Gender-based occupational segregation: A multi-country analysis

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Abstract

Gender-based occupational segregation remains a feature of labour markets worldwide, with crucial implications for wages, working conditions, and economic opportunities. While extensively studied in high-income countries, less is known about how segregation varies across countries at different stages of development and how it evolves over time. This paper addresses this gap using harmonized microdata covering 117 countries – representing approximately 65.5 per cent of global employment – and a panel of 75 countries over the period 2010–2014 to 2020–2024. The analysis documents three main findings. First, occupational segregation is high globally: 39.8 per cent of working women would need to change occupations to match men's distribution, with only limited progress in reducing segregation over the past decade. Second, segregation follows an inverse U-shaped relationship with economic development. We refer to it as a Kuznets curve for gender-based occupational segregation. Third, a decomposition of changes in segregation shows that gender imbalances within occupations have narrowed across countries, but that in developing economies these improvements are partly offset by shifts in employment toward more segregated occupations such as Sales workers. These results highlight the central role of structural transformation in shaping segregation dynamics and imply that policy priorities differ by level of development.

Keywords: Occupational segregation, Feminist economics, Development

JEL codes: J16, J21, J24

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1 Introduction

As early as pre-industrial Britain, women were reported to earn roughly half the wages of men. The onset of industrialization further widened gender disparities by increasing the demand for "brawn" skills, in which men held a comparative advantage (Burnette, 1997). Although the nature of work has changed dramatically since then, gender imbalances in labour markets have proven remarkably persistent, driven by social norms, institutional constraints, and structural features of the economy.

Gender-based occupational segregation – the unequal distribution of men and women across occupations – continues to shape labour markets worldwide. It influences not only the types of jobs held by women and men, but also the wages they earn, the working conditions they face, and their career trajectories.

The economic implications of occupational segregation are substantial. First and foremost, occupational segregation is an important contributor to the gender pay gap. In the United States, different allocations of women and men across occupations account for about one third of the gender pay gap (Blau and Kahn, 2017). Sizeable magnitudes are also observed elsewhere: gender-based occupational segregation explains up to 43 per cent of the gender pay gap in Serbia and around 19 per cent in Switzerland (Aleksić et al., 2025; Roos, 2025). Occupational segregation also undermines the principles of equal remuneration and non-discrimination enshrined in International Labour Organization (ILO) Conventions No. 100 (1951) and No. 111 (1958), as well as the Sustainable Development Goal 8.5 commitment to "equal pay for work of equal value".

Beyond pay inequality, occupational segregation has broader social and health consequences. At the macro level, Alwago (2023) demonstrates that gender inequality and occupational segregation negatively affect economic growth in Sub-Saharan Africa. At the micro level, female-dominated occupations are often associated with higher rates of sickness absence or disability pension, as documented in Sweden (Gonäs et al., 2019). Gender-based discrimination – often rooted in occupational segregation – has been linked to adverse mental health outcomes (de la Torre-Pérez et al., 2022). Finally, lower levels of occupational segregation are also associated with greater gender diversity in leadership positions (ILO, 2019). These patterns highlight that occupational segregation is not merely a distributional issue but a structural feature of labour markets with implications for well-being and long-term economic resilience.

Although gender-based occupational segregation has been studied for more than half a century, the majority of the existing empirical evidence comes from high-income countries, particularly the United States (England, 2010; Blau et al., 2013; Kübler et al., 2018; Bugallo et al., 2024). This literature documents a long-run decline in segregation beginning in the mid-20th century, followed by a plateau in recent decades (Fortin and Huberman, 2002; Boll et al., 2017; Strawinski et al., 2018). The decline in occupational segregation in high-income countries has been closely linked to rising female labour force participation, improvements in women's educational attainment, and shifts in the structure of employment toward service-sector occupations (Blau and Kahn, 2017; Bach et al., 2024). Yet even in high-income contexts, progress has been uneven, and occupational integration has slowed considerably since the early 2000s.

Evidence from developing countries is far more limited but suggests that the dynamics of segregation differ markedly from those observed in high-income economies. All BRICS countries face serious challenges in facilitating women's access to jobs, particularly in high-paid occupations (Sychenko et al., 2022). Borrowman and Klasen (2020) find that occupational segregation increased between 1980 and 2011 in many developing countries, even when women's education and labour force participation improved.

Importantly, cross-country studies that examine patterns of occupational segregation across different contexts remain relatively scarce. Early efforts such as Anker et al. (2003) were limited to 15 countries. Chang (2004) expanded coverage to 16 developing countries using a detailed occupational classification. Borrowman and Klasen (2020) extended the scope to 69 countries but relied on a coarse 10-group occupational taxonomy. As a result, global patterns of occupational segregation – particularly the relationship between segregation and structural transformation – remain insufficiently understood.

This paper addresses these gaps by providing the most comprehensive cross–country analysis of gender based occupational segregation to date. Using harmonized microdata from the ILO Harmonized Microdata collection, the paper covers 117 countries – representing 65.5 per cent of global employment in 2024 – and employs a granular International Standard Classification of Occupations 2008 (ISCO–08) two-digit classification comprising 37 occupational groups.[1] This level of detail allows us to capture gender imbalances within occupations that would be obscured in broader classifications. Furthermore, the richness of the ILO Harmonized Microdata collection allows for an analysis of changes in occupational segregation over time. For this exercise, we leverage comparable data for 75 countries between 2010–2014 and 2020–2024. The breadth of coverage is not merely a methodological virtue: it is what makes it possible to treat economic development itself as a variable, and to ask whether the dynamics observed in developed countries hold more generally.

Our contributions are manifold. First, we document that, globally, 39.8 per cent of working women would need to change occupations to match men's occupational distribution. This interpretation follows directly from the measure of segregation used in the paper – the dissimilarity index (Duncan and Duncan, 1955). Drawing on a panel of 75 countries observed in both 2010–2014 and 2020–2024, we show that this figure has changed very little over the past decade: the dissimilarity index declined by only 0.6 percentage points on average, underscoring the remarkable persistence of occupational segregation over time.

Second, countries with large agricultural sectors are characterized by lower levels of occupational segregation, as a substantial share of workers – both men and women – are concentrated in agriculture. By contrast, occupations outside agriculture exhibit more unequal gender distributions, a pattern that holds across countries.

Third, we document that the relationship between gender-based occupational segregation and economic development follows an inverse U-shape. Segregation rises as economies industrialize and diversify away from agriculture. It peaks among middle-income countries, and subsequently declines as deindustrialization and the expansion of service-based activities take hold. We refer to this inverse U-shaped pattern as a *Kuznets curve for gender-based occupational segregation*.[2] This concept is useful to understand the dynamics of gender-based occupational segregation in a cross-country analysis where developing and developed countries are analyzed together.

Fourth, we decompose changes in occupational segregation into two components: a sex composition effect, which captures changes in the gender balance within occupations holding the occupational structure fixed, and an occupation mix effect, which captures changes in the distribution of employment across occupations holding within-occupation gender balances fixed. This decomposition reveals that progress toward gender integration within occupations has been real and broad-based: the sex composition effect is negative in both developing and developed countries, by around 1.5 to 1.8 percentage points, respectively. The key difference lies in the occupation mix effect. In developed countries, this effect is close to zero, meaning that the occupations expanding over the past decade are on average no more segregated than the rest and the overall modest decline in segregation therefore reflects genuine within-occupation progress. In developing countries, by contrast, the occupation mix effect is positive and sizeable, at 1.65 percentage points: the occupations that are gaining employment tend to be more gender-segregated than those that are shrinking. Within-occupation improvements are thus being partly offset by the direction of structural change. This distinction has important policy implications: in developing countries, reducing segregation requires attention not only to gender dynamics within occupations, but also to the pattern of occupational growth.

Fifth, we identify the occupations that contribute most to overall segregation and trace how these contributions vary across income groups. Drivers and mobile plant operators are overrepresented by men in virtually every country covered; Health associate professionals and Customer services clerks are overrepresented by women almost everywhere. Other occupations such as, Agricultural workers, Sales workers, Teaching professionals display wide heterogeneity across countries, with the direction of gender imbalances often reversing depending on the level of development and the structure of the local economy. Finally, looking ahead, we show that the occupations most exposed to Generative Artificial Intelligence (Gen AI) are disproportionately overrepresented by women in high- and upper-middle-income countries, raising the question of whether technological change will reinforce existing patterns of segregation or reshape them.

The remainder of the paper is structured as follows. Section 2 reviews the literature on gender-based occupational segregation. Section 3 presents the measure of occupational segregation. Section 4 describes the data. Section 5 documents the current state of play with respect to the level of gender-based occupational segregation and the most imbalanced occupations. Section 6 examines how segregation has evolved over the past decade and assesses the correlates associated with these changes. Section 7 explores the implications of Gen AI for the future of occupational segregation. The last section concludes.

2 Literature

Occupational segregation has been studied for several decades, with its gender dimension gaining increasing attention since the 1980s, as shown in Annex A. In the United States, Blau and Kahn (2017) show that occupational sorting explains a substantial share of the gender wage gap (around one third of the gender wage gap), often more than differences in human capital. Trends toward reduced segregation have been uneven and have contributed to increasing inequality among women (England, 2010). In particular, segregation has declined partly due to the movement of highly educated women out of traditionally female-dominated occupations.

Occupational segregation takes both vertical and horizontal forms. Vertical segregation ("glass ceiling") refers to women's under-representation in higher-level positions, while horizontal segregation ("glass walls") captures the concentration of men and women in different occupations at similar skill levels (ILO, 2018). Even when women enter high-skill occupations, they tend to cluster in a limited set of fields, such as health, education, and care (Charles and Grusky, 2005). This paper focuses on horizontal segregation.

The literature typically highlights three sets of mechanisms: demand-side, supply-side, and institutional factors. On the demand side, discrimination and gender stereotypes shape hiring decisions (Becker, 2010). Evidence from audit and correspondence studies shows that women often face lower callback rates, particularly in male-dominated and STEM occupations (Adamovic and Leibbrandt, 2023; Zhang et al., 2021). However, recent evidence from some high-income countries suggests that such biases may be declining (Birkelund et al., 2022). The extent to which segregation translates into wage inequality also varies across contexts and interacts with other dimensions such as race and migration status (Bertrand and Mullainathan, 2004; Gradín, 2021; Nazari, 2024).

Supply-side explanations emphasize preferences, personality traits, and socialization. Differences in risk aversion, competitiveness, and attitudes toward work may influence occupational choices, although these differences are themselves shaped by social norms (Heckman et al., 2019; Blau and Kahn, 2017). While women now surpass men in tertiary education in many countries (Goldin, 2024), gendered patterns persist in fields of study, career aspirations, family attitudes and stereotype threat (Steele and Aronson, 1995; Ridgeway, 2011; Alon and DiPrete, 2015; Avolio et al., 2020).

Institutional factors also play a central role. Female-dominated occupations are often undervalued, discouraging men from entering them and slowing integration (England, 2010). Legal changes matters in guiding women toward occupations that are already female-dominated (Ngai and Petrongolo, 2017). Family policies and workplace norms interact with labour market outcomes: even in countries with generous parental leave, gender gaps in participation and earnings persist (Goldin, 2024). Wage structures that reward long or inflexible hours disproportionately disadvantage women, particularly those with caregiving responsibilities (Goldin, 2014; Kleven et al., 2019). More broadly, the impact of public policies on gender inequality remains mixed and depends on their design (Blau et al., 2013; Kleven et al., 2024; Arora et al., 2023).

While the literature has extensively documented the drivers of occupational segregation, the paper contributes to the literature by analyzing the evolution of occupational segregation across countries at different stages of development.

3 Measuring occupational segregation

3.1 Dissimilarity index

The most widely used metric for assessing occupational segregation is the dissimilarity index, originally developed by Duncan and Duncan (1955). This index estimates the proportion of women (or men) who would need to change occupations to achieve an identical occupational distribution across genders. Formally, it is defined as:

$$D_j = \frac{1}{2} \sum_i \left(|s_{ij,f} - s_{ij,m}| \right) \tag{1}$$

with i the occupation, and $s_{ij,f}$ the share of working women in occupation i among all working women, and $s_{ij,m}$ is the male counterpart.[3] The index j denotes the country.[4]

An index equal to zero implies that no women would need to change occupations to replicate men's occupational distribution. The world of work would then be perfectly integrated. On the contrary, an index of 100 per cent implies perfect segregation and all women would need to change occupations to replicate men's distribution, because men and women would systematically differ in the occupations chosen.

Even if the index is symmetric – measuring equally the share of women who would need to change occupations to match men's distribution and *vice versa* – we interpret it primarily from the perspective of women. Empirically, reductions in segregation tend to occur more through women entering occupations where men are overrepresented than through men entering occupations where women are overrepresented, reflecting differences in pay and career opportunities across occupations (England, 2010).

Although it is the most common indicator capturing segregation, the dissimilarity index faces the potential issue of *margin dependency* (see subsection B.2 in the Annex for a discussion on it). The dissimilarity index combines two distinct dimensions. First, it reflects differences in the gender composition within each occupation. Second, it depends on the distribution of employment across occupations. As a result, changes in the index may arise either from shifts in gender balances within occupations or from changes in the occupational structure itself. This distinction is central to the analysis developed in the remainder of the paper (in particular, in subsection 6.4 and subsection B.3 in the Annex).

To ensure that the results developed in the present paper are not driven only by the use of this specific indicator, two alternative measures of segregation are discussed in subsection B.4 in the Annex, the Theil H index and the Isolation indicator. They are very tightly connected to the dissimilarity index, the main findings hold using these alternatives.

3.2 Occupational concentration

Beyond gender differences in occupational allocation, cross-country comparisons of segregation are also affected by differences in the overall structure of employment. In particular, countries differ widely in how employment is distributed across occupations (men and women together), for example, due to the relative importance of agricultural occupations.

Massey and Denton (1988) stress that there are different measures to capture the differentials in distribution across groups. To capture these structural differences, we compute the Herfindahl-Hirschman Index (HHI), which measures the concentration of employment across occupations. For each occupation i in country j, it is defined as:

$$HHI_j = \sum_i s_{ij}^2 \tag{2}$$

bounded by $100 \times 1/37 \approx 2.7$ per cent (the reciprocal of the number of occupations) and by 100 per cent.[5] The larger the HHI the more concentrated are workers in a few – if not a single – occupations.

In this paper, the HHI is computed using total employment shares, irrespective of sex. Accounting for occupational concentration is particularly important when interpreting cross-country differences in segregation, as similar levels of the dissimilarity index may arise in economies with very different employment structures.

3.3 Defining concepts

This subsection introduces the main concepts used throughout the analysis and clarifies the terminology employed in the empirical sections. Table 1 summarizes these concepts and their associated measures.

At the core of the analysis are *gender imbalances*, defined as the difference between the share of women and the share of men in a given occupation, each expressed relative to their respective total employment. Formally, this corresponds to $s_{ij,f} - s_{ij,m}$. A positive value indicates that women are more likely than men to be employed in occupation i, while a negative value indicates the opposite. The dissimilarity index, introduced in the previous subsection, aggregates these imbalances across all occupations (taking absolute values).

Two related but distinct concepts are used throughout the paper: *overrepresentation* and *dominance*. A woman is considered *overrepresented* in an occupation whenever the share of women among all working women exceeds the corresponding share for men, *i.e.* $s_{ij,f} > s_{ij,m}$. An occupation is *female-dominated* when the absolute number of women employed in that occupation exceeds the number of men. These two conditions do not necessarily coincide. For example, agricultural occupations are often not female-dominated in absolute terms, yet women can be overrepresented in them relative to their overall employment distribution.

Finally, to assess how individual occupations contribute to aggregate segregation, we compute a measure of *relative contribution*. This metric captures the share of the dissimilarity index accounted for by a given occupation, relative to its share in total employment. It therefore combines information on both the magnitude of gender imbalances and the size of the occupation, allowing us to identify which occupations disproportionately drive overall segregation.

Table 1: Main concepts used in the paper

Concept	Definition	Measure or source
Gender-based occupational segregation	The unequal distribution of female and male workers across and within job types.	Carranza et al. (2023)
Gender imbalances	Gap in shares. If positive then a woman, among all women, is more likely to work in occupation i than a man is (among all men).	$s_{ij,f} - s_{ij,m}$
Dissimilarity Index *Segregation measure*	A measure of occupational segregation. The share of women (or men) who would need to change occupation to reach perfect integration. The larger the index the higher the segregation.	$DI_j = \frac{1}{2}\sum_i (\lvert s_{ij,f} - s_{ij,m}\rvert)$
Herfindahl-Hirschman Index *Concentration measure*	A measure of occupational concentration. The larger the index the more concentrated the occupation.	$HHI_j = \sum_i s_{ij}^2$
Overrepresentation of women in occupation i	Occurs for a positive gender imbalance (opposite case for men's overrepresentation).	$s_{ij,f} > s_{ij,m}$
Female-dominated occupation	Women outnumber men in the occupation (opposite for male-dominated occupation).	$Workers_{ij,f} > Workers_{ij,m}$
Relative contribution	Share of the dissimilarity index explained by occupation i, relative to the share of employment in i.	$\frac{100 \times \frac{1}{2} \times \frac{s_{ij,f} - s_{ij,m}}{DI_j}}{s_{ij,fm}}$

4 Data

4.1 Data sources

The primary data source is the ILO Harmonized Microdata collection, which compiles nationally representative labour force and household survey microdata from a large number of countries. These data are harmonized *ex post* to ensure consistent definitions of employment, occupations, and key demographic variables across countries and over time. The data distinguish between men and women; accordingly, gender is operationalized as a binary variable in this analysis. This makes the dataset particularly well suited for cross-country analyses of gender segregation, as it provides comparable individual-level information on employment by occupation for both women and men. This, in turn, allows for the construction of consistent segregation measures and the analysis of their evolution across countries and over time.[6]

For the cross-sectional analysis, the most recent survey available for each country within the 2020–2024 period is used, covering all countries for which microdata on the number of workers by sex are available.[7] This yields a sample of 117 countries, of which 87.2 per cent have their most recent survey in the 2022–2024 years, together representing 65.5 per cent of global employment in 2024.

To examine changes in gender-based occupational segregation over time, an additional set of surveys is collected for the 2010–2014 period, again prioritizing the most recent available year. To ensure comparability of occupational classifications across countries and over time, only surveys using the 2008 version of International Standard Classification of Occupations (ISCO–08) are retained.[8] Applying this restriction reduces the sample to 75 countries, representing 32.3 per cent of global employment in 2014.[9]

To identify the factors associated with occupational segregation, a set of country-level variables is included in the regression analysis presented in Section 6.5.[10] These variables are organized around four dimensions.

First, the economic structure of each country is captured through employment shares by sector and by sex, drawn from ILO modelled estimates (ILO, 2025a). These modelled series are used to maximize country coverage. The sole exception is the Herfindahl-Hirschman Index, which is derived from the same survey-based microdata as the dissimilarity index and therefore shares its country coverage. The sectoral contribution to economic output is measured using value added shares from the World Development Indicators (WBG, 2025), providing a complementary perspective on economic structure alongside the employment-based measures.

Second, human capital is measured through the share of men and women with tertiary education, sourced from the World Development Indicators. Access to higher education has been shown to be an important determinant of women's entry into high-skill occupations (England, 2010; Bach et al., 2024; Goldin, 2024).

Third, the level and distribution of economic activity are captured through two variables. The natural logarithm of Gross Domestic Product (GDP) per capita in Purchasing Power Parity (PPP) serves as a measure of living standards. Income inequality is measured by the share of national pre-tax income accruing to the top 10 per cent of earners, drawn from the World Inequality Database (Facundo et al., 2024): a higher share indicates a more unequal income distribution.

Fourth, the share of dependent persons in the population is included to proxy the care burden faced by working-age adults. Using data from the United Nations World Population Prospects (UN, 2024), two variables are constructed: the share of persons aged under 15 and the share of persons aged 65 or over. Together these capture the extent to which active household members may face competing demands on their time from the care of children or elderly relatives, which has been shown to fall disproportionately on women and to shape their occupational choices.

4.2 Data construction

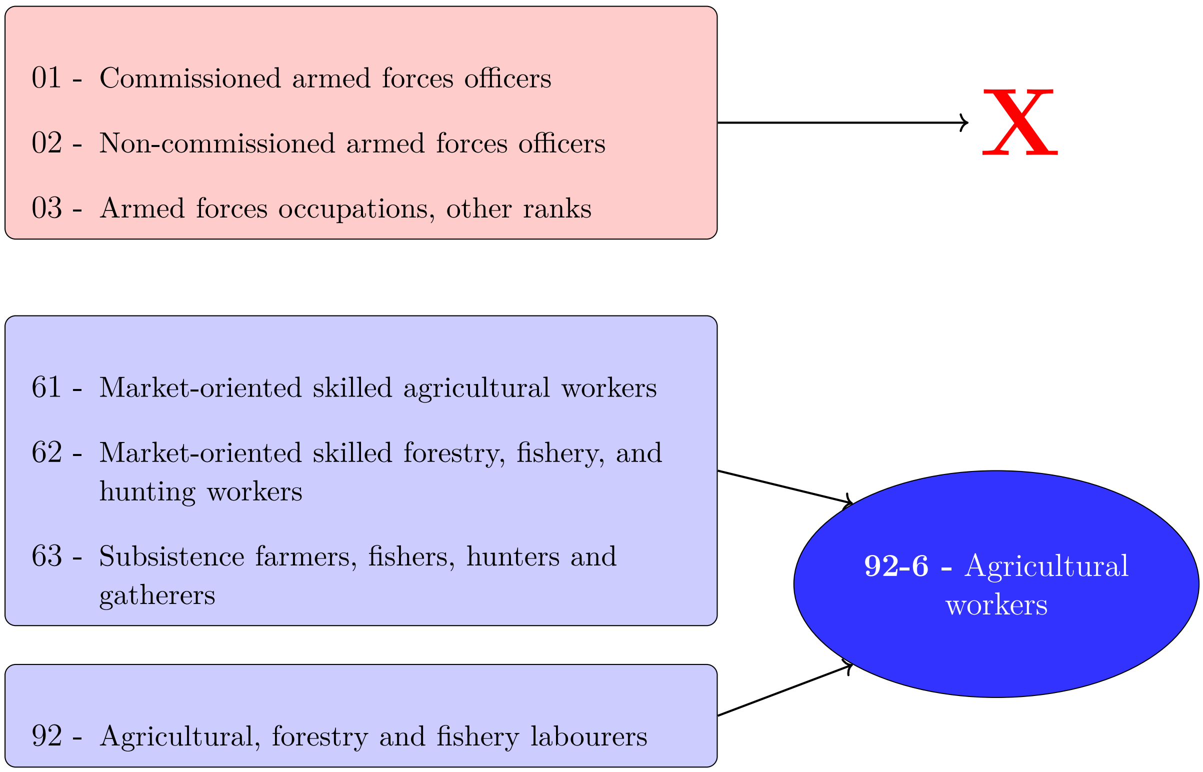
Studies of occupational segregation differ considerably in the granularity of the occupational classification used. Single-country analyses can draw on highly detailed classifications. Goldin (2014), for instance, examines the distribution of workers by sex across 469 occupational categories. Cross-country studies are more constrained, as data harmonization requirements and differences in national classification systems limit the level of occupational detail that can be achieved consistently across countries.

A key contribution of the present analysis is to bridge this gap by conducting a cross-country study at a finer level of occupational disaggregation than has previously been achieved. Specifically, we use the sub-major groups of ISCO–08, which allow us to distinguish, for instance, between Chief executives, senior officials and legislators on the one hand, and Administrative and commercial managers on the other, rather than treating all managerial occupations as a single group.

Of the 43 sub-major occupational groups defined under ISCO–08, the present analysis retains 37. The three occupational groups related to the armed forces are excluded for two reasons. First, data collection practices for these groups vary considerably across countries, raising comparability concerns. Second, the gender composition of armed forces occupations is heavily shaped by country-specific policies, such as mandatory military service applying exclusively to men in South Korea and Switzerland, which would introduce a source of variation unrelated to the labour market dynamics of interest here.

Four sub-major groups relate to agriculture. They are merged into a single occupational category to ensure consistency across countries and over time in the classification of agricultural workers, whether skilled or unskilled, and whether engaged in subsistence or market-oriented farming.[11] Figure 1 summarizes the modifications made to the original ISCO–08 classification with respect to both the armed forces and agricultural occupations. The resulting classification comprises 37 sub-major occupational groups, which form the basis of all analyses presented in this paper. These groups differ considerably in their share of total employment, as detailed in Table 10 in the Annex.

Figure 1: Modifications of the sub-major groups of occupations



The five largest occupational groups together account for more than half of total employment, while the 12 smallest groups collectively account for around ten per cent. Agricultural occupations alone represent more than a quarter of all workers across the countries covered, though with considerable variation: in many low-income African countries, Agricultural workers exceed half of the total workforce, whereas in most high-income countries they account for less than ten per cent.

Table 10 in the Annex reports the share of women employed in each occupation among all working women, the equivalent share for men, and the share of women within each occupation. The difference between columns (1) and (2) (the gap between the share of women among all working women and the share of men among all working men in each occupation) writes $(s_{ij,f} - s_{ij,m})$ and is the above-defined *gender imbalance*.

5 Segregation and gender imbalances in 2020–2024

5.1 Segregation, concentration and economic development

Table 2 presents summary statistics on the level of gender-based occupational segregation across the full sample of countries and by income group. The global dissimilarity index amounts to 39.8 per cent, indicating that approximately four in ten working women would need to change occupations to replicate men's occupational distribution. Disaggregating by income group reveals a positive association between the level of development and the degree of segregation: the index is highest among high-income countries (44.2 per cent) and lowest among low-income countries (21.2 per cent).[12]

The relatively low dissimilarity index in low-income countries reflects, in part, the overwhelming concentration of workers irrespective of sex in agricultural occupations, which mechanically reduces the index. When agricultural occupations are excluded from the calculation, as in column (2), the pattern changes considerably: the segregation index approximately doubles in low-income countries, increases by about a quarter in lower-middle-income countries, and by about ten per cent in upper-middle-income countries, while remaining nearly identical in high-income countries. Once agricultural occupations are set aside, gender-based occupational segregation is strikingly similar across all income levels.

This pattern represents a first stylised fact: economic diversification that accompanies economic development does not necessarily imply an increase in gender-based occupational segregation when agricultural occupations are excluded from the analysis. Occupations outside agriculture are segregated regardless of the level of development, and it is the changing weight of agriculture in total employment rather than changes in segregation within other occupational groups that drives much of the observed cross-country variation in the aggregate index.

To clarify the analysis that follows, it is useful to distinguish clearly between two related but distinct concepts: occupational segregation and occupational concentration. Segregation, as measured by the dissimilarity index, captures the degree to which men and women are distributed differently across occupations relative to one another. Concentration, as measured by the Herfindahl-Hirschman Index (HHI), captures the degree to which all workers (regardless of sex) are clustered in a small number of occupational groups. A country can exhibit high concentration and low

Table 2: Segregation and concentration across income groups

	Segregation Index, % (1)	Segregation Index (no agriculture), % (2)	Share employment in agriculture, % (3)	Hirschman-Herfindahl index, % (4)	Share of employment within group % (5)
World	39.78	45.22	26.3	15	65.53
Low-income	21.19	42.69	64.44	44.71	69.4
Lower-middle-income	39.16	47.87	40.09	20.3	83.43
Upper-middle-income	40.94	44.9	18.05	8.76	37.82
High-income	44.22	44.25	2.65	4.55	86.3

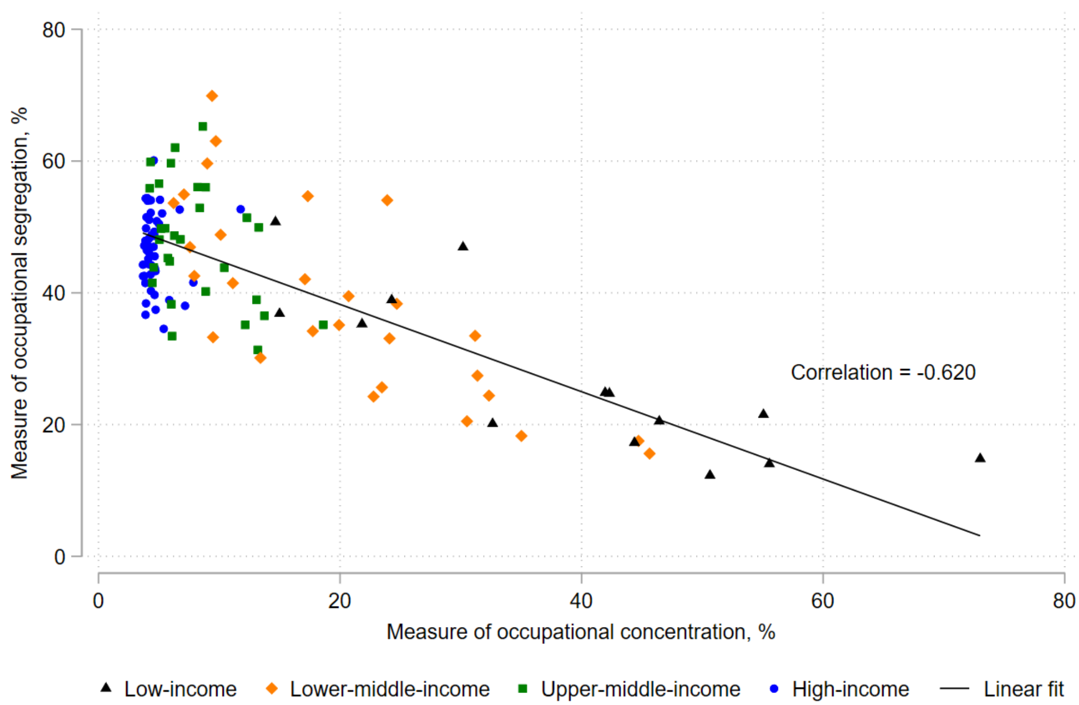
Note: This table reports the gender-based occupational segregation for all 117 countries for which the most recent survey falls within the 2020–2024 period. Column (1) presents the dissimilarity index for all 37 occupations. Column (2) displays the dissimilarity index for 36 occupations; that is, the gender-based occupational segregation once Agricultural workers are dropped. Column (3) shows the share of employment in agriculture for both men and women in the countries covered (using the survey-based data). Column (4) indicates the concentration index named the Herfindahl-Hirschman index. Column (5) reports the data coverage with respect to global employment. China accounts for 54.9 per cent of employment among upper-middle-income countries and is not included in the sample. It explains the modest employment coverage among upper-middle-income countries.

segregation, if most workers of both sexes are employed in the same few occupations, or low concentration and high segregation, if employment is spread across many occupations but men and women sort into systematically different ones. The two measures are related empirically but they capture distinct features of the occupational structure and carry different implications for the interpretation of cross-country differences in segregation.

Unsurprisingly, the share of employment in agriculture – shown in column (3) – and the level of development are negatively related. The share of workers in agriculture is the highest for developing countries, in particular in low-income countries where almost two thirds of the workers are in agricultural occupations while less than three per cent of workers in high-income countries are in such occupations.[13] The concentration index shown in column (4), follows the same pattern: it is highest in low-income countries, where the dominance of agricultural employment produces a highly concentrated occupational structure. The linear correlation coefficient (weighted by employment) between the segregation index and the HHI is -0.62, and Figure 2 illustrates the negative relationship between gender-based occupational segregation and occupational concentration of workers.

Once countries have moved well beyond agricultural dominance, variation in the HHI reflects a broader range of structural features and the relationship between concentration and segregation becomes less straightforward. This is illustrated by the reversal of the concentration-segregation relationship among the most economically diversified countries. For the 74 countries with a concentration index below 10 per cent (those with the most diversified occupational structures) the correlation between concentration and segregation becomes positive.[14] Whereas high concentration reflects the dominance of agriculture, a sector that is relatively integrated by sex, greater diversification brings a more varied occupational structure in which industrial and service occupations – often more sharply divided by sex – account for a larger share of employment. This tends to raise overall segregation. Once countries reach sufficiently high diversification – and thus high levels of development – the occupational structure is decisively tilted toward services and segregation begins to decline. This phenomenon is not only observed when using concentration to proxy economic development.

Figure 2: Segregation and concentration, 2020–2024



Note: The y-axis on both figures represents the dissimilarity index, computed following equation 1. The x-axis represents the Herfindahl-Hirschman Index, computed following equation 2.

Economic development is more commonly proxied by GDP per capita than by occupational concentration. Figure 3 plots the dissimilarity index against the logarithm of GDP per capita and reveals an inverse U-shaped relationship, *i.e.* segregation rises with income per capita up to a maximum reached among upper-middle-income countries, before declining among high-income countries.[15] This pattern aligns with the income level at which industrial activity peaks: upper-middle-income countries have the highest average share of industry in GDP (31.5 per cent), compared to 27.2 per cent in lower-middle-income countries, 24.3 per cent in low-income, and 23.7 in high-income countries. The inverse U-shaped relationship between income per capita and an outcome of interest, known as the Kuznets curve, has been documented for income inequality (Kuznets, 2019), environmental degradation (Grossman and Krueger, 1995), and the complement of the female labour force participation rate (Goldin, 1994). The present analysis extends this pattern to gender-based occupational segregation.[16]

Figure 3 further highlights that the dispersion in segregation levels is greatest among low-income countries and narrows with economic development. The employment-weighted standard deviation of the dissimilarity index decreases by approximately 17.3 per cent between low-income and high-income countries. This convergence suggests that as economies reach higher levels of development and their occupational structures become more similar, their levels of gender-based occupational segregation also tend to converge.

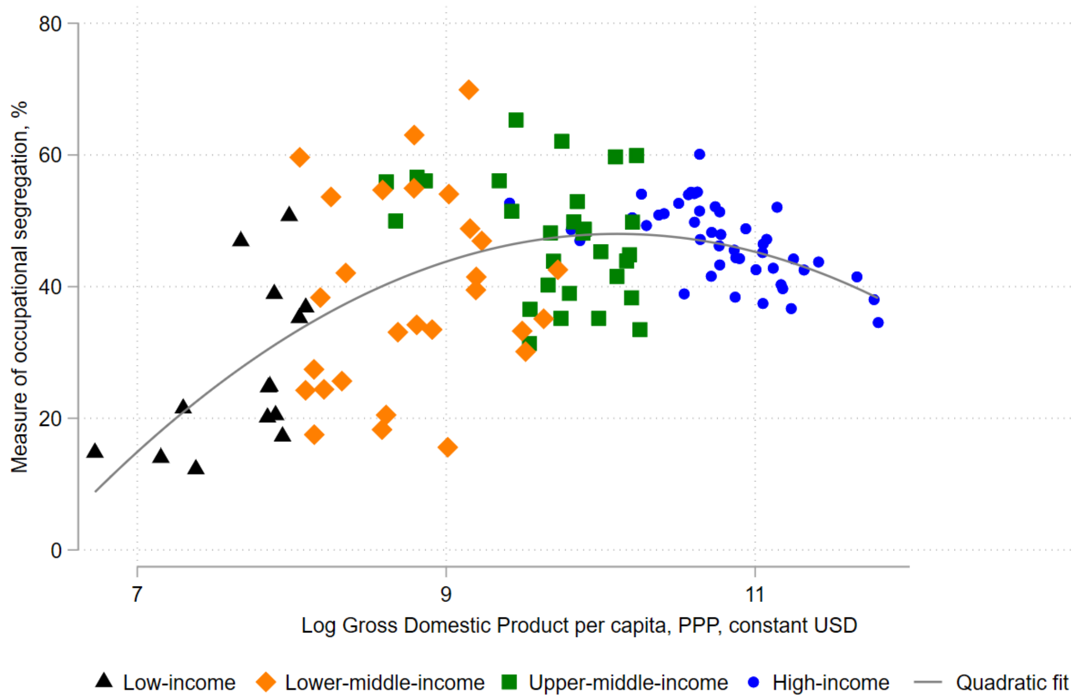
A second stylised fact emerges from these findings: gender-based occupational segregation rises as economies diversify away from agriculture and industrialize, reaches a peak at the upper-middle-income stage, and subsequently declines as deindustrialization and the expansion of service-based activities proceed. This transition is also associated with a gradual reduction in the dispersion of segregation levels as countries move toward service-oriented economies.

5.2 Global imbalances across occupations

5.2.1 Dominating and/or being overrepresented in an occupation

Having documented the aggregate patterns of gender-based occupational imbalances, we now turn to the question of which occupations drive the aggregate measure of segregation and to what extent. The dissimilarity index aggregates imbalances across all occupations, but individual occupations contribute to overall segregation to varying degrees.

Figure 3: Segregation and log GDP per capita, 2020–2024



Note: The y-axis represents the dissimilarity index, computed following equation 1. The x-axis represents the logarithm of GDP per capita in PPP, constant USD.

Table 10 in the Annex shows the share of women and the share of men, respectively, and the difference between columns (1) and (2) captures the aggregate imbalances for each occupational group. Globally, 28.4 per cent of women work in agricultural occupations, a share that exceeds that of men by 3.5 percentage points. Although women are overrepresented in agricultural occupations in this sense, they account for only 42.8 per cent of all workers in this occupational group. Agricultural occupations are therefore not female dominated, reflecting the lower overall labour force participation rate of women relative to men.

Among Personal care workers, 82.9 per cent of workers are women, making this one of the most heavily female-dominated occupational groups. A working woman is more than seven times more likely than a working man to be employed as a Personal care worker. Out of the 37 occupational groups considered, eleven are female-dominated.[17] These groups tend to cluster around health, education, and care services oriented toward direct interactions with persons.

On the other hand, men are more likely to select into physically demanding industrial and operational jobs. Drivers and mobile plant operators is the most male-dominated occupational group, with women accounting for only 2.6 per cent of workers. Similarly, most workers in Metal, machinery and related trades, and in Building and related trades, excluding electricians, are men.

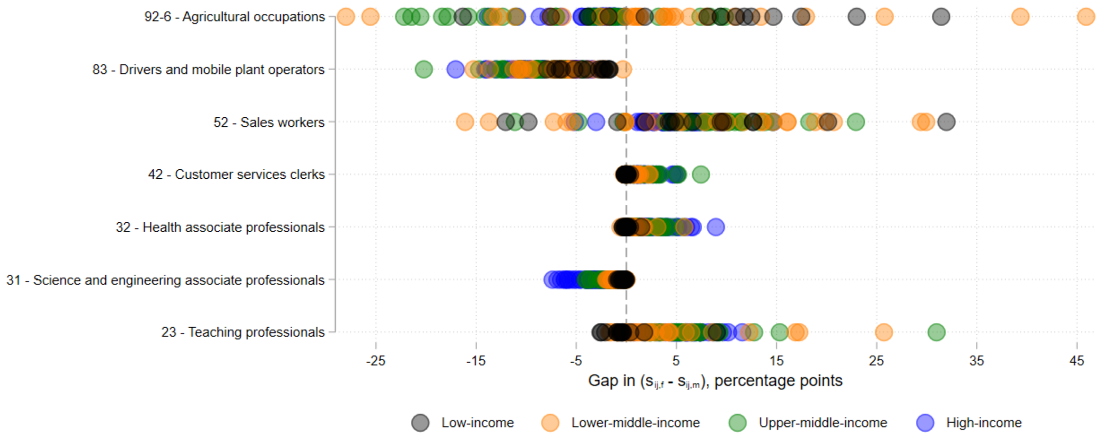
5.2.2 Cross-country imbalances across occupations

Gender-based occupational imbalances vary considerably across countries. Figure 4 illustrates these imbalances for a selection of occupations, with each dot representing the gap between the share of women and the share of men in a given occupation in a given country.[18] The (halved) distance between a dot and the vertical line at $(s_{ij,f} - s_{ij,m}) = 0$ corresponds to the contribution of that occupation to the country's overall dissimilarity index: the further away a dot lies from the vertical line, the greater the contribution of that occupation to gender-based occupational segregation in absolute terms. Positive values indicate occupations where women are more likely to sort into than men, *i.e.* occupations in which women are overrepresented and negative values indicate occupations in which men are overrepresented relative to women.

Two broad patterns emerge from the figure. Some occupational groups display highly heterogeneous imbalances across countries, while others cluster tightly showing common patterns across all countries. Overall, imbalances tend to be more homogeneous across countries at higher levels of development, suggesting that the occupational sorting of men and women converges as countries move toward high-income economies. This convergence in high-income countries suggests that policy approaches to reducing segregation may be more transferable across countries at similar levels of development, whereas the greater heterogeneity observed in developing economies calls for more context-specific interventions.

Agricultural workers, Sales workers, and to a lesser extent Teaching professionals, fall into the first category, displaying heterogeneous imbalances across countries. The largest imbalances within these groups are generally found in low-income and lower-middle-income countries. The overrepresentation of women in agricultural occupations is most pronounced in South Asian and Sub-Saharan African countries, where subsistence farming is prevalent.[19] By contrast, several small island economies – including Grenada, Kiribati, Samoa, and Tonga – exhibit an overrepresentation of

Figure 4: Imbalances across a selection of occupations, 2020–2024



Note: Each dot represents a gap in shares for occupation i in country j, as in $s_{ij,f} - s_{ij,m}$, expressed in percentage points. Dot colors represent the income groups.

men in agriculture, reflecting the dominant role of tourism in their economies and the corresponding prevalence of women in services-related occupations such as Sales workers, Personal service workers, and Customer services clerks. In countries such as Ethiopia and Guatemala, the overrepresentation of men in agriculture reflects a different structural pattern. In both countries, agriculture is heavily oriented toward export markets, accounting for 80.2 and 48.6 per cent of merchandise exports respectively, in contrast to the subsistence-oriented farming that characterizes the South Asian cases.[20]

Among Sales workers, women are overrepresented in many countries in Sub-Saharan Africa and Latin America, including Togo, Senegal, Benin, El Salvador, and Honduras. In these economies, informal retail accounts for a substantial share of economic activity and is characterized by low barriers to entry, which tends to facilitate women's participation (ILO, 2023). The opposite pattern prevails in South Asian and Arab States, including Bangladesh, Pakistan, Afghanistan, Iraq, Sudan, Palestine, Jordan, and India, where prevailing gender norms restrict women's access to formal retail and men are overrepresented in these occupations.

Other occupational groups display a remarkable degree of consistency across countries in the direction of gender imbalances. Men are overrepresented among Drivers and mobile plant operators and Science and engineering associate professionals in virtually all countries covered, while women are overrepresented among Customer services clerks and Health associate professionals nearly everywhere.

An important nuance concerns the magnitude of these imbalances: high-income countries tend to exhibit the largest gaps for these consistently imbalanced occupational groups, not because the underlying sorting patterns differ, but because these occupations account for a larger share of total employment in developed economies. In low-income countries, the dominance of agricultural employment leaves a smaller share of the workforce in other occupational groups, which mechanically limits the size of the gaps that can be observed.

To illustrate, Science and engineering professionals account for 0.26 per cent of working women and 0.73 per cent of working men in low-income countries, yielding a gap of -0.47 percentage points. In high-income countries, the same occupational group accounts for 2.4 per cent of working women and 5.4 per cent of working men, producing a gap more than six times larger. This observation motivates the analysis in the following subsection, which examines the relative contribution of each occupation to overall segregation in a way that accounts for its share in total employment.

5.3 Relative contribution to segregation

The dissimilarity index aggregates imbalances across occupations, yet the contribution of each occupation to overall segregation differs. An occupation with a large employment share does not necessarily contribute proportionally more to overall segregation, just as an occupation with a small employment share can contribute disproportionately to overall segregation. To capture this, it is necessary to assess each occupation's contribution to the dissimilarity index relative to its share of total employment, a measure we refer to as the relative contribution.

The following Angola example illustrates this distinction. In Angola, 33.48 per cent of women would need to change occupations to replicate men's occupational distribution. The share of women workers in agricultural occupations exceeds that of men by 8 percentage points. Hence, agricultural occupations account for 11.95 ($\approx 100 \times \frac{1}{2} \times \frac{8}{33.48}$) percentage points of the segregation in the country. However, the share of workers in agricultural occupations in Angola is 52.65 per cent, it is almost five times the contribution of agriculture to the segregation. Agricultural occupations therefore *under-contribute* to segregation: their contribution to the dissimilarity index is proportionally smaller than their share of employment. On the contrary, Drivers and mobile plant operators in Angola account for 3.57 per cent of the employment and the (absolute) gap in shares of women and men amounts to 7.34 per cent. This translates into a contribution of approximately 5.33 ($\approx 100 \times \frac{1}{2} \times \frac{3.57}{33.48}$) per cent of the overall occupational segregation in the country, representing a relative *over-contribution* of Drivers and mobile plant operators by 49.3 per cent ($100 \times \frac{5.33}{3.57}$).

More formally, the relative contribution of occupation i in country j is defined as:

$$Relative\ contribution_{ij} = \frac{100 \times \frac{1}{2} \times \frac{s_{ij,f} - s_{ij,m}}{DI_j}}{s_{ij,fm}} \tag{3}$$

where $s_{ij,fm}$ denotes the share of all workers employed in occupation i in country j, $s_{ij,f}$ and $s_{ij,m}$ denoting the share of female and male workers respectively. When $|Relative\ contribution_{ij}| > 1$, the occupation over-contributes to segregation relative to its employment share; when $|Relative\ contribution_{ij}| < 1$, it under-contributes. A positive (negative) $Relative\ contribution_{ij}$ for a given contribution implies that the women (men) are overrepresented in this occupation and country.

Figure 5 displays the relative contribution of each occupational group, aggregated at the income group level and weighted by total employment. Lighter colors indicate contributions close to zero while darker shading indicates stronger relative contributions in either direction. Darker blue rectangles correspond to occupations where women are overrepresented and that over-contribute to segregation, while darker red rectangles correspond to occupations where men are overrepresented and that over-contribute to segregation from the male side. In other words, both darker blue and darker red signal over-contribution to segregation, but from the perspective of different sexes. Across all income groups except high-income countries, agricultural occupations consistently under-contribute to overall segregation, acting as a dampening force on the aggregate index.

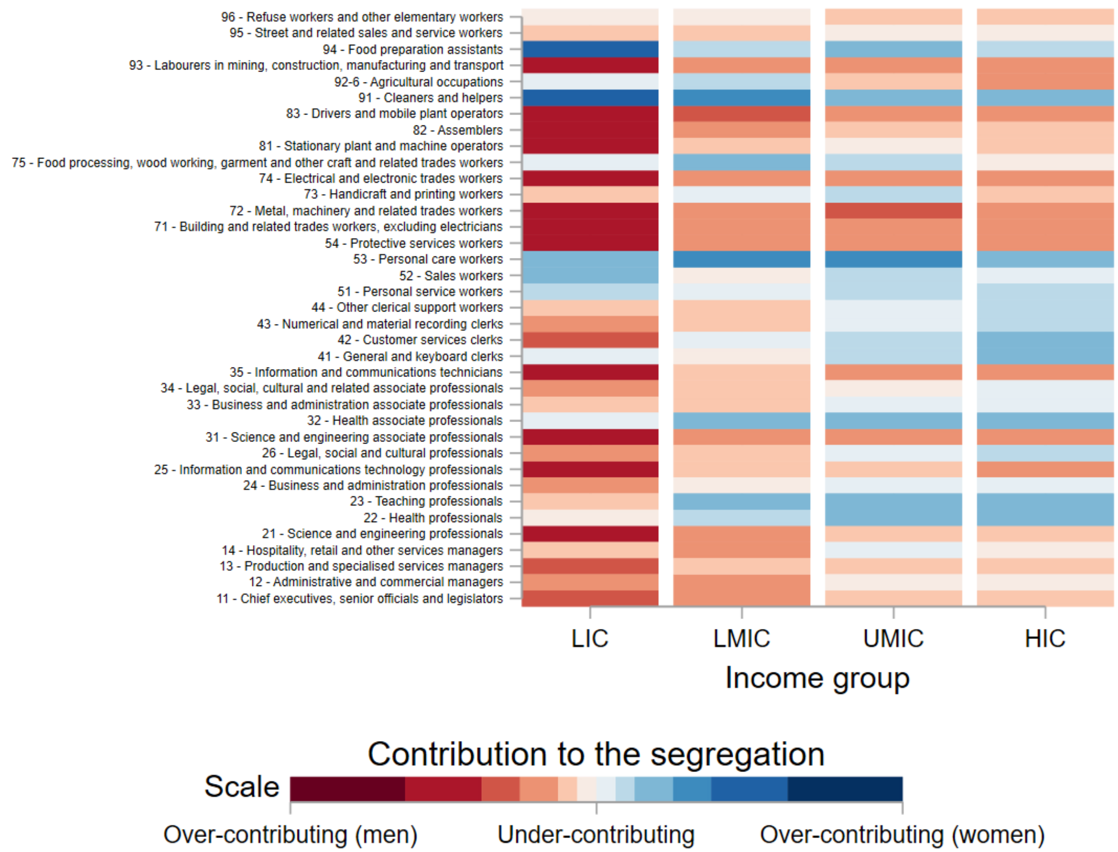
In low-income countries, over-contribution is more widespread across occupational groups than in other income groups, which further reflects the dampening role of agricultural occupations. Their dominance in total employment reduces the scope for other occupations to contribute proportionally to segregation, making the over-contributions of non-agricultural occupations more pronounced by comparison.

At the level of major occupational groups (ISCO–08 one-digit), Managers, Clerical support workers, and Service and sales workers (barring Protective services workers in low-income countries) tend to under-contribute to gender-based occupational segregation. On the contrary, occupational groups such as Professionals, Technicians and associate professionals, Craft and related trades, Plant and machine operators and assemblers, and some Elementary occupations tend to over-contribute to the gender-based occupational segregation. As economies diversify, a policy focus on these latter groups may help contain the rise in segregation that tends to accompany early-stage economic development.

At the sub-major group level, several occupational groups over-contribute to segregation consistently across all income levels. These are predominantly male-dominated occupations, including Labourers in mining, construction, manufacturing and transport, Electrical and electronic trades workers, and Science and engineering associate professionals. Among female-dominated occupational groups, Personal care workers and Cleaners and helpers also over-contribute consistently, though female-dominated occupations more generally display heterogeneous contributions across income levels. For certain occupational groups, such as clerical occupations and Health professionals, the degree of over-contribution increases with the level of development, reflecting the growing gender imbalances that emerge in these occupations as economies mature.

Beyond under- and over-contributions, Figure 5 shows that women are overrepresented in only about one quarter of occupations in low-income countries, compared with more than 40 per cent in upper-middle- and high-income countries. As economies diversify, women are overrepresented across a broader range of occupations, with smaller degrees of over-contribution than in less diversified economies.

Figure 5: Heatplot on the relative contribution by occupation, 2020–2024



Note: The occupation's relative contribution to segregation is computed as in equation 3. Lighter colors indicate less relative contribution. The magnitudes are weighted by total employment in each country. LIC stands for Low-Income Country, LMIC stands for Lower-Middle-Income Country, UMIC stands for Upper-Middle-Income Country, and HIC stands for High-Income Country.

While the cross-sectional analysis presented in this section provides a comprehensive account of the current state and structure of gender-based occupational segregation, it does not capture how segregation has evolved within countries over time. The following section addresses this by drawing on repeated surveys for a subset of countries, allowing for a more detailed examination of the dynamics of segregation over the past decade.

6 The evolution of segregation and gender imbalances over the past decade

6.1 Panel coverage and comparability over time

Segregation in levels identifies the occupations that contribute most to gender-based occupational segregation and allows comparisons across countries at a given point in time. To analyze how segregation evolves, repeated observations are needed. In this paper, we compare two time windows, 2010–2014 and 2020–2024. This choice makes the analysis complementary to earlier cross-country studies, which typically end, at the latest, around 2010 (Chang, 2004; Borrowman and Klasen, 2020).

Only countries with a survey in 2010–2014 and a survey in 2020–2024 are included in the panel sample. It sharply reduces the sample relative to the cross-sectional analysis: coverage falls from 117 countries to 75 countries, and from 65.5 per cent to 32.3 per cent of global employment. As shown in Table 8 in the Annex, of the 75 countries in the panel, 40 are high-income countries and 35 are non-high-income countries. For the latter group in particular, potential limitations in representativeness should be kept in mind when interpreting the results below. Given the more limited coverage outside the high-income group, most of our analysis of segregation over time distinguishes between two broad categories: (i) high-income countries, referred to hereafter as "developed countries", and (ii) non-high-income countries, referred to as "developing countries".

The next subsections present the general changes in segregation; then it decomposes this change in two effects – the change in gender composition within occupation and the change in employment across occupations; and, lastly, it highlights what macro variables correlate with changes in segregation.

6.2 Changes in segregation over the past decade

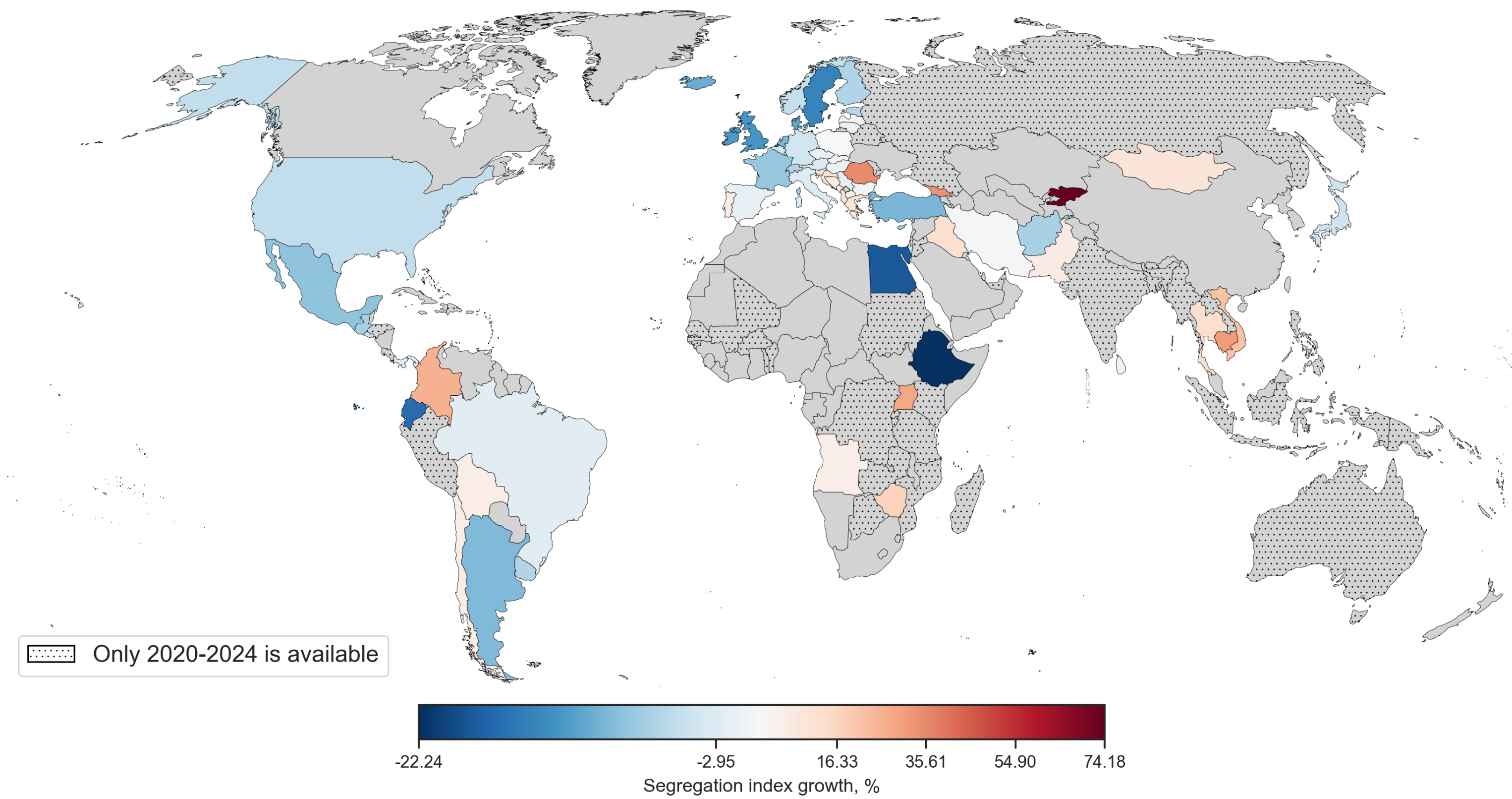
Over the past decade, the average change in gender-based occupational segregation is modest. Across the 75 countries covered, the dissimilarity index declines from 41.6 per cent in 2010–2014 to 41 per cent in 2020–2024. Excluding agricultural occupations yields a similar result, with the index falling from 40.1 per cent to 39.3 per cent. The linear correlation coefficient of the dissimilarity index across the two periods is high, at 86.1 per cent, underscoring the persistence of occupational segregation over time.[21]

The magnitude of this decline is small. The share of women who would need to change occupation in order to match the occupational distribution of men falls by only 0.6 percentage points. At the same time, because the number of women in employment increased over the period, the absolute number of women who would need to reallocate across occupations rises by 10.9 per cent in the sample (amounting to around 18 million working women). In other words, segregation eased slightly, but the scale of the underlying reallocation challenge did not.

Moreover, this modest decline partly reflects changes in the distribution of employment across countries. Holding country employment weights constant at their initial levels, the number of women who would need to change occupations would be higher in 2020–2024 than in 2010–2014. This indicates that the reduction in segregation is driven in part by countries in the sample that experienced both large employment growth and declining segregation, such as the United States, Mexico, and Brazil.

Behind the small average decline lies substantial cross-country heterogeneity. Figure 6 shows that developed countries generally experienced a reduction in occupational segregation over the past decade. This is consistent with the longer-run evidence for countries such as the United States, where segregation had already been declining (Blau et al., 2013). Using sub-major occupational groups, the dissimilarity index in the United States falls by 2.1 percentage points from 38.8 per cent in 2014 to 36.7 per cent in 2024.

Figure 6: Change in the dissimilarity index between 2010–2014 and 2020–2024



Disclaimer: The boundaries used on this map do not imply official endorsement or acceptance by the authors. The presentation of material on this map do not imply the expression of any opinion whatsoever on the part of the Secretariat of the United Nations concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined. Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. A dispute exists between the Governments of Argentina and the United Kingdom of Great Britain and Northern Ireland concerning sovereignty over the Falkland Islands (Malvinas).

Among developed countries, there are only a few exceptions, such as Portugal, Romania or several Balkan countries, where occupational segregation increased. These countries are also the only developed countries where the employment share in industry increased over the period. Out of 40 developing countries, 8 experience an increase in the dissimilarity index. Among these 8 countries, 7 recorded an increase in either the employment share or the GDP share of industry. Changes are more uneven in developing countries. In South and South-East Asia, several countries – including Cambodia, Pakistan, Sri Lanka and Vietnam – register increases in occupational segregation, alongside rising industrial employment shares. In Latin America, the pattern is mixed: Bolivia, Chile and Colombia record increases, while most other countries in the subregion register declines. For example, occupational segregation declines in Argentina and Ecuador. In both countries, the share of workers in industry and the share of GDP that goes to industry are declining, which may indicate premature deindustrialization (Rodrik, 2016). African and Middle Eastern countries are also heterogeneous, ranging from sharp declines in Ethiopia and Egypt to substantial increases in the Gambia, Iraq, Uganda and Zimbabwe.

Figure 17 in the Annex helps situate these changes in development terms. In both periods, the relationship between occupational segregation and log GDP per capita is inverse U-shaped. Segregation is highest neither among the poorest countries, nor among the richest, but around the middle of the income distribution. Over time, the peak of that curve appears to shift from high-income countries toward upper-middle-income countries. This suggests that high-income economies are moving onto a less segregated path, while many middle-income countries are becoming the most exposed to persistent or rising segregation.

6.3 Which occupations changed the most?

The modest average decline in segregation conceals large shifts in the occupational structure. These shifts for each occupation differ by sex and by level of development. To examine them, we compare changes in occupational shares over time, separately for women and men: $(s^1_{ij,f} - s^0_{ij,f})$ and $(s^1_{ij,m} - s^0_{ij,m})$, where period 0 denotes 2010–2014 and period 1 denotes 2020–2024.[22] Figure 18 in the Annex reports the full set of changes by occupation and by level of development.

In developed countries, employment shares tend to decline in many clerical, services and production occupations for both women and men. By contrast, managerial, professional and associate professional occupations generally expand. This points to a gradual upgrading of the occupational structure, albeit with some signs of polarization, since a few elementary occupations also grow over the period.[23] Put differently, developed countries appear to be moving away from many routine-intensive middle occupations and toward a mix of higher-skill jobs and a smaller set of low-paid elementary jobs.[24] This polarization phenomenon in developed countries has been documented (in Europe: Goos et al., 2009 and Goos et al., 2014; in the United States: Autor and Dorn, 2013).

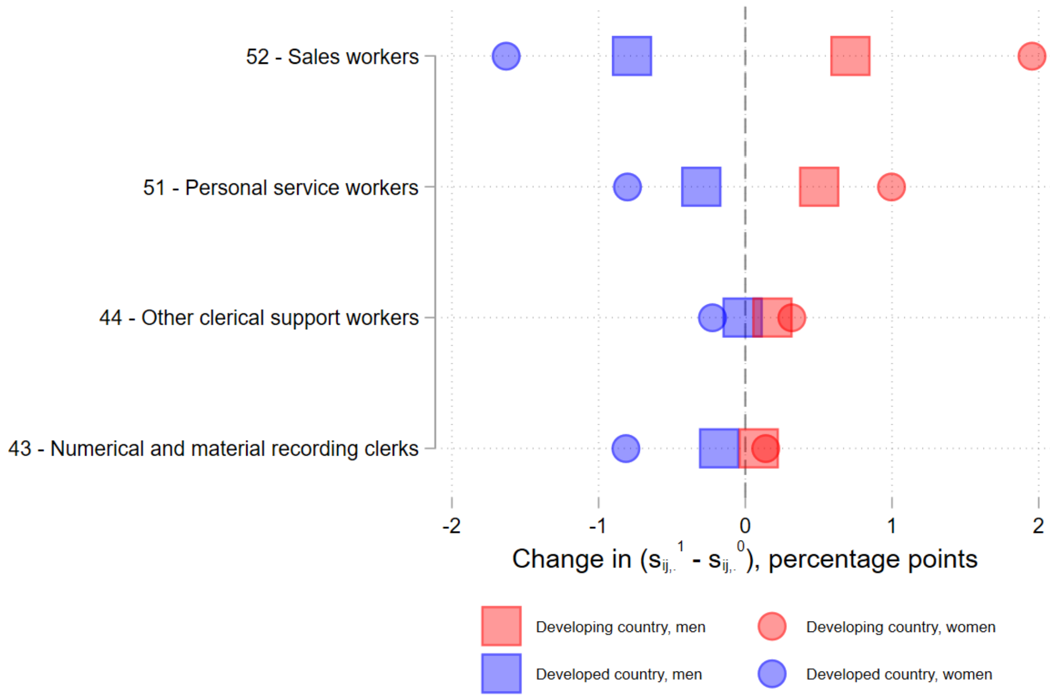
In developing countries, the pattern is different and less researched. The most pronounced decline concerns agricultural occupations, which remain a major source of employment in many countries at the beginning of the period. This decline is especially marked for women: across the sample, the average fall in the female employment share in agricultural occupations is 5.5 percentage points, compared with 3 percentage points for men. Country examples illustrate the magnitude of the shift. In Iran, agricultural occupations account for 17.1 per cent of employment in 2014 and 13.6 per cent in 2023; in Uganda, they fall from 72.7 per cent in 2014 to 67 per cent in 2021. For women, the shares decrease from 21.6 per cent to 13 per cent in Iran and from 78.7 per cent to 72.6 per cent in Uganda.

This movement out of agriculture is accompanied by a broader diversification of employment. In developing countries, employment shares rise not only in many managerial and professional occupations, but also in services and sales, clerical work and several industrial occupations. The transition is not always uniformly stage-based. In some cases, it resembles diversification into both services and industry rather than a simple, sequential move from agriculture to manufacturing and then to advanced services.

A particularly clear illustration is provided by the selection of four sub major occupations shown in Figure 7: Numerical and material recording clerks, Other clerical support workers, Personal service workers, and Sales workers. Together, these four sub-major groups account for about 17 per cent of employment in the covered countries.[25] For all four, developed and developing countries move in opposite directions. Their employment shares shrink in developed countries but expand in developing countries, and the contrast is especially pronounced for women.

This contrast is important for the interpretation of later results. On the one hand,

Figure 7: Change in occupational shares for selected occupations, by sex and country group, 2010–2014 and 2020–2024



Note: Each marker represents a gap in shares for occupation i between the time window 2020–2024 and the time window 2010–2014, as in $(s_{ij,1} - s_{ij,0})$, expressed in percentage points. Blue markers inform on the developed countries and red markers inform on the developing countries (average shares weighted by total employment in each country). Dots account for the shares of women among all women in each occupation. Squares represent the equivalent for men.

it is consistent with a global reallocation of routine clerical and service activities toward developing economies. On the other hand, it may also reflect domestic processes: occupational upgrading in developed countries and the gradual formalization and diversification of employment in developing countries. The evidence presented here does not identify which mechanism dominates (such as the relocation of labour where in excess supply, following Baldwin, 2016; replacement of routine-based tasks, as in Hidalgo and Micco, 2024; or other mechanisms), but it strongly suggests that the occupations expanding in developing countries are not the same as those driving change in developed countries.

6.4 Decomposing gender-based occupational segregation

The small average change in occupational segregation masks two distinct forces, first introduced by Fuchs (1975) and frequently implemented, for example by Blau et al. (2013). As shown in Annex B.2, the segregation index can change because gender composition within occupations changes while the occupational structure remains fixed. It is the *sex composition effect*. Alternatively, the segregation index can change because the distribution of employment across occupations changes while within-occupation gender balances remain fixed. It is the *occupation mix effect*. The overall change in segregation reflects the combined contribution of these two components. The two effects can evolve together or in opposite direction.[26]

Applying this decomposition to the 75-country panel helps reconcile the descriptive results above. In both developing and developed countries, the sex composition effect is negative: -1.5 percentage points in developing countries and -1.8 percentage points in developed countries. This indicates that, within occupations, women and men are becoming more evenly distributed over time. In other words, there is progress toward lower segregation inside occupations in both country groups.

The difference between the two groups lies in the occupation mix effect. In developing countries, the occupation mix effect is positive and sizeable, at 1.65 percentage points. This means that the occupations gaining employment over time tend, on average, to be more segregated than the occupations that are shrinking. As a result, improvements in gender balance within occupations are partly offset by structural change in the composition of employment.

In developed countries, by contrast, the occupation mix effect is nearly zero. This implies that the occupations expanding over time are, on average, neither more nor less segregated than the rest. The modest decline in segregation observed in developed countries therefore mainly reflects within-occupation changes rather than a strong compositional effect.

Figure 8 reinforces this conclusion. The share of countries in which the occupation mix effect dominates in absolute value declines sharply with income level: it is 50 per cent among low-income countries, 45.5 per cent among lower-middle-income countries, 45 per cent among upper-middle-income countries, and only 17.5 per cent among high-income countries. Structural transformation therefore plays a much larger role in shaping segregation dynamics in poorer countries than in richer ones.

This result is central to the overall narrative of the section. It shows that the

Figure 8: Share of countries in which the occupation mix effect dominates the change in segregation

limited reduction in average segregation does not reflect a lack of progress within occupations. Rather, it reflects the fact that in many developing countries the occupations that are expanding are themselves relatively segregated. This is also consistent with the occupation-level evidence above: movement out of agriculture does not automatically translate into movement into less segregated jobs.

6.5 Correlates of changes in segregation

The change in occupational segregation is multi-factorial and a small average change in occupational segregation does not imply that all countries behave homogeneously. Economic structure, human capital, national reforms relate to gender-based occupational segregation (Chang, 2004; Borrowman and Klasen, 2020). The present study pursues a similar line of inquiry, further decomposing the economic structure using both the employment shares in agriculture and industry and the share in value added of these two sectors.

The models displayed in Table 3 follow a standard linear structure of two-way fixed effect models with the dissimilarity index (DI_{jt}) in country j and at time t:[27]

$$DI_{jt} = \alpha_j + \delta_t + X_{jt}\beta + \varepsilon_{jt} \tag{4}$$

with α_j and δ_t the country and time fixed effects, respectively; X_{jt} the matrix of covariates and β the vector of point estimates attached to each covariate, ε_{jt} represents the disturbances. The country fixed effects α_j absorb all time-invariant country characteristics, such as geography or culture, while the time fixed effects δ_t control for common shocks affecting all countries in a given period. This model is preferred over other options for its simplicity and ease of interpretation.

To examine which country characteristics are associated with occupational segregation over time, Table 3 reports country fixed-effects panel regressions of the dissimilarity index. The specifications include country and time fixed effects and are weighted by total employment. Standard errors are clustered at the country level. The preferred specification is model (2), which uses the full sample and the complete set of covariates. Models (3) and (4) then show that the correlates of segregation differ substantially between developing and developed countries.[28]

Three results stand out. First, what matters is not only the sectoral structure of the economy, but also the gender allocation of jobs within sectors. Across the full sample, a higher male employment share in industry is associated with higher occupational segregation, whereas a higher female employment share in industry is associated with lower segregation. In model (2), a one-percentage-point increase in the male share of industrial employment is associated with a 0.6 percentage point increase in the dissimilarity index, while the corresponding increase in the female share is associated with a 1 percentage point decline. This is an important nuance: industrialization *per se* is not mechanically associated with more segregation; rather, segregation depends on whether the expansion of industrial employment is male-dominated or more gender-balanced.

Second, the role of agriculture differs sharply by level of development. In developing countries, a larger female employment share in agriculture is associated with higher segregation, whereas in developed countries the association is reversed. This difference is consistent with the broader descriptive evidence: in less developed countries, agriculture remains a large and often gender-differentiated reservoir of employment, while in richer countries it is a small residual sector with a very different composition.

Third, the strongest non-sectoral correlates are concentrated in developing countries. Higher female tertiary enrollment is associated with lower occupational segregation, while higher male tertiary enrollment is associated with higher segregation. Similarly, higher shares of children and older persons in the population are positively associated with segregation in developing countries, but not in developed countries. These patterns suggest that, outside developed countries where welfare states are well-institutionalized, access to higher education and the demographic burden of care remain closely linked to women's occupational allocation. It also points to a higher heterogeneity of the correlates among developing countries where economies differ more in terms of economic structure but also social aspects.

The results on income inequality point in different directions across country groups. In developing countries, higher pre-tax income concentration at the top is associated with higher occupational segregation; in developed countries, the association is negative. In developing countries, income inequalities are the highest in the lower part of the income distribution, while the situation is opposite in developed countries (ILO, 2024a). This contrast should be interpreted with caution, but it is consistent with the idea that rising inequality in developing countries is associated with stronger segmentation at the lower end of the labour market, whereas in developed countries it may partly reflect women's growing presence in better-paid occupations that remain disproportionately male.[29]

By contrast, once sectoral structure is controlled for, the log GDP per capita and the Herfindahl-Hirschman Index play a more limited role in the subgroup regressions. Their coefficients are informative in the pooled sample, but they do not appear to be the most robust within-group correlates. This again suggests that the mechanisms differ between developing and developed countries, and that the average relationship between development and segregation partly masks distinct underlying processes.

The regression results reinforce the descriptive and decomposition evidence. In developing countries, segregation is more closely tied to structural transformation, educational inequality and demographic constraints. In developed countries, segregation appears less driven by shifts in the occupational structure and more by gradual within-occupation rebalancing.

Overall, five conclusions emerge from this section. First, average occupational segregation declines only marginally over the past decade. Second, gender imbalances within occupations shrink in both developing and developed countries. Third, in developing countries, these within-occupation improvements are partly offset by

Table 3: Baseline panel regressions

Dependent variable: Dissimilarity index				
	Including agriculture		Developed countries	
	(1)	(2)	(3)	(4)
	No	Yes	No	Yes
Share of employment in agriculture, men	-0.663**	-1.109***	-0.782	0.784**
	(0.289)	(0.358)	(0.489)	(0.308)
Share of employment in agriculture, women	-0.149**	0.219*	0.467***	-1.869***
	(0.072)	(0.112)	(0.086)	(0.330)
Share of employment in industry, men	0.578***	0.622**	0.306	0.848***
	(0.201)	(0.253)	(0.306)	(0.192)
Share of employment in industry, women	-0.703***	-0.952***	-0.438	-1.049
	(0.239)	(0.304)	(0.428)	(0.688)
Agriculture, forestry, and fishing, value added (% of GDP)	-0.085	0.292	0.118	0.638
	(0.324)	(0.364)	(0.413)	(1.043)
Industry (including construction), value added (% of GDP)	-0.324***	-0.274*	-0.134	0.212
	(0.121)	(0.157)	(0.202)	(0.219)
Herfindahl-Hirschman Index	1.603	2.588**	0.887	-1.464
	(1.014)	(1.219)	(1.019)	(1.007)
Men school enrollment, tertiary (share gross)	0.152	0.187	0.244*	0.105
	(0.106)	(0.121)	(0.136)	(0.132)
Women school enrollment, tertiary (share gross)	-0.109	-0.153*	-0.330***	-0.124
	(0.080)	(0.089)	(0.109)	(0.118)
log GDP per capita, PPP, USD constant	-7.506*	-9.643*	-4.538	2.826
	(4.094)	(5.217)	(7.689)	(3.935)
Share of national income of the top 10 percent (pre-tax)	0.331*	0.350	0.797***	-0.393***
	(0.196)	(0.245)	(0.253)	(0.144)
Share of persons aged less than 15 yo	0.325	0.758**	1.420**	-0.243
	(0.275)	(0.339)	(0.606)	(0.491)
Share of persons aged 65 yo or more	0.218	0.705**	0.906***	-0.283
	(0.256)	(0.301)	(0.330)	(0.321)
Constant	96.130**	100.780*	8.417	27.463
	(43.144)	(56.370)	(74.453)	(39.479)
N	150	150	70	80
Countries	75	75	35	40
Adj. R-squared	0.680	0.626	0.791	0.826

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the country level in parentheses. The regressions are weighted by total employment per country.

changes in the occupational structure, as employment expands in relatively more gender-segregated occupations; in developed countries, this occupation-mix effect is close to neutral. Fourth, segregation dynamics differ markedly across country groups, reflecting differences in economic structure, income inequality, educational attainment, and demographic constraints. Fifth, industrial growth is not associated with higher segregation *per se*; rather, segregation is greater when industrial expansion remains disproportionately male-dominated.

7 The segregation of tomorrow and artificial intelligence

Looking ahead, Generative Artificial Intelligence (Gen AI) is likely to reshape the occupational structure of employment in ways that interact directly with the patterns of segregation documented above. Because women and men distribute unevenly across occupations, such transformations are unlikely to be gender neutral. A key question is therefore whether the occupations most exposed to Gen AI are also those where gender imbalances are already most pronounced.

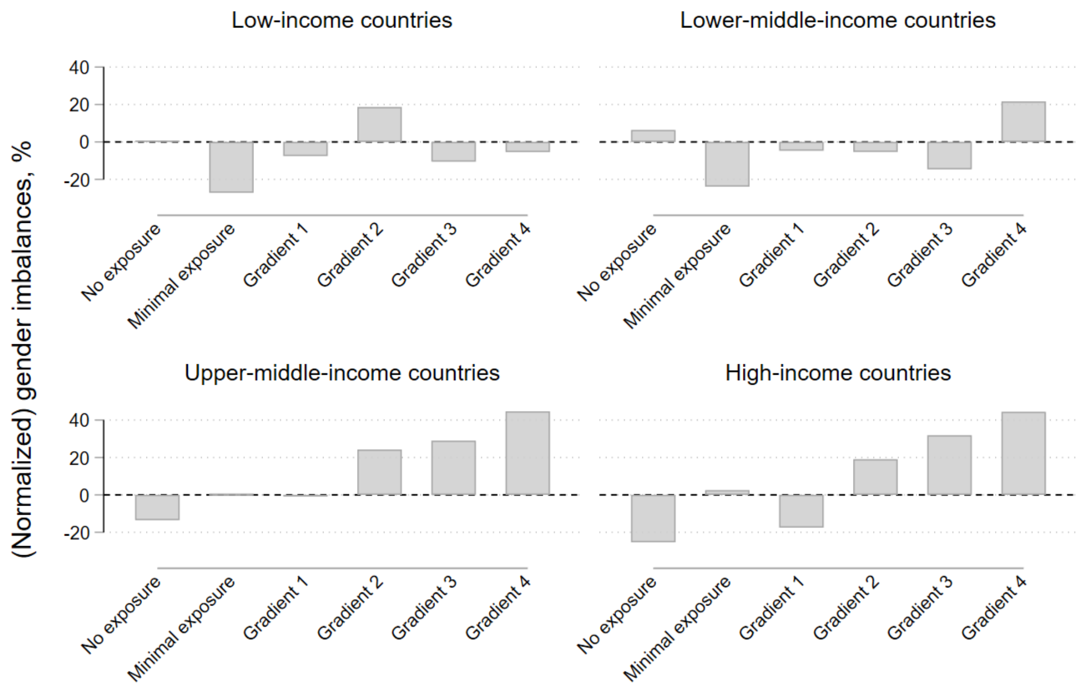
Recent evidence suggests that Gen AI is already affecting labour market outcomes. For example, Brynjolfsson et al. (2025) document a decline in employment among early-career workers in occupations with a high prevalence of automatable tasks in the United States. Longer-term projections also point to sizeable employment reallocation associated with Gen AI, with labour force participation potentially declining by up to 7 percentage points (Karger et al., 2026).

To assess exposure across occupations, we rely on the taxonomy developed by Gmyrek et al. (2023) and Gmyrek et al. (2025), which classifies occupations along gradients of exposure to Gen AI. These range from occupations with no exposure to those with high exposure and low task variability (Gradient 4). At the ISCO–08 2-digit level (see Annex E), only one occupation – Customer services clerks – falls into the highest exposure category, while a small number of clerical and administrative occupations fall into gradients 3 or 2 categories of Gen AI exposure.

Figure 9 shows that, across most income groups, occupations with the highest exposure to Gen AI are disproportionately overrepresented by women. We measure gender imbalance using a normalized index, $100 \times \frac{s_{g,f} - s_{g,m}}{s_{g,f} + s_{g,m}}$, where positive values indicate overrepresentation of women. This normalization accounts for differences in the size of occupational groups.

In high-income and upper-middle-income countries, the occupation with the highest exposure to Gen AI (Gradient 4) exhibits a large excess share of women, on the order of 40 per cent. The excess remains substantial, though smaller, in lower-middle-income countries (around 20 per cent). Only in low-income countries is this occupation not overrepresented by women. More broadly, women tend to be overrepresented in occupations with medium to high exposure to Gen AI, whereas men are overrepresented in occupations with little or no exposure.

Figure 9: Overrepresentation of women by Gen AI exposure gradient, 2020–2024



Note: The sample data covers 117 countries with a survey between 2020 and 2024. Gradients are computed following Gmyrek et al. (2023). Gradient 4 has a high exposure to Gen AI with little task variability, endangering the occupation as a whole. Gradient 3 has a high exposure but with a high task variability, thereby endangering the automation of only some tasks performed by the occupation. Gradient 2 has moderate exposure with high task variability. Gradient 1 has little exposure with high task variability. Minimal exposure has little exposure and low task variability. A positive (negative) normalized gender imbalance implies that women are overrepresented (underrepresented) in this group of occupations.

This pattern suggests that the diffusion of Gen AI is likely to have uneven gender effects across occupations, as it will disproportionately affect occupations where women are already overrepresented. However, the direction of these effects remains uncertain. In some occupations, Gen AI may substitute for existing tasks, while in others it may complement workers and transform job content rather than reduce employment. The evidence presented here therefore points to differential exposure rather than predetermined outcomes.

To complement this static picture, Figure E.3 in the Annex reports employment growth by Gen AI exposure gradient over the past decade.[30] The patterns indicate that exposure is shaped not only by existing occupational structures, but also by differential employment growth across gradients. In several middle-income countries, employment has expanded in occupations with higher exposure to Gen AI, often with stronger growth for women than for men. By contrast, in high-income countries, employment growth is more pronounced in occupations with moderate exposure.

These patterns should be interpreted in light of the broader dynamics documented in the previous section. While gender imbalances within occupations have been narrowing over time, structural changes in employment have played a key role in shaping overall segregation. If future employment growth is stronger in highly exposed occupations that are already gender-imbalanced, Gen AI could reinforce existing segregation patterns. Conversely, if exposure is accompanied by more balanced entry of women and men into these occupations, it could contribute to reducing segregation within them.

8 Conclusion

This paper revisits gender-based occupational segregation using harmonized microdata covering up to 65.5 per cent of global employment. Across the 117 countries analysed, approximately four women out of ten would need to change occupations to replicate men's occupational distribution. While this magnitude is large, it masks substantial cross-country differences that are closely linked to the structure of employment. In particular, lower levels of segregation observed in low-income countries largely reflect the concentration of workers in agricultural occupations, rather than more gender-balanced labour markets. As economies diversify, segregation tends to increase before declining at later stages of development.

To account for this heterogeneity, the paper develops a unified framework linking occupational segregation to structural transformation. It shows that segregation follows an inverse U-shaped relationship with economic development: it increases during early stages of diversification and industrialization, and declines as economies transition toward service-based structures. This pattern can be interpreted as a Kuznets curve for gender-based occupational segregation.

A key contribution of the paper is to demonstrate that changes in segregation are driven by two distinct and often opposing forces. On the one hand, gender imbalances within occupations have been narrowing over time in both developing and developed countries. On the other hand, the distribution of employment across occupations has shifted in ways that can either reinforce or offset this progress. In developing countries, employment has expanded in relatively more gender-segregated occupations, generating a positive occupation-mix effect that counteracts within-occupation convergence. In developed countries, by contrast, the occupation-mix effect is largely neutral, so that changes in segregation primarily reflect gradual rebalancing within occupations.

The analysis further shows that the correlates of segregation differ markedly across country groups. In developing countries, changes in segregation are more strongly associated with structural transformation, education, demographic constraints, and income inequality. In developed countries, these factors appear less strongly associated with segregation, which instead reflects more gradual within-occupation adjustments. Importantly, industrialization *per se* is not systematically associated with higher segregation; rather, higher segregation is observed in contexts where industrial expansion is more male-dominated.

Looking ahead, the paper highlights the potential role of Generative Artificial Intelligence in shaping future segregation patterns. Occupations most exposed to Gen AI are disproportionately overrepresented by women, particularly in middle- and high-income countries. Moreover, recent employment trends suggest that growth is occurring in several of these highly exposed occupations. This raises the possibility that technological change may amplify the occupation-mix effect identified in the paper. Even if gender imbalances within occupations continue to decline, future segregation could increase if employment expands in highly exposed and already gender-imbalanced occupations. Quantifying the impact of Generative AI on the occupation-mix effect, and its implications for future segregation dynamics, constitutes a key direction for future research and policy design.

Notes

[1]In this paper, each sub-major group of occupation is written with a capitalized first letter. For example, Sales workers, Health associate professionals, *etc*.

[2]Several economic and social phenomena – including income inequality and environmental degradation – are known to follow a Kuznets curve with the level of development, but this pattern has not previously been established for gender-based occupational segregation (Kuznets, 2019; Grossman and Krueger, 1995).

[3]Although initially developed to measure racial segregation in urban settings, the dissimilarity index has since been applied to various fields, including residential, educational, and occupational segregation (Van Ham et al., 2021; Mann et al., 2024). It remains the most commonly used metric in gender-based occupational segregation studies (e.g., Albelda, 1986; Chang, 2004; Borrowman and Klasen, 2020; Gradín, 2021; Bugallo et al., 2024; Cortés et al., 2024).

[4]The computation of aggregated indices is explained in Annex B.1.

[5]In the covered data, the maximum HHI amount to 73 per cent for Burundi and the minimum is 3.7 per cent for France

[6]Annex C provides details on country coverage, survey years, and data sources. Labour force surveys are the most common source, accounting for approximately 80 per cent of the datasets included in the analysis.

[7]Türkiye is an exception: the 2020 survey is retained rather than more recent ones due to missing information on the frequency of workers by occupation in subsequent years.

[8]Although crosswalks between ISCO revisions exist (Blau et al., 2013; Humlum, 2021), they are not implementable at the ISCO 2-digit level for the purposes of this paper. For example, occupations coded "12 - Corporate managers" in ISCO–88 can correspond to sub-major groups of occupation coded either "11 - Chief executives, senior officials and legislators", or "12 - Administrative and commercial managers". At the sub-major group of occupations, it is not possible to allocate the number of workers from one ISCO–88 sub-major group to the possible ISCO–08 sub-major groups.

[9]Figure 6 in Section 6 displays the country coverage. Countries on the blue to red colour scale belong to the 75 countries covered in the analysis of gender-based occupational segregation over time. Dotted countries are those available only in the 2020–2024 period.

[10]Descriptive statistics for all covariates are provided in Table 9 in the Annex.

[11]The dissimilarity index is slightly higher if agricultural occupations are not merged (by 0.51 percentage points), especially in low- and lower-middle-income countries (by 1.36 percentage point), where possible misclassifications are expected to be the largest, but the patterns discussed remain similar.

[12]Comparing dissimilarity indices bears the margin dependency issues, as discussed in Annex B.2. The discussion on the decomposition of the dissimilarity index in subsection 6.4 addresses this issue.

[13]Figure 13 in the Annex shows the distributions of employment by sector and level of development.

[14]Figure 14 in the ANnex shows the same scatter plot as in Figure 2, but highlighting that the relationship segregation-concentration is opposite between countries with high occupational concentration and countries with low occupational concentration.

[15]The difference in the observed pattern between Figure 3 and Table 2 reflects the difference in aggregation. Table 2 reports weighted aggregate dissimilarity indices by income group, while Figure 3 plots each country as an individual data point with a quadratic fit. The two are not directly comparable as they capture different aspects of the data; the country-level figure is the appropriate lens through which to assess the relationship between segregation and economic development, and it is Figure 3 that reveals the inverse U-shaped relationship documented above.

[16]Figure 15 in the Annex shows the joint relationship between the GDP per capita and the segregation but once agricultural occupations are excluded. The dispersion of the segregation shrinks but the U-shaped trend remain – it is in fact even more pronounced.

[17]At the major group level (ISCO–08 1-digit), two occupations are female-dominated: professionals and Clerical support workers.

[18]Figure 16 in the Annex reports the full distribution of imbalances for each sub-major group of occupations. The five occupations shown in Figure 4 are chosen to represent the diversity of cases, from female-dominated to male-dominated, and most frequent occupation to relatively infrequent occupations.

[19]Data from the Food and Agriculture Organization indicates that 68 and 40 per cent of food production in India and Pakistan respectively is carried out by farming units of up to two workers, pointing to the prevalence of subsistence farming in these countries.

[20]Based on the World Development Indicators for the year of the survey used.

[21]Using employment in the 2010–2014 period as weights. If 2020–2024 employment were used as weights, the correlation would be virtually identical.

[22]The subscripts f and m indicate shares for, respectively, women and men. The share of working women in occupation i in the time window 2010–2014 is denoted $s^0_{ij,f}$.

[23]For a correspondence between the skill levels and the occupations, please refer to the following webpage.

[24]Elementary occupations, including agricultural occupations, decreased faster in developing countries, by 3.31 percentage points, than in developed countries (by 0.78 percentage points). In both groups of countries, the decrease is mainly driven by a reduction of the share of employment in agricultural occupations. High-skill occupations relate to managing, professional (and associate) occupations.

[25]Interestingly, in the time window 2010–2014, these four occupations accounted for around 18 per cent of employment in the developed countries and 16 per cent of employment in developing countries. In the 2020–2024 time window it is the opposite: these four occupations account for around 16 per cent in developed countries and 18 per cent in developing countries.

[26]More information on the decomposition can be found in Annex B.3, including the computation method and the correlate of each effect.

[27]Since each country has two surveys included in the analysis, the two-way fixed effects structure of the estimation corresponds to a long difference model, comparing outcomes between the 2010–2014 and 2020–2024 time windows.

[28]Given the modest size of the sample, we run bootstrapped standard errors and note that the large majority of the points estimates remain statistically significant at the traditional significance

thresholds. These results are available in the replication material.

[29]Running the same models with wealth inequality in place of income inequality yields no significant correlation with segregation, suggesting that the income inequality result may reflect a growing presence of women in better-paid occupations rather than broader wealth dynamics.

[30]For this figure, the panel sample is used, covering 75 countries.

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Data availability

The data used in the present paper is entirely public, except for the Generative Artificial Intelligence exposure indicators at the ISCO–08 4–digit. The aggregated scores are made available, as well as the method to retrieve them. Replication code and data are shared with editor.

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Competing interests

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Ethical statements

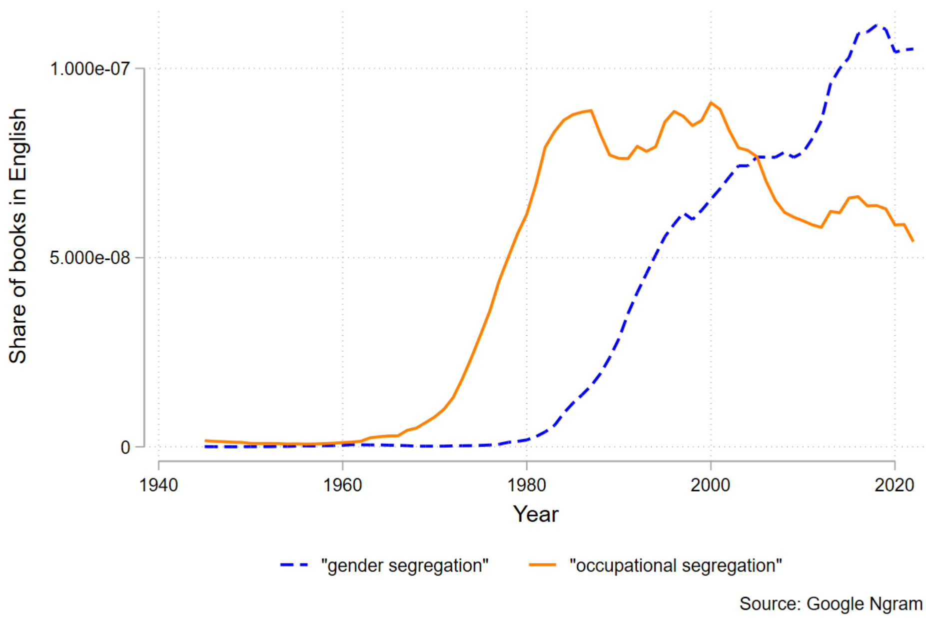
Ethical approval was not required as no human participants were involved in this research.

Appendix

A Segregation in the literature

The frequency of the term "gender segregation" in English-language books has risen sharply over time and now exceeds that of "occupational segregation", reflecting the growing focus on gender-specific dynamics.

Figure 10: Occurrence of segregation-related terminology



B Measuring segregation

B.1 Aggregating the dissimilarity index

The dissimilarity index is constructed at the country level. Computing it directly at the global level, or at any other level of aggregation such as income groups, would implicitly assume a perfectly globalized world of work. Under such an assumption, a woman in a given occupation in one country could move to a different occupation in another country to achieve full integration. While international labour migration is substantial, with 167.7 million migrants in the global labour force, this represents less than five per cent of total global employment (ILO, 2024b), making such an assumption untenable.

To construct the dissimilarity index at the global level, or other levels of aggregation, we draw directly on the interpretation of the index. For each country, the number of women who would need to change occupations is obtained by multiplying the country-level dissimilarity index by the total number of working women in that country. These country-level figures are then summed across all countries in the relevant group. Dividing this sum by the total number of working women in the group yields an aggregate dissimilarity index, representing the share of women who would need to change occupations to replicate men's occupational distribution at that level of aggregation. It writes $\frac{\sum_{j\in\mathcal{G}(j)}(DI_j\times F_j)}{\sum_{j\in\mathcal{G}(|)}F_j}$ with F_j the number of women in employment in country j and $\mathcal{G}(j)$ the group of country of interest such as the income groups.

B.2 Margin dependency - a mock example

Despite its intuitive appeal, the dissimilarity index is sensitive to changes in the margins of the occupational distribution, a phenomenon known as margin dependency. This implies that even if the conditional distribution of women across occupations remains constant, changes in overall labour force participation or occupational structure can affect the index. To address this, several decomposition methods have been proposed to distinguish between "pure segregation" and compositional effects (Fuchs, 1975; Bridges, 2003; Elbers, 2023). The level of occupational disaggregation also significantly influences the index. A simple triangle inequality illustrates the mechanism at stake: for $\forall a, b \in \mathbf{R}$, $|a+b| \leq |a| + |b|$. Hence, summing separately two sub-major groups of occupations absolute values in gaps in shares is at least as large as the absolute value of the gap in share of the major group of occupations.

For instance, using ISCO–08 one-digit major groups, the ILO (2025b) reports that 22 per cent of women would need to change occupations to match men's distribution. Details on the classification of occupations is to be found here: International Standard Classification of Occupations (ISCO) - ILOSTAT. At the two-digit level, in the present paper, this figure nearly doubles to 39.8 per cent. Therefore, cross-country comparisons must ensure consistent levels of occupational granularity.

Tables 4 and 5 provide a mock example of the margin dependency issue that comparisons of a dissimilarity index are facing. Only two occupations are assumed in this simple example, occupation A and occupation B, and it is assumed that the same country is depicted over two time periods. In both time periods, there are 100 workers and in both cases the share of women in occupation A is 20 per cent while the share of women in occupation B is 80 per cent. However, in time period 2 more women and less men are working. Furthermore, occupation A shrunk while occupation B expanded. Put simply, the margins changed, and these changes affect the measure.

Table 4: Margin dependency, example at time $t = 1$

	Occupation		
Sex	A	B	Total
Women	16	16	32
Men	64	4	68
Total	80	20	100

Table 5: Margin dependency, example at time $t = 2$

	Occupation		
Sex	A	B	Total
Women	10	40	50
Men	40	10	50
Total	50	50	100

As a result, 44.1 per cent of women in time period 1 would need to change occupations to replicate men's occupational distribution while 60 per cent of women would need to change in time period 2. Because the number of workers by occupation is largely skewed in time period 1, less women (or men) would need to change occupation to replicate men's (or women's) distribution. Therefore, a change in the dissimilarity index over time, or across countries may not imply that the conditional distribution of women in each occupation changed. Rather, it may imply that the labour force participation of women largely differs and/or the distribution of workers across occupation widely varies.

B.3 Decomposition of the dissimilarity index

B.3.1 How and why decomposing the dissimilarity index?

Identical levels of the dissimilarity index could arise (i) from the occupational structure or (ii) the gender-based composition of each occupation. On the one hand, a change due to the occupational structure implies that the change in segregation is mainly driven by a few occupations, concentrating most employment and most imbalances. To leverage on the change in segregation due to the occupational structure, policies targeted to specific occupations such as agricultural occupations or health-related occupations may be the most efficient ones to reduce gender-based occupational segregation. On the other hand, a change in segregation driven by the gender-based composition of each occupation implies that the whole set of occupations is leaning toward more (or less) segregation and therefore policies targeting all occupations may be more suitable (for example, policies against gender-based discrimination or policies related to access to pension, to maternity or paternity leaves).

This decomposition is a classic decomposition that was introduced by Fuchs (1975). It was further discussed and implemented by Blau et al. (2013). The decomposition is better illustrated when rewriting the dissimilarity index:

$$DI_{jt} = \frac{1}{2}\sum_i (|s_{ijt,f} - s_{ijt,m}|) = \frac{1}{2}\sum_i (|\frac{s_{ijt,f}(F_{ijt} + M_{ijt})}{\sum_i s_{ijt,f}(F_{ijt} + M_{ijt})} - \frac{s_{ijt,m}(F_{ijt} + M_{ijt})}{\sum_i s_{ijt,m}(F_{ijt} + M_{ijt})}|) \tag{5}$$

with F_{it} and M_{it} the number of women - and respectively men - workers in occupation i at time t (in country j). The decomposition indicates the change from the dissimilarity index from the first period to the second period and what is due to a change in the share of women within each occupation in the first component and a change in the share of each occupation in all employment in the second component. To numerically compute that, a counterfactual dissimilarity index is needed. It is the dissimilarity index, DI^*, using the employment levels (and share) across occupations of the first period, but the share of women (and men) of the second period. It indicates what the segregation level would be in the case where only the sex composition changed over time.

$$DI^*_j = \frac{1}{2}\sum_i (|\frac{s_{ij2,f}(F_{ij1} + M_{ij1})}{\sum_i s_{ij2,f}(F_{ij1} + M_{ji1})} - \frac{s_{ij2,m}(F_{ij1} + M_{ij1})}{\sum_i s_{ij2,m}(F_{ij1} + M_{ij1})}|) \tag{6}$$

The gap between DI_j^* and DI_{j1} captures the *sex composition effect* and the gap between DI_{j2} and DI_j^* captures the *occupation mix effect*.

$$Sex\ composition\ effect_j = DI_j^* - DI_{j1} \tag{7}$$

$$Occupation\ mix\ effect_j = DI_{j2} - DI_j^* \tag{8}$$

Interestingly, Blau et al. (2013) found that the gender composition effect tended to shrink, relative to the occupation mix effect, over the years 1970-2010 in the USA. Although in practice both components matter, the subsection below illustrates extreme cases where only one component induces the change in segregation.

B.3.2 Changes in the dissimilarity index by component - a mock example

Table 4 shows a situation with a dissimilarity index of 44.1 per cent, a share of women among occupation A workers of 20 per cent, a share of women among occupation B workers of 80 per cent. The share of occupation A workers accounts for 80 per cent of all workers and the share of occupation B workers is its complement.

Table 5 displays a second distribution of workers by sex and occupation but where the shares of women with occupations are unchanged: 20 per cent of workers in occupation A are women and 80 per cent of workers in occupation B are women. The two occupations do not account for the same share of workers anymore: the share of employment that accrues to occupation A shrinks and the share of employment that accrues to occupation B grows. Since occupation B is women-overrepresented and female-dominated, more workers in this occupation without changing the share of women workers in this occupation will tend to increase the number of women workers relative to the number of men workers.

Therefore, in this special case, $DI_1 = DI_j^*$. Hence, the change in dissimilarity index is here captured by the occupation mix effect alone. Since $D_2 = 60$ per cent, the occupation mix effect between the two period explains an increase in the index by 15.9 percentage points.

In contrast, if in period 2 the share of employment accruing to each occupation stayed the same but not the share of women within each occupation, only the sex component would contribute to a change in the dissimilarity index. The dissimilarity index in Table 6 would be $DI_2 = 0$, a perfectly integrated world of work where women and men distribute themselves identically across occupations. More importantly, although the share of women in each occupation changed from period one (shown in Table 4), the share of occupation A remains 80 per cent and the share of occupation B remains 20 per cent, as in the first period. Therefore, the change in the dissimilarity index would be entirely driven by the sex composition effect: $0 - 44.1 = -44.1$ per cent. In this case, the gender-based occupational segregation shrunk dramatically due to the change in the share of women within each occupation.

Table 6: Change in segregation from Table 4 only due to the sex component, example at time $t = 2$

	Occupation		
Sex	A	B	Total
Women	40	10	50
Men	40	10	50
Total	80	20	100

The examples shared above are only illustrative. The real effects are unlikely to be zero, the may be of the same sign – both contributing together to an increase or to a decrease in segregation – or of opposite sign – one contributing to more segregation and the other to less segregation.

B.4 Two alternative measures

Other indices have been developed to address the limitations of the dissimilarity index. The Theil index, for example, is suitable for contexts involving more than two groups, such as ethnic segregation. Measures like the isolation index assess segregation through the exposure of the other groups. While these alternatives provide valuable insights, the dissimilarity index remains the preferred measure when the focus is on the evenness of occupational distributions (Massey and Denton, 1988). Sub-section B.4 in the Annex provides a comparison using the Theil H index and the isolation index as alternative measures to assess gender-based occupational segregation.

The dissimilarity index interprets as the need for reallocation to reach integration in the world of work. The first alternative measure is the Theil H index. As a measure of entropy, underscores the evenness in the distribution of men and women across occupation. A large difference with the dissimilarity index would imply distributional shifts by sex. The second alternative measure is the (normalized) isolation index captures the exposure of individuals toward peers with similar characteristics.

$$Theil\ H_j = \frac{E_j - \sum_i t_{ij} E_{ij}}{E_j} \tag{9}$$

with $E_j = -(\frac{F_j}{F_j+M_j} \times ln(\frac{F_j}{F_j+M_j}) + \frac{M_j}{F_j+M_j} \times ln(\frac{M_j}{F_j+M_j}))$, where F_j is the employment of women in country j and M_j the men employment in that country. With $t_{ij} = \frac{f_{ij}+m_{ij}}{F_j+M_j}$ where f_{ij} is the women employment in occupation i and country j, and m_{ij} is its men counterpart. And with $E_{ij} = -(\frac{f_{ij}}{f_{ij}+m_{ij}} \times ln(\frac{f_{ij}}{f_{ij}+m_{ij}}) + \frac{m_{ij}}{f_{ij}+m_{ij}} \times ln(\frac{m_{ij}}{f_{ij}+m_{ij}}))$. Similar to the dissimilarity index, a Theil H equal to zero indicates perfect integration across sexes, and a Theil H equal to one indicates perfect segregation.

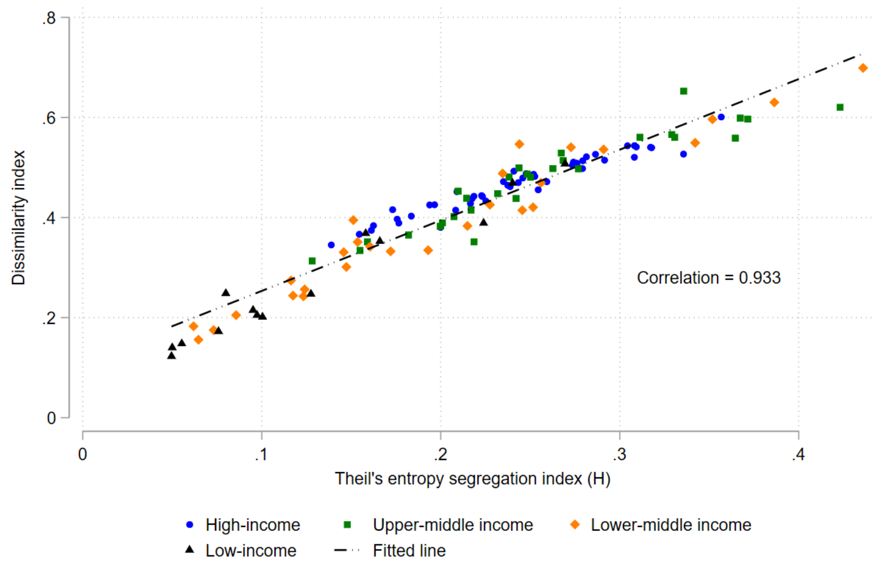
$$Isolation\ Index_j = \sum_i (s_{ij,f} \times \frac{f_{ij}}{f_{ij}+m_{ij}}) \tag{10}$$

A normalized version is used, $Normalized\, Isolation\ Index_j = \frac{Isolation\ Index_j - \frac{F_j}{F_j+M_j}}{1-\frac{F_j}{F_j+M_j}}$ so that the index is bounded with zero and one.

The Isolation Index provides a measure of the exposition of a person to another with similar characteristics, here the sex: how likely is a woman in a given occupation to have another woman as colleague?

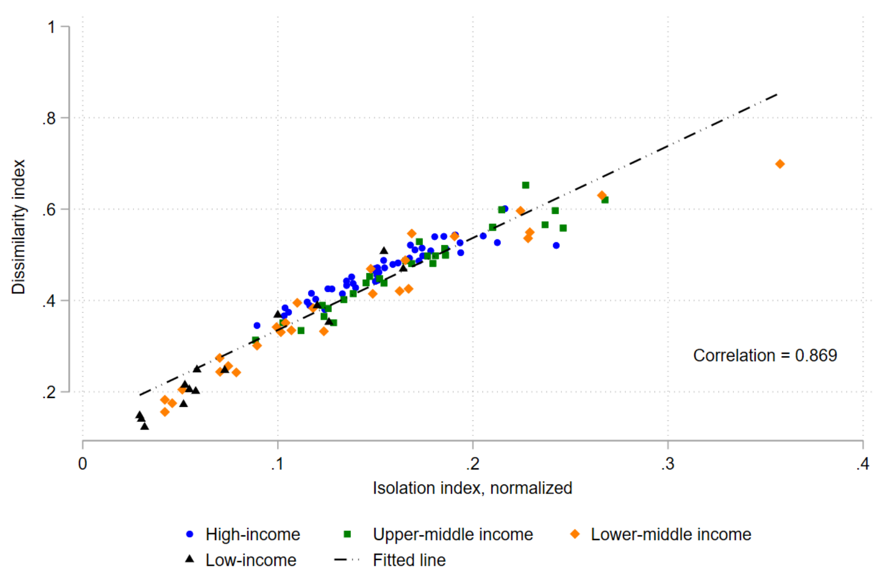
Figures 11 and 12 display the joint relationship between the dissimilarity index with the Theil H index and the (normalized) isolation index, respectively. The linear correlation coefficients are very strong in both cases, implying that the alternatives measures capture similar segregation patterns across countries. Given the virtually one-to-one relationship between the dissimilarity index and the Theil H index on the one hand, and between the dissimilarity index and the (normalized) isolation index on the other, the conclusions raised in Section 5 would be closely replicated using the Theil H index or the Isolation index.

Figure 11: Dissimilarity index and Theil H index



Note: The y-axis represents the Dissimilarity Index, computed following equation 1. The x-axis represents the Theil H Index, computed following equation 9.

Figure 12: Dissimilarity index and (normalized) isolation index



Note: The y-axis represents the dissimilarity index, computed following equation 1. The x-axis represents the (normalized) isolation index, computed following equation 10.

C Data

C.1 Survey coverage

Table 7: Survey and Year Information by Country

ID	Country	Year 1	Survey 1	Year 2	Survey 2	In panel?
1	Afghanistan	2014	HIES	2021	LFS	Yes
2	Angola	2014	PC	2022	LFS	Yes
3	Albania	2014	LFS	2023	LFS	Yes
4	United Arab Emirates	.	.	2022	LFS	No
5	Argentina	2014	LFS	2024	LFS	Yes
6	Australia	.	.	2024	LFS	No
7	Austria	2014	LFS	2023	LFS	Yes
8	Burundi	.	.	2020	HIES	No
9	Belgium	2014	LFS	2023	LFS	Yes
10	Benin	.	.	2022	HIES	No
11	Burkina Faso	.	.	2024	LFS	No
12	Bangladesh	.	.	2023	LFS	No
13	Bulgaria	2014	LFS	2023	LFS	Yes
14	Bosnia and Herzegovina	2014	LFS	2023	LFS	Yes
15	Belarus	.	.	2023	LFS	No
16	Bolivia (Plurinational State of)	2014	HIES	2023	LFS	Yes
17	Brazil	2014	HS	2024	HS	Yes
18	Barbados	.	.	2023	LFS	No
19	Brunei Darussalam	2014	LFS	2023	LFS	Yes
20	Bhutan	.	.	2024	LFS	No
21	Botswana	.	.	2023	HS	No
22	Switzerland	2014	LFS	2024	LFS	Yes
23	Chile	2013	HS	2022	HS	Yes
24	Congo, Democratic Republic of the	.	.	2020	HIES	No
25	Colombia	2014	LFS	2024	LFS	Yes
26	Costa Rica	.	.	2024	LFS	No
27	Cyprus	2014	LFS	2023	LFS	Yes
28	Czechia	2014	LFS	2023	LFS	Yes
29	Germany	2014	LFS	2023	LFS	Yes
30	Denmark	2014	LFS	2023	LFS	Yes
31	Dominican Republic	.	.	2024	LFS	No
32	Ecuador	2014	LFS	2024	LFS	Yes

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ID	Country	Year 1	Survey 1	Year 2	Survey 2	In panel?
33	Egypt	2013	LFS	2023	LFS	Yes
34	Spain	2014	LFS	2023	LFS	Yes
35	Estonia	2014	LFS	2023	LFS	Yes
36	Ethiopia	2013	LFS	2021	LFS	Yes
37	Finland	2014	LFS	2023	LFS	Yes
38	France	2014	LFS	2023	LFS	Yes
39	United Kingkom*	2014	LFS	2024	LFS	Yes
40	Georgia	2014	HS	2020	LFS	Yes
41	Gambia	2012	LFS	2023	LFS	Yes
42	Guinea-Bissau	.	.	2022	HIES	No
43	Greece	2014	LFS	2024	LFS	Yes
44	Grenada	.	.	2023	LFS	No
45	Guatemala	2014	LFS	2023	HIES	Yes
46	Honduras	.	.	2024	HS	No
47	Croatia	2014	LFS	2023	LFS	Yes
48	Hungary	2014	LFS	2023	LFS	Yes
49	Indonesia	.	.	2023	LFS	No
50	India	.	.	2024	LFS	No
51	Ireland	2014	LFS	2023	LFS	Yes
52	Iran (Islamic Republic of)	2014	LFS	2023	LFS	Yes
53	Iraq	2012	HIES	2021	LFS	Yes
54	Iceland	2014	LFS	2023	LFS	Yes
55	Israel	2014	LFS	2023	LFS	Yes
56	Italy	2014	LFS	2023	LFS	Yes
57	Jordan	.	.	2023	LFS	No
58	Japan	2014	LFS	2022	LFS	Yes
59	Kenya	.	.	2022	HS	No
60	Kyrgyzstan	2014	LFS	2023	LFS	Yes
61	Cambodia	2014	HIES	2023	HIES	Yes
62	Kiribati	.	.	2023	HIES	No
63	Lao People's Democratic Republic	.	.	2022	LFS	No
64	Sri Lanka	2014	LFS	2022	LFS	Yes
65	Lithuania	2014	LFS	2023	LFS	Yes
66	Luxembourg	2014	LFS	2023	LFS	Yes
67	Latvia	2014	LFS	2023	LFS	Yes
68	Madagascar	.	.	2022	HS	No
69	Mexico	2014	LFS	2024	LFS	Yes
70	Marshall Islands	.	.	2021	PC	No

Continued on next page

ID	Country	Year 1	Survey 1	Year 2	Survey 2	In panel?
71	North Macedonia	2014	LFS	2024	LFS	Yes
72	Mali	.	.	2022	HIES	No
73	Myanmar	.	.	2020	LFS	No
74	Montenegro	2014	LFS	2023	LFS	Yes
75	Mongolia	2014	LFS	2023	LFS	Yes
76	Mozambique	.	.	2022	HIES	No
77	Mauritius	2014	LFS	2023	LFS	Yes
78	Netherlands	2014	LFS	2023	LFS	Yes
79	Norway	2014	LFS	2023	LFS	Yes
80	Nauru	2013	HIES	2021	PC	Yes
81	Pakistan	2014	LFS	2021	LFS	Yes
82	Panama	2014	LFS	2024	LFS	Yes
83	Peru	.	.	2024	LFS	No
84	Philippines	.	.	2022	LFS	No
85	Palau	2014	HIES	2020	PC	Yes
86	Papua New Guinea	.	.	2022	HS	No
87	Poland	2014	LFS	2024	LFS	Yes
88	Portugal	2014	LFS	2024	LFS	Yes
89	Occupied Palestinian Territory	2014	LFS	2024	LFS	Yes
90	Romania	2014	LFS	2023	LFS	Yes
91	Russian Federation	.	.	2024	LFS	No
92	Rwanda	.	.	2024	LFS	No
93	Sudan	.	.	2022	LFS	No
94	Senegal	.	.	2022	HIES	No
95	Singapore	.	.	2024	LFS	No
96	El Salvador	2014	HS	2023	HS	Yes
97	Serbia	2014	LFS	2024	LFS	Yes
98	Slovakia	2014	LFS	2023	LFS	Yes
99	Slovenia	2014	LFS	2023	LFS	Yes
100	Sweden	2014	LFS	2023	LFS	Yes
101	Eswatini	.	.	2023	LFS	No
102	Seychelles	2014	LFS	2023	LFS	Yes
103	Togo	.	.	2022	HIES	No
104	Thailand	2014	LFS	2024	LFS	Yes
105	Timor-Leste	2013	LFS	2022	PC	Yes
106	Tonga	.	.	2023	LFS	No
107	Türkiye	2014	LFS	2020	LFS	Yes
108	Tuvalu	.	.	2022	PC	No

Continued on next page

ID	Country	Year 1	Survey 1	Year 2	Survey 2	In panel?
109	Tanzania, United Republic of	.	.	2020	LFS	No
110	Uganda	2014	HIES	2021	LFS	Yes
111	Uruguay	2014	LFS	2024	LFS	Yes
112	United States of America	2014	LFS	2024	LFS	Yes
113	Viet Nam	2014	LFS	2023	LFS	Yes
114	Vanuatu	.	.	2020	PC	No
115	Samoa	2012	LFS	2022	LFS	Yes
116	Zambia	.	.	2023	LFS	No
117	Zimbabwe	2011	LFS	2023	LFS	Yes

Note 1: * "United Kingdom" stands for "United Kingdom of Great Britain and Northern Ireland".

Note 2: "HIES" stands for Household Income and Expenditure Survey; "HS" stands for Household Survey; "LFS" stands for Labour Force Survey; "PC" stands for Population Census.

Note 3: For ten countries - namely Afghanistan, Angola, Bolivia (Plurinational State of), Georgia, Guatemala, Iraq, Nauru, Palau, Timor-Leste, Uganda - different sources of data are used and may imply extra care for these countries.

Note 4: The survey used are compiled following the 13th International Conference of Labour of Statisticians (ICLS). In 2013, another conference round (19th ICLS) provided a new framework where both unpaid and paid work are integrated, changing the classifications of agricultural occupations.

C.2 Data coverage

Table 8 informs on the data coverage, in terms of countries covered and employment covered. For example, when looking at the cross-section in the last time window (2020–2024), 14 low-income countries are included in the analysis and these account for 69.4 per cent of the employment of all low-income countries.

C.3 Descriptive statistics on the covariates

C.3.1 Descriptive statistics

Table 9 informs on the descriptive statistics on the covariates use in the present analysis. Given the large change in the country coverage between the sample of countries with at least one survey in 2020–2024 (Panel A), and countries with at least one survey in 2010–2014 and one survey in 2020–2024 (Panel B), the descriptive statistics differs in both samples. For example, the share of employment in agriculture shrinks by about 7 percentage points in the *Panel B* compared to *Panel A*. The rate of school enrollment often exceeds 100 because the base rate is the number of men (or women) in the age group that corresponds to tertiary education and whenever overage

Table 8: Country and employment coverage, by income group and by region

	Only 2020–2024		Panel: 2010–2014 & 2020–2024	
	Countries	Employment (%)	Countries	Employment (%)
Global	117	65.53	75	32.32
Income groups				
Low-income countries	14	69.40	4	32.37
Lower-middle-income countries	28	83.43	11	18.69
Upper-middle-income countries	29	37.82	20	23.17
High-income countries	46	86.3	40	72.14
Regions				
Africa	25	54.36	8	23.43
Americas	18	89.67	12	82.98
Arab States	4	33.53	2	19.97
Asia and the Pacific	29	58.93	14	14.83
Europe and Central Asia	41	87.83	39	67.61

Note: The share of employment uses employment in 2024 in the cross-section dataset, and employment in 2014 in the panel dataset.

learners are in tertiary education the share of gross school enrollment is beyond 100.

Table 9: Descriptive statistics for covariates

Panel A: Full sample	mean	sd	min	max	count
Share of employment in agriculture, men	24.68	17.59	0.10	86.00	117
Share of employment in agriculture, women	31.14	27.33	0.04	96.80	117
Share of employment in industry, men	27.04	6.69	5.66	66.49	117
Share of employment in industry, women	13.62	5.22	0.60	58.24	117
Agriculture, forestry, and fishing, value added (% of GDP)	10.74	8.21	0.01	44.33	117
Industry (including construction), value added (% of GDP)	26.99	7.06	4.37	78.90	117
log GDP per capita, PPP, USD constant	9.66	1.00	6.73	11.79	117
Herfindahl-Hirschman Index	15.00	12.18	3.67	73.00	117
Men school enrollment, tertiary (share gross)	43.49	24.93	0.25	161.73	117
Women school enrollment, tertiary (share gross)	52.51	31.97	0.37	171.99	117
Share of national income of the top 10 percent (pre-tax)	48.90	8.31	26.20	63.66	117
Share less 15yo or more 65yo	35.06	4.75	18.12	49.39	117
Panel B: Subsample	mean	sd	min	max	count
Share of employment in agriculture, men	15.90	16.91	1.09	86.00	75
Share of employment in agriculture, women	15.46	21.43	0.41	96.80	75
Share of employment in industry, men	28.67	6.87	7.27	66.49	75
Share of employment in industry, women	13.07	6.06	1.08	58.24	75
Agriculture, forestry, and fishing, value added (% of GDP)	7.35	8.81	0.19	44.33	75
Industry (including construction), value added (% of GDP)	25.22	6.97	9.29	78.90	75
log GDP per capita, PPP, USD constant	10.13	0.96	7.67	11.77	75
Herfindahl-Hirschman Index	9.38	9.62	3.67	46.43	75
Men school enrollment, tertiary (share gross)	53.05	27.87	0.94	161.73	75
Women school enrollment, tertiary (share gross)	67.12	33.98	0.37	171.99	75
Share of national income of the top 10 percent (pre-tax)	45.95	8.83	26.20	63.66	75
Share less 15yo or more 65yo	35.81	4.31	27.54	47.53	75

Note: Covariates are interpolated linearly from the series whenever there are gaps in the series and the merging year, at the country-series level, was missing. Countries are weighted by the number of employed persons in the year included in the 2020–2024 time window.

C.3.2 Economic structure

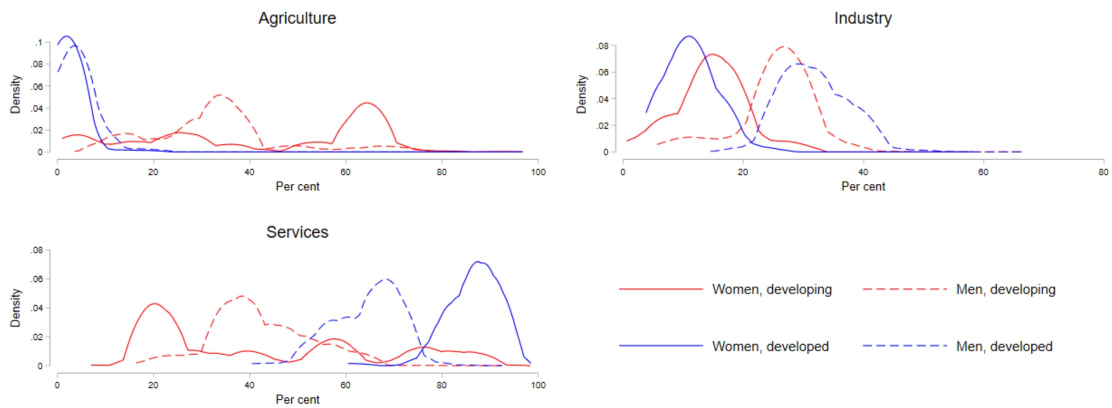
Figure 13 displays the share of employment by sex, sector, and economic development. The plots include all 117 countries, but it is important to note that comparable patterns remain when using only the countries included in the panel analysis.

That is, agriculture is a popular sector in developing economies, especially among women, with around two thirds of the women workforce working in this sector. In developed countries, the difference of the share of women and men working in agriculture is modest and this sector rarely accounts for more than ten per cent of all workers. For agricultural sector, both the level of development and the sex affect the share of workers. In developing countries, the gap between men and women workers in agriculture is formidable.

The share of men in industry is relatively comparable across levels of development, accounting for around one third of the male workforce (slightly more in developed countries). The share of women in industry is around ten per cent in developed countries and around 15 per cent in developing countries. Hence, for industrial jobs, the main difference is the sex, not the level of development.

The service sector displays a somehow symmetric version of the employment distribution in agriculture, with more heterogeneity across sexes in developed countries.

Figure 13: Employment distribution by sector, sex and level of development, 2020–2024



Note: The kernel density plots use a bandwidth of 3 to smoothen the distribution. The 117 countries of the whole sample are depicted. Developed countries correspond to high-income countries and non-high-income countries are developing countries. The kernel density plots are weighted by the total employment in each country.

C.4 Occupational shares, 2020–2024

Table 10: Employment across sexes and occupations

Occupations (sub-major groups)	Women in all women, % (1)	Men in all men, % (2)	Women in the occupation, % (3)
92-6 - Agricultural occupations	28.42	24.91	42.78
52 - Sales workers	11.71	9.14	45.66
93 - Labourers in mining, construction, manufacturing and transport	2.44	8.53	15.77
83 - Drivers and mobile plant operators	.32	7.69	2.64
51 - Personal service workers	5.57	3.03	54.64
71 - Building and related trades workers, excluding electricians	.52	5.84	5.51
23 - Teaching professionals	5.8	2.1	64.41
75 - Food processing, wood working, garment and other craft and related trades workers	4.32	2.58	52.36
91 - Cleaners and helpers	4.97	1.2	72.99
33 - Business and administration associate professionals	3.24	2.24	48.63
72 - Metal, machinery and related trades workers	.15	3.63	2.68
41 - General and keyboard clerks	3.3	1.41	60.47
24 - Business and administration professionals	2.46	1.65	49.39
81 - Stationary plant and machine operators	1.49	2.11	31.62
21 - Science and engineering professionals	1.05	1.97	25.83
22 - Health professionals	2.76	.85	68.09
26 - Legal, social and cultural professionals	2	1.28	50.6
32 - Health associate professionals	2.76	.64	73.84
54 - Protective services workers	.41	2.17	10.95
96 - Refuse workers and other elementary workers	1.13	1.63	31.21
31 - Science and engineering associate professionals	.55	1.98	15.28
53 - Personal care workers	2.68	.36	82.85
13 - Production and specialised services managers	.93	1.29	32.11
43 - Numerical and material recording clerks	1.36	.96	48.14
14 - Hospitality, retail and other services managers	1.06	1.13	38.16
42 - Customer services clerks	1.74	.68	62.68
25 - Information and communications technology professionals	.57	1.29	22.51

Continued on next page

Occupations (sub-major groups)	Women in all women, % (1)	Men in all men, % (2)	Women in the occupation, % (3)
74 - Electrical and electronic trades workers	.17	1.55	6.52
12 - Administrative and commercial managers	.88	1.04	35.82
11 - Chief executives, senior officials and legislators	.47	1.22	20.25
73 - Handicraft and printing workers	1.01	.84	44.19
34 - Legal, social, cultural and related associate professionals	.96	.69	47.44
44 - Other clerical support workers	.85	.58	48.97
94 - Food preparation assistants	.99	.38	62.82
82 - Assemblers	.4	.5	34.34
95 - Street and related sales and service workers	.41	.45	37.7
35 - Information and communications technicians	.17	.46	20.05

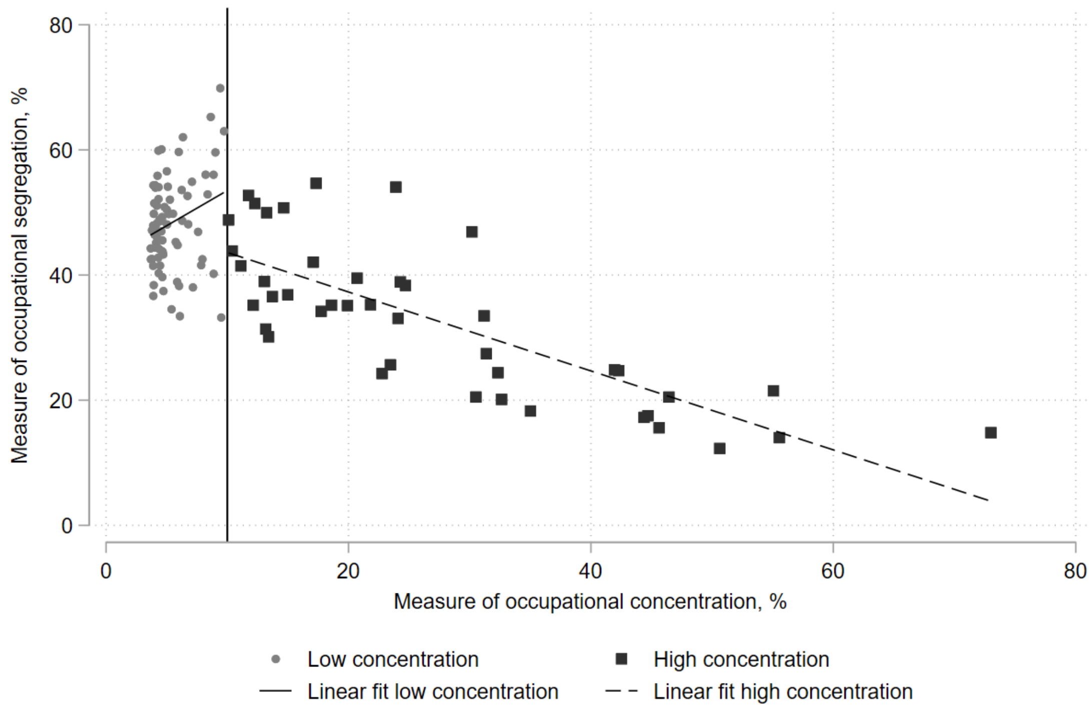
Note 1: Occupations are ordered from the most frequent (all employment) to the least frequent.

Note 2: Bold sub-groups of occupations are female-dominated occupations (the share of women among workers in this occupation exceeds 50 per cent).

C.5 Segregation, concentration, and GDP

C.5.1 Segregation and concentration

Figure 14: Relationship between the dissimilarity index and the concentration index, 2020–2024

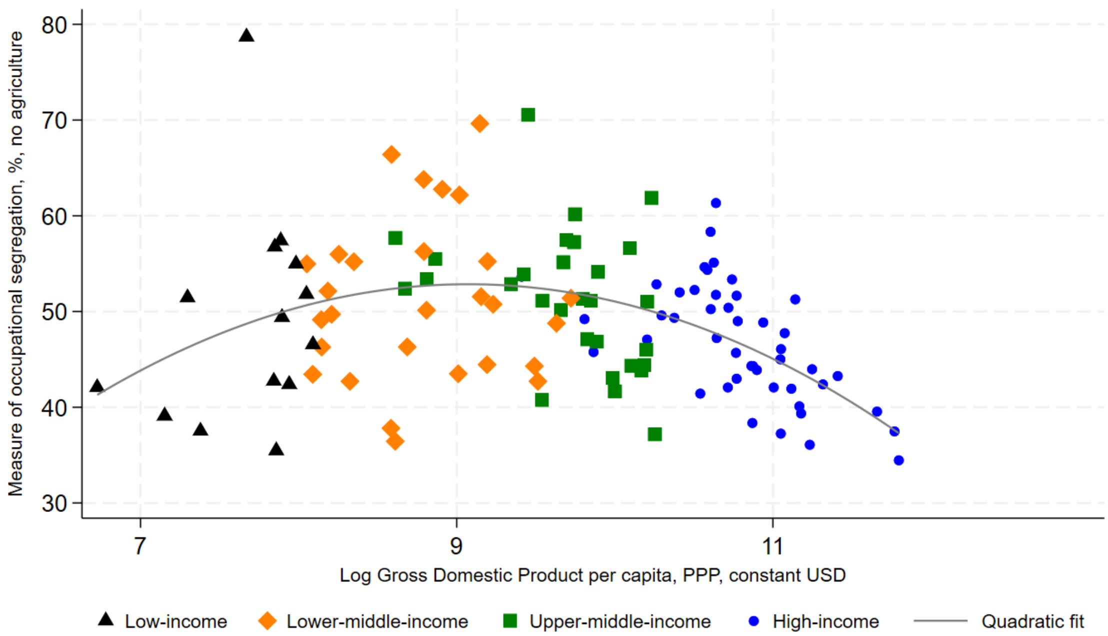


Note: The y-axis corresponds to the dissimilarity index. The x-axis represents the Herfindahl-Hirschman index to measure concentration of occupations.

C.5.2 Segregation (not including agricultural occupations) and GDP

The quadratic relationship in Figure 15 is maximum about the log GDP per capita of the lower-middle-income countries. When using the dissimilarity index that includes agricultural occupations, the maximum was reached between upper-middle-income and high-income countries.

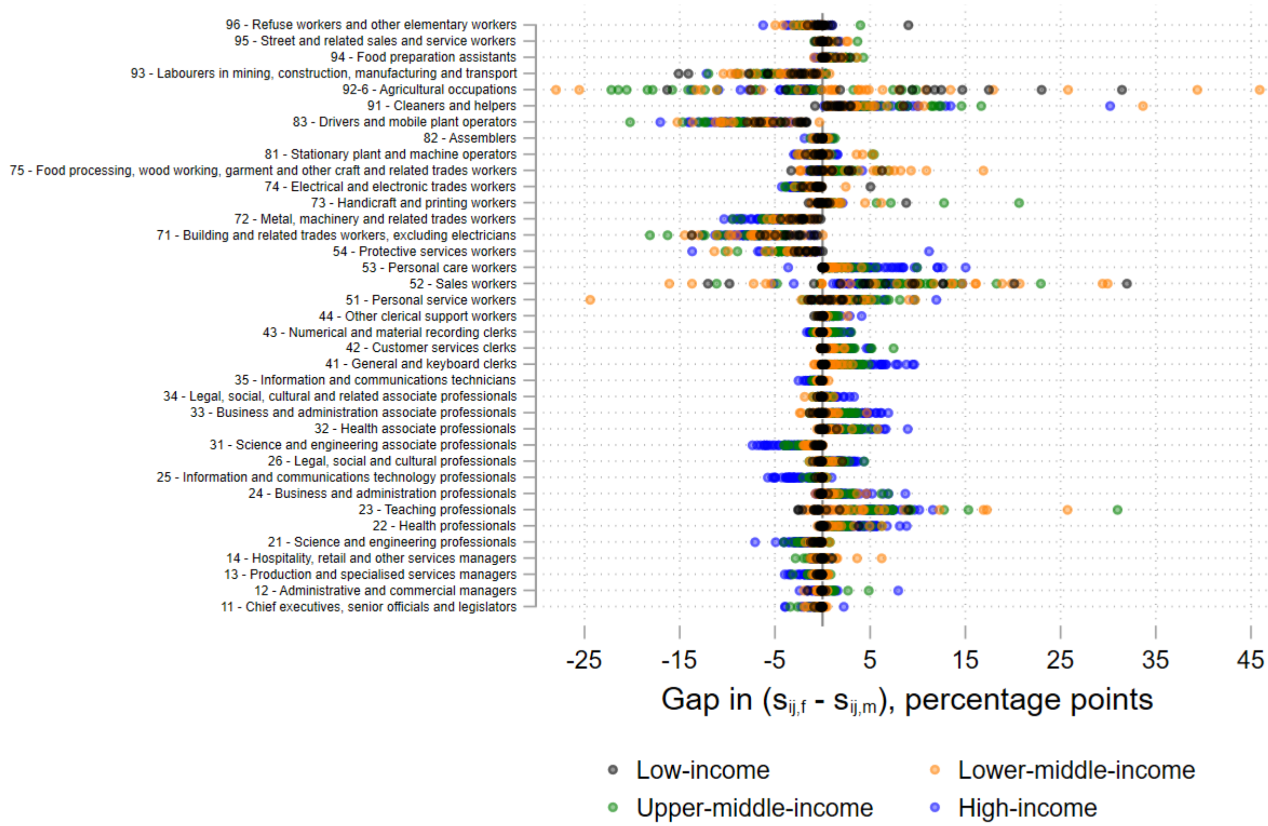
Figure 15: Relationship between segregation without agricultural occupations and the log GDP per capita, 2020–2024



Note: The y-axis corresponds to the Dissimilarity Index when agricultural occupations are excluded. The x-axis represents the logarithm of GDP per capita in PPP, constant USD.

C.6 Gender imbalances per country and per occupations (2020–2024)

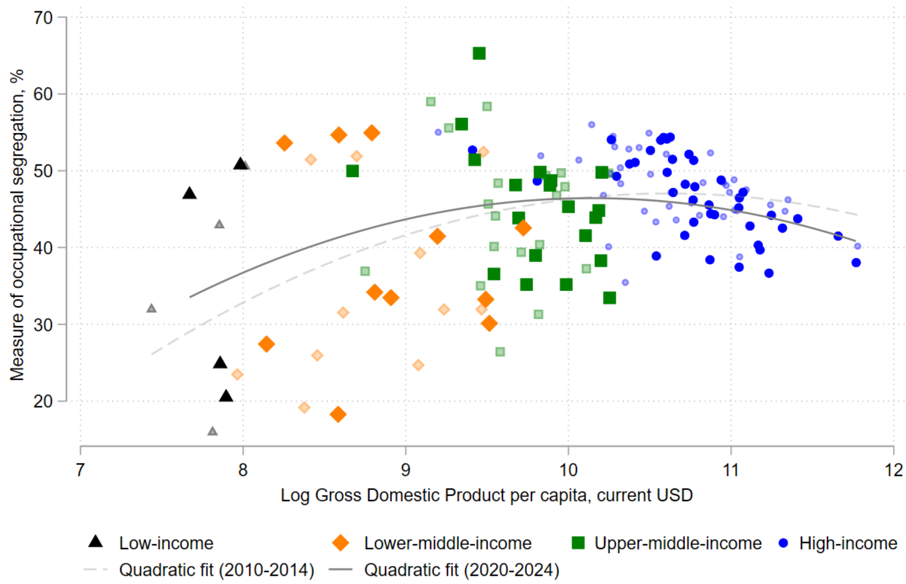
Figure 16: Imbalances across occupations and countries, 2020–2024



D Segregation over time

D.1 Changes in segregation and level of development

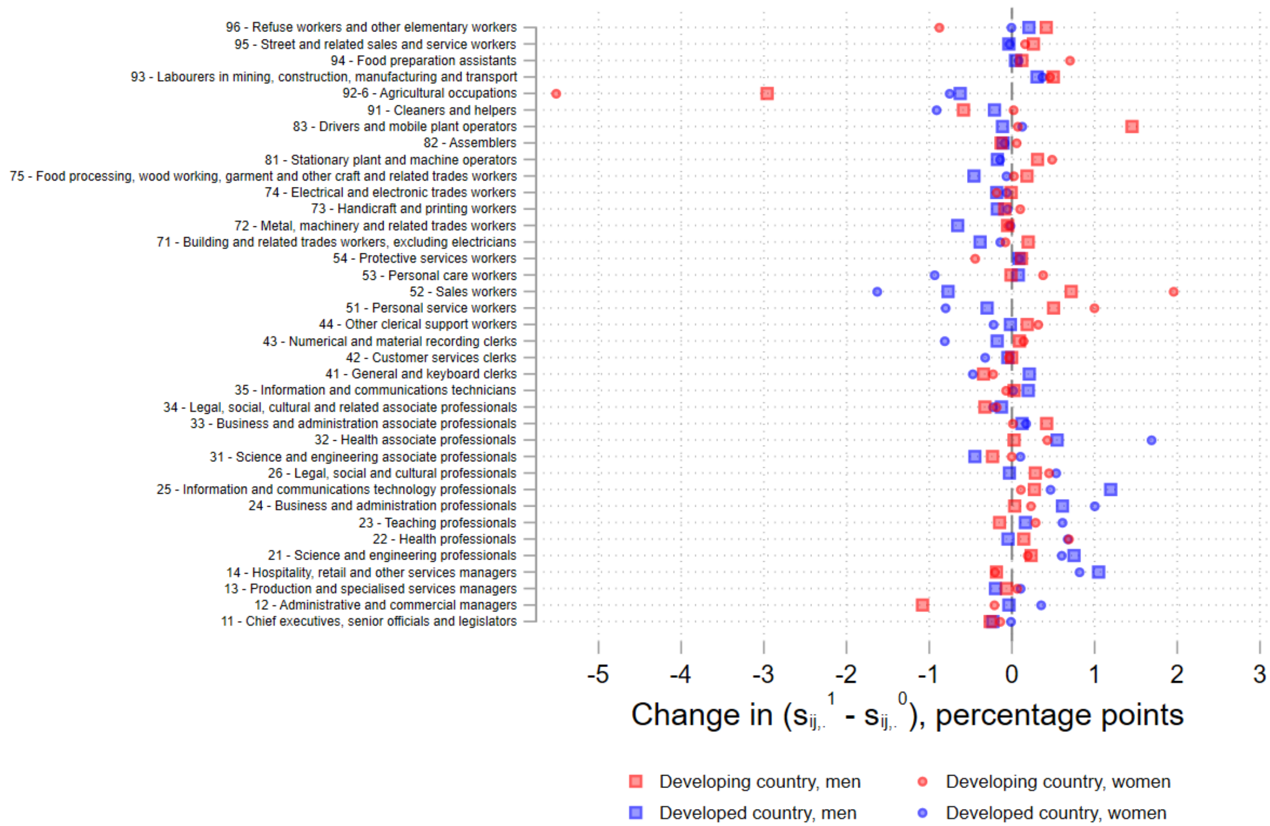
Figure 17: Joint distribution between occupational segregation and Log GDP per capita



Note: Each marker represents a country. Each country is represented twice, once in 2010–2014, and once in 2020–2024. Transparent markers concern countries over 2010–2014 and opaque markers concern countries over 2020–2024.

D.2 Gender imbalances per country and per occupations 2010–2014 and 2020–2024

Figure 18: Changes in the shares of workers over the past decade, by sex and level of development



D.3 Correlates of the decomposed effect of the changes in segregation

As discussed in the main text, changes in occupational segregation are associated with a range of structural, economic, and demographic factors, including the sectoral composition of the economy, income levels, education, and population structure. A key question is whether these factors relate similarly to the two components of segregation – namely, the sex composition effect and the occupational mix effect.

Table 11 reports estimates from first-difference models using changes in all covariates. Models (1)–(3) estimate:

$$Sex\ composition\ effect_j = \Delta X_j \beta + \varepsilon_j \tag{11}$$

while Models (4)-(6) estimate:

$$Occupation\ mix\ effect_j = \Delta X_j \beta + \varepsilon_j \tag{12}$$

Pooling all 75 countries, Models (1) and (4) indicate that the explanatory power of the covariates is substantially higher for the occupation mix component ($R^2 = 0.68$) than for the sex composition component ($R^2 = 0.33$). This suggests that shifts in the distribution of employment across occupations are more closely linked to observable structural changes than gender imbalances within occupations.

A comparison of Models (1) and (4) further reveals that the set of statistically significant covariates differs across the two components, with the notable exception of changes in log GDP per capita. Increases in log GDP per capita are positively associated with segregation through the occupation mix effect, but negatively associated with segregation through the sex composition effect. This apparent contrast is consistent with development dynamics. In developing countries, rising income levels often coincide with early-stage industrialization, which increases occupational differentiation and thus segregation through the occupational mix channel. At the same time, higher income levels are associated with rising female labour force participation, which tends to reduce segregation through the sex composition channel. Contrary to the pattern documented by Goldin (1994), the employment-weighted correlation between female labour force participation and log GDP per capita in the present sample is positive in developing countries (58 per cent) and negative in developed countries

(–14 per cent). A similar pattern holds in an extended sample of 117 countries for the period 2020–2024.

Beyond GDP per capita, changes in the employment shares of men and women in agriculture and industry significantly predict segregation only through the sex composition effect. While the corresponding coefficients in the occupation mix models have similar signs, they are smaller and not statistically significant. These patterns reflect sector-specific gender specialization: women are disproportionately represented in agricultural occupations, whereas men remain concentrated in industrial activities.

By contrast, changes in sectoral value-added shares are significantly associated with segregation through the occupation mix effect, but not through the sex composition effect. This suggests that sectoral transformations influence segregation through distinct mechanisms: via employment composition and gender sorting across occupations, and via changes in the relative economic weight of sectors, which affect demand for different types of labour.

Demographic dependency also exhibits a differentiated relationship. Increases in the shares of young and elderly populations are significantly associated with higher segregation through the sex composition effect, but are not significantly related to the occupation mix effect. Higher dependency ratios raise unpaid care demands, which disproportionately constrain women's labour supply in developing countries. This relationship is largely absent in developed economies, where welfare systems mitigate the impact of demographic pressures on labour force participation.

Overall, the correlates of segregation differ markedly between the sex composition and occupation mix components, and these relationships vary by level of development. Models (2) and (3) explain approximately 70 per cent of the variation in the sex composition effect, highlighting substantial heterogeneity between developing and developed countries. Notably, six of the thirteen covariates change sign across these two models, underscoring the importance of development-specific mechanisms. For example, in developing countries, a one percentage point increase in the share of the population under age 15 is associated with a 1.8 percentage point increase in the sex composition effect, consistent with stronger care constraints reducing female labour force participation. In contrast, in developed countries, the same demographic change is associated with a 1 percentage point decrease in the sex composition effect, likely reflecting institutional support systems that alleviate care burdens.

Table 11: Cross-section DI change by component

	Sex composition effect			*Occupation mix effect*		
	All	Developing	Developed	All	Developing	Developed
	(1)	(2)	(3)	(4)	(5)	(6)
Change of Share of employment in agriculture, men	0.680	-0.002	3.903	-0.318	-0.507	5.016*
	(0.731)	(0.536)	(3.532)	(0.711)	(0.517)	(2.710)
Change of Share of employment in agriculture, women	0.579*	0.638***	2.719	0.103	-0.037	2.757
	(0.292)	(0.170)	(2.749)	(0.239)	(0.206)	(2.107)
Change of Share of employment in industry, men	2.797***	2.640*	0.841	-0.554	-1.041	-0.431
	(1.015)	(1.266)	(1.046)	(0.525)	(0.858)	(0.614)
Change of Share of employment in industry, women	0.946	0.866*	-0.688	-0.880**	-0.495	-0.856
	(0.626)	(0.454)	(1.226)	(0.424)	(0.471)	(0.766)
Change of Agriculture, forestry, and fishing, value added (% of GDP)	-0.396	-0.660*	-0.224	0.598**	0.641*	1.434**
	(0.333)	(0.323)	(1.573)	(0.295)	(0.335)	(0.587)
Change of Industry (including construction), value added (% of GDP)	-0.213	-0.207	0.271	-0.256**	-0.123	0.008
	(0.139)	(0.225)	(0.206)	(0.113)	(0.206)	(0.075)
Change of Herfindahl-Hirschman Index	-0.005	0.525*	-1.046	-0.450	-0.548	0.015
	(0.447)	(0.303)	(0.757)	(0.387)	(0.530)	(0.505)
Change of log GDP per capita, PPP, USD constant	-13.631**	-19.300***	0.942	6.052*	13.670*	0.656
	(5.200)	(6.374)	(5.689)	(3.501)	(7.292)	(2.731)
Change of Share of national income of the top 10 percent (pre-tax)	0.256	0.395**	-0.467*	0.279**	0.425**	0.218**
	(0.221)	(0.148)	(0.237)	(0.115)	(0.195)	(0.098)
Change of Men school enrollment, tertiary (share gross)	0.102	0.112	0.054	-0.007	0.113	0.028
	(0.139)	(0.158)	(0.153)	(0.087)	(0.133)	(0.050)
Change of Women school enrollment, tertiary (share gross)	-0.088	-0.182	-0.041	-0.006	-0.134	-0.050
	(0.103)	(0.120)	(0.136)	(0.065)	(0.097)	(0.040)
Change of Share of persons aged less than 15 yo	0.712**	2.128***	-0.692	0.126	-0.537	0.872**
	(0.306)	(0.412)	(0.466)	(0.256)	(0.570)	(0.322)
Change of Share of persons aged 65 yo or more	0.580*	0.897**	0.084	0.014	-0.046	0.202
	(0.331)	(0.341)	(0.526)	(0.228)	(0.344)	(0.175)
Change of Share of employment in agriculture (with interpolations)	-1.835*	-1.505**	-6.954	-0.081	0.747	-8.120
	(1.057)	(0.566)	(6.252)	(1.004)	(0.812)	(4.897)
Change of Share of employment in industry (with interpolations)	-3.987**	-3.970**	-0.772	1.255	1.670	1.727
	(1.538)	(1.719)	(1.887)	(0.809)	(1.341)	(1.100)
Constant	-1.077	4.371***	-3.078	-0.786	-0.861	1.180
	(1.291)	(1.523)	(1.950)	(0.797)	(1.733)	(0.818)
N	75	35	40	75	35	40
Adj. R-squared	0.440	0.757	0.676	0.680	0.640	0.856

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the country level in parentheses. The regressions are weighted by total employment per country. Control variables are the first difference between the two time periods.

D.4 Correlates of changes in segregation using alternative measures

Out of the 75 countries covered in the panel, only four have a difference in the sign of the change in three alternative measures of segregation. Interestingly, all other countries experience either a decline or an increase in gender-based occupational segregation for all three measures. The four countries with a difference in sign among measures are all Balkan countries: Bosnia and Herzegovina, North Macedonia, Serbia, and Slovakia.

For the first two, both the dissimilarity index and the isolation index increased and the Theil H index decreased. This implies that the main occupations (in terms of employment) become more mixed, reducing the entropy and thereby the Theil H index. On the other hand, less frequent occupations may become more segregated, especially among occupations where women are already dominating, leading to an increase in both the dissimilarity index and the concentration index.

Serbia experiences a decrease in the dissimilarity index but an increase in the two other metrics. This could hint toward a higher concentration of the most frequent occupations and a higher gender-based occupational integration among the less frequent occupations. Lastly, Slovakia experiences an increase in the dissimilarity index but not in the two other metrics. The pattern would be the exact opposite of the one in Serbia.

Table 12 shows the same results as for Models (2) to (4) in Table 3, but using the Theil H index for models (1)-(3) and the normalized isolation index for models (4)-(6). Comparing the dissimilarity index, the Theil H index, and the normalized isolation index, the models are remarkably similar. The structural factors and the income inequality measure tend to be related to the segregation measures more than the other variables. The overall fit of the models are comparable across the different segregation measures.

Using the alternative measures allows two conclusions: (i) results are robust to different metrics, (ii) gender-based occupational segregation concern both evenness and exposure and in a comparable way.

Table 12: Baseline panel regressions with alternative segregation measures

	Theil H index			*Isolation index (normalized)*		
	All	Developing	Developed	All	Developing	Developed
	(1)	(2)	(3)	(4)	(5)	(6)
Share of employment in agriculture, men	-0.499*	-0.576	0.196	-0.520*	-0.600	0.287
	(0.264)	(0.446)	(0.237)	(0.287)	(0.470)	(0.250)
Share of employment in agriculture, women	0.015	0.158**	-0.717**	0.042	0.191**	-0.933***
	(0.070)	(0.071)	(0.287)	(0.078)	(0.080)	(0.292)
Share of employment in industry, men	0.523**	0.311	0.463***	0.585**	0.370	0.519***
	(0.236)	(0.278)	(0.138)	(0.264)	(0.318)	(0.153)
Share of employment in industry, women	-0.833***	-0.638	-0.852	-0.912***	-0.708	-1.092
	(0.304)	(0.437)	(0.574)	(0.334)	(0.483)	(0.674)
Agriculture, forestry, and fishing, value added (% of GDP)	0.320	0.205	0.650	0.377	0.228	0.369
	(0.362)	(0.389)	(1.049)	(0.384)	(0.433)	(1.191)
Industry (including construction), value added (% of GDP)	-0.359***	-0.372**	0.286*	-0.377**	-0.379*	0.348*
	(0.133)	(0.183)	(0.158)	(0.144)	(0.204)	(0.186)
Herfindahl-Hirschman Index	-0.410*	-0.060	-1.251**	-0.549**	-0.176	-1.178**
	(0.219)	(0.320)	(0.528)	(0.245)	(0.359)	(0.559)
log GDP per capita, PPP, USD constant	-1.687	1.858	1.500	-2.611	0.407	1.631
	(3.703)	(6.357)	(3.466)	(4.044)	(7.124)	(3.952)
Share of national income of the top 10 percent (pre-tax)	0.398**	0.564**	-0.066	0.360*	0.534**	-0.229
	(0.167)	(0.208)	(0.132)	(0.182)	(0.245)	(0.143)
Men school enrollment, tertiary (share gross)	0.086	0.078	0.104	0.122	0.127	0.132
	(0.096)	(0.140)	(0.107)	(0.104)	(0.159)	(0.126)
Women school enrollment, tertiary (share gross)	-0.067	-0.127	-0.100	-0.086	-0.152	-0.124
	(0.071)	(0.117)	(0.095)	(0.078)	(0.132)	(0.110)
Share of persons aged less than 15 yo	0.358	0.975*	-0.110	0.404	1.080*	-0.268
	(0.231)	(0.527)	(0.366)	(0.248)	(0.551)	(0.421)
Share of persons aged 65 yo or more	0.193	0.155	0.025	0.402**	0.371	0.035
	(0.179)	(0.281)	(0.344)	(0.199)	(0.298)	(0.355)
Constant	22.930	-30.097	3.499	33.211	-17.563	15.266
	(38.972)	(66.021)	(36.666)	(42.741)	(73.412)	(41.857)
N	150	70	80	150	70	80
Countries	75	35	40	75	35	40
Adj. R-squared	0.617	0.648	0.816	0.609	0.629	0.820

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the country level in parentheses. The regressions are weighted by total employment per country.

E Generative Artificial Intelligence (Gen AI) and gender imbalances

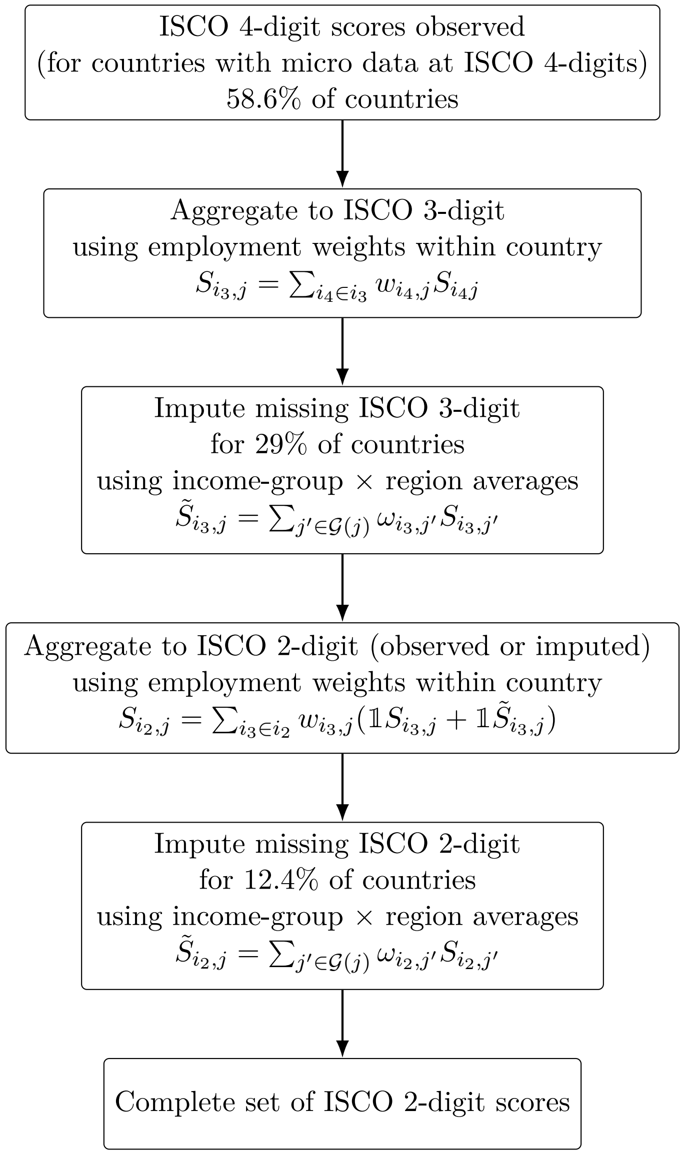
E.1 Upstreaming the Gen AI gradients

Gmyrek et al. (2023) gather unit groups of occupations based on the potential for augmentation and automation of tasks. There are 436 unit groups while in the present analysis we focus only on 37 sub-major groups of occupations. Each unit group is assigned a mean and a standard deviation capturing the augmentation and automation scores of the tasks in each group. From the combination of these two scores a Gen AI gradient is constructed.

Moving from ISCO 4-digit to ISCO 2-digit implies to find the mean and standard deviation scores at the sub-major group level. A simple solution could be to simply take the average of the scores for each unit group composing a sub-major group. However, this will fail to capture which unit group is more represented, it assumes that all unit group have the same level of employment. Since this is not the case, we approximate the ISCO 2-digit mean and standard deviation scores.

We construct scores at the 2-digit ISCO level using a sequential aggregation and imputation procedure. Figure 19 illustrates the procedure to retrieve or approximate the mean and standard deviation scores at the ISCO 2-digit. The notation S denotes the score of interest, either the mean or the standard deviation of the task augmentation/automation. Indices $i4$ indicates the unit groups of occupations, $i3$ indicates the minor groups of occupations, and $i2$ indicates the sub-major groups of occupations.

Figure 19: Sequential aggregation and imputation of occupational scores across ISCO levels



Note: $w_{i_4,j}$ denotes the employment share of occupation i_4 within its parent 3-digit group in country j and $S_{i_4,j}$ denotes the score attached to occupation i_4. By construction, at ISCO 4-digit the scores are identical for all countries.

E.2 Taxonomy of sub-major groups of occupations and Gen AI

Table 13 lists the sub-major occupations in the analysis and indicates the gradient to which they belong. Gradients are constructed following Gmyrek et al. (2023).

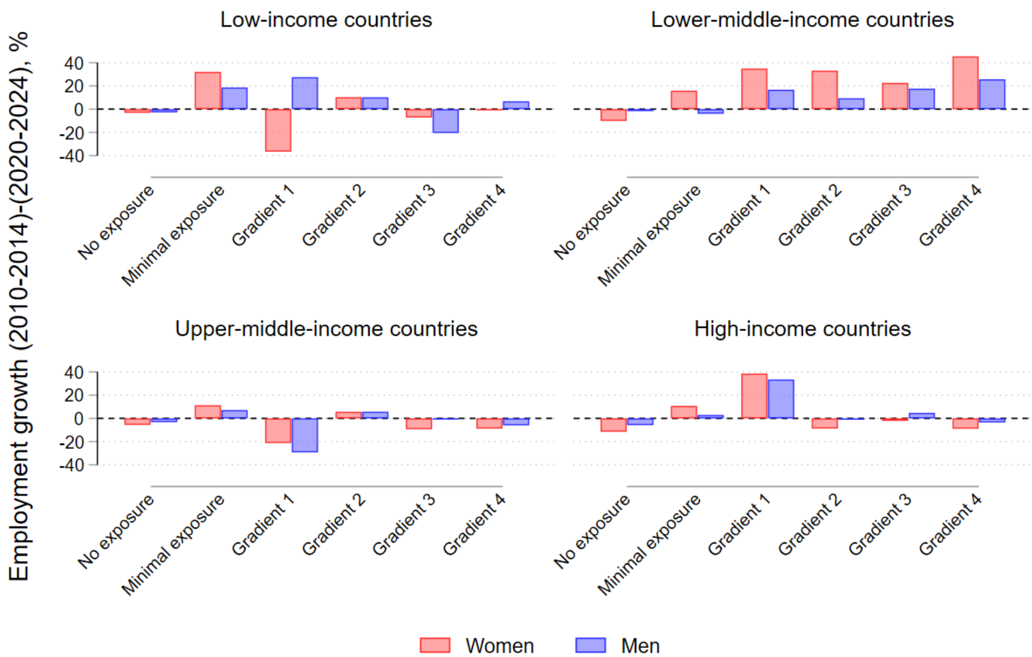
Table 13: Sub-major groups of occupations and Gen AI exposure

Exposure	Sub-major groups of occupations
Gradient 4	42 - Customer services clerks
Gradient 3	41 - General and keyboard clerks; 33 - Business and administration associate professionals
Gradient 2	43 - Numerical and material recording clerks; 24 - Business and administration professionals; 35 - Information and communications technicians; 52 - Sales workers
Gradient 1	82 - Assemblers; 14 - Hospitality, retail and other services managers
Minimal exposure	25 - Information and communications technology professionals; 26 - Legal, social and cultural professionals; 13 - Production and specialised services managers; 21 - Science and engineering professionals; 23 - Teaching professionals; 31 - Science and engineering associate professionals; 11 - Chief executives, senior officials and legislators; 34 - Legal, social, cultural and related associate professionals; 12 - Administrative and commercial managers; 32 - Health associate professionals; 22 - Health professionals; 51 - Personal service workers; 83 - Drivers and mobile plant operators
No exposure	44 - Other clerical support workers; 96 - Refuse workers and other elementary workers; 53 - Personal care workers; 95 - Street and related sales and service workers; 54 - Protective services workers; 81 - Stationary plant and machine operators; 74 - Electrical and electronic trades workers; 72 - Metal, machinery and related trades workers; 75 - Food processing, wood working, garment and other craft and related trades workers; 73 - Handicraft and printing workers; 71 - Building and related trades workers, excluding electricians; 92-6 - Agricultural occupations; 91 - Cleaners and helpers; 93 - Labourers in mining, construction, manufacturing and transport; 94 - Food preparation assistants

Note: The ordering of the sub-major group of occupation is sorted from the highest exposure to the lowest exposure, within each gradient. A sub-major group is gradient 4 is the mean score μ of augmentation and automation is more than (or equal to) 0.6 and the gap $\mu - \sigma \geq 0.5$ (with σ the score of the standard deviation of the tasks sensibility to Gen AI). Gradient 3 requires $0.5 \leq \mu < 0.6$ and $\mu + \sigma \geq 0.5$. Gradient 2 corresponds to occupations where $0.4 \leq \mu < 0.5$ and $\mu + \sigma \geq 0.5$. An occupation is deemed gradient 1 if $\mu < 0.4$ and $\mu + \sigma > 0.4$. Minimal exposure occupations are those where $\mu < 0.5$ and $\mu + \sigma > 0.4$. Not exposed occupations are the ones not matching with the previous criteria.

E.3 Changes in occupations by Gen AI sensibility

Figure 20: Changes in the shares of workers over the past decade, by gradient, sex and level of development



Note: The panel sample data is used here, amounting to 75 countries. A bar that exceeds zero indicates that this group of occupations, for a given sex and a given group of countries was growing over the last decade.