

Zuazu, Izaskun

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Structural change and gender sectoral segregation in sub-Saharan African countries

Izaskun Zuazu 

Institute for Socio-Economics, University of
Duisburg-Essen, Duisburg, Germany

Correspondence

Izaskun Zuazu, Institute for Socio-Economics,
University of Duisburg-Essen, Duisburg,
Germany.

Email: izaskun.zuazu-bermejo@uni-due.de

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Abstract

Structural change has long been at the core of economic development debates. However, the gender implications of structural change are still largely unexplored. This paper helps to fill this gap by analysing the role of structural change in the gender distribution of sectoral employment in sub-Saharan African countries. I employ aggregate and disaggregate measures of gender sectoral segregation in employment, which measure the difference between the gender distribution across sectors with respect to the overall participation of women and men in the labour market. I build a panel database consisting of 10 sectors and 11 countries during 1960–2010. Fixed effects and instrumental variables' regression models show a significant, nonlinear link between labour productivity and gender segregation. Increasing labour productivity depresses gender segregation at initial phases of structural change. However, further productivity gains beyond a certain threshold of sectoral development increases gender segregation. Country-industry panel data models complement the analysis showing that relative labour productivity has a nonlinear impact in gender segregation: Initial increases in relative productivity increases feminization but further relative productivity gains foster the masculinization of sectors. The estimates suggest that manufacturing, utilities, construction, business, and government services are key to correct gender biases in employment along the process of structural change.

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KEYWORDS

association index, dissimilarity index, gender sectoral segregation, instrumental variables, structural change

JEL CLASSIFICATION

E0, J1, Q5

1 | INTRODUCTION

Structural change is the process of shifting production from agriculture to manufacturing and service sectors, followed by a decline in manufacturing share and an increase in service sector share in the total economy. The prominent debates on economic development in sub-Saharan African (SSA) countries are concerned with structural change patterns that depart from the canonical model that depicts declining agriculture, hump-shaped manufacturing, and rising high-productive services (de Vries et al., 2015; Tregenna, 2015). Structural heterogeneity—the isolation of highly productive activities from the rest of the economy—and premature deindustrialization—a prompt shift into a service economy without proper development of the industrial sector—are among the pathological phenomena identified in the literature (Rodrik, 2016; Tregenna, 2016). While the canonical works on this topic (Kuznets, 1966; Lewis, 1965) have been complemented by research on the impacts of general structural change on economic development (de Vries et al., 2021; Herrendorf et al., 2014; McMillan et al., 2017; McMillan & Rodrik, 2011), the gender implications of such a transformation are less understood (Dinkelman & Ngai, 2022; Gottlieb et al., 2022; Seguino & Were, 2014).

This paper adds to the literature in structural change by analysing whether and how labour productivity and gender segregation are linked in sub-Saharan African countries. Gender sectoral segregation refers to the sectoral distribution of female and male employment, that is, the proportion of women (men) in each sector relative to the total female (male) employment in the economy. Gender sectoral/horizontal segregation differs from occupational/vertical segregation: The former considers the sectoral economic structure, whereas the latter considers the occupational economic structure of a given country or region.¹ In this paper, we look at how key phenomena regarding structural change, such as labour productivity and sectoral productivity gaps, affect the gender distribution of sectors in both formal and informal employment.

The key argument of this paper is that labour productivity—computed as the ratio between value added and employment—might have a nonlinear relationship to gender sectoral segregation. Initial productivity gains derived from the process of structural change can imply a lower demand for physical requirements. As lower physical requirements are found to increase the demand for women in the paid workforce (Rendall, 2013, 2017), one might expect an increasing participation of women in all sectors of the economy. However, further productivity gains above certain levels can couple with gender stereotypes and discrimination to deter the entrance of women in specific sectors, thus fostering the crowding of female employment in other specified sectors (Bergmann, 1981; Seguino & Braunstein, 2019).

This paper empirically tests the link between labour productivity and gender segregation using panel data models at both country level and country-industry levels. The term “country-industry” is employed here to differentiate between segregation measures at country level (which vary according to countries and years) and industry-level measures of gender-sectoral segregation (which vary according to sectors, countries, and years). These two measurements refer to the same phenomenon, namely, gender-sectoral segregation. I collect data on sectoral (formal and informal) employment, disaggregated by gender, and sectoral value added from the Africa Sector Database (ASD) by de Vries et al. (2015), and build a panel database consisting of 10 industries operating in 11 countries during 1960–2010. Using this database allows a higher level of data disaggregation than previous related works (Borrowman & Klasen, 2020). Descriptively, I show that gender segregation has increased in certain countries (i.e., Senegal, Ethiopia,

and Botswana), but it was reduced in others (i.e., Zambia, South Africa) during the period considered. At the same time, I identify that those countries with reduced gender segregation had, at the same time, higher levels of labour productivity.

I merge the ASD database with information on female labour force participation and other country-level covariates that can play a role in gender segregation. As a preview of the econometric analysis, I find a nonlinear relationship between labour productivity and gender segregation: productivity gains depress segregation up to a certain threshold. Beyond that threshold, further productivity gains increase gender segregation by sectors. This result is robust to alternative estimation techniques, such as instrumental variables, that circumvent endogeneity issues regarding the inclusion of female labour force participation in the set of independent variables. Additionally, the main result holds when using alternative dependent variables, such as aggregate and disaggregate measures of gender sectoral segregation, namely, the Dissimilarity index of Duncan and Duncan (1955), the so-called IP index of Karmel and MacLachlan (1988), and the Association index of Charles and Grusky (1995).

The remainder of the paper goes as follows. Section 2 reviews the literature. Section 3 provides the data and the measurements of aggregate gender sectoral segregation. Section 4 specifies the econometric models while Section 5 shows the results and provides different robustness checks. Section 6 concludes and discusses policy implications.

2 | LITERATURE REVIEW

Structural change at large, and the differences in aggregate and sectoral labour productivity in particular, interact in complex ways with gendered labour markets. These structural changes come with profound demographic movements and urbanization and allow for technological diffusion at both market and home production levels (Boserup et al., 2013; Dinkelman & Ngai, 2022; McMillan et al., 2017; Uberti & Douarin, 2022). Fundamentally, these changes might transform the pre-existing gender distribution of paid and unpaid work. This theoretical section first analyses the general patterns of structural change at large and contextualizes them within developing regions, specifically sub-Saharan African countries. Second, this section reviews the stylized facts on the gender implications of structural change, together with the specific empirically informed factors of gender segregation. Finally, the section zooms in on specific implications of structural change in gender sectoral segregation in the region.

Structural transformation affects productivity and growth: as resource reallocations shift labour out of low-productive sectors towards high-productive, modern economic activities, there is an aggregate labour productivity rise and an expansion of income (McMillan & Rodrik, 2011; Naveed & Ahmad, 2016; Van Ark, 1995). As suggested by McMillan and Rodrik (2011), when labour and other resources move from less productive to more productive sectors, overall productivity grows even in the absence of within-sector productivity growth. The process of structural change shows great cross-country heterogeneity, as some countries transition faster from one phase of structural change to another, or fail to fully develop a modern manufacturing sector before moving into a service economy (Herrendorf et al., 2014; Rodrik, 2016). Thus, it is important to consider economy-wide labour productivity and sectoral gaps in labour productivity as key phenomena related to the process of structural change.

Developing countries show large sectoral gaps in labour productivity and dual economies, with high shares of low-productivity, largely rural activities and low shares of high-productive (urban) activities. For the specific case of the sub-Saharan African region, cross-sectoral labour reallocation was productivity reducing during 1990s but it promoted productivity growth in the 2000s, and this improved performance in the 2000s (McMillan et al., 2014). While the existing literature has identified the relevance of structural change in the productivity levels, productivity growth, and sectoral gaps in productivity in SSA, its impact on labour market outcomes are far less well known (Mensah et al., 2023), let alone the gender labour market implications of structural change.

In the sample of SSA countries here considered, manufacturing expanded greatly from 1960 to 1975, corresponding to the shifts from subsistence agricultural societies towards modern manufacturing (de Vries

et al., 2015). However, after 1970, the region suffered a political and economic turmoil, which coincided with structural adjustment programmes. These programmes had crucial, gendered implications, which are still felt today (Elson, 1995). In the late phases of the period considered in this paper (1990–2010), SSA countries expanded employment shares in service sector whereas manufacturing shares remained low, which is coined as premature deindustrialization (Rodrik, 2016) or even, deindustrialization without industrialization (Tregenna, 2016).

Mensah et al. (2023) provide an analysis of the effects of structural change in labour productivity growth in a set of 18 SSA countries during 1960–2018, expanding the country and time coverages of the ASD, originally developed by the Groningen Growth and Development Centre (GGDC) by de Vries et al. (2015). Their findings using this updated database suggest that structural change in SSA has been underestimated in previous studies. Agricultural employment declined during the period considered, leading to an increase of low-productive service sectors. Thus, these changes had limited enhancing effects in aggregate labour productivity. Mensah et al. (2023) point at typical labour market institutions setting of the SSA region, such as the significant variation in the degree of enforcement of laws and regulation, as barriers to successful experiences of structural change. The authors also highlight the link between structural change and labour mobility, with labour shifts defining the type of structural process. Structural change might increase aggregate labour productivity, but simultaneously, it might also foster temporary unemployment and worker reallocations rising low-paid jobs or informal employment and employee uncertainty. However, Mensah et al. (2023) do not consider gender disparities in these labour market implications of process of structural change. Hence, the current paper provides a direct contribution to their work in particular and to the literature on structural change at large.

The process of structural change can lead to domestic disparities, such as increasing income inequality (Kuznets, 1966; Lewis, 1965) and gender redistribution of paid work and unpaid household production (Dinkelman & Ngai, 2022; Gaddis & Klasen, 2014; Uberti & Douarin, 2022). In this context, structural change is linked to the emergence of new types of paid work opportunities for women (Dinkelman & Ngai, 2022). Notwithstanding some broad similarities in female and male employment shifts over the structural change path, the literature identifies significant gender disparities. For instance, Dinkelman and Ngai (2022) use historical cross-country data for developed economies to find that women leave the agriculture sector and move into the service sector faster than men do and that manufacturing rises more steeply for men than for women. However, Dinkelman and Ngai's (2022) paper only focuses on a rather broad sectoral perspective. In the current paper, I complement their analysis by providing a more nuanced sectoral analysis that uses a greater level of data disaggregation by sector. This allows me to identify how structural change is linked to gender disparities as well as which sectors are driving these disparities. Economic development and sectoral composition have a profound impact on the women's distribution of paid and unpaid work, as predicted by the so-called feminization U-shape. In a nutshell, this theory was first uncovered using historical data for the United States in Goldin (1995), suggesting that initial increasing levels of economic development are associated with depressing women in the paid workforce due to an income effect. Further increases of economic development are governed by a substitution effect that pushes women back to the labour market.

A growing body of research followed up the U-shaped feminization hypothesis of Goldin (1995) and casts doubts in the external validity of the hypothesis. Gaddis and Klasen (2014) suggest that structural change should be included in our understanding of the U-shaped correlation between economic development and female labour market participation. They also ensure that the nonlinear link is inconsistent depending on the data and quantitative method employed. Uberti and Douarin (2022) find that the use of the plough matters for the feminization U-shape, as physical requirements of the plough can mediate the bulk of women in paid and unpaid work. In related works, Rendall (2013, 2017) considers the role of structural change in altering the composition of “brain” and “brawn” tasks by sectors: Lower physical requirements might lead to increasing opportunities for paid work for women, as women have a comparative advantage in brain jobs. Beyond female labour force participation, working conditions of female employment can be disparate and differ substantially from those of male employment.

Extant literature has also focused on the role of structural change in the gender wage gap in SSA countries. Van den Broeck et al. (2023) use decomposition methods to analyse how structural change affected gender wage

differentials in Malawi, Tanzania, and Nigeria to find that structural transformation does not consistently help bridge the gender pay gap. Additionally, their analysis suggests a rural–urban divide in the driving forces behind gender pay inequality; while in rural areas occupation is the most relevant factor, in urban areas both occupation and sector are similarly important. In this sense, the current paper complements the existing literature by placing special attention on the role of sectoral segregation in the process of structural change to affect differently the livelihoods of women and men, controlling at the same time for urbanization.

Gender segregation in SSA countries is lower in comparison to other regions in the world. Borrowman and Klasen (2020) use a database of 69 countries, of which 24 are SSA countries, and find that gender segregation is generally lower in this region where women and men are disproportionately employed in agriculture. While they find a limited and mostly insignificant role of structural change in gender segregation, their estimates associate female labour force participation with lower gender-sectoral segregation.² Other recent works in the gender implications of structural change find that higher industrial productivity is associated with lower presence of women in good jobs, namely, industry jobs in 15 Latin American countries (Arora et al., 2023) using panel data econometric models during 1990–2018.

Yeboah et al. (2022) analyse the role of female labour force participation in structural change, but they do not focus on the implications for gender segregation, but rather, the extent to which rising female labour force participation in SSA countries is linked to value-added shares in the agriculture, industry, and service sectors. Using dynamic panel data models on a balanced dataset of 33 SSA countries during 1990–2017, they find that rising female labour force participation leads to an increased share of services in total value added, but they do not find a significant role in industry or agriculture sectors. This is a mediating effect of infrastructure—measured in terms of either fixed telephone subscriptions or gross-fixed-capital formation as proportion of GDP—which magnifies this positive link between women in the paid workforce and the share of services.

The current paper draws on the above-mentioned stylized facts of structural change and gender to speculate the extent to which productivity matters for gender segregation by sector. This paper comes close to the works of Borrowman and Klasen (2020) in identifying the drivers of gender-sectoral segregation and combines it with the sectoral-disaggregated perspective in de Vries et al. (2015). Further, the current paper complements the argument in Rendall (2013) in asserting that higher labour productivity can favour female employment by considering that productivity might have a nonlinear relationship with female employment in certain sectors. At sufficiently high levels of labour productivity, further gains can block the entrance of women mediated by gender discrimination and stereotypes in the competition between women and men for newly created “good” jobs (Seguino & Braunstein, 2019).

3 | EMPIRICAL ANALYSIS

3.1 | Data

I collect data from the ASD produced by de Vries et al. (2015). This database provides sectoral-level disaggregated data (ISIC Rev. 3.1) on value added, employment, and female share of employment for 10 sectors operating in 11 SSA countries, namely, Botswana, Ethiopia, Ghana, Kenya, Malawi, Mauritius, Nigeria, Senegal, South Africa, Tanzania, and Zambia, during 1960 to 2010.³ Using this database, I look at two fundamental phenomena of structural change, as discussed in Section 2: aggregate labour productivity and relative labour productivity. The ASD provides information on formal and informal employment, as it defines employment as “all persons engaged,” thus including all paid employees and self-employed and family workers of 15 years and older. An important feature of the ASD is that it provides sectoral purchasing power parities (PPPs) for the year 2005 (Herrendorf et al., 2022). I convert labour productivity levels measured in domestic prices to comparable measures of labour productivity levels measured in international prices using the sectoral-level PPPs.

Figure 1 shows the sectoral distribution of female employment and male employment together with sectoral-relative labour productivity.⁴ Agriculture concentrates the bulk of both female and male employment, with respectively 65% and 60% shares. To the contrary, the agricultural-relative labour productivity level is around 0.5 during the period, meaning that labour productivity in the sector is half that of the total economy. The trade services sector comprises a higher percentage of female employment (12%) than male employment (8%), and its relative productivity level is slightly above the total economy productivity level. The personal services sector also employs a greater proportion of females to males, although the labour productivity is lower than the average (0.8). The transport services, construction, and mining sectors concentrate low shares of female employment, while maintaining among the highest labour-productivity shares. The manufacturing sector concentrates a similar percentage of female and male employment, while its productivity levels are around two times that of the total economy. The sectoral perspective taken in Figure 1 should be complemented with country-level measures of segregation that account for differences in structural change patterns. To do so, the next subsection proposes the use of standard country-level measures of segregation that are computed based on cross-country, time-series, and sectoral-level disaggregated data.

3.2 | Measuring gender segregation

To measure gender segregation, I employ the Duncan index of dissimilarity (ID), which is a standard measure of either vertical or horizontal segregation (Charles & Grusky, 2005; Duncan & Duncan, 1955) at country level. For the purposes of this paper, I focus on sectoral segregation, and use a 10-sector level of industrial classification (ISIC Rev. 3.1) (see Equation 1).

$$ID = 1/2 \sum_{i=1}^n \left| \frac{F_i}{F} - \frac{M_i}{M} \right| 100 \quad (1)$$

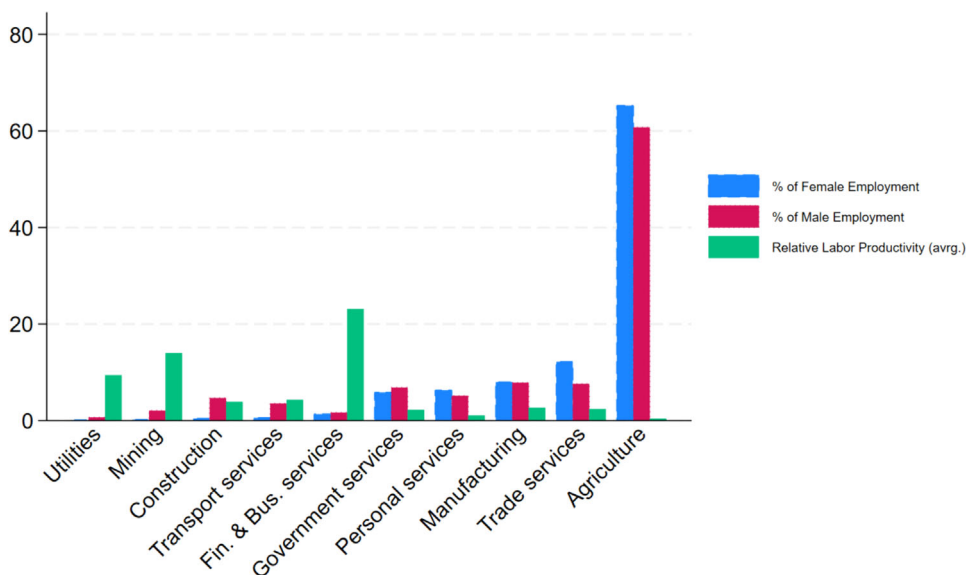


FIGURE 1 Sectoral shares of employment by gender and relative labour productivity. *Source:* Own elaboration using the ASD (de Vries et al., 2015).

$$i = [1, \dots, n]$$

F_i is the number of women in sector i , where F is the total of women employed in the economy, M_i is the number of men in sector i , M is the total of men employed in the economy, and n equals 10 (total number of sectors, as the database here employed there are 10 sectors i). One of the benefits of using the ID as a measure of segregation is its simple interpretation: It provides the percentage of women who need to change sectors in order to bring about a gender-equal distribution across sectors within an economy. The higher the value of the ID, the higher the segregation in a country. In the sample, ID has increased from 13% in 1960 to 20% in 2010. It should be noted that this measure of gender segregation compares the sectoral distribution of male employment with that of women. Nonetheless, the ID is not exempt from limitations. As noted in Borrowman and Klasen (2020), the foremost limitation of the ID is its mechanical sensitivity to cross-country and temporal changes in the employment share by sector. The index is thus influenced by large sectors, which can be worrisome in studying structural transformation and gender segregation in a panel-data setting. To alleviate this difficulty, I employ the so-called “IP index” (IP) (Karmel & MacLachlan, 1988) as an alternative measure of segregation, which serves also as a robustness check of the econometric models below. Figure A2 in Appendix A shows the evolution of ID and IP.⁵ A common limitation of the ID and IP is that both depend greatly on the breadth of the sectoral classification. Narrow classifications yield higher levels of ID than broad classifications; hence, they can be manipulated to offer higher or lower levels of segregation (Nelson, 2017).

Table 1 provides the evolution of ID in each country in the sample, together with that of the logarithm of total labour-productivity levels. In six out of the 11 countries (Botswana, Ethiopia, Malawi, Nigeria, Senegal, and Tanzania), gender segregation has increased over the period at scrutiny. The most remarkable increase is shown by Senegal, where ID increased from 8% in 1970 to 23% in 2010.

At the same time, the growth rate of total labour productivity between 1970 and 2010 is the lowest in the sample (1.6%). To the contrary, gender segregation decreased remarkably in Zambia (−38 percentage points, p.p.) and, together with Ghana, is the country with the highest growth rate of total labour productivity in the period (10%).

Figure 2 documents correlations between either aggregate labour productivity (log) or female labour force participation (FLFP, %) and gender segregation (measured by ID). Figure 2a tends to show that at initial levels of labour productivity, gender segregation reduces. However, this curve is nonlinear, as it slightly flattens at higher levels of productivity. The correlation of aggregate labour productivity with gender sectoral segregation seems to vary by country, where Zambia shows the greatest change in both segregation and productivity. Ghana and Tanzania seem to follow a clearer nonlinear pattern between productivity and segregation, whereas South Africa and Nigeria show an inverted pattern. The stagnation of FLFP in SSA countries suggested in Backhaus and Loichinger (2022) can be seen in Figure 2b, as there is scarce variation of FLFP by country. The correlation between women in the paid workforce, proxied using FLFP (%) in x-axis, and gender sectoral segregation, proxied by ID (%) in y-axis, is a linear and negative. Thus, we can consider preliminary evidence of a negative, strong association between rising women in the labour market and the crowding of women in specific sectors of the economy, as previously found in Borrowman and Klasen (2020).

There are limits to what can be discerned from aggregate cross-country analyses in the context of structural change and gendered impacts (Wamboye & Seguino, 2015). Both ID and IP indices are country-level measures of gender segregation. While they provide information on the share of workers who should change sectors to increase a gender-balanced distribution across sectors, these indices are not able to identify which precise sectors should be defeminized or demasculinized. To solve for this, in this paper, I combine the use of country-level measures of segregation (viz., ID and IP) with a measure of the concentration of gender employment, namely, the Association Index (A index) proposed by Charles and Grusky (1995). The A index takes a log-linear approach to circumvent the limitations of both ID and IP indices, solving therefore for the mechanical dependence of the latter on variations in sectoral shifts of employment and participation of women in the labour market. Additionally, the A identifies which

TABLE 1 Gender segregation and labour productivity levels in sub-Saharan Africa.

	Disimilarity index (%)						Total labour productivity					
	1970	1980	1990	2000	2010	Change (p.p.)	1970	1980	1990	2000	2010	Change (%)
Botswana	8.8	18.5	25.1	21.9	14.1	5.3	3.5	5.7	7.3	8.4	9.5	5.9
Ethiopia	6.3	5.7	5.5	7.3	16.0	9.7	4.4	4.7	4.7	5.4	6.9	2.4
Ghana	27.5	28.1	24.5	14.8	26.5	-1.0	-4.1	-2.0	1.5	4.0	6.0	10.1
Kenya	22.0	23.1	20.1	20.3	19.9	-2.1	6.1	7.2	8.1	8.9	9.6	3.5
Malawi	17.2	17.2	17.3	16.5	17.7	0.5	3.1	4.1	5.3	8.1	9.5	6.4
Mauritius	27.4	26.2	29.4	31.0	25.0	-2.4	6.4	7.8	9.0	10.0	10.8	4.4
Nigeria	28.5	28.4	23.7	20.1	30.2	1.7	3.9	5.4	7.1	9.7	11.1	7.2
Senegal	7.7	14.0	20.2	19.9	22.5	14.9	10.2	10.6	10.9	11.4	11.8	1.6
South Africa	34.0	33.9	35.0	28.5	27.5	-6.4	5.1	6.6	7.8	8.7	9.7	4.7
Tanzania	11.4	13.9	10.5	9.7	13.8	2.4	6.1	7.2	9.2	11.0	12.0	5.9
Zambia	49.2	35.3	23.2	14.6	11.6	-37.7	4.6	5.6	8.6	12.7	14.6	10.0

Source: Own elaboration using the ASD (de Vries et al., 2015).

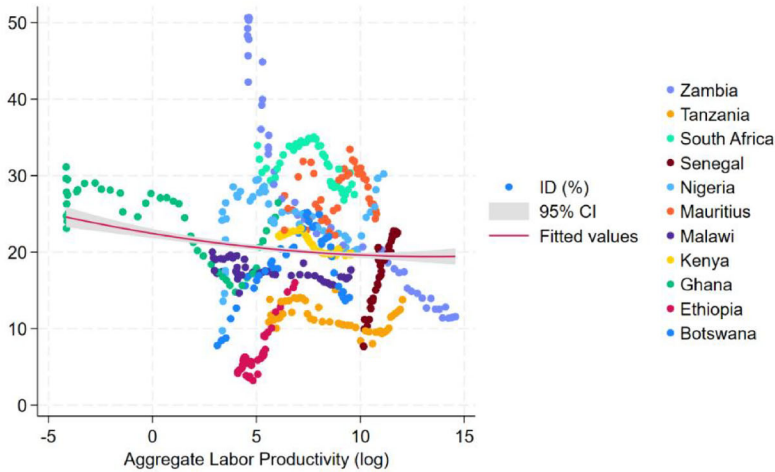
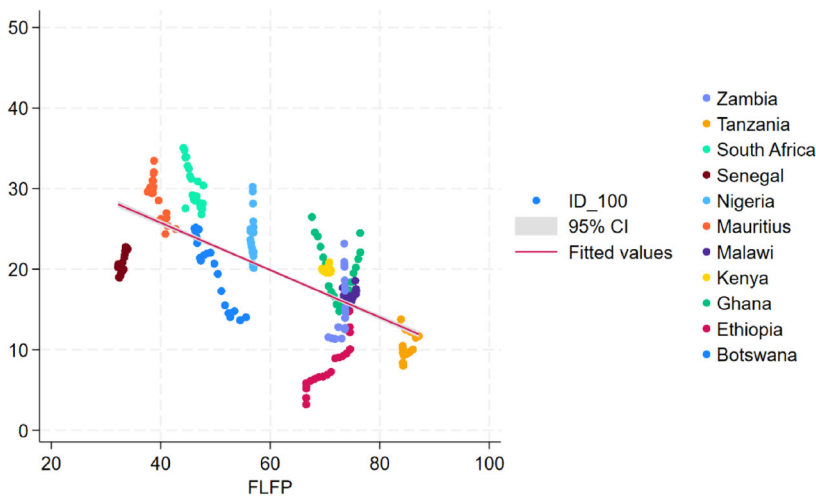
(a) Scatter plot of Aggregate Labor Productivity and Dissimilarity Index**(b) Scatter plot of Female Labor Force Participation and Dissimilarity Index**

FIGURE 2 Correlations between labour productivity or women in paid work and gender sectoral segregation. (a) Scatter plot of aggregate labour productivity and dissimilarity index. (b) Scatter plot of female labour force participation and dissimilarity index. *Source:* Own elaboration using the ASD (de Vries et al., 2015), y-axis is the dissimilarity index (%), x-axis in panel a is aggregate labour productivity and in panel b is female labour force participation.

sectors are male-dominated, gender neutral, or female-dominated and allows for better intertemporal and cross-sectional comparisons than the indices explored above.

The formula for the A index is given by the following equation:

$$A_i = \ln(F_i/M_i) - \left[1/I \sum_{i=1}^n \ln(F_i/M_i) \right] \quad (2)$$

$$i = [1, \dots, n] \quad (3)$$

where terms correspond to the same as in Equation (1) and I is the total number of sectors ($I = 10$). Negative values of the A index represent female underrepresentation in that specific sector, and positive values indicate female overrepresentation relative to other sectors. Values closer to zero are indicative of greater gender integration. One important advantage of using the A index is that we can compare the degree of segregation in each sector irrespective of whether it is male or female dominated. The extents of male-domination or female-domination in each sector allow also for cross-country and temporal comparisons as the index does not suffer from the technical dependencies of the afore-mentioned indices. Previous literature in gender segregation by field of education has applied the A index using data for advanced economies in cross-sectional or panel-data, econometric settings (Charles & Bradley, 2009; Zuazu, 2020).

Figure 3 provides the sample average levels of the A index for different periods.⁶ The most segregated sector, which shows little variation during the period considered, is construction, which is a male-dominated sector. Transport services and mining are also highly segregated sectors (male-dominated), together with trade services (female-dominated). Nonetheless, female-dominated sectors are, on average, less segregated than male-dominated sectors. Except for construction and personal services, all sectors have reduced the level of segregation between 1970 and 2010. An important feature of industry-level gender segregation in the sample is that the government services sector was transformed from a male-dominated sector in the beginning of the period (before 1975) to an increasingly female-dominated sector in subsequent periods. Importantly, the use of the A index uncovers the fact that manufacturing is a female-dominated sector.

4 | ECONOMETRIC SPECIFICATION

This paper explores the role of aggregate labour productivity, measured as the log-transformed ratio between value added by number of employees, in gender sectoral segregation in a panel-data framework using both country-level and country-industry panels. This econometric analysis first focuses on country-level gender sectoral segregation

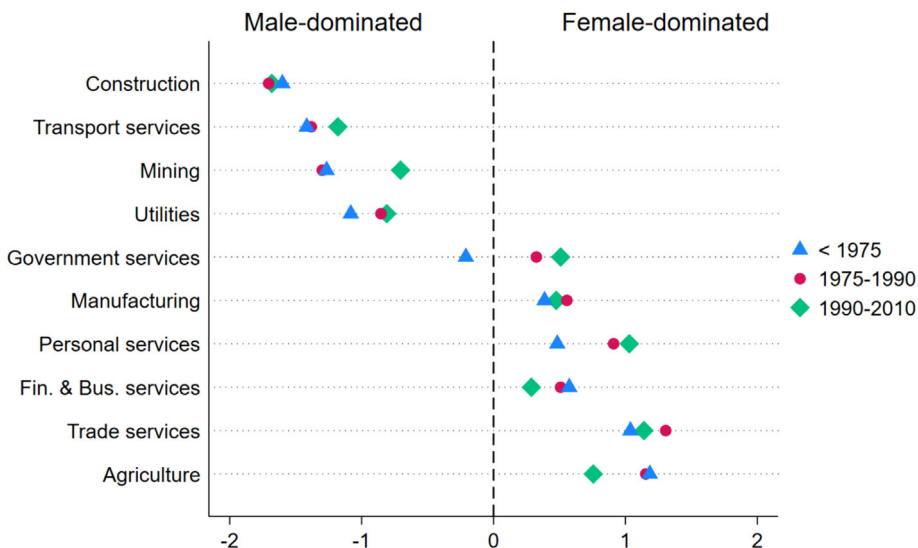


FIGURE 3 Evolution of industry-level gender segregation. Source: Own elaboration using the ASD (de Vries et al., 2015).

using ID or IP as outcome variables. To model a potential nonlinear relationship between productivity and gender segregation, the regression model specifies gender segregation (measured by ID) as a quadratic function of the log of aggregate labour productivity.

$$\log(ID_{ct}) = \beta_0 + \beta_1 LP_{c,t-s} + \beta_2 LP_{c,t-s}^2 + \beta_3 FLFP_{c,t-s} + X'_{c,t-s} \beta + \vartheta_{ict} \quad (3)$$

$$\vartheta_{ct} = \delta_c + \gamma_t + \varepsilon_{ct}$$

$$c = \text{country}; t = \text{year}$$

$$s = [1, 5]$$

where ID_{ct} is the dissimilarity index measures gender segregation in country c in time t and is expressed in logs to ease the interpretation of the coefficients. $LP_{c,t-s}$ corresponds to aggregate labour productivity (in logs), that is, the ratio of total value added to total employment in the economy.

The quadratic term of total labour productivity is included to test a nonlinear relationship between structural change and gender segregation. $FLFP_{c,t-s}$ corresponds to female labour force participation in a country, whereas $X'_{c,t-s}$ is a set of control variables, further explained below. Time-fixed effects are included in the model γ_t , as well as the error term (ε_{ct}). As a panel data model, Equation (3) is able to control for country-level, time-invariant unobserved heterogeneity, which is a major advantage in comparison to cross-sectional settings. All independent variables are one or five periods lagged (s) to alleviate reverse causation and serial correlation issues.

Previous econometric analyses of gender segregation and structural change downplay the role of reverse causality emerging from a two-way link between segregation and either economic growth, sectoral share of employment, or trade (Borrowman & Klasen, 2020) but are concerned with the endogeneity biases caused by the inclusion of FLFP in the model (Klasen & Pieters, 2015). As suggested by Borrowman and Klasen (2020), segregation can drive lower FLFP by reducing the opportunities of female paid labour, unleashing negative effects in female education and, at the same time, raising fertility rates. Importantly, the linkages between FLFP and fertility (Bloom et al., 2009) or economic growth (Goldin, 1995; Uberti & Douarin, 2022) can yield biased estimates if not accurately accounted. In what follows, I delve into this issue by using an instrumental variables approach.

The link between FLFP and gender segregation is far from clear, as previous research suggests both negative and positive links. A negative link is found in Borrowman and Klasen (2020). A greater presence of women in the labour market (measured by FLFP) can help modify traditional gender norms to allow the entrance of women in male-dominated sectors. To the contrary, Seguino and Braunstein (2019) suggest that higher FLFP can pose a threat to male jobs, which, when mediated by gender stereotypes and discrimination in the hiring practices, will ultimately increase gender segregation. The crowding and segmentation theories support this hypothesis: women's access to industrial sector jobs—which are comparatively better paid than service sector jobs—is blocked as female presence in the paid workforce increases. Further, it considers that industrial employment will be male dominated, whereas low-productivity sectors in services will be female dominated as FLFP increases. Structural change and gender economic literature outlined already the role of FLFP in increasing feminization of service sector (Ngai & Petrongolo, 2017). See Figure A3 for the evolution of FLFP in the different countries in the sample.

Additional control variables in the model in Equation (3) are economic development (measured as the log of GDP per capita), international trade (exports and imports as a percentage of GDP), foreign direct investment (FDI as a percentage of GDP), and urban population in percentage and fertility rate (in logs). Total enrolment in secondary education is included in order to account for the educational gender inequality Kuznets curve found in Baten et al. (2021), which suggests that initial increases in male educational attainment lead to greater gender inequality in education but is reduced at the top distribution of male education. All these variables are collected from the World Bank Development Indicators Database (WDI).

Following Borrowman and Klasen (2020), I consider the potential implications of within-country income inequality in driving segregation as SSA is one of the most unequal regions around the world (Milanovic, 2003; Rios-Avila et al., 2021). Hence, the full set of control variables includes a measure of income inequality (Gini net per cent), collected from the Standardized World Income Inequality Database (SWIID) provided by Solt (2020). Appendix A includes a summary of descriptive statistics in Table A1 and the evolution of ID, total labour productivity, and FLFP in Figure A1.

Although it is not a perfect solution for reverse causation (Bellemare et al., 2017; Leszczensky & Wolbring, 2022), all the independent variables are one-period lagged to help alleviate the strong and untestable strict exogeneity assumption at the contemporary level.⁷ I estimate Equation (3) using fixed effects (within) regression models with Driscoll and Kraay (1998), standard errors that are consistent in the presence of heteroskedasticity, and autocorrelation, and account for spatial dependency (Hoechle, 2007).

5 | RESULTS

5.1 | Country-level panel data estimates

Table 2 provides the estimates of the regression model in Equation (3). The results show a significant and negative impact of rising total labour productivity in gender segregation at a 1% level. Column 1 includes only total labour productivity and time-fixed effects, whereas columns 2 and 3 introduce respectively the role of women in the paid workforce together with the full set of controls, and the quadratic term of productivity. The results suggest that a 1% increase in aggregate labour productivity is related with reduction of around 0.5% and 0.13% of the index of gender segregation. Nonetheless, the coefficient of the squared term of total labour productivity is significant and positive, meaning that the link between productivity and gender segregation is nonlinear. This is found in column 3 of Table 2, where the quadratic term is included in the regression. At very low levels of total labour productivity, increasing productivity is linked to a reduction of segregation, whereas the same labour productivity gains unleash a positive effect in segregation when productivity is at mid-levels or higher. As of the coefficient of FLFP, the estimates associate rising participation of women in the paid workforce with decreasing gender segregation. One per cent increase of FLFP reduces the ID index by around 7% to 11%. This result agrees with the findings in Borrowman and Klasen (2020), who also find a negative effect of rising women's participation in the paid workforce in gender segregation. Column 4 considers five period-lagged independent variables to further consider serial correlation issues, with similar results on the focal variables of this analysis: a negative, nonlinear effect of total labour productivity on gender segregation, and a negative effect of rising FLFP in gender segregation.⁸

The significant control variables in the models in Table 2 are fertility, which exerts a strong, positive effect in gender segregation, and urbanization, which shows a small, positive effect. Rising fertility implies an increase in unpaid care responsibilities for women, thus constraining their participation in the paid labour market and increasing the crowding of women in certain sectors. Importantly, the positive effect of urbanization can be interpreted along the lines of the feminization U-shaped theories exposed in Section 2, and the limited opportunities for women's employment in high-productive sectors during the demographic transition of structural change. The FDI is related with a negative role in segregation, which might be along the lines of greater international competition forces and reduction of gender stereotypes and discrimination. Columns 5–8 in Table 2 replicate the analysis using an alternative measure of country-level gender segregation (IP), which yields similar results. Finally, it should be noted that the number of observations and groups (countries in the set of country-level panel data regressions) reduces considerably once the model incorporates the full set of controls. Ethiopia and Malawi are dropped from the sample as there is no sufficient temporal information available on trade data.

Figure 4 plots in detail the marginal effects of total labour segregation at different levels of productivity (based on Table 2, column 3). For low levels of productivity, the segregation effect is negative. Nonetheless, this negative effect reduces as productivity increases. For high levels of productivity, the effect is nonsignificant.

5.2 | Instrumental variables

The main result of this paper is that total labour productivity has a negative, although nonlinear, effect on gender sectoral segregation. However, a causal interpretation of the models above is limited by potential endogeneity issues. First, omitted variables that correlate with both gender segregation (dependent variable) and FLFP (independent variable) can cause the correlation between the latter and the residual. Another potential source of endogeneity is that both gender segregation and FLFP are determined simultaneously. Third, another source might be reverse causation, as gender segregation can also cause varying FLFP. This third endogeneity issue is discussed only from the surface in previous related works (Borrowman & Klasen, 2020) and is not directly tackled in the literature. However, instrumental variables can help to correct multiple endogeneity sources in the previous model.

In this subsection, I propose an instrumental variables approach that uses the size of the household, measured by means of the number of total members within the household (collected from the IPUMS-International), as an instrument for the ratio of the labour market participation of women. This instrument draws on previous literature that stresses the role of household composition in the participation of women in the labour market (Agarwal, 1997; Spierings, 2014). More recently, Dhanaraj and Mahambare (2019) employ data from India to find that, depending on whether they live in joint or nuclear families, women differ in their probability of working in the labour market. SSA households are among the biggest around the world (UN, 2019), with a sample average of five members, although there is also high cross-country heterogeneity in terms of level and evolution of the composition of the household in the database. I predict that larger families are a deterrent for women to join the paid workforce as it increases the burden of unpaid care work and that, ultimately, it depresses FLFP. At the same time, I consider that there is no direct link between household size and gender segregation, thus fulfilling the requirements of the IV strategy insofar as the instrument is not a driving factor of the outcome variable of the second stage. Figures A2 and A5 in Appendix A show further information on FLFP and the instrument.

Equations (4) and (5) provide, respectively, the first and second models of the instrumental variables model:

First-stage equation:

$$FL\tilde{F}P_{c,t} = \beta_0 + \beta_1 HHsize_{c,t} + X'_{c,t}\beta + \omega_{ct} \quad (4)$$

Structural equation:

$$Y_{(i)c,t} = \beta_0 + \beta_1 LF_{(i)c,t} + \beta_2 LP^2_{(i)c,t} + \beta_3 FL\tilde{F}P_{c,t} + X'_{c,t}\beta + \varepsilon_{(i)ct} \quad (5)$$

where $Y_{(i)c,t}$ can be either a dissimilarity index, an IP index, or an association index with pooled countries in specific industries.

Table 3 presents the instrumental variable results, using as dependent variables ID or alternatively IP indices. The estimates are similar to those in the previous section, although the threshold at which productivity increases segregation is lower in the IV estimates. Figure 5 plots the marginal effects of productivity in the ID index at different values of the former (column 1, Table 3), where the y-axis reflects the predicted effects in gender segregation at various levels of aggregate labour productivity (x-axis). Increasing labour productivity at low levels of productivity depresses gender segregation. However, in more productive economies, further productivity gains increase gender segregation. The threshold for this change of the effect is approximately at a value of 7 in the log-transformed aggregate labour productivity. Column 2 uses the IP index as dependent variable, as an alternative to ID index, showing

TABLE 2 Aggregate labour productivity and gender segregation (FE estimates).

Dependent variable	(1) ID	(2) ID	(3) ID	(4) ID	(5) IP	(6) IP	(7) IP	(8) IP
	5 years				5 years			
Aggregate labour productivity (log)	−0.137*** (0.012)	−0.185*** (0.042)	−0.414*** (0.044)	−0.521 (0.091)	−0.157*** (0.012)	−0.198*** (0.043)	−0.433*** (0.044)	−0.517*** (0.091)
Aggregate labour productivity sq			0.020*** (0.002)	0.026*** (0.005)			0.021*** (0.002)	0.026*** (0.005)
FLFP		−0.074*** (0.008)	−0X.111*** (0.008)	−0.103*** (0.013)		−0.074*** (0.008)	−0.113*** (0.008)	−0.102*** (0.013)
GDP pc (log)		−0.016 (0.069)	−0.130** (0.053)	−0.006 (0.061)		0.012 (0.070)	−0.105* (0.052)	0.019 (0.060)
Trade		0.001 (0.001)	0.000 (0.001)	0.004*** (0.001)		0.001 (0.001)	0.001 (0.001)	0.004*** (0.001)
FDI		−0.007*** (0.002)	−0.005*** (0.001)	−0.001 (0.001)		−0.006*** (0.002)	−0.005*** (0.001)	−0.001 (0.001)
Urban pop.		0.012** (0.005)	0.021*** (0.004)	0.042*** (0.007)		0.009 (0.005)	0.018*** (0.004)	0.040*** (0.007)
Fertility		1.687*** (0.197)	0.525** (0.209)	0.993*** (0.291)		1.554*** (0.206)	0.363 (0.212)	0.868** (0.300)
Gini disp.		0.013 (0.013)	0.026** (0.009)	0.062*** (0.010)		0.017 (0.014)	0.030*** (0.010)	0.062*** (0.010)
Education		−0.001 (0.003)	−0.002 (0.002)	−0.013*** (0.002)		−0.001 (0.003)	−0.002 (0.002)	−0.014*** (0.002)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	487	105	105	80	487	105	105	80
No. of groups	11	9	9	9	11	9	9	9
Within R ²	0.385	0.795	0.851	0.879	0.442	0.770	0.830	0.874

Note: Driscoll and Kraay standard errors in parentheses. All independent variables one period lagged (columns 1–3 and 5–7) or five periods lagged (columns 4 and 8). Dissimilarity index and IP index in logs. Ethiopia and Malawi are missing when using the full set of controls.

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

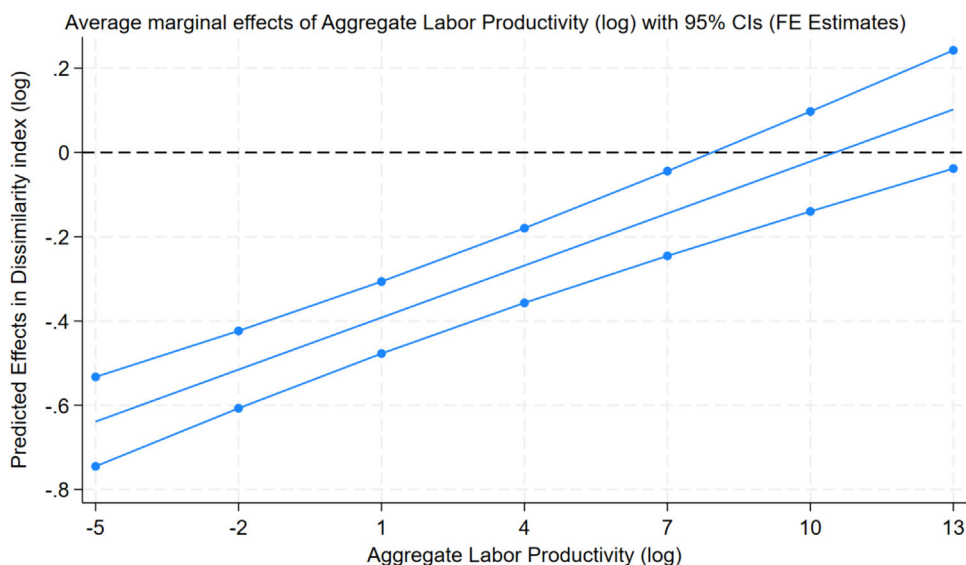


FIGURE 4 Marginal effects of labour productivity in gender sectoral segregation. Source: Based on regression results of model in column 3 in Table 2.

TABLE 3 Total labour productivity levels and gender segregation (instrumental variables).

Dependent variable:	(1) ID	(2) IP	(3) ID 5 years	(4) IP 5 years
Aggregate labour productivity (log)	-0.349*** (0.025)	-0.356*** (0.024)	-0.736*** (0.190)	-0.756*** (0.195)
Aggregate labour productivity (log) sq.	0.024*** (0.002)	0.023*** (0.001)	0.050*** (0.009)	0.050*** (0.009)
FLFP	-0.154*** (0.008)	-0.154*** (0.008)	-0.297*** (0.056)	-0.303*** (0.058)
Full set of controls	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes
No. of observations	60	60	46	46
No. of groups	7	7	7	7
Within R ²	0.971	0.972	0.962	0.961
First stage F stat	185.37	185.37	135.46	135.46
Underidentification test (Kleibergen–Paap rk LM statistic)	18.500	18.500	32.659	32.659
p value	0.000	0.000	0.000	0.000
Weak identification test (Kleibergen–Paap rk Wald F statistic)	26.589	26.589	18.666	18.666

Note: Driscoll and Kraay standard errors in parentheses. All independent variables one period lagged (columns 1 and 2) or 5-year period lagged (column 3 and 4). Dissimilarity index and IP index in logs. Kleibergen–Paap LM test null hypothesis is that the rank condition fails in second stage equation, that is, underidentified (Kleibergen & Paap, 2006). Kleibergen–Paap rk Wald F critical values varying between 5.53 and 16.38 (Stock & Yogo, 2005). Coefficient on the instrument in the first stage was negative (−0.68) and statistically significant at the 0.01 level for columns 1 and 2 and −0.32 at 0.05 level for the 5-year overlapping for columns 3 and 4. Countries in sample: Botswana, Ghana, Kenya, Nigeria, Senegal, South Africa, and Zambia. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

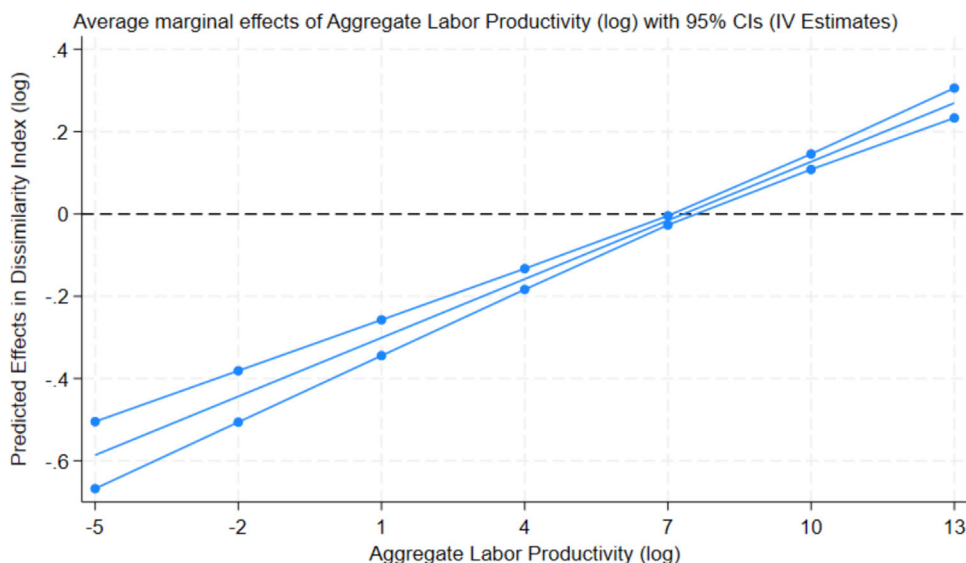


FIGURE 5 Marginal effects of aggregate labour productivity in gender sectoral segregation (IV estimates). Source: Based on regression results of model in column 1 in Table 3.

similar results. It should be noted that, when using the instrumental variables approach, the sample of countries is reduced as there is no information on the instrument (size of the household) for Mauritius and Tanzania. Columns 3 and 4 replicate the models using augmented, overlapping five-period lags of the independent variables. The results remain similar: aggregate labour productivity is associated with a negative effect in segregation, but its quadratic term is associated with a segregation-enhancing effect. Rising women in the paid economy, measured by FLFP, is associated with a negative coefficient; thus, higher participation of women in the labour market is linked to reducing gender sectoral segregation. The magnitudes of these coefficients are larger when using 5-year lags models.

I perform postestimation tests of the validity and weakness of the instrument. Concretely, I conduct the Kleibergen–Paap test for the underidentification of the first-stage regression because the models are computed using heteroscedasticity-robust standard errors. Further, the Kleibergen–Paap test is robust against violations of the i.i.d. assumption (Kleibergen & Paap, 2006). We reject the null hypothesis of underidentification at the 1% level of significance. As of the weakness of the instruments, the Kleibergen–Paap F statistic is higher than the standard rule-of-thumb of 10 and is beyond the critical values at any level of acceptable bias.

To delve deeper on this nonlinear relationship between aggregate labour productivity and gender sectoral segregation, I replicate the model in column 1 (Table 3) using partitions of the database on the basis of low-productivity and high-productivity country-level values. The critical value of aggregate labour productivity that sets the threshold for a positive link between productivity gains and gender segregation is provided in Table A2 in Appendix A. This value is also shown in Figure 5, which sets this value at of 7 of the log-transformed aggregate labour productivity. Using the subsample of low-productive observations (at country-year level), the estimates suggest that initial gains of aggregate labour productivity increase the dissimilarity index (the proxy of gender sectoral segregation), and further increases are associated to lower segregation, hence, an inverted-U-shape link between productivity and segregation. To the contrary, using the partition of the high-productive observations, the estimates show again the U-shaped nonlinearity between aggregate labour productivity and gender segregation by industries. These partitions provide further leverage to the main findings of the paper (see the estimates of this partitions in Table A3 in Appendix A).⁹

5.3 | Country-industry-level panel data estimates

$$A_{ict} = \beta_0 + \beta_1 RLP_{ic,t-1} + \beta_2 RLP_{ic,t-1}^2 + \beta_3 FLFP_{c,t-1} + X'_{c,t-1} \beta + v_{ict} \quad (6)$$

$$v_{ict} = \omega_i + \delta_c + \gamma_t + \varepsilon_{ict}$$

i = industry; c = country; t = year

Equation (6) uses as dependent variable the country-industry measure of gender segregation; namely, the association index ($A_{ic,t}$), ($RLP_{ic,t-1}$) is the relative labour productivity level, a standard measure of sectoral labour productivity that is computed as the ratio between labour productivity of sector i , country c , and time t to aggregate labour productivity in country c and time t (de Vries et al., 2015). Relative labour productivity level refers to the share of each sector in total labour productivity. The expected sign of the relationship between relative labour productivity in gender segregation at industry-specific levels is increasing, and this will confirm the results above. If increasing labour productivity by sectors exerts a positive effect in the association index, it will imply that this sector employs a higher proportion of women. To correspond to the previous results; however, the link between relative productivity and the association index should reverse at higher levels of the former. Thus, the quadratic term in the model in Equation (4) should be negative, implying that a high level of sectoral productivity creates a tendency to employ men. FLFP and the full set of controls, as explained in the previous section, are included in the country-industry panel data model.

Table 4 shows fixed-effects and IV estimates of the country-industry panel data model. Structural change is linked with an increasing feminization of sectors. However, the estimates confirm a nonlinear relationship between relative labour productivity and gender segregation. At high levels of relative labour productivity, further increases of productivity reduce the female employment in highly productive sectors. It should be noted that the explanatory power of the country-industry panel data models is lower relative to that of country panel data models presented above, as there is limited availability of data at country-industry level. Nonetheless, some insights from the results in Table 4 can be drawn related to fertility rates and income inequality. Fertility depresses the feminization of sectors, a result that can represent the higher unpaid care responsibilities that women shoulder with a rising number of children and a limitation to join the paid workforce (Bloom et al., 2009). Contrary to the country panel data models, income inequality exerts a significant role in the association index, reducing the presence of women in sectors using fixed-effects models. This result provides some empirical leverage to those in Borrowman and Klasen (2020), who find an increasing effect of income inequality in sectoral gender segregation using the dissimilarity index. When using an instrumental variables model, the coefficient associated with relative labour productivity is positive, and the coefficient of its quadratic term is negative. This suggests again that, for initial increases in relative productivity, sectoral feminization is increased, while further increases in relative productivity depress the presence of women. The effect of FLFP is not significant in the instrumental variables model.

Figure 6 shows IV estimates of the marginal effect of increasing relative labour productivity on the association index. The confidence intervals are reported in the graph, showing that, for certain levels of relative labour productivity, the effect is not significant. However, for low levels of relative labour productivity and high levels of relative labour productivity, the effect is significant. Further, I find again a reversal of the productivity link with segregation. As this last model uses the association index as the dependent variable, the interpretation of the estimates suggests that initial escalations in relative productivity increase the presence of women. However, further increases at already high levels of productivity are related to a decrease in women in the sector.

The last step in the empirical analysis of the role of structural change in gender sectoral segregation is to consider each sector separately. Hence, I replicate the IV model in Equation (6) using one sector at a time. By doing

TABLE 4 Structural change and industry-specific gender segregation (FE and IV estimates).

Dependent variable: Association index					
Regression model	(1) FE	(2) FE	(3) FE	(4) IV	(5) IV
Relative labour productivity	0.009***	0.029***	0.024**	0.004*	0.032*
Relative labour productivity sq	(0.002)	(0.009)	(0.009)	(0.002)	(0.016)
		−0.000**	−0.000**		−0.000*
		(0.000)	(0.000)		(0.000)
Aggregate labour productivity	0.084**	0.100***	0.133***	0.001	0.000
	(0.035)	(0.036)	(0.044)	(0.088)	(0.009)
FLFP			−0.009*	−0.002	−0.003
			(0.005)	(0.046)	(0.002)
GDP pc (logs)	0.024	0.037	−0.007	−0.004	0.030
	(0.020)	(0.022)	(0.037)	(0.153)	(0.019)
Trade	0.000	0.001	−0.000	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)
FDI	0.001*	0.001	0.001	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)
Urban pop.	−0.003	−0.000	−0.001	−0.004	−0.001
	(0.003)	(0.003)	(0.007)	(0.028)	(0.001)
Fertility (logs)	−0.315**	−0.254*	−0.561***	−0.005	−0.176**
	(0.131)	(0.141)	(0.174)	(0.832)	(0.086)
Gini net	−0.012**	−0.016**	−0.032***	0.002	0.000
	(0.005)	(0.006)	(0.009)	(0.073)	(0.002)
Education	0.000	−0.001	−0.000	0.001	−0.002**
	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)
No. of observations	1,456	1,456	1,027	790	790
No. of groups	89	89	89	69	69
Within R ²	0.028	0.040	0.063	0.010	0.024
First stage F stat				86.81	86.81
Underidentification test (Kleibergen–Paap rk LM statistic)				10.450	10.389
p value				0.0012	0.0013
Weak identification test (Kleibergen–Paap rk Wald F statistic)				8.345	8.319

Note: Driscoll and Kraay standard errors in parentheses (columns 1–3). Country-industry clustered standard errors in parentheses (columns 4 and 5). Kleibergen–Paap LM test null hypothesis is that the rank condition fails in second stage equation, that is, underidentified (Kleibergen & Paap, 2006). Kleibergen–Paap rk Wald *F* critical values varying between 5.53 and 16.38, and 6.66 at the 20% maximal IV size (Stock & Yogo, 2005). Coefficient on the instrument in the first stage was negative (−1.27) and statistically significant at the 0.01 level.

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

this, I am able to identify the role of structural change in each particular sector and, at the same time, consider the gender domination of each. Since the association index is not an aggregate measure of segregation, but a sector-level one, in interpreting separate models by sector, one should consider the general gender label of each sector.

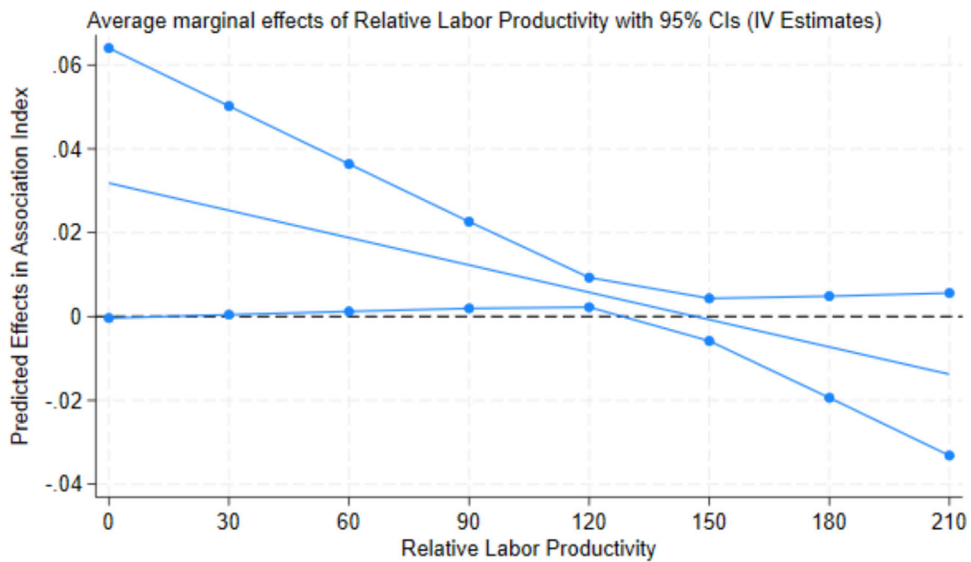


FIGURE 6 Marginal effects of relative labour productivity in association index. *Source:* Based on Regression results of model in column 5, Table 4.

Table 5 pools the 11 countries in the sample and focuses on regressions separately by each industry. The table provides information on the gender label of each sector, that is, F for female, M for male, and N for neutral (these categories were provided based on the average association index for each sector in the database). The only neutral sector is government services, where the rest are divided into F or M. To interpret the sign of the estimated coefficients, one should consider whether the sector is female dominated, male dominated, or gender neutral: a positive (negative) coefficient would imply an increase in gender segregation in a female-dominated (male-dominated) sector. A positive (negative) coefficient of a neutral sector will imply feminization (masculinization) of that sector.

The results provided in the regression models above are driven by certain industries such as manufacturing, utilities, construction, financial and business services, and government services, as these are the industries where relative productivity gains are found to have a significant link to gender segregation. Increasing relative productivity in manufacturing (column 3, Table 5), which is on average a female-dominated sector, probably due to the textile subsector, reduces the gender segregation of the sector, making it a more gender-neutral sector. However, I do not find a nonlinear link in this association, as the quadratic term of relative productivity is not statistically significant.

Rising relative labour productivity in utilities and construction (columns 4 and 5, Table 5) is associated with an increasing female representation in those sectors, but this reverses when this productivity gains occur in higher levels of relative productivity. Thus, for low levels of sectoral labour productivity, increasing productivity reverts the male domination of utilities and construction. This goes in line with the findings of Rendall (2013, 2017), suggesting that technological adoption and subsequent rises in productivity reduces the entry barriers of women in such sectors. So long as relative labour productivity is considered a proxy of technological upgrading, as in Seguino and Braunstein (2019) and Tejani and Kucera (2021), we can distil two opposing mechanisms behind the findings in the industry-level models. A *brawn* versus *brain* trade-off, as suggested by Rendall (2017), might induce the entrance of women in previously dominated sectors where physical demands are particularly important, as it is the case for utilities and construction. Nonetheless, the estimates of the quadratic term of relative labour productivity might suggest that it depends on the level of sectoral technological adoption. At certain levels of technological adoption, gender stereotypes and discriminatory hiring practices might countervail the gender equality gains of a *pro-brain* effect of rising productivity and induce the crowding of women in gender traditional sectors and low-productive sectors.

TABLE 5 Pooled industry-level regressions (instrumental variables).

Dependent variable: Association Index		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Agri.		Agri.	Mining	Manuf.	Utilities	Construction	Trade	Transp.	Fin. & Bus. Services	Government services	Personal services
Gender association		F	M	F	M	M	F	M	F	N	F
Relative labour productivity	Gender association	0.470	−0.044	−1.283**	0.140***	1.010*	1.132	−0.415	−0.148***	−0.304**	0.621
		(3.492)	(0.029)	(0.520)	(0.038)	(0.548)	(2.425)	(0.332)	(0.027)	(0.127)	(1.940)
Relative labour productivity sq	Gender association	−0.103	0.000	0.268	−0.002***	−0.409**	−0.117	0.055	0.003***	0.096***	−0.914
		(3.176)	(0.000)	(0.165)	(0.001)	(0.200)	(1.010)	(0.033)	(0.001)	(0.025)	(1.332)
FLFP	Gender association	−0.070**	0.192**	−0.108**	0.104*	0.027	−0.134**	0.082**	−0.068	−0.064*	0.001
		(0.032)	(0.081)	(0.040)	(0.061)	(0.107)	(0.059)	(0.040)	(0.042)	(0.033)	(0.035)
Aggregate labour productivity	Gender association	−0.096	0.429	0.032	0.352*	−0.280	−0.323	−0.465**	−0.040	0.071	0.046
		(0.175)	(0.463)	(0.105)	(0.203)	(0.441)	(0.303)	(0.221)	(0.148)	(0.123)	(0.104)
Full set of controls	Gender association	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Gender association	80	80	80	80	80	80	80	80	79	80
		7	7	7	7	7	7	7	7	6	7
No. of groups	Gender association	0.792	0.895	0.962	0.989	0.874	0.927	0.915	0.942	0.980	0.981
		7	7	7	7	7	7	7	7	6	7
Within R ²		0.792	0.895	0.962	0.989	0.874	0.927	0.915	0.942	0.980	0.981

Note: Country-industry clustered standard errors. Models are pooled by each of the 10 sectors in the ASD database. Gender association refers to the sample average of each sector: F refers to female-dominated, M refers to male-dominated, and N refers to gender-neutral industries. No data on government services for Zambia (column 9).

*p < 0.1. **p < 0.05. ***p < 0.01.

Increasing relative labour productivity of financial and business services (column 8, Table 5) reduces gender segregation, but again this is reversed as relative productivity is large enough. The heterogeneity of the subindustries considered in financial and business services, which also account for real estate, should be considered when interpreting this model, as the limited access of African women in the financial sector (Morsy, 2020) can be countervailed by the presence of women in small firms in real estate services.

Finally, government services (column 9, Table 5), which include care, health, and educational services, are the only industries on average that are gender-neutral sectors. Increasing relative productivity at low levels of that variable tilts the sector towards males, but further gains of productivity favour a more gender-balanced distribution in the sector. Gender equal access to education and the access of women to higher education in those countries where government productivity is high might be a potential mechanism behind these results.

6 | CONCLUSION

Development economics has long been directed at the role of structural change in understanding regional disparities in economic growth. Indeed, the role of structural change in sub-Saharan Africa is at the core of the economic development debates in recent literature. However, little is known regarding the gendered impacts of this transformation. Structural change produces composition shifts from low-productivity sectors to high-productivity sectors, both in terms of value-added and employment shares. These shifts are likely to affect women's and men's employment differently, mediated by complex interactions. This paper has documented a significant interplay between structural change and gender-sectoral segregation in a sample of sub-Saharan African countries.

Using a database with information on 10 sectors operating in 11 SSA countries during 1960–2010, I identify that those countries where gender segregation has decreased show, simultaneously, an increase in labour productivity. To consider the causal role of structural change in the gender distribution of sectoral employment, the paper specifies data models at both aggregate (country-year) and disaggregate levels (country-industry-year). Together with instrumental variable approaches, the results here suggest a nonlinear correlation between labour productivity and gender segregation.

This paper finds a nonlinear relationship between rising labour productivity and gender sectoral segregation. Initial gains in productivity increase female employment across sectoral levels. Nonetheless, further productivity gains imply increasing sectoral segregation by gender, possibly through higher barriers for women to enter highly productive sectors, and a crowding effect in the service sector. Another important result of this paper is in the role of female labour force participation in gender-sectoral segregation. Rising female labour force participation appears to reduce sectoral segregation, probably by changing cultural norms and eroding traditional gender roles in paid and unpaid work.

The main results of the paper remain when circumventing endogeneity issues of female labour force by using an instrumental variables approach. The estimates strongly support the view that fertility decline can equalize the gender distribution of sectoral employment. Urbanization and income inequality are generally associated with increasing segregation. Finally, the results do not associate economic growth with a significant role in gender segregation. Country-industry-level panel data estimates further allow identification of which specific sectors are mediated by structural change in the feminization or masculinization of employment. Specifically, the effects of structural change in gender-sectoral segregation in SSA seem to be mediated through manufacturing, utilities, construction, business, and government services.

These findings add to the general literature in structural change and gender-aware macroeconomics. There are important policy implications that can be derived from the empirical analysis here. First, the process of structural change comes along with complex transformations of the production of market and nonmarket activities, formal and informal sectors, as well as paid and unpaid work. A gender-sectoral perspective is needed to fully understand the implications of structural change for the whole economy and the workers. While female labour force participation is

found to reduce gender segregation, other factors of structural change, such as employment shifts in highly productive sectors, can countervail these gender equality trends. The interplays between the participation of women in the paid force and sectoral segregation can be interpreted as evidence that, as some gender inequalities are eroded, other, new types of inequalities emerge. Finally, declining fertility appears to be of first-order importance in promoting a gender-balanced distribution of sectoral employment.

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DATA AVAILABILITY STATEMENT

The data and replication materials of this paper are available from the author upon reasonable request.

ORCID

Izaskun Zuazu  <https://orcid.org/0000-0003-0638-2567>

ENDNOTES

- ¹ See Bettio et al. (2009) for a further insight in the distinction between vertical and horizontal segregation. For examples of structural analysis of gender vertical and horizontal segregation, see Borrowman and Klasen (2020) and Arora et al. (2023).
- ² It should be noted that the measure of structural change in Borrowman and Klasen (2020) is exclusively based on sectoral employment, with is at odds with the suggestion in Tregenna (2015) on that both employment and value added should be considered in studying the consequences of structural change.
- ³ Some countries start the time series at different years (Botswana: 1964; Ethiopia: 1961; Kenya: 1969; Malawi: 1966; Mauritius: 1970; Senegal: 1970; Tanzania: 1961; Zambia: 1965). Mensah and Szirmai (2018) updated the ASD although did not provide information on the female share of employment, and thus, the most recent year this paper utilizes is 2010. See de Vries et al. (2015) for more details on the ASD.
- ⁴ The statistical capacity of African countries suffered from limited funding and thus deteriorated the accuracy of estimates of informal economic activities. This should be considered when interpreting the descriptive and econometric analysis using ASD database (de Vries et al., 2013).
- ⁵ The IP index is given by the following formula: $IP = (1/T) \sum_{i=1}^n |F_i - a(M_i + F_i)|$, where T is total employment and a is the share of women in total employment. F_i and M_i correspond respectively to the number of women and number of men in sector i . See Watts (1998) for more discussion on segregation measures.
- ⁶ See Figure A4 in Appendix A for the evolution of A and relative labour productivity by sector.
- ⁷ Models using overlapping and nonoverlapping 5 years periods, which are available upon request, yield similar results as exposed in the paper.
- ⁸ Augmenting lagged periods is also employed in a related work by Tejani and Kucera (2021), to ensuring the exogeneity of the regressors.
- ⁹ I am thankful to an anonymous reviewer for suggesting this partition, which serves as a robustness check of the non-linear link between labour productivity and gender sectoral segregation.

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APPENDIX A

TABLE A1 Summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max	Data source
Aggregate labour productivity (log)	487	6.967	3.367	−4.158	14.568	ASD
Dissimilarity index (ID)	487	20.365	8.669	3.215	50.645	Own elaboration (ASD)
Karmel and MacLachlan index (IP)	487	9.76	4.076	1.568	25.0425	Own elaboration (ASD)
FLFP	105	60.893	16.225	32.197	87.109	ILO estimates
Education	105	32.033	24.05	2.667	93.737	Word Bank Database
GDP pc log	105	6.392	1.11	4.006	9.006	Word Bank Database
Trade	105	62.042	30.786	6.32	137.112	Word Bank Database
FDI	105	6.355	13.204	−24.478	165.275	Word Bank Database
Urban population	105	28.943	15.128	5.249	62.412	Word Bank Database
In Fertility	105	1.69	.357	.451	2.09	Word Bank Database
Gini net	105	46.281	7.863	31.795	60.336	SWIID Solt (2020)
Household size	85	5.117	1.409	3.61	9.39	IPUMS

TABLE A2 Marginal effects of aggregate labour productivity in dissimilarity index.

Aggregate labour productivity (log)	dy/dx	Delta-method St. err.	z	p value
−5	−0.586	0.042	−14.10	0.000
−2	−0.443	0.032	−13.93	0.000
1	−0.301	0.022	−13.55	0.000
4	−0.158	0.013	−12.28	0.000
7	−0.016	0.006	−2.77	0.000
10	0.127	0.01	13.25	0.000
13	0.269	0.019	14.52	0.000

Source: Based on regression results of model in column 1 in Table 3.

TABLE A3 Partitions of the database based on critical values of aggregate labour.

Dependent variable: ID		
	(1)	(2)
Regression model	IV	IV
Subsample based on level of aggregate labour productivity (log)	Low	High
Aggregate labour productivity (log)	15.704*** (0.000)	−1.983*** (0.312)
Aggregate labour productivity (log) sq	−1.645*** (0.000)	0.111*** (0.020)
FLFP	−16.359*** (0.000)	0.147* (0.076)
Full set of controls	Yes	Yes
Time fixed-effects	Yes	Yes
No. of observations	13	47
No. of countries	3	6
Within R^2	0.830	0.909

Note: Driscoll and Kraay standard errors in parentheses. All independent variables one period lagged. Dissimilarity index and IP index in logs. Column 1 (column 2) uses observations below (above) the critical value of aggregate labour productivity (log) as shown in Table A2.

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

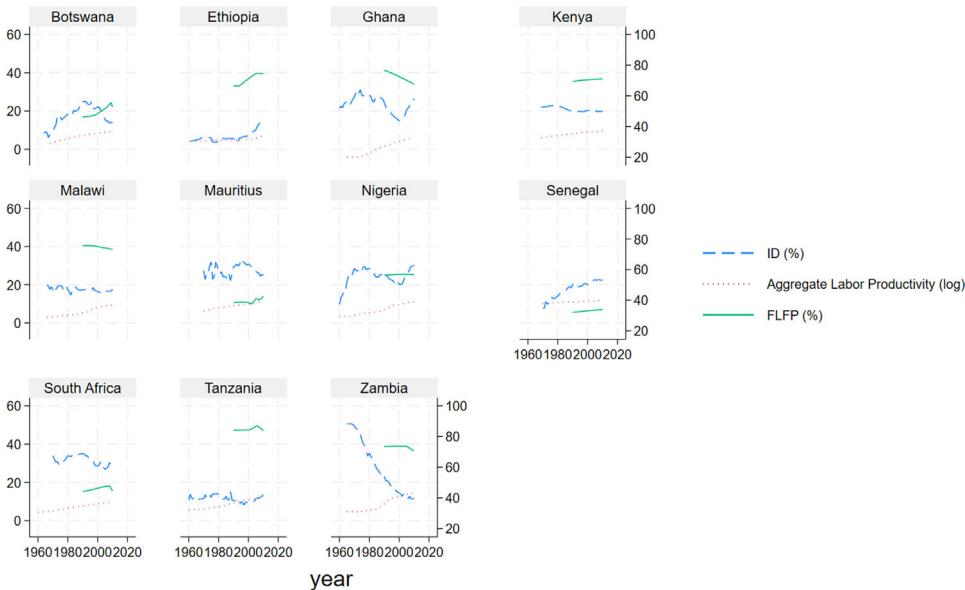


FIGURE A1 Country-level gender segregation, total labour productivity, and FLFP. Source: Own elaboration based on ASD and World Bank. ID is the dissimilarity index (%), FLFP is female labour force participation (%).

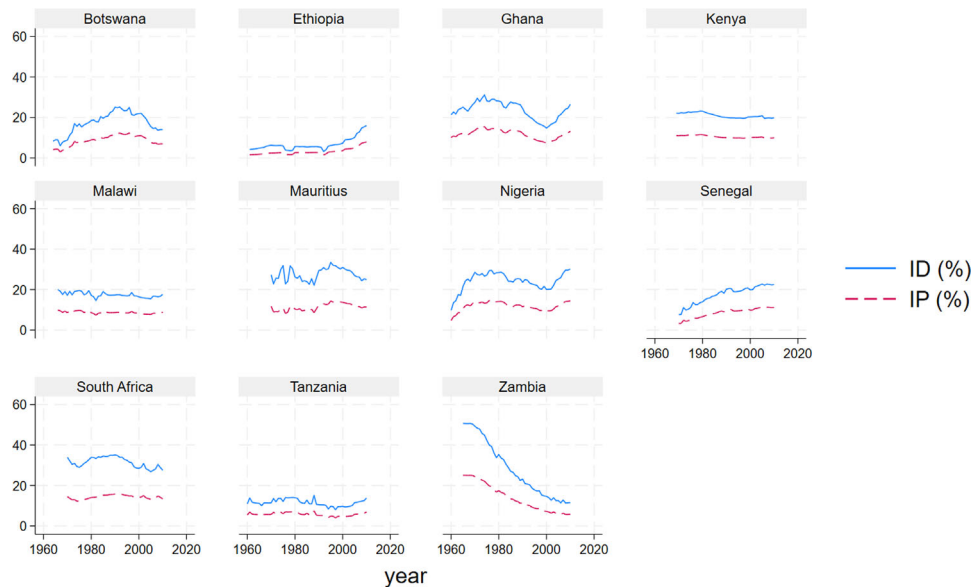


FIGURE A2 Alternative measure of gender segregation (IP Index). *Source:* Own elaboration based on ASD. ID is the dissimilarity index (%), IP is the Karmel and MacLachlan (1988) (%).

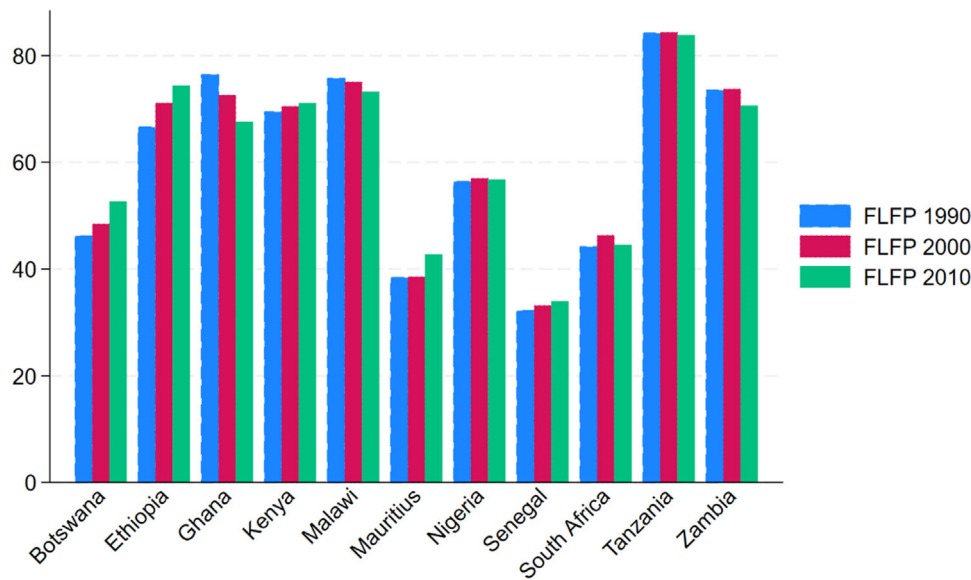


FIGURE A3 Stagnation of female labour force participation. *Source:* Own elaboration based on World Bank World Development Indicators (WDI) Database. FLFP is female labour force participation, in three points in time (1990, 2000, 2010).

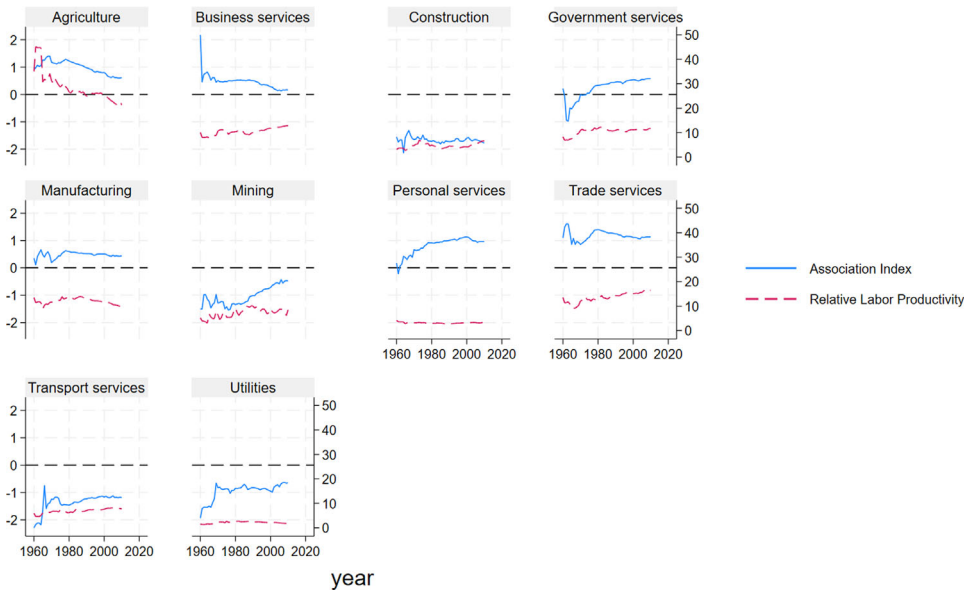


FIGURE A4 Industry-specific gender sectoral segregation. *Source:* Own elaboration based on ASD. Association index shows positive values for female-dominated sectors, values close to zero show gender neutrality of the sector, and negative values indicate a male-domination of the sector.

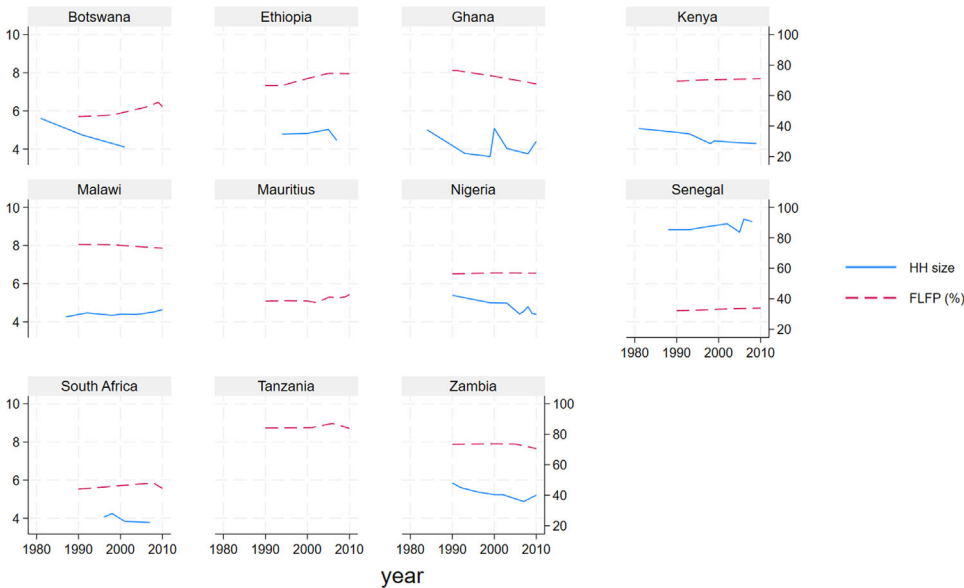


FIGURE A5 Instrumental variable for FLFP, household composition, and FLFP. *Source:* Own elaboration based on IPUMS and World Bank. HH size refers to household size, that is, the number of members living in the same household.