

**Improving Labor Market Outcomes for Skilled Women in
Kisumu County**

Grant Proposal

Trade and Development
(2025-P-01)



AFRICA CENTER
FOR STRATEGY & POLICY
ACSTRAP

© 2025 Africa Center for Strategic Policy

The economic projections and policy recommendations presented here emanate strictly from the Trade and Development (TD) staff, which do not entirely represent the views of ACTRAP's management team. This report is publicly available.

**Africa Center For Strategic Policy
Headquarters, USA:
1300 I St NW, Suite 400 E,
Washington, D.C 20005**

**Africa Center For Strategic Policy
Headquarters, Africa:
Britam Towers, 24th Floor
Hospital Road, Upper Hill
P. O. BOX 12295-00100
Nairobi, Kenya**

TRADE AND DEVELOPMENT GROUP- GRANT PROPOSAL

This was written by Dr. Moon Oulatta approved for by the Chief Editor. This grant proposal was written at the Africa Center for Strategic Policy.

First release, October 27, 2025



Contents

1	Objective	4
2	Significance	7
3	Supporting Empirical Evidence	8
4	Survey Methodology	11

1. Objective

Women account for more than 50 percent of the working-age population in Sub-Saharan Africa [3]. However, Figure 1 corroborates the widely held view that gender inequality in the labor outcomes remains an unequivocal problem in Sub-Saharan Africa [2].

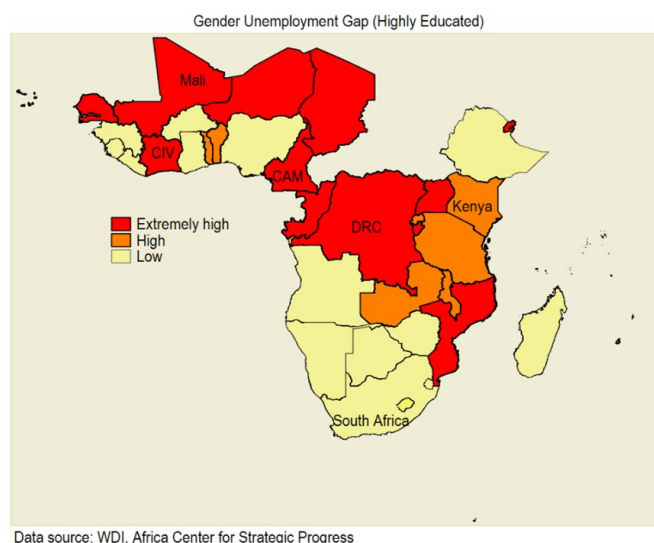


Figure 1.1: Gender Gap (Sub-Saharan Africa): Skilled Labor

For Kenya, the latest observable statistics indicate that women remain underrepresented in all wage employment sectors [5].¹ Even so, the proportion of informal employment in non-agriculture employment in Kenya is approximately 44 percent for females in contrast to 56 percent for males [7]. More importantly, as shown in Figure 2, women employment in the non-informal sector is on

¹The number of women employed in manufacturing declined from 79000 in 2013 to 49000 in 2016. For Kenyan women, this drastic collapse in wage employment was also observed in the wholesale sector.

declining trend, whereas men employment in the modern sector is rampant in all wage employment sectors in Kenya.

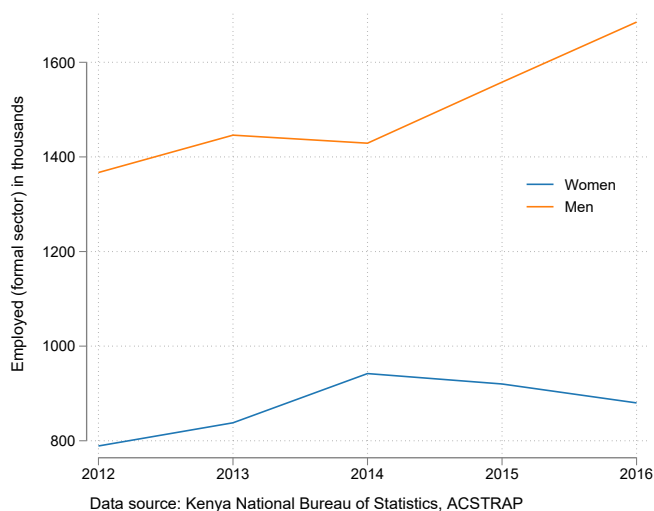


Figure 1.2: Modern Sector Employment (Kenya): Gender Gap

For highly educated Kenyan women, the latest world development indicators evince that the unemployment rate is approximately 28 percent higher in contrast to Kenyan men with similar educational attributes [2]. Another stylized fact worth highlighting is that unemployment among educated women is extensively high in Kenyan counties where women make up a sizable proportion of the working-age population (for example, Kisumu county). In Kisumu county, the 9.3 percent of female residents with secondary education or higher are unemployed, which is surprisingly higher in contrast to females with either no education or just primary education [6]. Evidently, recent studies support evidence of higher levels of underemployment and unemployment among highly educated women in the East African Community [1].

For Sub-Saharan African countries, the empirical literature on gender inequality in the labor market focuses extensively on the youth and the informal sector. Few studies address the issue highlighted here: which is the predicament of high unemployment and underemployment among highly educated women in Sub-Saharan African countries. Expectedly, the latest data collected world development indicators reiterate that the latter issue remains acute in Kenya and other emerging African countries. Figure 1 portrays the gender unemployment gap for the highly educated population in various African regions. The data projected in Figure 1 reiterate that gender inequality in the labor market remains acute in Sub-Saharan Africa. As suggested in the empirical literature, this latter problem emanates from multiple factors discussed in this paper.

In general, women labor market choices tend to be influenced by their background, financial constraints, socioeconomic conditions, and the pressure to kowtow to traditional gender roles (International Labor Organization 2018). Other less known variables such as discouragement, marginal attachment, and mismatch in skills are likely to be instrumental in understanding the low participation rate of skilled women in the non-agricultural sector in Sub-Saharan Africa. Regrettably for researchers, the data needed to compute these latter variables are rarely available in most countries in Sub-Saharan Africa, especially at the county level: hence the principal motivation in this study.

USAID's 2020 gender analysis report indicates that most Kenyan women participate in the Agricultural sector, rather than participating in wage employment, i.e., primarily the modern sector [4]: hence the key issue that this study highlights and seeks to understand. Although the agricultural sector in Kenya plays a significant role in reducing poverty, gender inequality and women disempowerment in the labor market remains an abhorrent reality that rarely gets exposure in the empirical literature.

Firstly, the motivation behind this study hinges on the desire to improve labor outcomes for educated women in Kenya, by identifying the key factors that contribute to the low participation rate of women observed in the formal sector. Secondly, the Africa Center for Strategic Policy (ACSTRAP) aims to rely on this study's findings as means to design a policy intervention program in coordination with the location universities and domestic companies to create a testable labor program capable of enhancing the participation rate of skilled women in the non-agricultural sector.

As discussed in Chapter 1, Kisumu County exemplifies the main issue highlighted in this study: overall, women account for the largest proportion of the working age population, but they remain underrepresented in most wage employment sectors [6]. Using Kisumu County as the main case study, the first part of this project aims to:

1. Develop a survey questionnaire capable of generating demographic and social economic data about Kisumu's educated population (for example, ACSTRAP will collect data on age, tribal affiliation, gender, marital status, income, education, and employment status).
2. Conduct multiple focus group discussions (FGD) to get a better sense of understanding of the challenges that skilled women face in Kisumu's the labor market.
3. Compute three indices for skilled females: (i) an unorthodox gender unemployment gap, which excludes the underemployed population, (ii) a mismatched in skills index, (iii) a social economic development index.
4. Conduct a study that aims to identify the underlying drivers of unemployment among skilled women, by disaggregating unemployment status in three components: (i) voluntary unemployment, (ii) involuntary unemployment, (iii) and underemployment, which will be considered as unemployed.
5. Develop the basis for a policy intervention, by identifying a randomly selected treatment and control group of skilled females workers who will be participating in the second phase of the study.

2. Significance

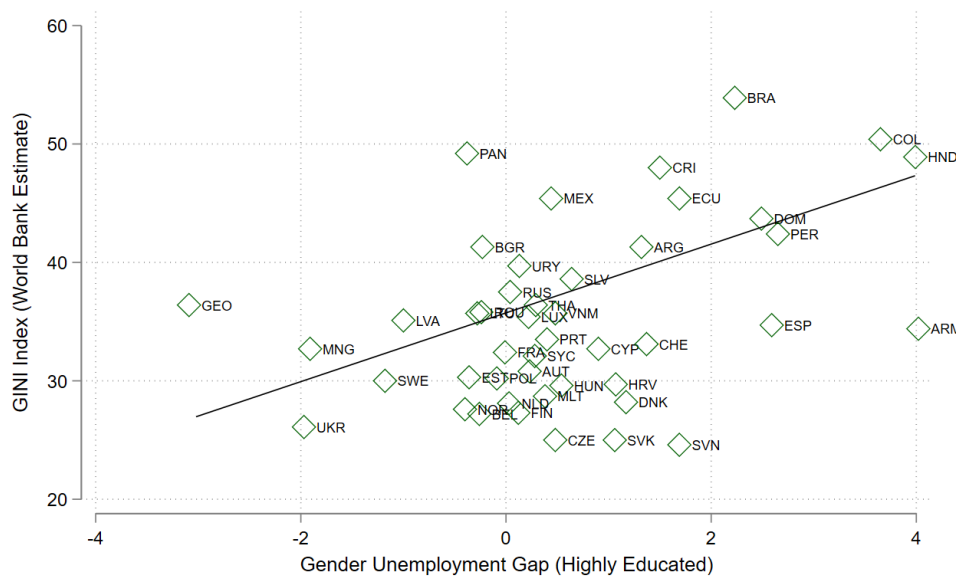
Firstly, this study is significant, because it provides an opportunity to collect specific data about skilled females which are not currently available at the county level in Kenya. The survey questionnaire devised in this study will equip future researchers with adequate information to efficiently assess unemployment conditions among skilled workers at the county level. Secondly, ACSTRAP has a unique strategy to develop a policy intervention program capable of alleviating the probability of women being mismatched in the labor market in Kisumu County. If successful, this approach may serve as model for multiple countries in Sub-Saharan Africa.

Labor market outcomes influence productivity and long-term growth. In theory, productivity is a negative function of unemployment. Empirical findings corroborate the latter claim: Bräuninger and Pannenberg (2002) show that rising unemployment impedes labor productivity growth. Moreover, underemployment is also a potent source of market failures, because of the resulting inefficient allocation of resources, which eventually causes loss of income and consumption in the economy.

The low participation rate of women in the formal sector observed in Kisumu reinforces the necessity to conduct this study. The outcome of this study will be instrumental for Kisumu's policymakers for two specific reasons. Firstly, policymakers will gain insights on the causes of underemployment, including the several types of unemployment that buffet educated women in Kisumu County. Secondly, by relying on this study's findings, politicians in Kisumu County will be better informed and equipped to build policies that can foster employment for educated women and consequently reduce labor market frictions. Figure 3.1 strengthens the importance of the issue highlighted here: gender inequality in the labor market proxy by the gender unemployment gap for skilled workers explains close 35 percent of variation in income inequality across the world.

3. Supporting Empirical Evidence

Using the latest cross-sectional data collected from the World Bank, this section estimates the casual effect of the gender unemployment gap for highly educated individuals on the GINI index (income inequality index) as means to demonstrate the magnitude of the effect of gender inequality in the economy and the relative importance of the issue raised here. The cross-sectional sample utilized in this section only includes one African country (Seychelles), due to data unavailability. The unavailability of labor market data for the highly educated population in Sub-Sahara Africa is another gap found in the literature that this study aims to fill with the fruition of this research.



Data source: Africa Center for Strategic Policy, WDI

Figure 3.1: Gender Unemployment Gap (Skilled) and Inequality

Given the linearity observed between the main variables in Figure 3.1, it is reasonable to model the relationship between income inequality and the gender unemployment gap via the linear regression as follows

$$g = X\beta + \varepsilon \quad (3.1)$$

Due to data unavailability, the data set contains a sample of 43 countries from every region of the world, excluding the following regions: West Africa, East Africa, Central Africa, and South Africa. The sample is assumed to be a random sample: each observation is independent and identically distributed and outliers were removed from the sample. Equation (1) models a linear relationship between income inequality (g) and k regressors over n observations (the sample size contains 43 countries). g is an (43×1) column vector which captures the observations of the dependent variable, β is a $(k + 1) \times 1$ vector of unknown population parameters that need to be estimated using the appropriate linear estimators. X is a $43 \times (k + 1)$ matrix of explanatory variables (for example, domestic credit provided by banks and the unemployment gap for skilled workers). ε is an (43×1) column vector, comprising the random errors. First, this study relies on the ordinary least squares (OLS) estimator to estimate the unknown population parameters of the model as follows

$$\gamma_{OLS} = (X'X)^{-1}X'g \quad (3.2)$$

Nonetheless, estimating equation (3.1) via OLS directly does not guarantee that the distribution of error term is independent of the regressors, particularly because it is possible to assume that the direction of causality maybe bi-directional: the other case where it is the inequality in income that drives the gender unemployment gap for highly educated people. If the condition of reverse causality holds in equation (3.1), then one can conclude that the gender unemployment gap is endogenous and no longer strictly exogenous. The endogeneity problem arises from the fact that the gender unemployment gap ($ungap$) is now correlated with the error term as follows

$$cov(X, \varepsilon) \neq 0 \quad (3.3)$$

The condition derived in equation (3.3) violates the GAUS-Markov assumptions, which means that relying on the OLS estimator to estimate equation (3.1) should lead to a bias estimate of the effect of the gender unemployment gap on income inequality. Therefore, to avoid the latter problem, this section proposes to rely on the efficient generalized method of moment (GMM) estimator. In the presence of heteroskedasticity, the GMM estimator is superior to other instrumental variables estimators such as the two-stage least squares estimator (2SLS). The efficient GMM estimator is defined as follows

$$\beta_{GMM} = (X'Z\delta^{-1}Z'X)^{-1}X'Z\delta^{-1}Z'g \quad (3.4)$$

where X includes all the regressors (both the exogenous and endogenous covariates) and Z is a matrix of instruments. Here, the gender unemployment gap is the main variable that is being instrumented. This section relies on the inflation rate (CPI), labor laws indexes, and the level of gross agricultural production as instruments for the gender unemployment gap.¹

The optimal weighting matrix is a function of the covariance matrix of the instruments (moment conditions). The optimal weighting matrix serves a specific function: it is used to minimize the

¹ $(\delta)^{-1}$ is the optimal weighting matrix referred to by Hansen (1982).

asymptotic variance of the estimators, which is useful to minimize the possibility of making a type-2 error. It is important to acknowledge that weighing the instruments only affects efficiency, but not the consistency of the estimators. Using the residuals of the IV-estimator, one can compute a consistent estimator for the optimal weighting matrix: where weights are assigned based on the strength of the relationship observed between the instrument and the endogenous variable. Table 3.1 reports the main empirical estimates. The three estimators yield significant parameters estimates.

	(OLS) GINI	(OLS) GINI	(2SLS) GINI	(GMM) GINI
UNGAP	2.158*** (0.770)	2.078*** (0.767)	4.316*** (1.591)	3.795** (1.648)
CREDIT		-0.0529*** (0.0193)	-0.0470** (0.0222)	-0.0556*** (0.0206)
_cons	34.06*** (1.035)	37.70*** (1.924)	36.04*** (2.136)	36.63*** (1.969)
<i>N</i>	45	43	43	43
<i>R</i> ²	0.173	0.231	0.046	0.119

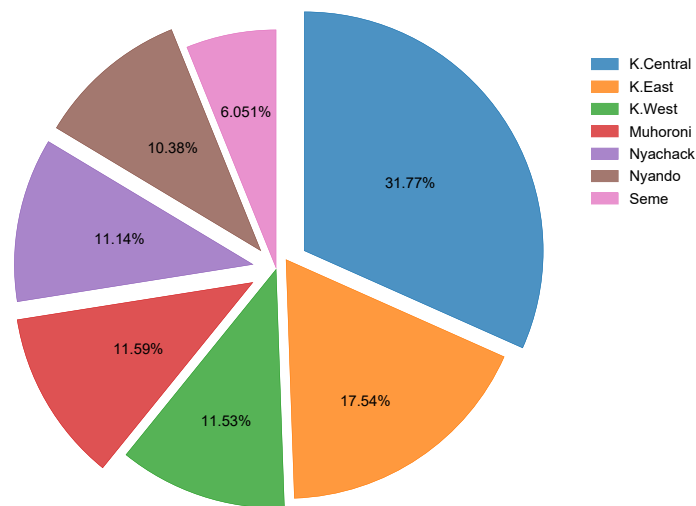
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 3.1: Supporting Empirical Evidence

4. Survey Methodology

Geographically, Kisumu County is administratively divided into constituencies and wards. Therefore, the survey methodology focuses on the seven constituencies of Kisumu County: Kisumu East, Kisumu Central, Kisumu West, Seme, Muhoroni, Nyando, and Nyakach. The population of interest is the adult population (for example, females and males who are heads of households) with at least secondary education or higher. Available data indicates that approximately 42 percent of Kisumu’s residents have access to secondary education or higher [6]. Figure 4.1 portrays the proportion of residents with secondary education or higher across the seven constituencies in Kisumu County.



Data source: Kenyan National Bureau of Statistics, ACSTRAP

Figure 4.1: Secondary Education or Higher (% of Residents): Kisumu County

The sample population consists of:

- Women of working-age 15 to 64 years with secondary education or higher.

- Men of working-age 15 to 64 years with secondary education or higher.

The survey questionnaire serves the purpose of collecting quantitative data. On the other hand, the focused group discussions (FGDs) and key informant interviews provide a qualitative approach to the data collecting process. Here, the main objective is to select a representative sample size of the target population. Cochran's approach is a valid method for achieving the latter objective, particularly because the degree of variability in the population is unknown. Consider the following equation

$$n_0 = \frac{Z^2 pq}{e^2} \rightarrow 384 \quad (4.1)$$

where equation (4.1) denotes the Cochran's approach for estimating the required sample size. There is always room for error when drawing a sample from a population. Here, this study argues for a 95 percent confidence level: this implies that if multiple samples of the same size were to be selected from the population, the probability of selecting an accurate representative sample of the population is 95 percent. Unsurprisingly, the sample size (n_0) in equation (4.1) is an increasing function of the critical value associated value the confidence level (Z); which means that choosing a higher confidence of level minimizes the probability of selecting an inaccurate sample of the population.

The degree of variability (p) in the population is unknown. However, we can make a reasonable assumption regarding p . The higher the heterogeneity in the population, the higher the sample size. Following the literature, a proportion of 50 percent is selected, which indicates the maximum level of variability.¹ The degree of precision implied by (e) is the sampling error: the margin error that one is willing to tolerate in selecting a sample size from the population. Here, this section considers a ± 5 percent margin error.

The required sample size based on equation (4.1) works out to be 384 units per gender group. However, given the fact that the educated population in Kisumu is known from the latest census report,² the sample size can be adjusted as follows

$$n_1 = \frac{n_0}{1 + \frac{(n_0-1)}{N}} \rightarrow 383 \quad (4.2)$$

Alternatively, given the known population, the sample size can also be estimated by relying on Slovin's approach as follows

$$n_2 = \frac{N}{1 + Ne^2} \rightarrow 399 \quad (4.3)$$

This section prioritizes Slovin's approach for estimating the sample size. Consequently, using the target population (males and females heads of household with secondary education or higher), the sample size per constituency is estimated by using equation (4.3). The primary sampling units (PSUs) for each constituency are reported in Table 4.1. Next, two wards are randomly selected from each constituency,³ and the PSUs are distributed across 14 wards (for example, see Figure 4.2).

¹Note that ($q = 1 - p$).

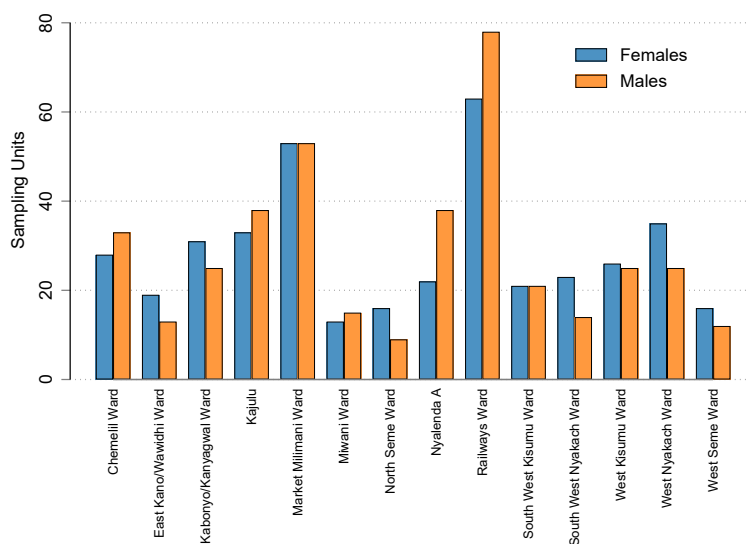
²Note that N represents the population size.

³Each ward is given an equal probability of being selected.

<i>Constituency</i>	Females		Males	
	<i>Population</i>	<i>Sample</i>	<i>Population</i>	<i>Sample</i>
K. East	8240	55	28424	76
K. West	7081	47	16994	46
K. Central	17292	116	49127	131
Seme	4772	32	7945	21
Nyando	7507	50	14194	38
Muhuroni	6195	41	18090	48
Nyakach	8651	58	14627	39

Table 4.1: Kisumu: Population (Secondary+)

In addition to the quantitative technique, this study introduces a qualitative approach to the data collection process as a means to better understand the labor market in Kisumu. The objective is to conduct FGDs among women aged 15-64 years to learn from their experience in the labor market.



Data source: Africa Center for Strategic Policy

Figure 4.2: Sampling Distribution (Males and Females With Secondary Education or Higher)

References

- [1] Abel Egessa. Determinants of youth unemployment in Uganda: Binomial Logit Model Approach. *Master dissertation, Makerere University, Kampala, Uganda, 2020.*
- [2] World Bank Group. World development indicators. <https://wdi.worldbank.org>, 2016. [Last Accessed: June, 2 of 2022].
- [3] World Bank Group. World development indicators. <https://wdi.worldbank.org>, 2020. [Last Accessed: June, 2 of 2022].
- [4] Aurelia Munene Victoria Rames Mia Hyun, Wendy Okolo and David Morgan. Usaid's kenya final gender analysis report. <https://banyanglobal.com/wp-content/uploads/2020/05/USAID-Kenya-Final-Gender-Analysis-Report.pdf>, 2020. [Last Accessed: June, 2 of 2022].
- [5] Kenya National Bureau of Statistics. Women and men in kenya facts and figures. <https://www.genderinkenya.org>, 2017. [Last Accessed: June, 2 of 2022].
- [6] Kenyan National Bureau of Statistics. Exploring kenya's inequality. <https://www.knbs.or.ke>, 2013. [Last Accessed: July, 12 of 2022].
- [7] Kenyan National Bureau of Statistics. Sdg gender fact sheet. <https://www.knbs.or.ke>, 2021. [Last Accessed: June, 2 of 2022].