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Structural Change and Gender Sectoral Segregation in Sub-Saharan Africa

by

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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 analyzing 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 on a panel database consisting of 10 sectors and 11 countries during 1960–2010. Fixed effects and instrumental variables' regression models show a significant, non-linear link between labor productivity and gender segregation. Increasing labor 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 by considering relative labor productivity as a determinant of sectoral feminization. The estimates suggest that manufacturing, utilities, construction, business, and government services are key to correcting gender biases in employment along the process of structural change.

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

JEL CODES: 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 (Lewis 1965; Kuznets 1966) have been complemented by research on the impacts of general structural change on economic development (McMillan and Rodrik 2011; Herrendorf et al. 2014; McMillan et al. 2017; De Vries et al. 2021), the gender implications of such a transformation are less understood (Seguino and Were 2014; Dinkelman and Ngai 2022; Gottlieb et al. 2022).

This paper adds to the literature in structural change by analyzing whether and how labor productivity and gender segregation are linked in sub-Saharan African countries. The key argument of this paper is that labor productivity—computed as the ratio between value added and employment—might have a non-linear relationship to gender 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 and Braunstein 2019).

This paper empirically tests this hypothesis 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 country-sector 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 and 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 labor productivity.

I merge the ASD database with information on female labor 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 non-linear relationship between labor 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 labor 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 Karmel and MacLachlan (1988) index, 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

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). At the same time, structural change and the divergent patterns thereof have complex interactions with gendered labor market outcomes. It potentially transforms the pre-existing gender distribution of paid and unpaid work, comes with profound demographic movements and urbanization, and allows for technological diffusion at both market and home production levels (Boserup et al. 2013; McMillan et al. 2017; Uberti and Douarin 2022; Dinkelman and Ngai 2022). This section first historically contextualizes the general patterns of structural change in SSA countries. Second, it reviews the stylized facts on structural change and gender implications, together with the empirically-informed factors of gender segregation. Finally, it zooms in on specific implications of structural change in gender sectoral segregation in the region.

In the sample of SSA countries here considered, manufacturing expanded greatly from 1960 to 1975, corresponding to the shifts from subsistence agricultural societies toward modern manufacturing (De Vries et al. 2015). However, after 1970, the region suffered a political and economic turmoil which coincided with structural adjustment programs. These programs 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 the service sector whereas manufacturing shares remained low, which is coined as premature deindustrialization (Rodrik 2016) or even, deindustrialization without industrialization (Tregenna 2016).

The process of structural change can lead to domestic disparities, such as increasing income inequality (Lewis 1965; Kuznets 1966) and gender redistribution of paid work and unpaid household production (Gaddis and Klasen 2014; Uberti and Douarin 2022; Dinkelman and Ngai 2022). In this context, structural change is linked to the emergence of new types of paid work opportunities for women (Dinkelman and 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 US 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 labor 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 labor market participation. They also ensure that the non-linear 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 opportunists for paid work for women, as women have a comparative advantage in brain jobs. Beyond female labor 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 analyze 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 labor force participation with lower gender-sectoral segregation.[1]

Yeboah et al. (2022) also analyze the role of female labor force participation in structural change, but they do not focus on the implications for gender segregation, but rather, the extent to which rising female labor 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 labor 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

[1] 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.

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 labor productivity can favor female employment by considering that productivity might have a non-linear relationship with female employment in certain sectors. At sufficiently high levels of labor 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 and Braunstein 2019).

3 EMPIRICAL ANALYSIS

3.1 Data

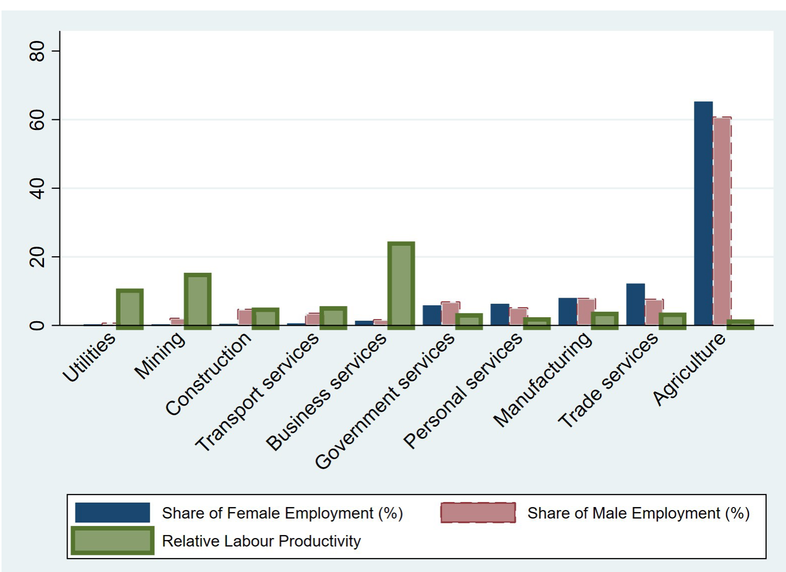
I collect data from the Africa Sector Database (ASD) produced by De Vries et al. (2015). This database provides sectoral-level disaggregated data (ISIC Rev. 3.1) on value added, employment and female share of employment for 10 sectors operating in 11 SSA countries, namely Botswana, Ethiopia, Ghana, Kenya, Malawi, Mauritius, Nigeria, Senegal, South Africa, Tanzania, and Zambia, during 1960 to 2010.[2] 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 labor productivity levels measured in domestic prices to comparable measures of labor productivity levels measured in international prices using the sectoral-level PPPs.

Figure 1 shows the sectoral distribution of female employment and male employment together

[2] 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 et al. (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.

with sectoral-relative labor productivity.[3] Agriculture concentrates the bulk of both female and male employment, with respectively 65 and 60 percent shares. To the contrary, the agricultural-relative labor productivity level is around 0.5 during the period, meaning that labor productivity in the sector is half that of the total economy. The trade services sector comprises a higher percentage of female employment (12 percent) than male employment (8 percent), 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 labor 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 labor-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.

Figure 1: Sectoral Shares of Employment by Gender and Relative Labor Productivity



Source: Own elaboration using the ASD

[3] 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).

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 (Duncan and Duncan 1955; Charles and Grusky 2005) 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]).

$$ID = \frac{1}{2}\sum_{i=1}^{n} |\frac{F_i}{F} - \frac{M_i}{M}| * 100$$
$$i = [1, ..., n] \quad (1)$$

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 percent in 1960 to 20 percent 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 and MacLachlan 1988) as an alternative measure of segregation, which serves also as a robustness check of the econometric models below. Figure

A2 in the appendix shows the evolution of ID and IP.[4] 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 labor-productivity levels. In 6 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 percent in 1970 to 23 percent in 2010.

At the same time, the growth rate of total labor productivity between 1970 and 2010 is the lowest in the sample (1.6 percent). 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 labor productivity in the period (10 percent).

Table 1: Gender Segregation and Labor Productivity Levels in Sub-Saharan Africa

	Dissimilarity Index (%)						Total Labor 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

[4] The IP index is given by the following formula:

$$IP = \left(\frac{1}{T}\right)\sum_{i=1}^{n}|F_i - a(M_i + F_i)|$$
$$i = [1, \ldots, n]$$

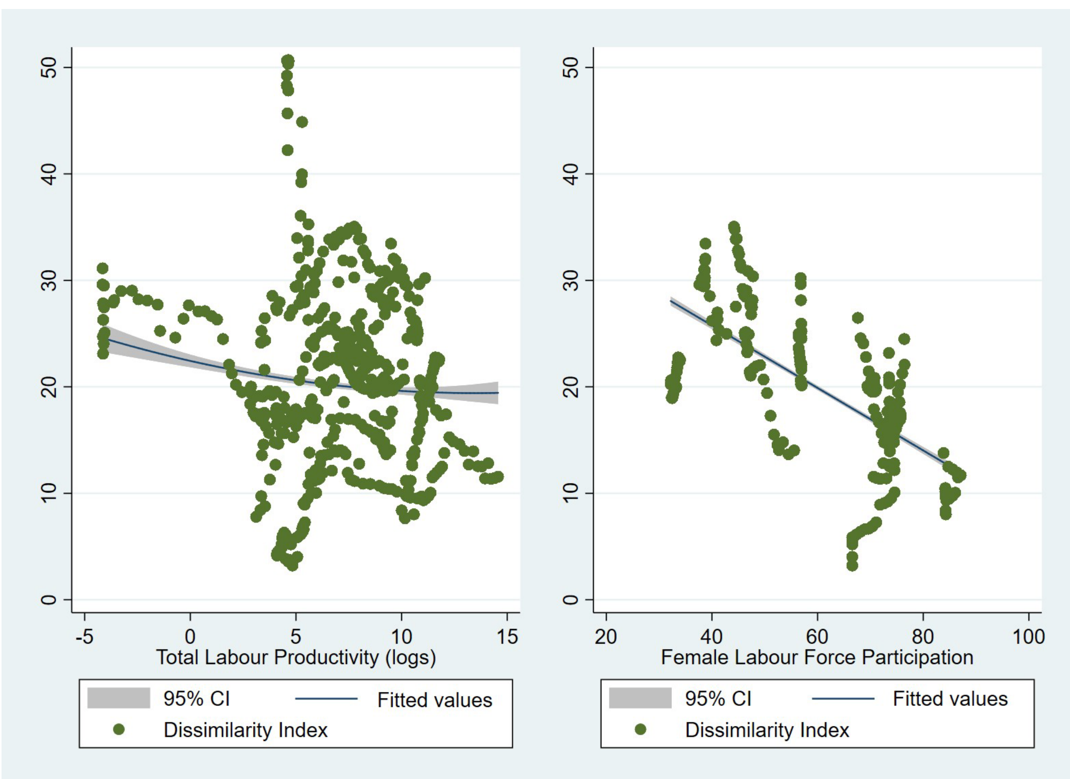
where T is total employment and a is the share of women in total employment. F_i and M_i correspond respectively to the number of women and number of men in sector i. See Watts (1998) for more discussion on segregation measures.

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

Figure 2 documents correlations between gender segregation (measured by ID) and either total labor productivity (in logs) in the left-hand graph or female labor force participation (FLFP) in the right-hand graph. At initial levels of labor productivity, gender segregation reduces. However, this curve is non-linear, as it flattens at higher levels of productivity. The stagnation of FLFP in SSA countries suggested in Backhaus and Loichinger (2021) can be seen in Figure 2 as well, as there is scarce variation of FLFP by country. In this case, there is a clear linear, negative association between increasing participation of women in the paid workforce and gender segregation.

Figure 2: Labor Productivity and Female Labor Force Participation in Gender Segregation



Source: Own elaboration using the ASD and ILO databases

There are limits to what can be discerned from aggregate cross-country analyses in the context of structural change and gendered impacts (Wamboye and 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 de-feminized or de-masculinized. To solve for this, in this paper, I combine the use of country-level measures of segregation (namely 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 labor market. Additionally, the A identifies which sectors are male-dominated, gender neutral, or female-dominated, and allows for better inter-temporal and cross-sectional comparisons than the indices explored above.

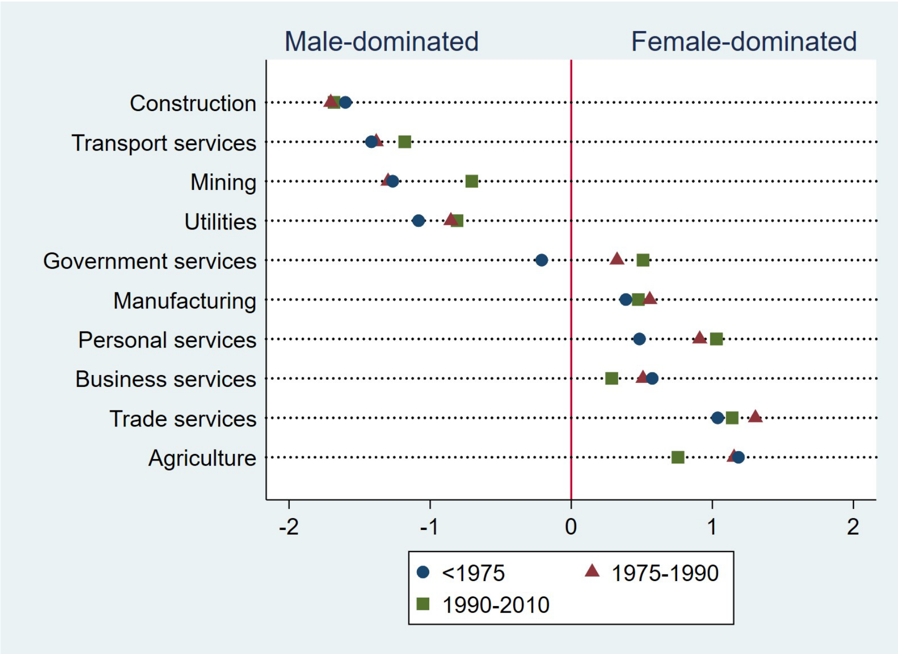
The formula for the A index is given by the following equation:

$$Ai = ln(\frac{F_i}{M_i}) - [\frac{1}{I} * \sum_{i=1}^{n} ln(\frac{F_i}{M_i})]$$
$$i = [1, ..., n] \tag{2}$$

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 under-representation in that specific sector, and positive values indicate female over-representation 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 and Bradley 2009; Zuazu 2020).

Figure 3 provides the sample average levels of the A index for different periods.[5] 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 1970–2010. 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.

Figure 3: Evolution of Industry-Level Gender Segregation



Source: Own elaboration using the ASD

[5] See Figure A4 in Appendix for the evolution of A and relative labor productivity by sector.

4 ECONOMETRIC SPECIFICATION

I explore the role of total labor productivity in gender 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 using ID or IP as outcome variables. To model a potential non-linear relationship between productivity and gender segregation, the regression model specifies gender segregation (measured by ID) as a quadratic function of (the log of) total labor productivity.

$$
\begin{aligned}
log(ID_{ct}) &= \beta_0 + \beta_1 LP_{c,t-s} + \beta_2 LP^2_{c,t-s} + \beta_3 FLFP_{c,t-s} + X'_{c,t-s}\beta + v_{ict} \\
v_{ct} &= \delta_c + \gamma_t + \epsilon_{ct} \\
c &= country; t = year \\
s &= [1,5]
\end{aligned}
\tag{3}
$$

IDct 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. LPc,t−1 corresponds to total labor productivity (in logs), that is, the ratio of total value added to total employment in the economy.

The e quadratic term of total labor productivity is included to test a non-linear relationship between structural change and gender segregation. $FLFP_{c,t-1}$ corresponds to female labor force participation in a country, whereas $X'_{c,t-1}$ 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 and Klasen 2020), but are concerned with the endogeneity biases caused by the inclusion of FLFP in the model (Klasen and Pieters

2015). As suggested by Borrowman and Klasen (2020), segregation can drive lower FLFP by reducing the opportunities of female paid labor, 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 and 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 labor 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 fFLFP in increasing feminization of service sector (Ngai and Petrongolo 2017).

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), urban population in percentage, fertility rate (in logs) and total enrollment in secondary 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). The full set of control variables includes a measure of income inequality (Gini net percent, collected from the Standardized World Income Inequality Database [SWIID] [Solt 2020]). The appendix includes a summary of descriptive statistics in Table A1 and the evolution of ID, total labor productivity, and FLFP in Figure A1.

Although it is not a perfect solution for reverse causation (Bellemare et al. 2017; Leszczensky and Wolbring 2022), all the independent variables are one-period lagged to help alleviate the strong and untestable strict exogeneity assumption at the contemporary level.[6]

I estimate equation (3) using fixed effects (within) regression models with Driscoll and Kraay (1998), standard errors which 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 labor productivity in gender segregation at a 1 percent level. Column 1 includes only total labor 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 percent increase in total labor productivity is related with reduction of around .5 percent and .13 percent of the ID. Nonetheless, the coefficient of the squared term of total labor productivity is significant and positive, meaning that the link between productivity and gender segregation is non-linear. This is found in Column 3 of Table 2, where the quadratic term is included in the regression. At very low levels of total labor productivity, increasing productivity is linked to a reduction of segregation, whereas the same labor 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 percent increase of FLFP reduces the ID index by around 7 to 11 percentage points. 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, non-linear effect of total labor productivity on gender segregation, and a negative effect of rising FLFP in gender segregation.

The significant control variables in the models in Table 2 are fertility, which exerts a strong, positive effect in gender segregation, and urbanization, that shows a small, positive effect. Rising fertility implies an increase in unpaid care responsibilities for women, thus constraining their participation in the paid labor 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.

Table 2: Total Labor Productivity Levels and Gender Segregation (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	ID	ID	ID	ID	IP	IP	IP	IP
				5-yr				5-yr
Productivity	-0.137***	-0.185***	-0.414***	-0.521***	-0.157***	-0.198***	-0.433***	-0.517***
	(0.012)	(0.042)	(0.044)	(0.091)	(0.012)	(0.043)	(0.044)	(0.091)
Productivity sq			0.020***	0.026***			0.021***	0.026***
			(0.002)	(0.005)			(0.002)	(0.005)
FLFP		-0.074***	-0.111***	-0.103***		-0.074***	-0.113***	-0.102***
		(0.008)	(0.008)	(0.013)		(0.008)	(0.008)	(0.013)
GDP pc (log)		-0.016	-0.130**	-0.006		0.012	-0.105*	0.019
		(0.069)	(0.053)	(0.061)		(0.070)	(0.052)	(0.060)
Trade		0.001	0.000	0.004***		0.001	0.001	0.004***

		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
FDI		-0.007***	-0.005***	-0.001		-0.006***	-0.005***	-0.001
		(0.002)	(0.001)	(0.001)		(0.002)	(0.001)	(0.001)
Urban pop.		0.012**	0.021***	0.042***		0.009	0.018***	0.040***
		(0.005)	(0.004)	(0.007)		(0.005)	(0.004)	(0.007)
Fertility		1.687***	0.525**	0.993***		1.554***	0.363	0.868**
		(0.197)	(0.209)	(0.291)		(0.206)	(0.212)	(0.300)
Gini disp.		0.013	0.026**	0.062***		0.017	0.030***	0.062***
		(0.013)	(0.009)	(0.010)		(0.014)	(0.010)	(0.010)
Education		-0.001	-0.002	-0.013***		-0.001	-0.002	-0.014***
		(0.003)	(0.002)	(0.002)		(0.003)	(0.002)	(0.002)
No. of Observations	487	105	105	80	487	105	105	80
No. of Groups	11	9	9	9	11	9	9	9
Within R-squared	0.385	0.795	0.851	0.879	0.442	0.770	0.830	0.874

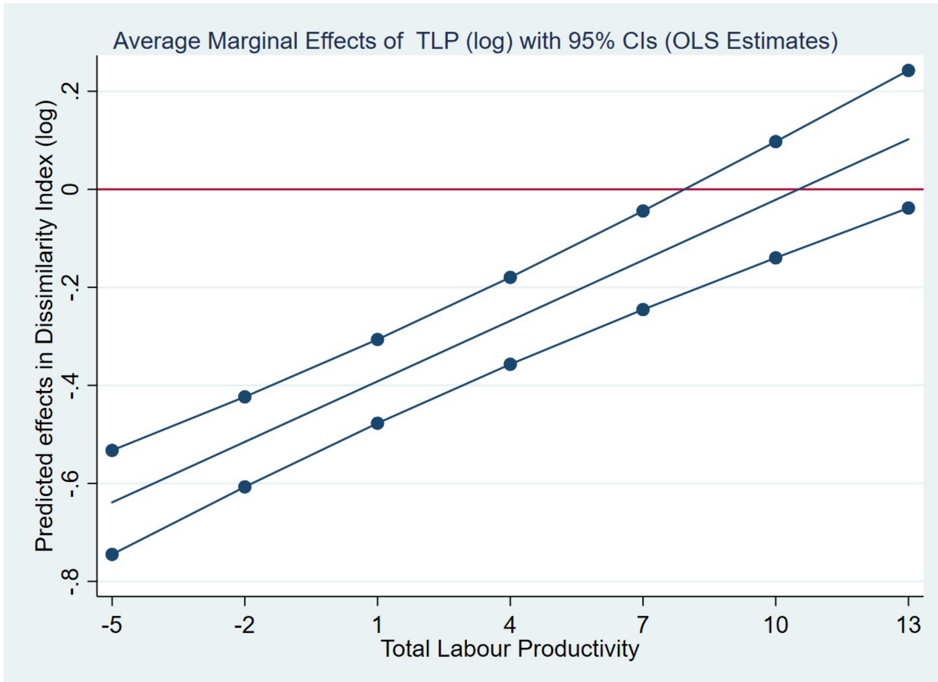
Driscoll and Kraay standard errors in parentheses Time fixed-effects included

All independent variables one period lagged (Columns 1–3 and 5–7) or 5 periods lagged (Columns 4 and 8) Ethiopia and Malawi are missing when using the full set of controls

* $p < .1$, ** $p < .05$, *** $p < .01$

Figure 4 plots in detail the marginal effects of total labor 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 non-significant.

Figure 4: Marginal Effects of Labor Productivity in Segregation



Source: Based on Regression results of model in Column 3 in Table 2.

5.2 Instrumental Variables

The main result of this paper is that total labor productivity has a negative, although non-linear, effect on gender sectoral segregation. However, a causal interpretation of the models above are 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. Thirdly, 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 and 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 labor market participation of women. This instrument draws on previous literature that stresses the role of household composition in the participation of women in the labor market (Folbre 1986; 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 labor 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 the appendix show further information on FLFP and the instrument.[8]

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

First-stage equation:

$$\widetilde{FLFP}_{c,t} = \beta_0 + \beta_1 HHsize + X'_{c,t}\beta + w_{ct} \tag{4}$$

Structural equation:

$$Y_{(i)c,t} = \beta_0 + \beta_1 LP_{(i),c,t} + \beta_2 LP^2_{(i),c,t} + \beta_3 \widetilde{FLFP}_{c,t} + X'_{c,t}\beta + e_{(i)ct} \tag{5}$$

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. Increasing labor productivity at initial low levels of productivity depresses gender segregation. However, as economies become more productive, further productivity gains increase gender segregation. 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 five-period lags of the independent variables. Whereas the main effect of total labor productivity remains, the signs of the quadratic term and FLFP inverse, and are related respectively with a negative and positive sign.

Table 3: Total Labor Productivity Levels and Gender Segregation (Instrumental Variables)

(1)		(2)	(3)	(4)
Dependent variable:	ID	IP	ID	IP
5-yr				
Productivity	-0.349***	-0.356***	-0.297***	-0.303***
	(0.025)	(0.024)	(0.056)	(0.058)
Productivity sq	0.024***	0.023***	-0.736***	-0.756***
	(0.002)	(0.001)	(0.190)	(0.195)
FLFP	-0.154***	-0.154***	0.050***	0.050***
	(0.008)	(0.008)	(0.009)	(0.009)
Controls	yes	yes	yes	yes
No. of Observations	60	60	46	46
No. of Groups	7	7	7	7
Within R-squared	0.971	0.972	0.9622	0.9613
First stage F-stat	185.37	185.37	135.46	135.46

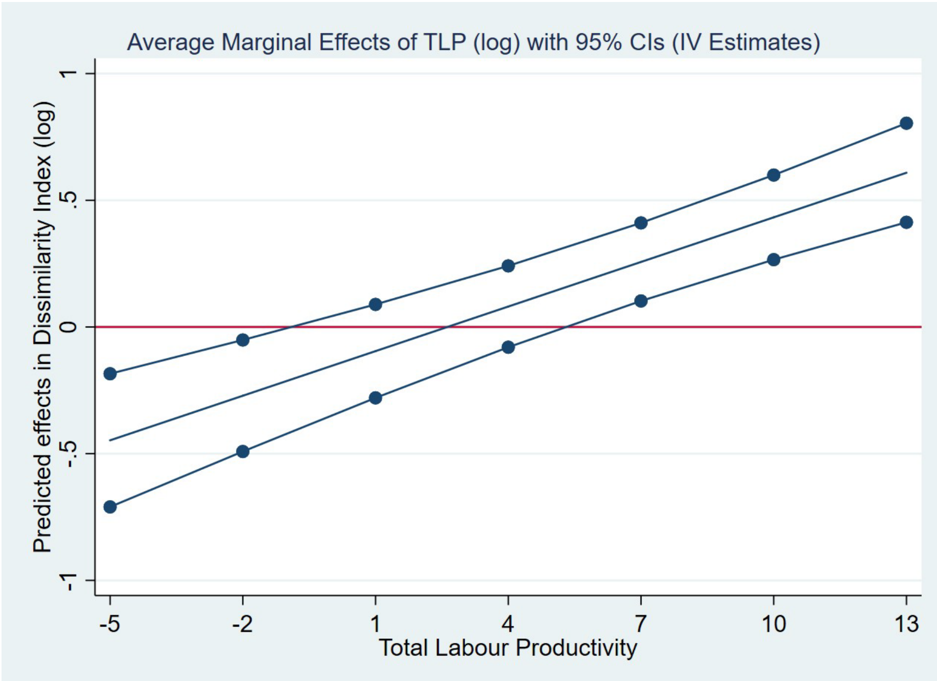
Driscoll and Kraay standard errors in parentheses Time fixed-effects included

All independent variables one period lagged

* $p < .1$, ** $p < .05$, *** $p < .01$

Coefficient on the instrument in the first stage was negative (-.68) and statistically significant at the 0.01 level for Columns 1-2 and -.32 at 0.05 level for the 5 year-overlapping for Columns 3–4

Figure 5: Marginal Effects of <u>Labor</u> Productivity in Segregation (IV Estimates)



Source: Based on Regression results of model in Column 1 in Table 3.

5.3 Country-industry-level panel data estimates

$$
\begin{aligned}
A_{ict} &= \beta_0 + \beta_1 RLP_{ic,t-1} + \beta_2 RLP^2 ic, t-1 + \beta_3 FLFP_{c,t-1} + X'_{c,t-1}\beta + v_{ict} \\
v_{ct} &= \omega_i + \delta_c + \gamma_t + \epsilon_{ict} \\
i &= industry; c = country; t = year
\end{aligned}
\tag{6}
$$

In equation (6), ($RLP_{ic,t-1}$) is the relative labor productivity level, a standard measure of sectoral labor productivity which is computed as the ratio between labor productivity of sector *i*, country *c* and time *t* to aggregate labor productivity in country *c* and time *t* (De Vries et al. 2015). Relative labor productivity level refers to the share of each sector in total labor productivity.[9] The expected sign of the relationship between relative labor productivity in gender segregation at industry-specific levels is increasing, and this will confirm the results above. If increasing labor 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 OLS 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 non-linear relationship between relative labor productivity and gender segregation. At high levels of relative labor 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 OLS 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 labor 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.

Table 4: Structural Change and Industry-specific Gender Segregation (OLS and IV Estimates)

Dependent variable: Association index					
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	IV	IV
Rel. productivity	0.009***	0.028***	0.023**	0.004*	0.032*
	(0.002)	(0.009)	(0.008)	(0.002)	(0.016)
Rel. productivity sq		-0.000**	-0.000**		-0.000*
		(0.000)	(0.000)		(0.000)
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	1456	1456	1027	790	790
No. of Groups	89	89	89	69	69
Within R-squared	0.028	0.040	0.063	0.010	0.024
First stage F-stat				86.81	86.81

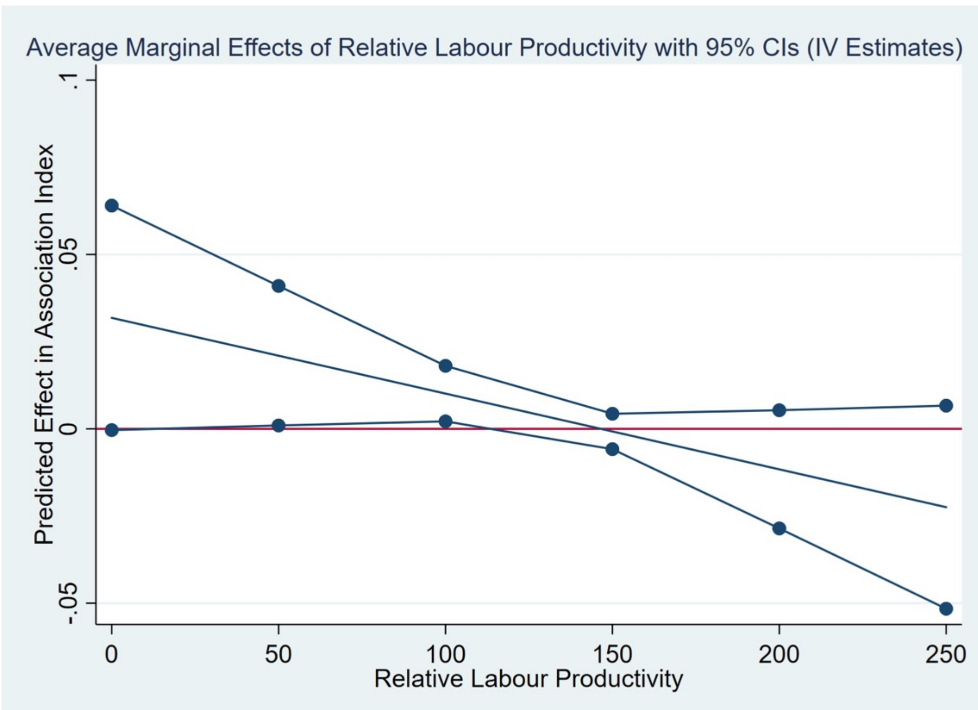
Driscoll and Kraay standard errors in parentheses (Columns 1-3) Country-industry clustered standard errors in parentheses (Columns 4-5)

* $p < .1$, ** $p < .05$, *** $p < .0$

Coefficient on the instrument in the first stage was negative (-1.27) and statistically significant at the 0.01 level

Figure 6 shows IV estimates of the marginal effect of increasing, relative labor productivity on the association index. The confidence intervals are reported in the graph, showing that, for certain levels of relative labor productivity, the effect is not significant. However, for low levels of relative labor productivity and high levels of relative labor 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.

Figure 6: Marginal Effects of Relative Labor Productivity in Association Index



Source: Based on Regression results of model in Column 5, Table 4.

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 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.

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, 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 reduces gender segregation, and I do not find a non-linear link (as the quadratic term of relative productivity is not statistically significant). Rising relative productivity of utilities and construction reduces gender segregation (as it has a positive effect in male-dominated sectors), but this reverses as relative productivity becomes sufficiently large. Finally, increasing the relative productivity of business services reduces gender segregation, but again this is reversed as relative productivity is large enough, and for government services, initially increasing relative productivity tilts the sector toward males, but further gains of productivity favor a more gender-balanced distribution in the sector.

Table 5: Pooled Industry-level Regressions (Instrumental Variables)

Dependent variable: Association index	(1) Agri.	(2) Mining	(3) Manuf.	(4) Utilities	(5) Construction	(6) Trade	(7) Transp.	(8) Business	(9) Government	(10) Personal
Gender association	F	M	F	M	M	F	M	F	N	F
Rel. productivity	0.859	-0.037	-1.288**	0.139***	0.906**	0.520	-0.126	-0.147***	-0.312**	0.505
	(3.200)	(0.024)	(0.536)	(0.041)	(0.442)	(2.160)	(0.307)	(0.026)	(0.120)	(1.900)
Rel. productivity sq	-0.431	0.000	0.271	-0.002***	-0.379**	0.101	0.024	0.003***	0.094***	-0.849
	(2.904)	(0.000)	(0.170)	(0.001)	(0.170)	(0.916)	(0.031)	(0.001)	(0.025)	(1.311)
FLFP	-0.062**	0.166**	-0.111***	0.079	0.053	-0.119**	0.108***	-0.065	-0.070**	-0.002
	(0.028)	(0.078)	(0.037)	(0.053)	(0.096)	(0.058)	(0.033)	(0.045)	(0.030)	(0.031)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
No. of Observations	80	80	80	80	80	80	80	80	79	80
No. of Groups	7	7	7	7	7	7	7	7	6	7
Within R-squared	0.792	0.895	0.962	0.989	0.874	0.927	0.915	0.942	0.980	0.981

No data on Government services for Zambia (Column 9)

* $p < .1$, ** $p < .05$, *** $p < .01$

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 labor 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 non-linear correlation between labor productivity and gender segregation.

This paper finds a non-linear relationship between rising labor 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 labor force participation in gender-sectoral segregation. Rising female labor 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 labor 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 countries 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 non-market 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 labor 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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APPENDIX

Table A1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Data Source
ln TLP	487	6.967	3.367	-4.158	14.568	ASD
ID	487	20.365	8.669	3.215	50.645	Own elaboration (ASD)
IP	487	9.76	4.076	1.568	25.0425	Own elaboration (ASD)
FLFP	105	60.893	16.225	32.197	87.109	World Bank WDI
Education	105	32.033	24.05	2.667	93.737	”
GDP pc log	105	6.392	1.11	4.006	9.006	”
Trade	105	62.042	30.786	6.32	137.112	”
FDI	105	6.355	13.204	-24.478	165.275	”
Urban population	105	28.943	15.128	5.249	62.412	”
ln Fertility	105	1.69	.357	.451	2.09	”
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

Figure A1: Country-level Gender Segregation, Total Labor Productivity and FLFP

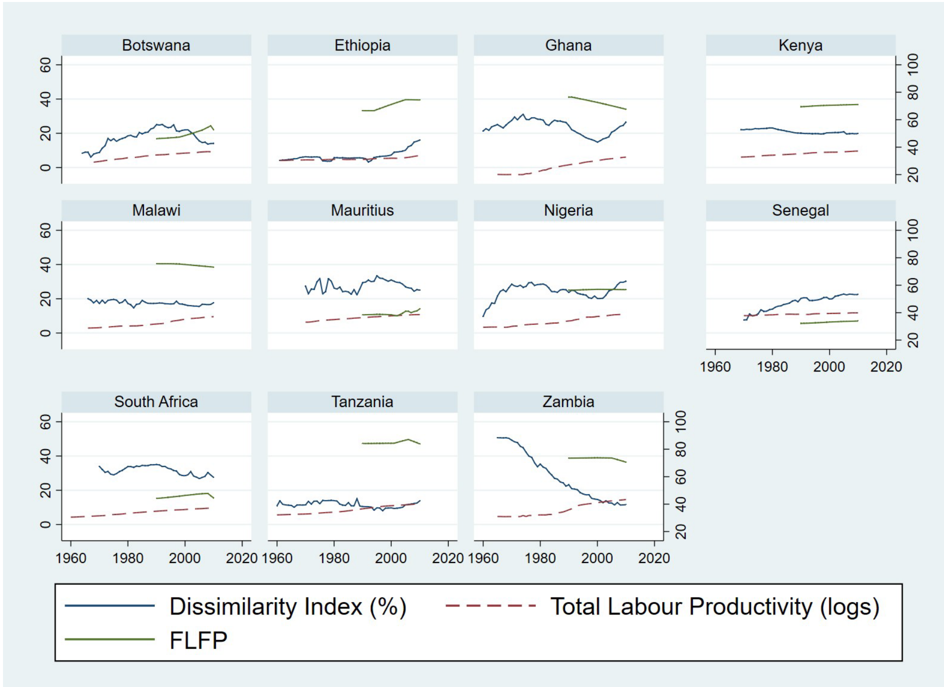

Figure A2: Alternative Measure of Gender Segregation (IP Index)

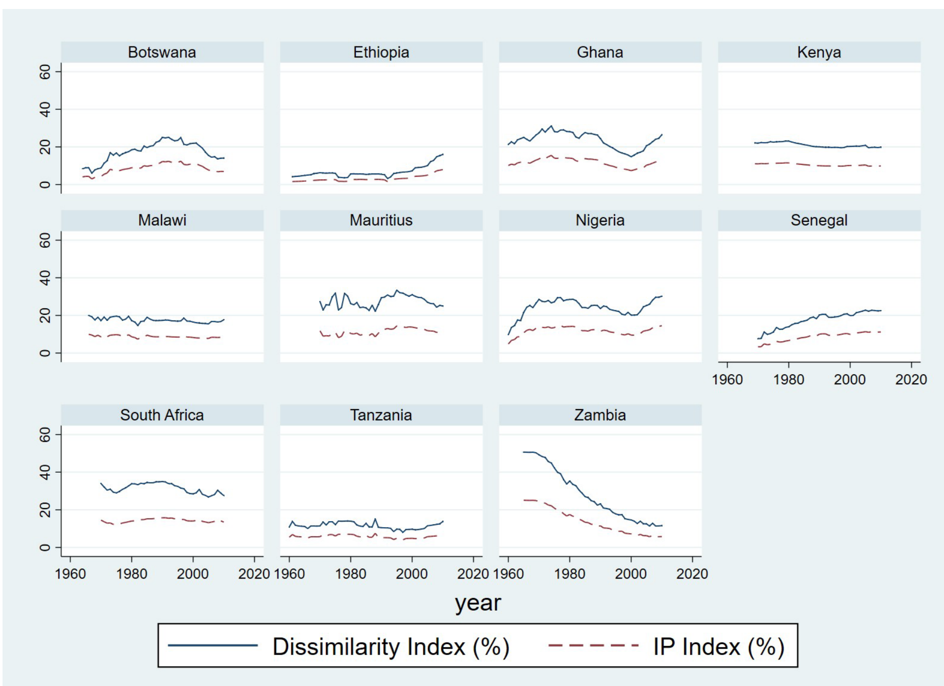

Figure A3: Stagnation of Female Labor Force Participation

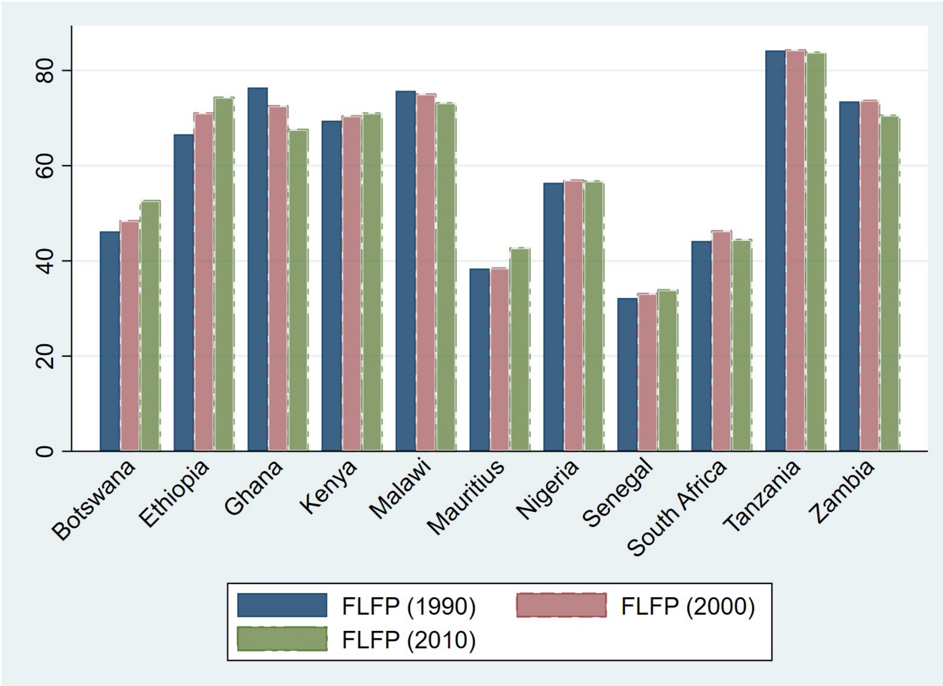

Figure A4: Industry-specific Gender Sectoral Segregation

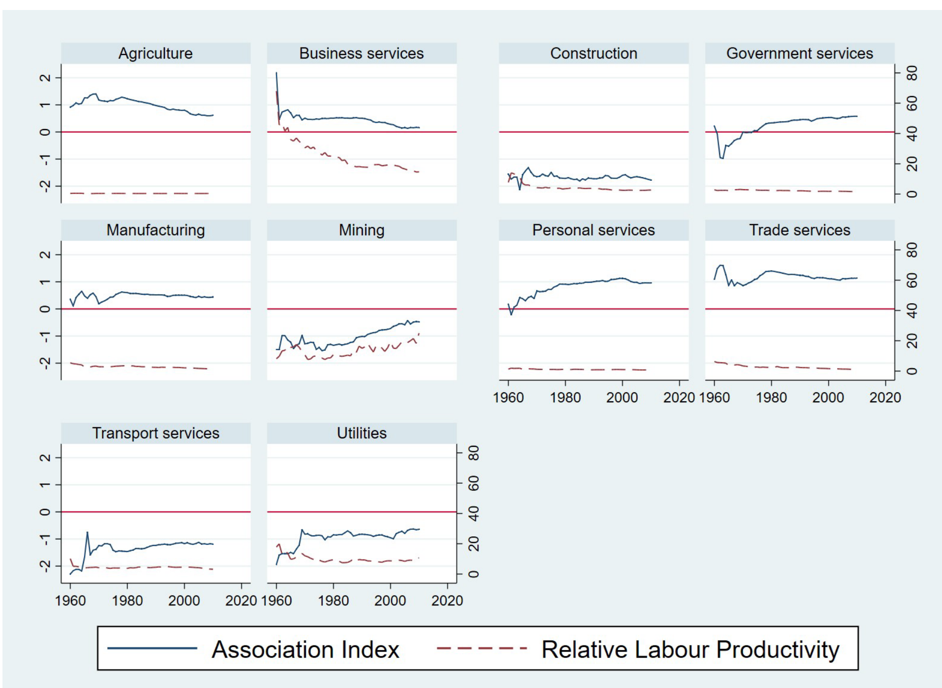

Figure A5: Instrumental Variable for FLFP, Household composition and FLFP