among SG immigrants (16.2%), and much smaller among FG immigrants (4.7%). This pattern is consistent with previous research showing that gender wage gaps tend to be smaller in groups with lower average wages and more compressed wage distributions (Blau et al., 2017; Arulampalam et al. (2007). The decomposition results further show that fields of study play an important role in explaining the gender wage gap among natives and SG immigrants. Among natives, differences in the distribution across fields account for 3.2 percentage points of the gender wage gap, while differences in returns account for 2.1 percentage points. Among SG immigrants, the corresponding figures are 3.1 and 3.7 percentage points, respectively. By contrast, the quantity effect is much smaller among FG immigrants (0.6 percentage points) and only weakly significant, while the price effect is not statistically significant. This reflects the fact that wage returns are generally low for FG immigrants in all fields for both men and women, so that differences in fields of study contribute less to explaining the gender wage gap in this group.

<Table 1 here>

Taken together, these results show that the contribution of fields of study to gender wage inequality varies substantially across origin groups. Among natives and SG immigrants, both gender segregation across fields and unequal returns within fields contribute to the gender wage gap. Among FG immigrants, by contrast, overall wage penalties associated with migration background dominate, reducing the relative importance of field-of-study differences. These findings motivate a closer examination of heterogeneity within immigrant groups, which we explore in the sensitivity analyses.

Sensitivity analysis

To further investigate the mechanisms underlying the differences observed across origin groups in the main analysis, we conduct two additional sensitivity analyses that explore heterogeneity within immigrant generations. First, we distinguish SG immigrants by whether they have one or two parents born in a developing country, a distinction that captures differences in access to native-specific resources. Second, within the FG, we distinguish individuals by age at arrival, which serves as a proxy for the country in which tertiary education was obtained.

Figure 3 reports wage returns by gender and field of study for SG immigrants with one versus two parents born in a developing country, using native women with a degree in Other fields as the reference category. Full regression results, including alternative reference categories, are reported in *Table A.4*. in the Appendix. The overall ranking of fields remains unchanged: LEM yields the highest returns, followed by STEM, while gender differences in returns in Other fields are small and often not statistically significant.

<Figure 3 here>

Within the SG, individuals with only one parent born in a developing country systematically achieve higher wage returns than those with two parents born in developing countries, for both men and women and across LEM and STEM fields (all relative to native women in Other fields, the reference category). In LEM fields, the relative wage premium for men amounts to 14.9% when only one parent is born in a developing country, compared with 9.1% when both parents are born in developing countries; for women, the corresponding figures are 8.3% and 5.2%, respectively. A similar pattern is observed in STEM fields, where men earn relative returns of 12.0% when only one parent is born in a developing country compared with 8.6% when both parents are born in developing countries, while women earn 4.3% and 2.0%. In contrast, returns in Other fields are lower and mostly not statistically significant across SG subgroups.

Despite these differences within the SG, wage returns for SG immigrants remain systematically below those observed for natives in high-return fields such as LEM and STEM. This indicates partial but incomplete convergence across generations and suggests that parental origin continues to shape labour market returns to education within the SG.

The second sensitivity analysis focuses on FG immigrants and examines heterogeneity by age at arrival. *Figure 4* shows that age at arrival plays a central role in shaping wage returns to fields of study among FG immigrants (see *Table A.4.* in the Appendix for full regression results). For individuals who arrived in Belgium before age 30, relative wage returns are modest but higher than for those who arrived later, although they remain substantially below those observed for natives.[8] Among early arrivals, returns in LEM amount to about −3.7% for men and are close to zero for women (1.0%), while in STEM they are approximately −0.3% for men and −1.0% for women. In Other fields, both men and women face negative returns (−11.2% for men and −8.9% for women). For individuals who arrived at age 30 or later, relative wage penalties are large and generalised across all fields of study. Returns in LEM amount to −19.6% for men and −25.7% for women, while in STEM they are −13.3% for men and −16.7% for women. In Other fields, the penalties are even larger, reaching −23.6% for immigrant men and −25.2% for women.

<Figure 4 here>

[8] Results are robust to using an alternative age-at-arrival threshold of 25 instead of 30 (available upon request).

Taken together, these results indicate that FG immigrants who arrived earlier experience higher and more differentiated returns across fields of study—specifically, early-arriving FG immigrants with a STEM degree, as well as early-arriving FG women with a LEM degree, no longer face wage penalties relative to native women with degrees in Other fields—whereas late arrivals face large wage penalties regardless of field. This pattern is consistent with the hypothesis that the transferability of foreign human capital is limited and that obtaining a degree in the host country substantially improves labour market returns. In line with this interpretation, gender differences in returns within the FG are small and, with the exception of LEM, statistically insignificant. Once age at arrival is taken into account, even the gender difference in LEM returns is confined to early arrivals, suggesting that differences in age at arrival largely explain the gender differences in wage returns observed in the pooled FG sample.

Additional gender wage gap decompositions by origin subgroups are reported in *Table 2*. The raw gender wage gap remains sizeable among SG immigrants, reaching 16.7% among those with one parent born in a developing country and 13.3% among those with two parents born in developing countries, indicating that SG men earn approximately 17% and 13% more than SG women, respectively. A sizeable gender wage gap of 6.0% is also observed among FG immigrants who arrived before age 30, whereas the gap is much smaller and not statistically significant among those who arrived at age 30 or later. This result is consistent with the previous findings showing that late-arriving FG immigrants face large and generalised wage penalties, which compress wage differences between men and women.

<Table 2 here>

The decomposition results indicate that the contribution of fields of study varies markedly across subgroups and is concentrated among SG immigrants with one parent born in a developing country. For this group, both the composition effect (approximately 4.9 percentage points) and the price effect (approximately 5.8 percentage points) are statistically significant, showing that gender differences in both the distribution across fields and the returns to those fields contribute substantially to the gender wage gap. By contrast, for SG immigrants with two parents born in developing countries, as well as for both FG subgroups, neither the composition effect nor the price effect is statistically significant.

Overall, the sensitivity analyses confirm the main results while highlighting substantial heterogeneity within immigrant groups. Among SG immigrants, parental origin plays an important role in shaping wage returns and the contribution of fields of study to gender wage inequality. Among FG immigrants, differences in wage returns are primarily related to the transferability of foreign human capital rather than to gender-specific mechanisms.

Conclusion

This paper examines gender differences in wage returns to fields of study and how these differences vary with workers' origin across immigrant generations. Using log-linear wage regressions and a Gelbach (2016) decomposition, we quantify the extent to which gender wage disparities reflect differences in the distribution across fields of study (composition effects) and unequal returns within fields (price effects). Drawing on a matched employer–employee dataset covering more than 62,000 university master's graduates in Belgium over the period 1999–2016, we provide a comprehensive assessment of how educational specialisation and migration background jointly shape gender wage inequalities among highly educated workers.

First, we document substantial heterogeneity in wage returns across fields of study. Degrees in law, economics, and management, as well as science, technology, engineering, and mathematics yield significantly higher wage premia than degrees in Other fields. Within each field, however, women systematically receive lower returns than men, with particularly pronounced differentials in high-paying disciplines. Decomposition results show that both gender segregation across fields and unequal returns within fields contribute meaningfully to the overall gender wage gap, indicating that gender wage inequality reflects both pre-market sorting and differential rewards in the labour market.

Second, the magnitude and nature of these mechanisms differ across origin groups. FG immigrants from developing countries experience the lowest wage returns regardless of field of study, while SG immigrants display returns closer to those of natives, although full convergence is not observed in LEM and STEM fields. Among natives and SG immigrants, fields of study play an important role in shaping the gender wage gap through both composition and price effects. Among FG immigrants, in contrast, the gender wage gap is smaller and largely driven by overall wage penalties associated with migration background.

Third, additional analyses reveal substantial heterogeneity within immigrant groups. Among SG immigrants, having only one parent born in a developing country is associated with higher returns and stronger field-related contributions to gender wage inequality. Among FG immigrants, age at arrival plays an important role: individuals arriving at younger ages experience higher and more field-differentiated returns than those arriving later, underscoring the importance of host-country human capital and early labour market integration.

Overall, these findings demonstrate that gender wage inequality among university graduates cannot be fully understood without jointly considering educational specialisation and migration background. While gendered sorting into high-return fields contributes to wage disparities among natives and SG immigrants, migration-related labour market penalties play a more dominant role among FG immigrants. More broadly, the results highlight that inequalities in highly skilled labour markets emerge from the interaction between educational choices, differential returns to specialisation, and processes of immigrant integration. Therefore, addressing gender and origin-based disparities requires policies that simultaneously tackle educational segregation and structural barriers in the labour market.

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Tables and figures

Table 1. Gender wage gap by origin: the field of study's role

	Natives	SG immigrants from developing countries	FG immigrants from developing countries
Raw wage gap	−0.256***	−0.162***	−0.047**
	(0.003)	(0.016)	(0.019)
Quantity effect	−0.032***	−0.031***	−0.006*
	(0.001)	(0.007)	(0.003)
Price effect	−0.021***	−0.037**	0.021
	(0.003)	(0.017)	(0.015)
Observations	57,856	2,216	2,591

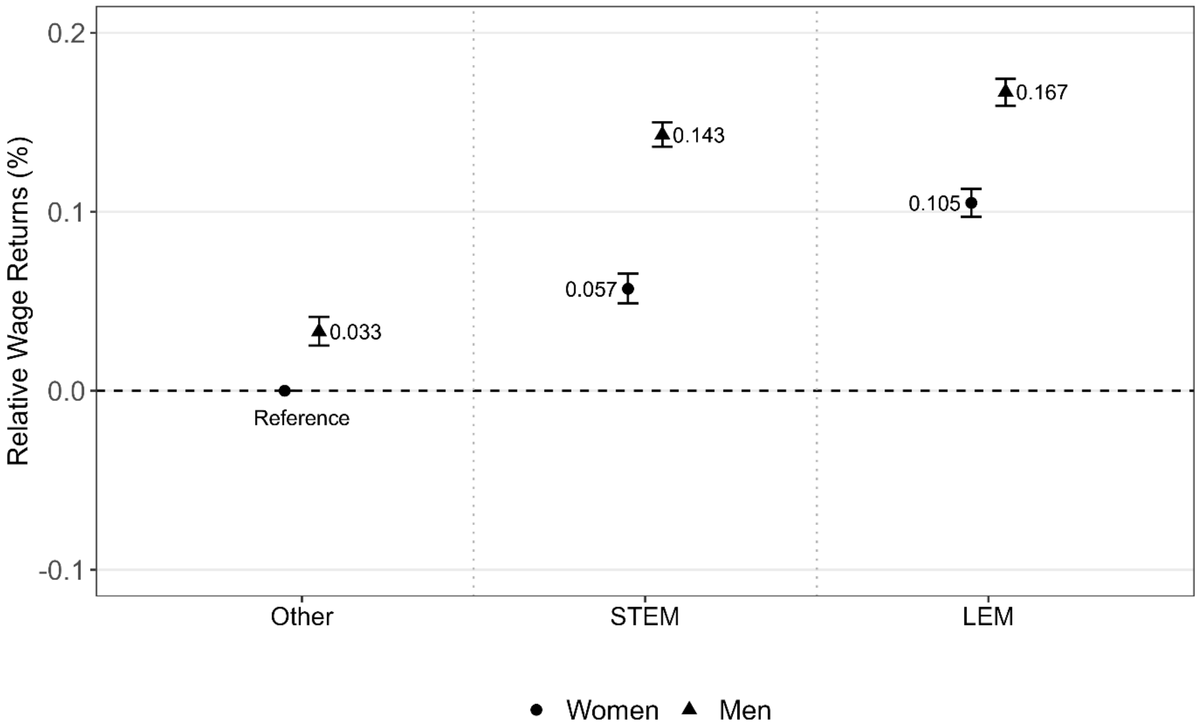
Notes: *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors (500 replications, standard nonparametric bootstrap with replacement) in parentheses. Estimates are obtained using the Gelbach (2016) decomposition. Men are the reference category. FG and SG denote first- and second-generation immigrants, respectively. The sample consists of wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). Real gross hourly wages are expressed in 2013 constant prices and include base pay, overtime pay, performance-related pay, commissions, and annual and/or irregular bonuses. 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For second-generation immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Source: STATBEL, 1999–2016.

Table 2. Gender wage gap by origin subgroups: the field of study's role

	SG immigrants from developing countries		FG immigrants from developing countries	
	One parents born in a developing country	Both parents born in a developing country	Arrived in Belgium before age 30	Arrived in Belgium at age 30 or later
Raw wage gap	−0.167***	−0.133***	−0.060***	−0.031
	(0.019)	(0.030)	(0.021)	(0.044)
Quantity effect	−0.049***	−0.006	−0.005	−0.005
	(0.009)	(0.018)	(0.004)	(0.004)
Price effect	−0.058***	0.053	0.028	0.015
	(0.018)	(0.049)	(0.017)	(0.036)
Observations	1,573	643	2,078	513

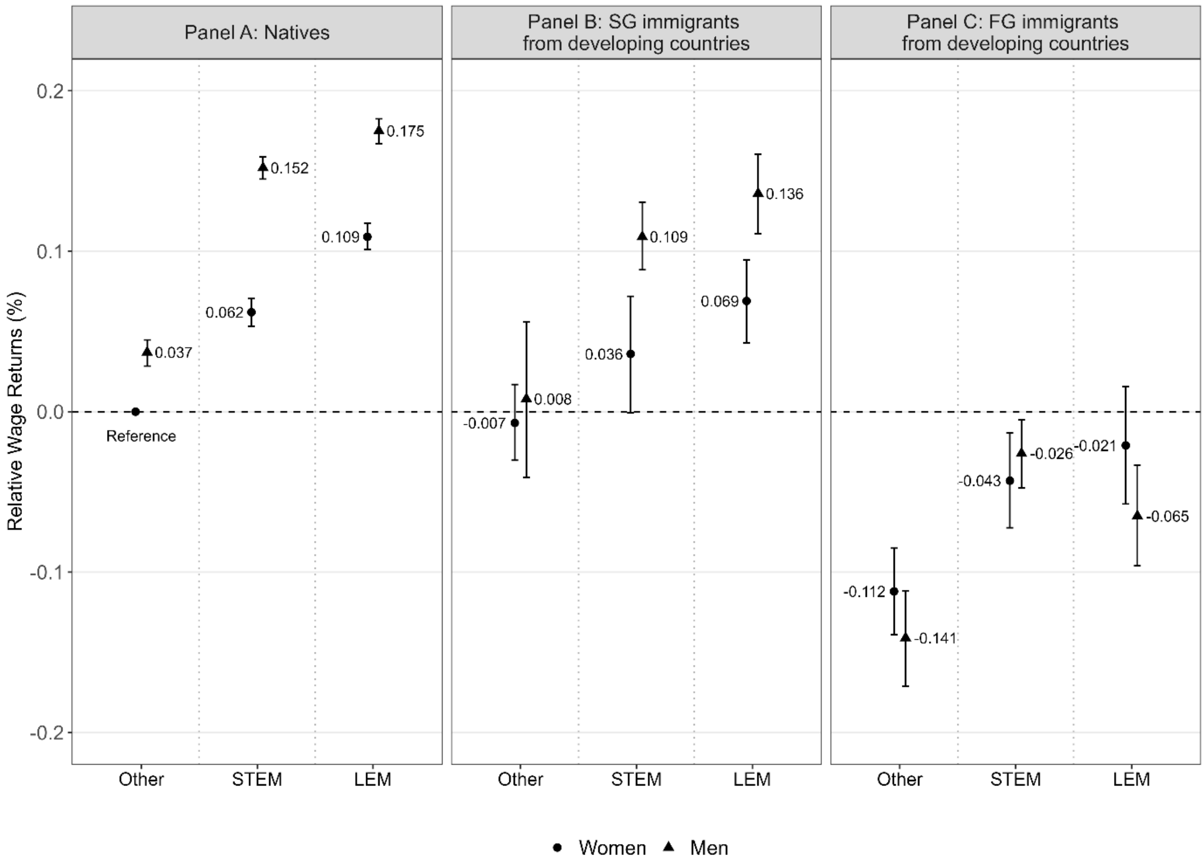
Notes: *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors (500 replications, standard nonparametric bootstrap with replacement) in parentheses. Estimates are obtained using the Gelbach (2016) decomposition. Men are the reference category. FG and SG denote first- and second-generation immigrants, respectively. The sample consists of wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). Real gross hourly wages are expressed in 2013 constant prices and include base pay, overtime pay, performance-related pay, commissions, and annual and/or irregular bonuses. 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For second-generation immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Second-generation immigrants from developing countries are therefore individuals born in Belgium with at least one parent born in a developing country. The group "both parents born in a developing country" includes a small number of cases (12% of the group) with a developing-country father and a developed-country mother. Source: STATBEL, 1999–2016.

Figure 1. Relative wage returns by gender and field of study



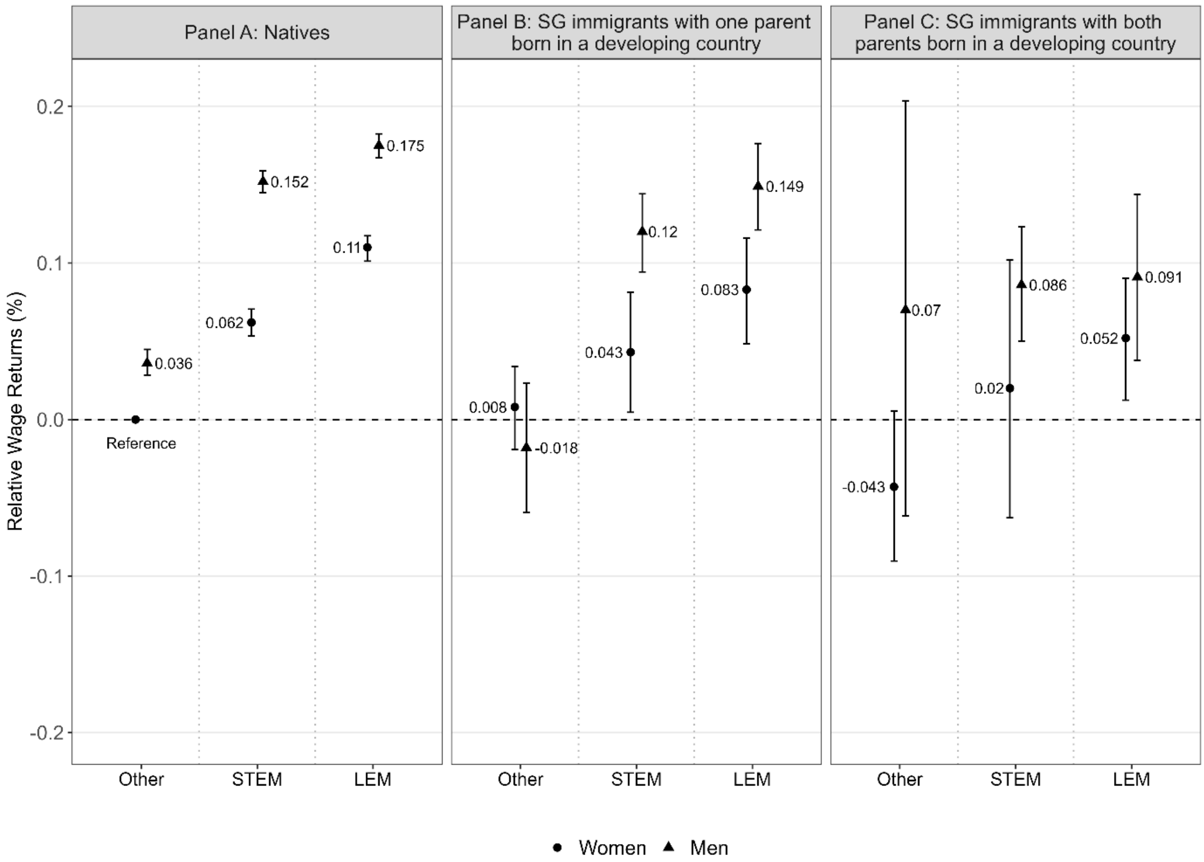
Notes: Coefficients are estimated from log-linear wage regressions including a full set of worker, job, firm, and year controls (see Section 3.3 for details). The reference category is women with a degree in Other fields of study. Error bars denote 95% confidence intervals. The sample consists of wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). Source: STATBEL, 1999–2016.

Figure 2. Relative wage returns by gender, field of study, and origin



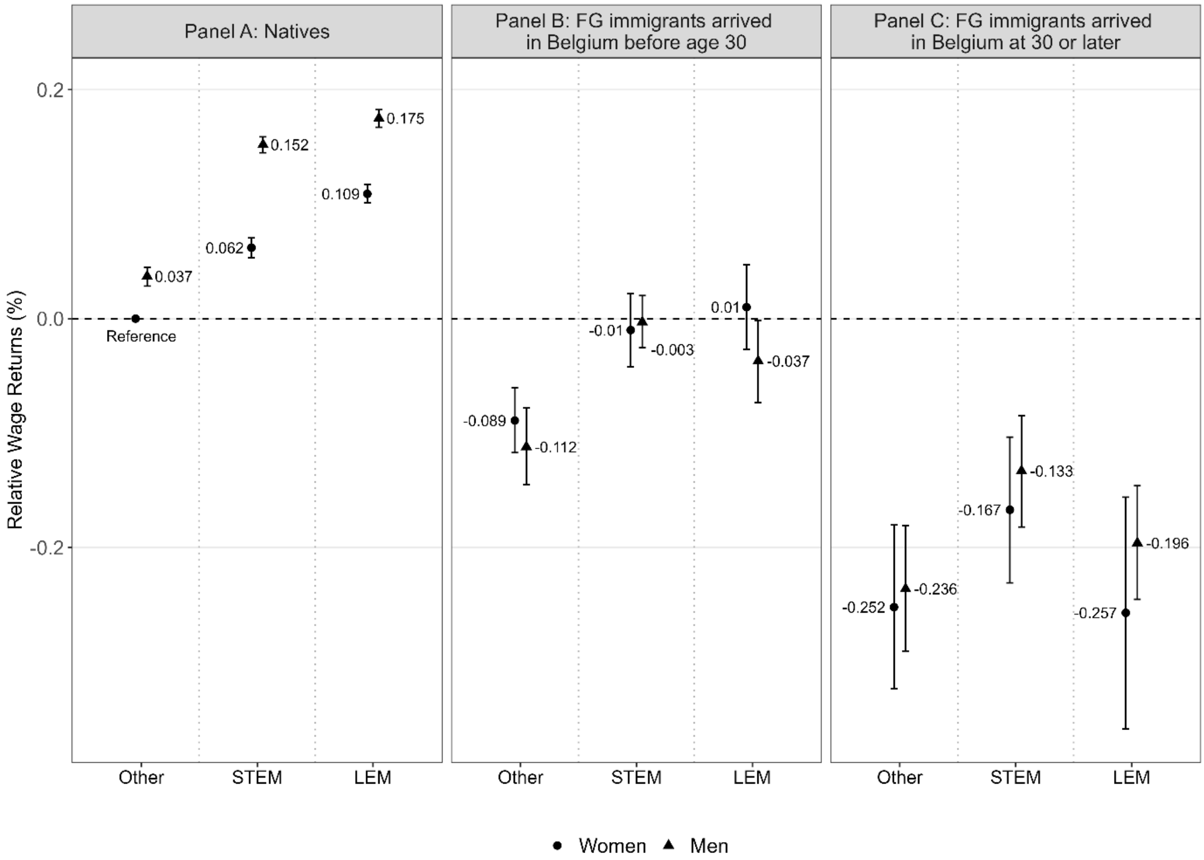
Notes*:* Coefficients are estimated from log-linear wage regressions with a full set of worker, job, firm, and year controls (see Section 3.3). The reference category is native women in Other fields of study. Error bars denote 95% confidence intervals. FG and SG denote first- and second-generation immigrants, respectively. The sample includes wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For SG immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Source: STATBEL, 1999–2016.

Figure 3. Relative wage returns by gender, field of study, and origin: SG split



Notes: Coefficients are estimated from log-linear wage regressions with a full set of worker, job, firm, and year controls (see Section 3.3). The reference category is native women in Other fields of study. Error bars denote 95% confidence intervals. SG denotes second-generation immigrants. The sample includes wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For SG immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Source: STATBEL, 1999–2016.

Figure 4. Relative wage returns by gender, field of study, and origin: FG split



Notes: Coefficients are estimated from log-linear wage regressions with a full set of worker, job, firm, and year controls (see Section 3.3). The reference category is native women in Other fields of study. Error bars denote 95% confidence intervals. FG denotes first-generation immigrants. The sample includes wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. Source: STATBEL, 1999–2016.

Appendix

Table A1. Descriptive statistics by gender and origin

	Full sample		Origin					
			Natives		Immigrants from developing countries			
					Second generation		First generation	
	men	women	men	women	men	women	men	women
Share of the sample by origin (%)	100.0		92.3		3.6		4.1	
Gender ratio by origin (%)	60.6	39.4	60.6	39.4	54.7	45.3	65.3	34.7
Number of observations	37,968	24,695	35,064	22,792	1,213	1,003	1,691	900
Real gross hourly wage (euro) [c]	34.5	26.4	35.1	26.6	28.9	24.1	25.3	23.1
Field of study								
Share of the sample (%)								
STEM	48.1	24.0	48.0	23.8	46.9	18.6	53.2	35.7
LEM	32.4	29.9	32.5	29.8	36.6	36.9	26.7	24.2
Other fields	19.5	46.1	19.5	46.4	16.5	44.5	20.1	40.1
Real gross hourly wage (euro)								
STEM	35.9	28.5	36.5	28.9	29.5	24.5	27.3	24.3
LEM	36.1	29.3	36.8	29.6	29.9	26.6	25.5	24.8
Other fields	28.3	23.4	28.8	23.6	24.7	21.9	19.8	21.0
Worker characteristics								
Tenure (years)	7.6	6.1	7.8	6.3	4.6	4.3	6.3	5.1
Age (%)								
[25-39]	17.1	25.0	17.1	24.8	32.2	39.1	8.4	14.9
[40-49]	38.1	44.5	37.9	44.7	48.1	45.1	35.1	39.9
[50-59]	29.1	23.7	29.3	23.7	15.2	13.8	34.9	33.1
>= 60	16.7	6.8	15.7	6.8	4.4	2.1	21.6	12.1
Employment characteristics								
Part-time work (%)	2.1	8.1	1.8	7.8	2.6	6.1	5.6	13.1
Type of contract (%)								
Permanent	97.7	96.7	97.9	96.9	97.1	95.3	94.9	92.2
Temporary	1.8	2.8	1.6	2.6	2.2	4.3	4.4	6.9
Internship	0.5	0.5	0.5	0.5	0.7	0.4	0.7	0.9
Occupations - ISCO1 (%)								
Managers	23.8	11.6	24.8	11.9	15.8	10.8	9.2	6.8
Professionals	50.4	43.8	51.0	43.9	56.8	47.6	32.4	35.9
Technicians and associate professionals	9.3	14.4	9.2	14.6	11.6	14.4	9.6	9.9
Clerical support	10.9	24.7	10.9	24.6	10.1	21.5	13.5	29.5
Service and sales workers	2.4	3.4	2.1	3.3	2.6	4.2	6.7	5.8
Craft and related trades workers	1.1	0.6	0.8	0.5	0.6	0.6	8.3	1.7
Plant and machine operators and assemblers	1.3	0.6	0.8	0.6	1.3	0.5	10.1	1.9
Elementary occupations	0.9	0.8	0.4	0.5	1.2	0.5	10.2	8.5

Table A1. Descriptive statistics by gender and origin (continued)

	Full sample		Origin					
			Natives		Immigrants from developing countries			
					Second generation		First generation	
	men	women	men	women	men	women	men	women
Firm characteristics								
Size of the firm (FTE number of employees)	332.3	244.8	323.2	240.6	326.9	318.8	299.7	268.2
Sector of activity - NACE1 (%) :								
B - Mining and Quarrying	0.4	0.2	0.4	0.2	0.3	0.0	0.0	0.2
C - Manufacturing	28.5	20.2	28.9	20.3	20.9	17.7	26.7	20.0
D - Electricity, gas, steam and air conditioning supply	2.5	1.4	2.6	1.4	2.6	2.9	1.1	0.7
E - Water supply, sewerage, waste management and remediation activities	1.3	0.9	1.4	1.0	1.1	0.6	0.5	0.6
F - Construction	3.6	1.6	3.6	1.6	3.9	1.8	3.0	1.3
G - Wholesale and retail trade, repair of motor vehicles and motorcycles	15.1	17.1	15.2	17.1	14.1	15.8	14.9	18.4
H - Transportation and storage	4.3	3.8	4.0	3.9	3.5	2.6	11.5	2.3
I - Accommodation and food service activities	0.7	0.9	0.4	0.8	1.2	0.5	5.4	3.2
J - Information and communication	16.3	11.8	16.3	11.8	19.9	11.4	13.8	13.1
K - Financial and insurance activities	4.5	4.7	4.4	4.6	8.0	6.3	3.7	5.4
L - Real Estate activities	0.4	0.5	0.4	0.6	0.2	0.5	0.1	0.2
M - Professional, scientific and technical activities	14.9	15.9	15.2	15.8	15.8	18.1	8.6	15.1
N - Administrative and support service activities	5.6	17.3	5.5	17.4	6.8	17.5	8.3	14.1
P - Education	0.2	0.2	0.2	0.2	0.1	0.5	0.3	0.6
Q - Human health and social work activities	0.7	2.3	0.7	2.3	0.4	2.7	0.9	3.0
R - Arts, entertainment and recreation	0.1	0.3	0.1	0.3	0.1	0.4	0.2	0.4
S - Other service activities	0.6	0.7	0.6	0.7	1.1	0.6	0.9	1.2

Notes: The sample consists of wage earners aged 25–65 holding a university master's degree. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). Real gross hourly wages are expressed in 2013 constant prices and include base pay, overtime pay, performance-related pay, commissions, and annual and/or irregular bonuses. 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For second-generation immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Part-time employment refers to working less than 30 hours per week (OECD definition). Firm size is measured in full-time equivalents (FTE). Source: STATBEL, 1999–2016.

Table A.2. Relative Wage Returns by Gender and Field of Study

	(1)	(2)
	Real gross hourly wage (in log)	
Other fields		
women	Reference	−0.033***
		(0.004)
men	0.033***	Reference
	(0.004)	
LEM fields		
women	0.105***	0.072***
	(0.004)	(0.005)
men	0.167***	0.134***
	(0.004)	(0.004)
STEM fields		
women	0.057***	0.024***
	(0.004)	(0.005)
men	0.143***	0.110***
	(0.003)	(0.004)
Control variables	yes	yes
Observations	62,545	62,545
Adjusted R-squared	0.61	0.61

Notes: *** p<0.01, ** p<0.05, * p<0.1. Coefficients are estimated from log-linear wage regressions with a full set of worker, job, firm, and year controls (see Section 3.3). Robust standard errors in parentheses. Results are presented for two alternative reference groups. The sample includes wage earners aged 25–65 holding a university master's degree. The real gross hourly wage is at 2013 constant prices. It includes base pay, overtime compensation, performance-related pay, commissions, and annual and/or irregular bonuses. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). Source: STATBEL, 1999–2016.

Table A.3. Relative Wage Returns by Gender, Field of Study, and Origin

	(1)	(2)	(3)	(4)	(5)	(6)
	Real gross hourly wage (in log)					
Belgium natives						
Other fields women	Reference	−0.037***	−0.109***	−0.175***	−0.062***	−0.152***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Other fields men	0.037***	Reference	−0.073***	−0.138***	−0.025***	−0.115***
	(0.004)		(0.005)	(0.004)	(0.005)	(0.004)
LEM fields women	0.109***	0.073***	Reference	−0.066***	0.047***	−0.043***
	(0.004)	(0.005)		(0.004)	(0.005)	(0.004)
LEM fields men	0.175***	0.138***	0.066***	Reference	0.113***	0.023***
	(0.004)	(0.004)	(0.004)		(0.005)	(0.004)
STEM fields women	0.062***	0.025***	−0.047***	−0.113***	Reference	−0.090***
	(0.004)	(0.005)	(0.005)	(0.005)		(0.004)
STEM fields men	0.152***	0.115***	0.043***	−0.023***	0.090***	Reference
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Immigrants from developing countries						
Second generation						
Other fields women	−0.007	−0.043***	−0.116***	−0.181***	−0.069***	−0.159***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Other fields men	0.008	−0.029	−0.102***	−0.167***	−0.054**	−0.144***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
LEM fields women	0.069***	0.032**	−0.040***	−0.106***	0.007	−0.083***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
LEM fields men	0.136***	0.099***	0.027**	−0.039***	0.074***	−0.016
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
STEM fields women	0.036*	−0.001	−0.074***	−0.139***	−0.026	−0.116***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)
STEM fields men	0.109***	0.073***	0.000	−0.065***	0.048***	−0.042***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
First generation						
Other fields women	−0.112***	−0.149***	−0.221***	−0.287***	−0.174***	−0.264***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Other fields men	−0.141***	−0.178***	−0.251***	−0.316***	−0.203***	−0.293***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
LEM fields women	−0.021	−0.058***	−0.130***	−0.196***	−0.083***	−0.173***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
LEM fields men	−0.065***	−0.101***	−0.174***	−0.239***	−0.127***	−0.217***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
STEM fields women	−0.043***	−0.079***	−0.152***	−0.218***	−0.105***	−0.195***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
STEM fields men	−0.026**	−0.063***	−0.136***	−0.201***	−0.088***	−0.178***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Control variables	yes	yes	yes	yes	yes	yes
Observations	62,545	62,545	62,545	62,545	62,545	62,545
Adjusted R-squared	0.61	0.61	0.61	0.61	0.61	0.61

Notes: *** p<0.01, ** p<0.05, * p<0.1. Coefficients are estimated from log-linear wage regressions with a full set of worker, job, firm, and year controls (see Section 3.3). Robust standard errors in parentheses. Results are presented for six alternative reference groups. The sample includes wage earners aged 25–65 holding a university master's degree. The real gross hourly wage is at 2013 constant prices. It includes base pay, overtime compensation, performance-related pay, commissions, and annual and/or irregular bonuses. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For second-generation immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Source: STATBEL, 1999–2016.

Table A.4. Relative Wage Returns by Gender, Field of Study, and Origin Moderators

	(1)	(2)	(3)	(4)	(5)	(6)
	Real gross hourly wage (in log)					
Belgium natives						
Other fields women	Reference	−0.036***	−0.110***	−0.175***	−0.062***	−0.152***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Other fields men	0.036***	Reference	−0.073***	−0.139***	−0.026***	−0.116***
	(0.004)		(0.005)	(0.004)	(0.005)	(0.004)
LEM fields women	0.110***	0.073***	Reference	−0.065***	0.047***	−0.043***
	(0.004)	(0.005)		(0.004)	(0.005)	(0.004)
LEM fields men	0.175***	0.139***	0.065***	Reference	0.113***	0.023***
	(0.004)	(0.004)	(0.004)		(0.005)	(0.004)
STEM fields women	0.062***	0.026***	−0.047***	−0.113***	Reference	−0.090***
	(0.004)	(0.005)	(0.005)	(0.005)		(0.004)
STEM fields men	0.152***	0.116***	0.043***	−0.023***	0.090***	Reference
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Immigrants from developing countries						
Second generation						
One parent born abroad						
Other fields women	0.008	−0.029**	−0.102***	−0.168***	−0.055***	−0.145***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Other fields men	−0.018	−0.054**	−0.128***	−0.193***	−0.080***	−0.170***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
LEM fields women	0.083***	0.046***	−0.027	−0.093***	0.020	−0.070***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
LEM fields men	0.149***	0.113***	0.039***	−0.026*	0.087***	−0.003
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
STEM fields women	0.043**	0.007	−0.066***	−0.132***	−0.019	−0.109***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
STEM fields men	0.120***	0.083***	0.010	−0.056***	0.057***	−0.033***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Second generation						
Born parents born abroad						
Other fields women	−0.043*	−0.079***	−0.152***	−0.218***	−0.105***	−0.195***
	(0.024)	(0.025)	(0.025)	(0.024)	(0.025)	(0.024)
Other fields men	0.070	0.034	−0.040	−0.105	0.008	−0.082
	(0.068)	(0.068)	(0.068)	(0.067)	(0.068)	(0.067)
LEM fields women	0.052***	0.015	−0.058***	−0.124***	−0.011	−0.101***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
LEM fields men	0.091***	0.055**	−0.019	−0.084***	0.029	−0.061**
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
STEM fields women	0.020	−0.017	−0.090**	−0.155***	−0.043	−0.133***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
STEM fields men	0.086***	0.050***	−0.023	−0.089***	0.024	−0.066***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)

Table A.4. Relative Wage Returns by Gender, Field of Study, and Origin Moderators (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Real gross hourly wage (in log)					
Reference category	**Other fields women**	**Other fields men**	**LEM fields women**	**LEM fields men**	**STEM fields women**	**STEM fields men**
First generation						
Arrived before age 30						
Other fields women	−0.089***	−0.125***	−0.198***	−0.264***	−0.151***	−0.241***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Other fields men	−0.112***	−0.148***	−0.221***	−0.287***	−0.174***	−0.264***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
LEM fields women	0.010	−0.026	−0.099***	−0.165***	−0.052***	−0.142***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
LEM fields men	−0.037**	−0.074***	−0.147***	−0.212***	−0.099***	−0.189***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
STEM fields women	−0.010	−0.046***	−0.120***	−0.185***	−0.072***	−0.162***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
STEM fields men	−0.003	−0.039***	−0.112***	−0.177***	−0.065***	−0.155***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
First generation						
Arrived at age 30 or later						
Other fields women	−0.252***	−0.288***	−0.361***	−0.427***	−0.314***	−0.404***
	(0.036)	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)
Other fields men	−0.236***	−0.272***	−0.345***	−0.411***	−0.298***	−0.388***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
LEM fields women	−0.257***	−0.294***	−0.367***	−0.432***	−0.319***	−0.409***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
LEM fields men	−0.196***	−0.232***	−0.305***	−0.371***	−0.258***	−0.348***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
STEM fields women	−0.167***	−0.203***	−0.277***	−0.342***	−0.229***	−0.319***
	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)
STEM fields men	−0.133***	−0.170***	−0.243***	−0.308***	−0.196***	−0.285***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Control variables	yes	yes	yes	yes	yes	yes
Observations	62,545	62,545	62,545	62,545	62,545	62,545
Adjusted R-squared	0.61	0.61	0.61	0.61	0.61	0.61

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Coefficients are estimated from log-linear wage regressions with a full set of worker, job, firm, and year controls (see Section 3.3). Robust standard errors in parentheses. Results are presented for six alternative reference groups. The sample includes wage earners aged 25–65 holding a university master's degree. The real gross hourly wage is at 2013 constant prices. It includes base pay, overtime compensation, performance-related pay, commissions, and annual and/or irregular bonuses. Fields of study are grouped into STEM (science, technology, engineering and mathematics), LEM (law, economics and management/business), and Other (other social sciences, education, services, arts, and humanities). 'Developing countries' follow the United Nations (2019) and IMF (2019) classifications. For second-generation immigrants, origin is defined by the father's country of birth, unless the father was born in Belgium and the mother abroad, in which case the mother's country of birth is used. Second-generation immigrants from developing countries are therefore individuals born in Belgium with at least one parent born in a developing country. The group "both parents born in a developing country" includes a small number of cases (12% of the group) with a developing-country father and a developed-country mother. Source: STATBEL, 1999–2016.

INSTITUT DE RECHERCHE
ÉCONOMIQUES ET SOCIALES

Place Montesquieu 3

1348 Louvain-la-Neuve

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