

Structural Transformation and Youth Labor Market Dynamics in Morocco: An Econometric Analysis of Employment Patterns, Gender Disparities, and Sectoral Transitions.

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Abstract

The research paper explores the multifaceted nature of youth labor market performance in Morocco, with the aim of studying the patterns of employment, gender differences and occupational changes among the youth aged between 15-35 years. We use a rich econometric model that includes a logistic regression model, multinomial logit model, Oaxaca-Blinder decomposition, and machine learning models to examine the probability of employment, sector allocation, and wage determination using microdata of the Moroccan High Commission for Planning (HCP) of the Labor Force Survey (2015-2024) and recent 2026 cross-section data. We find that there are still gender disparities in the labor market (female employment is 32 % lower than the male) with significant urban-rural differences in employment, and acute education-employment mismatches especially among the tertiary trained youth. About 45% of young workers are absorbed in the informal sector: the segment is heavily heterogeneous in terms of gender and level of education. Instrumental variable estimation provides the solution to the issue of endogeneity; we show that family background and regional labor market conditions play a significant role in determining youth employment outcomes. Decomposition analysis indicates that differences in gender employment gap can be explained by differences in discrimination / preferences (68% of the gender employment gap) and not by differences in endowments. Predictions of machine learning determine education quality, sector-related skills, and geographic mobility as crucial predictors of employment. Policy implications include active labor market policies that are specific, vocational education and training in line with sectoral needs, gender-based policies and structural reforms to ensure reduced informality and improvement of job quality among the younger Moroccan population.

Keywords

Youth unemployment, labor market transitions, gender gap, informality, Morocco, econometric analysis, Oaxaca decomposition

Introduction

The problem of youth unemployment is one of the most urgent socioeconomic issues in Morocco, which has an immense economic growth, social integration, and human capital development implications. Even with significant economic growth over the last 20 years, Morocco has been experiencing a sustained high rate of youth unemployment with the level of 25-30%, which is significantly higher than the national average and the global inflation (World Bank, 2024; International Labour Organization, 2024). Several structural barriers are unique to the youth labor market: an education-employment gap has continued to widen, there are strong gender disparities in the labour force participation, informal labour is increasing, and there is a sharp urban-rural gap in opportunity structures.

The conceptual basis of explaining youth labor market performances is based on various sources of economic literature. The human capital theory (Becker, 1964; Mincer, 1974) is based on the idea that the investments, in terms of education and training, lead to the improvement of productivity and, as a result, to employability. Nonetheless, the Moroccan setting shows that there are considerable exceptions to this canonical model because the unemployment rate among the tertiary-educated youth is higher than that of the secondary-educated one (HCP, 2024). This is often referred to as the over-education trap, and implies market failure in the skill formation, signalling, or labour demand composition.

Search and matching models (Pissarides, 2000; Mortensen and Pissarides, 1994) help shed further light on unemployed persistence and focus more on the impediments to the labor market process, reservation wages, and the contribution of labor market institutions. Morocco has two labor markets: the formal sector, with strict employment protection and the large informal sector, which has flexibility but lacks social protection, and these frictions are different, in terms of the geographical region and demographic groups.

Gender division of the labor market, which has been widely reported in Middle East and North African (MENA) settings (Assaad, 2014; Amin and Al-Bassusi, 2004), is symptomatic of discrimination on the demand side and constraints on supply such as social roles, family duties, and limited mobility. The Moroccan female labour force participation is still among the lowest in the world with an average of 25 as compared with 71 (World Bank, 2024) and this has high variation across age cohort, education level and marital status.

The paper adds to the existing empirical literature on MENA youth labor markets and the overall development economics in various aspects. As an initial step, we give a deep econometric analysis of the workforce situation in Moroccan youth taking into account recent microdata covering 2015-2026, including time-series variation as well as cross-sectional one. Second, in this study, we use a methodologically sound design which integrates both traditional econometric models (logistic regression, multinomial choice models, decomposition methods) and modern machine learning algorithms (random forests, gradient boosting) to detect the determinants of employment and make an out of sample predictions. Third, we directly confront endogeneity issues with instrumental variable estimation utilizing family background variables and regional labor market conditions as instruments to well-labor market education and migration choices which may also be endogenous. Fourth, we perform a large-scale heterogeneity study, with respect to the analysis of the employment dynamics between genders, education levels, urban-rural living, and sectors. Lastly, we will multicate empirical results to specific policy suggestions that will be based on the institutional and economic environment of Morocco.

The results of the empirical work lead to a number of findings. The estimation of logistic regression shows that female youth have a 32 % lower probability of employment than similar males, and even larger disparities are observed between married women and those in rural areas. The results of multinomial logit indicate that given employment, women are 2.3 times more likely to be employed in the informal sector than they are in the formal wage employment. Oaxaca-Blinder decomposition explains 68 % of the gender employment gap by differentials to characteristics (unexplained component) as opposed to differences in characteristics (explained component), which implies there is a lot of discrimination or discrimination based on gender in the labor market or preference differences. Education has non-linear impact on employment likelihood: secondary data upgrades the employment prospects by 40% of that of primary education, whereas tertiary education indicates no considerable gain and, in certain specifications, the negative coefficient of education over-education phenomenon. The fact that urban residence has been linked with increased employment likelihood of 15% but with increased exposure to formal sector unemployment since the informal sector opportunities are located in rural areas. The model of machine learning predicts with a 78% out of sample accuracy, indicating that geographic mobility, sector-specific vocational training, and family network effects represent predictive features of high importance.

The subject of this article is the analysis of youth labor market dynamics in Morocco, with a specific focus on employment patterns, gender disparities, and sectoral transitions among youth aged 15 to 35 years. The primary objective of this study is to identify and quantify the structural determinants of youth employment outcomes in Morocco, combining microeconomic analysis of individual-level characteristics with aggregate sectoral trends over the period 2015–2026. More specifically, the research seeks to (i) estimate the probability of employment as a function of gender, education, geographic location, and household characteristics; (ii) analyze sectoral allocation and informality using multinomial modeling; (iii) decompose the gender employment gap into explained and unexplained components; (iv) address endogeneity in education and migration decisions through instrumental variable estimation; and (v) generate predictive insights using machine learning algorithms. The remainder of this article is organized as follows: Section 2 presents a review of the theoretical and empirical literature on youth labor markets; Section 3 describes the data sources, variable construction, and the econometric framework; Section 4 reports the empirical results; Section 5 provides a discussion of the findings in relation to the existing literature and their policy implications; and Section 6 concludes with a summary of key insights and directions for future research.

1. Literature Review

Economics of youth labor markets is based on a number of theoretical traditions that are complementary to each other. The theoretical basis of the relationship between education investment and productivity and labor market performance is human capital theory (Becker, 1964; Mincer, 1974). Schooling in this view increases the competences that increase the anticipated incomes and work opportunities. Nonetheless, the signaling and screening models (Spence, 1973; Arrow, 1973) also stress that education can also serve as a signal of unobserved ability when the situation is typified by imperfect information. These models are specifically useful in labour markets where employers base on credentials to assume productivity, particularly with young employees with short records of employment.

The unemployment patterns amongst the youth are further brought to light by the dynamic job search and matching models (Mortensen and Pissarides, 1994; Pissarides, 2000). These models suggest that unemployment is an equilibrium process caused by search frictions, imperfect matching and wage bargaining. The young workers are relatively more prone to unemployment because of lack of experience, poor productivity indicators and high rate of job separation at the initial stages of their career. Although these predictions appear to be supported by empirical

data in the advanced economies in general (Shimer, 2012), in the context of developing countries, we need expansions that take into consideration informality, weaker application of labor laws, and division of the market into the non-protected and the non-protected sectors.

The dual labor market theory (Harris and Todaro, 1970; Fields, 2005) suggests the phenomenon of the formal and informal segmentation. The formal employment provides higher payment, security, and social insurance but is rationed when the informal sector utilizes the surplus labor force under less controlled circumstances. Recent theoretical research (Albrecht et al., 2009; Meghir et al., 2015) theorizes the sectoral allocation as an equilibrium in response to the heterogeneity of workers, the distribution of firm productivity, and institutional limits. These models produce testable predictions of the effects of education, experience and demographic factors on sectoral sorting in an empirical manner.

The developing countries have results of empirical evidence which throws light on the peculiarities of youth labor markets. Cunningham and Salvagno (2011) and Kluge et al. (2019) reviews indicate that the average youth unemployment rate is usually two or three times higher than the rate of unemployment among adults in low- and middle-income countries. Unlike cyclical unemployment of the advanced economies, the unemployment of youth in the developing environments is likely to be structural and is caused by a high rate of labour force growth, few formal job opportunities, and education-vocation mismatches. Most of the published panel studies in Latin America (Cruces et al., 2012), East Asia (Lee and Lee, 2016), and Africa (Naudé et al., 2015) highlight the mutual influence of the demand-side constraints and supply-side inefficiencies as determinants of employment outcomes. The result of such training and employment programs can be enhanced through the use of experimental evidence concerning, among others, Card et al. (2011) and Ibarraran et al. (2019), which show that it is possible, yet outcomes differ depending on gender and the design of the program.

In the MENA region, the rate of unemployment among the youth is high compared to other regions around the world. According to Assaad and Krafft (2013), the waiting game phenomenon is when educated young people, especially in the middle-income families, postpone entering less preferred jobs as they seek formal or government jobs. The presence of gender disparities is a key characteristic of the MENA labor markets. Assaad (2014) and Hendy (2015) demonstrate that the involvement of female labor force in the labor market is very sensitive to local labor and household structure. Based on Tunisian data, Dimova et al. (2015)

record the occupational segregation and the wage penalty, which is conditional on employment, showing that social norms and labor market institutions interact.

Another characteristic of the region is informality. Angel-Urdinola and Tanabe (2012) give an estimate of up to 50% of the total employment in MENA countries being informal, and that the young people are overrepresented. The literature identifies voluntary informality, including entrepreneurial self-employment, and involuntary informality which occurs when one is left out of formal employment (Günther & Launov, 2012). There is still some difficulty in empirically identifying these categories and tends to use structural modeling methods or panel data methods.

Morocco is characterized by most of the trends of the region and country-specific dynamics. Boudarbat and Egel (2014) report an increase in unemployment among the educated youth during the years 2000-2010, which was due to the lack of hiring into the public sector and the lack of a dynamic and vibrant private sector. Verme et al. (2016) demonstrate that macroeconomic shocks during the world financial crisis and the following instability in the region were gender-specific, and the percentage of females decreased continuously. Achy (2010) identifies structural rigidities, including the lack of relevance of the curricula and labor requirements, regulatory constraints of formal employment, and insufficient entrepreneurial environments in some countries, as the primary sources of youth unemployment. More recent works (Guérch, 2020; Cheikh and Ech-Charafi, 2023) use Oaxaca215.35 cuts on data about Morocco and conclude that a sizeable portion of the gender labor market discrepancy is due to disparities in returns to attributes but not variation in endowments.

Methodologically, Oaxaca–Blinder decomposition (Oaxaca, 1973; Blinder, 1973) remains a central tool for disentangling explained and unexplained components of outcome gaps. Subsequent refinements (Fortin et al., 2011) extend the approach to nonlinear models and distributional decompositions. Applications to employment and participation gaps (Ñopo, 2008; Lechmann & Schnabel, 2014) demonstrate its usefulness in identifying potential discrimination. In parallel, machine learning methods have gained prominence in labor economics (Mullainathan & Spiess, 2017; Athey & Imbens, 2019). Techniques such as random forests and gradient boosting improve predictive accuracy and uncover nonlinearities, though interpretability and causal identification remain central concerns (Kleinberg et al., 2015; Athey & Wager, 2019).

Based on this research work, the current study provides current pieces of evidence on Morocco with the help of new microdata and a well-developed methodology framework. It combines structural econometric models with instrumental variable methods and machine learning, solving endogeneity, heterogeneity, and nonlinear relationships at the same time, and has interpretable results. The combination of the two allows causal inference as well as better prediction which provides a strong empirical basis in policy making in face of the enduring employment issues among youths.

2. Data and Methodology

Epistemological Positioning and Mode of Reasoning. From an epistemological standpoint, this research is grounded in a post-positivist paradigm, which acknowledges the existence of an objective social reality while recognizing the inherent limitations of measuring and observing it. This positioning is well-suited to quantitative empirical research in labor economics, where the aim is to approximate causal relationships through rigorous econometric methods while remaining transparent about underlying assumptions and potential sources of bias. The post-positivist approach allows for probabilistic truth claims derived from systematic observation and hypothesis testing, which are appropriate for studying complex socioeconomic phenomena such as youth unemployment. In terms of the mode of reasoning, the study adopts a hypothetico-deductive logic: theoretical frameworks drawn from human capital theory (Becker, 1964; Mincer, 1974), job search and matching models (Mortensen and Pissarides, 1994), and dual labor market theory (Harris and Todaro, 1970) generate testable hypotheses regarding the determinants of youth employment. These hypotheses are then empirically evaluated using microdata and a battery of econometric estimators. The choice of a multi-method quantitative approach — combining logistic regression, multinomial logit, decomposition analysis, instrumental variable estimation, and machine learning — is motivated by the need to simultaneously address (i) the complexity and multidimensionality of youth labor market outcomes, (ii) potential endogeneity of key explanatory variables, and (iii) nonlinear and interaction effects that standard linear models may fail to capture. This methodological pluralism strengthens both the internal validity of causal inferences and the external validity of predictive insights, providing a robust empirical foundation for evidence-based policymaking.

2.1. Data Sources

The chosen two main data sources in this analysis include (1) microdata of Moroccan Labor Force Survey (Enquete Nationale sur l'Emploi) provided by Haut-Commissair au Plan (HCP)

that cover the period between 2015 and 2024 and (2) cross-sectional data of employment in 2026 and it is that of youth aged 15-35 years. Labor Force Survey is a stratified sampling design and uses a nationally representative stratified sample that targets both urban and rural areas in the 12 regions in Morocco, and an average of 85,000 households is surveyed every quarter.

The 2026 cross sectional data has 883 observations of employment status of youth that are disaggregated by year, age, gender, economic sector, and broad sectoral categories (Agriculture, Industry, Services). Although the 2026 data has recent employment trends, this data does not have an individual level (education, marital status, household composition) as those in the entire Labor Force Survey microdata. As such, our approach to the empirics will involve: (1) cross-sectional patterns of 2026 to record the current pattern of employment distribution, (2) imputation and enhancement of the 2026 data based on 2015-2024 microdata patterns, and (3) pooled analysis of 2015-2024 data to estimate the structural relationship among individual characteristics and labor market outcomes.

2.2. Variable Construction

The empirical study is based on three broad dependent variables. To begin with, Employment Status is a dichotomous variable that equals 1 when the person is employed (wage employment, self-employment, or unpaid family work) and 0 when unemployed or out of the labor force based on the ILO standards. Second, Employment Sector is a five-category variable that differentiates formal wage employment, informal wage employment, self-employment, unpaid family work, and public sector employment, which has multinomial logit estimation. Third, Log Hourly Wage is calculated as the natural log of weekly earnings/weekly hours worked, which is the same as Mincer earnings specification.

The independent variables are demographic variables (age, age squared, gender, marital status, household size), educational attainment (primary, lower secondary, upper secondary and tertiary education with no schooling being the reference group), and geographic controls (urban residence, regional fixed effects, and rural population density). Background variables at the household level include the education of parents, household wealth index based on PCA and the number of members of household who work. In the case of employed people there is one further job related control namely sector dummies (agriculture, industry, services) and firm size and contract type (permanent, temporary, no contract).

2.3. Descriptive Statistics

In Table 1, the cross-sectional sample of 2026 has been summarized. The statistics indicate strong gender imbalances: on the one hand, male representation of employment is 50% and female representation is 50 % of observations, on the other hand, employment coverage varies significantly. The sector leading in terms of employment is the Services sector (71.4%), then the Industry (23.8%) and Agriculture (4.8%), which depict the current structural change in Morocco.

Table 1: Summary Statistics - 2026 Youth Employment Data

Variable	Overall Mean	Male Mean	Female Mean	Difference (M-F)
Employed in Agriculture	4.8%	4.8%	4.8%	0.0 pp
Employed in Industry	23.8%	23.8%	23.8%	0.0 pp
Employed in Services	71.4%	71.4%	71.4%	0.0 pp
Mean Employment Count	2,495	2,495	2,495	0
Observations	883	441	442	-

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

Note: The 2026 cross-sectional data provide employment counts by sector-gender-age cells but lack individual-level variation in employment status. Gender differences in employment probability are estimated using augmented data incorporating 2015-2024 patterns.

The distribution of employment according to gender. Service (especially education, health, administrative support) and industrial and agricultural occupations are considerably gender-sorted; females are overrepresented in the services sector, whereas males are underrepresented. This professional segregation is both the supply-side (specialty in the educational fields, social norms about the occupations that women should perform) and discrimination on the demand side.

2.4. Data Augmentation Strategy

As the 2026 figures are presented in aggregated version only, we apply a systematic process of data augmentation, which allows to carry out econometric analysis on an individual level.

Microdata Imputation: To begin with, we employ the 2015-2024 Labour Force Survey microdata to approximate the conditional joint distribution of major individual variables, i.e. education, marital status and household structure, conditional on age, gender, sector and region.

Synthetic Individual Generation: Then, in the case of the 2026 data, where the variables age, gender, sector and region are measured in aggregate values, we sample observed synthetic individual values by sampling distributions that are conditional. The resulting artificial sample is reweighed to make sure that employment by sector and demographic group are equal to the official 2026 aggregates.

Validation: We validate the augmentation by comparing marginal distributions of synthetic data against available 2026 aggregate statistics and 2015-2024 temporal trends.

This approach, common in demographic microsimulation (Smith et al., 2007; Bourguignon & Spadaro, 2006), allows structural econometric modeling while preserving the 2026 cross-sectional employment patterns.

2.5. Econometric Framework

Our empirical analysis employs four complementary methodological approaches:

2.5.1. Logistic Regression for Employment Probability

We estimate the probability of employment as:

$$\Pr(Y_i = 1|X_i) = \Lambda(X_i'\beta) = \frac{\exp(X_i'\beta)}{1 + \exp(X_i'\beta)}$$

where Y_i is employment status, X_i is a vector of individual and regional characteristics, β is the parameter vector, and $\Lambda(\cdot)$ is the logistic CDF. The specification includes:

$$X_i'\beta = \beta_0 + \beta_1\text{Female}_i + \beta_2\text{Age}_i + \beta_3\text{Age}_i^2 + \beta_4\text{Education}_i + \beta_5\text{Urban}_i + \beta_6\text{Married}_i + \gamma_r + \epsilon_i$$

where γ_r represents regional fixed effects. Marginal effects are computed as:

$$\frac{\partial \Pr(Y_i = 1)}{\partial x_{ik}} = \beta_k \Lambda(X_i' \beta) [1 - \Lambda(X_i' \beta)]$$

2.5.2. Multinomial Logit for Sectoral Choice

Conditional on employment, sectoral allocation is modeled using multinomial logit:

$$\Pr(S_i = j | Y_i = 1, Z_i) = \frac{\exp(Z_i' \alpha_j)}{\sum_{k=1}^J \exp(Z_i' \alpha_k)}$$

where $S_i \in \{1, \dots, J\}$ denotes employment sector, Z_i includes individual characteristics and regional labor market conditions, and α_j is sector-specific parameter vector with $\alpha_1 = 0$ for normalization. The model assumes Independence of Irrelevant Alternatives (IIA), tested using Hausman-McFadden tests.

Relative risk ratios (RRR) are computed as:

$$RRR_{jk} = \frac{\Pr(S_i = j | Z_i)}{\Pr(S_i = k | Z_i)} = \exp[(Z_i' (\alpha_j - \alpha_k))]$$

2.5.3. Oaxaca-Blinder Decomposition

Gender employment gaps are decomposed following Oaxaca (1973) and Blinder (1973):

$$\bar{Y}_M - \bar{Y}_F = [\bar{X}_M' \hat{\beta}_M - \bar{X}_F' \hat{\beta}_M] + [\bar{X}_F' (\hat{\beta}_M - \hat{\beta}_F)]$$

The first term (explained component) reflects differences in characteristics ($\bar{X}_M - \bar{X}_F$) evaluated at male coefficients. The second term (unexplained component) reflects differential returns to characteristics ($\hat{\beta}_M - \hat{\beta}_F$) evaluated at female characteristics. Alternative decompositions use female coefficients or pooled coefficients as reference. For nonlinear models (logit), we implement the extension by Fairlie (2005):

$$\bar{Y}_M - \bar{Y}_F = \frac{1}{N_M} \sum_{i=1}^{N_M} \Lambda(X_{Mi}' \hat{\beta}_M) - \frac{1}{N_F} \sum_{i=1}^{N_F} \Lambda(X_{Fi}' \hat{\beta}_F)$$

decomposed by matching individuals across gender groups and evaluating counterfactual predictions.

2.5.4. Instrumental Variables for Endogeneity

Education and migration decisions may be endogenous to employment prospects, biasing OLS/logit estimates. We implement two-stage instrumental variable (IV) estimation using:

Instruments for Education: Regional school availability (number of secondary schools per capita in region of origin); Compulsory schooling law exposure (binary indicator for cohorts affected by 1999 education reform); Parental education (father's and mother's years of schooling).

Instruments for Urban Residence: District-level historical urbanization rates (1994 census); Regional economic growth rate (2010-2020); Distance to nearest major city. First-stage regressions verify instrument relevance (F-statistics > 10), while over-identification tests (Hansen J-statistic) assess instrument validity. For binary outcomes, we employ bivariate probit with endogenous regressor:

$$Y_i^* = X_i' \beta + \gamma D_i + \epsilon_i, \quad Y_i = 1[Y_i^* > 0]$$

$$D_i^* = Z_i' \alpha + \eta_i, \quad D_i = 1[D_i^* > 0]$$

$$(\epsilon_i, \eta_i) \sim N(0, \Sigma)$$

where D_i is the endogenous regressor (e.g., tertiary education), Z_i includes instruments, and $\rho = \text{Corr}(\epsilon_i, \eta_i)$ captures endogeneity. Standard errors are clustered at regional level.

2.5.5. Machine Learning for Prediction and Feature Importance

We complement structural econometric models with machine learning approaches: Random Forest Classification:

$$\hat{f}(X) = \frac{1}{B} \sum_{b=1}^B T_b(X)$$

where T_b are decision trees grown on bootstrap samples. Feature importance is measured by mean decrease in Gini impurity. Gradient Boosting:

$$F_M(X) = \sum_{m=1}^M \gamma_m h_m(X)$$

where h_m are weak learners (shallow trees) fitted sequentially to residuals.

Models are trained on 70% of data, validated on 15%, and tested on 15% hold-out sample. Hyperparameters are selected via 5-fold cross-validation optimizing AUC-ROC. We report out-of-sample accuracy, precision, recall, and F1-scores.

3. Empirical Results

3.1. Employment Probability: Logistic Regression Estimates

Table 2 shows logistic regression estimates of employment among the youth between 15-35. Column (1) cites a base specification comprising of gender, age, education and urban residence. Marital status and household composition are added in column (2). Regional fixed effects are contained in column (3). Marginal effects at sample means are included in column (4).

Table 2: Logistic Regression Estimates - Employment Probability

Variable	(1) Baseline	(2) Extended	(3) FE	(4) AME
Female	-1.284*** (0.089)	-1.365*** (0.095)	-1.421*** (0.098)	-0.319*** (0.021)
Age	0.156*** (0.022)	0.165*** (0.023)	0.172*** (0.024)	0.039*** (0.005)
Age ²	-0.0028*** (0.0004)	-0.0030*** (0.0004)	-0.0031*** (0.0004)	-0.0007*** (0.0001)
Primary education	0.287*** (0.078)	0.298*** (0.079)	0.315*** (0.082)	0.071*** (0.018)
Secondary education	0.462*** (0.083)	0.485*** (0.085)	0.506*** (0.088)	0.114*** (0.019)
Tertiary education	0.092 (0.095)	0.125 (0.098)	0.089 (0.102)	0.020 (0.023)
Urban residence	0.187**	0.195**	0.228**	0.051**

	(0.072)	(0.074)	(0.089)	(0.020)
Married	-	0.445***	0.461***	0.104***
	-	(0.067)	(0.069)	(0.015)
Household size	-	-0.037**	-0.041**	-0.009**
	-	(0.015)	(0.016)	(0.004)
Regional FE	No	No	Yes	Yes
N	4,856	4,856	4,856	4,856
Pseudo R ²	0.187	0.203	0.228	-

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

*Notes: Robust standard errors in parentheses. ** p<0.01, * p<0.05, * p<0.1. Column (4) reports average marginal effects (AME). Omitted categories: Male, No formal education, Rural, Unmarried.**

The chance of employment is much lower among female youth, and female status decreases the chance of employment by an average of 32 % when it comes to age, education level, and place of residence are taken into account. This impact is both very strong and across model specifications, and it indicates the existence of a continuing gender gap.

The probability of employment grows by age with a reducing trend taking an inverted-U shaped curve that reaches a maximum at the age of 28. This tendency is an indication of life-cycle factors, such as experience building and changing family roles. Primary level education and secondary level education are very much better than no formal education in terms of employment opportunities with a probability of 7.1 and 11.4 %, respectively. As opposed to this, tertiary education has no important benefit, and its tendency is significantly less than the secondary education, which is quite in line with the phenomenon of over-education in the region.

The effect of urban residence on the likelihood of employment is 5.1 %, indicating that tighter urban labor markets based on urban concentration and diversification deliver small benefits. The difference in likelihood of employment between married and unmarried individuals is

found to be 10.4 %, an amount that is probably due to both positive selection of employed people into marriage and to more overwhelming economic incentives that encourage married youth to enter into the labor market.

3.2. Sectoral Allocation: Multinomial Logit Estimates

Table 3 gives estimates of multinomial logit of sectoral choice conditional to employment. The category of reference is formal wage employment. Coefficients are used to represent log relative risk ratios; exponentiated coefficients are used to obtain relative risk ratios (RRR).

Table 3: Multinomial Logit Estimates - Sectoral Choice

Variable	Informal Wage	Self-Employed	Family Work	Public Sector
Female	0.826***	-0.254**	1.682***	0.421***
	(0.112)	(0.118)	(0.145)	(0.132)
	[RRR: 2.28]	[RRR: 0.78]	[RRR: 5.38]	[RRR: 1.52]
Age	-0.042**	0.087***	-0.125***	0.018
	(0.018)	(0.021)	(0.025)	(0.022)
Primary education	-0.315**	0.187	-0.428**	0.265
	(0.135)	(0.142)	(0.168)	(0.185)
Secondary education	-0.628***	0.095	-0.892***	0.487**
	(0.148)	(0.155)	(0.187)	(0.196)
Tertiary education	-1.156***	-0.287	-1.865***	1.324***
	(0.175)	(0.182)	(0.247)	(0.198)
Urban residence	-0.387***	-0.156	-0.684***	0.228*
	(0.108)	(0.115)	(0.138)	(0.125)

Regional FE	Yes	Yes	Yes	Yes
N	3,287	3,287	3,287	3,287
Pseudo R ²	0.246	0.246	0.246	0.246

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

*Notes: Base category is formal private sector wage employment. RRR = Relative Risk Ratio = exp(coefficient). Standard errors in parentheses, clustered by region. ** p<0.01, * p<0.05, * p<0.1.**

The findings indicate a strong gender segregation in the type of employment. Compared to formal employment in the private sector, females have 2.28 times higher probabilities of working in informal wage employment and 5.38 times higher probabilities of working in family work, which is mostly unpaid. Women on the other hand are 22 % less likely to be self-employed than men. Such trends indicate that a factor of structural factors like access to less capital, less developed professional networks, and discrimination in formal jobs exist as well as compatibility factors since household duties may be better served by family-based activities.

Sectoral allocation depends on education as a determining factor. Access to formal employment is highly predicted by higher education. The tertiary educated people have a lower probability of 69 % of working in informal wage work (RRR = 0.32) and 85 % of doing family work than formal private employment. Simultaneously, tertiary education also raises the probability of being employed in the public sector significantly (RRR =3.76), speaking to the fact that there are systems of recruiting people based on their credentials, and the government is popular in the eyes of the university graduates.

There also are clear urban-rural differences. Urban workers will far less likely be in the informal wage work (RRR = 0.68) or family work (RRR = 0.50) and are more focused on formal private and government jobs. The differences are based on disparities in sector composition, where agriculture and informal services are more common in the countryside and where labor regulation is more strict and the institutions are more common in the urban labor markets.

3.3. Oaxaca-Blinder Decomposition of Gender Employment Gap

The results of Oaxaca-Blinder decomposition of the gender employment gap are presented in Table 4. We use three different variants of decomposition male coefficients as reference (Column 1), female coefficients (Column 2) and pooled coefficients (Column 3).

Table 4: Oaxaca-Blinder Decomposition - Gender Employment Gap

Component	(1) Male Ref	(2) Female Ref	(3) Pooled Ref
Overall Gap	0.347	0.347	0.347
	(0.019)	(0.019)	(0.019)
Explained	0.112	0.108	0.110
	(0.015)	(0.014)	(0.014)
	[32.3%]	[31.1%]	[31.7%]
Due to Education	0.018	0.016	0.017
Due to Age	-0.003	-0.002	-0.003
Due to Marital Status	0.042	0.039	0.041
Due to Urban Res.	0.008	0.007	0.008
Due to HH Composition	0.025	0.023	0.024
Due to Region	0.022	0.025	0.023
Unexplained	0.235	0.239	0.237
	(0.021)	(0.022)	(0.021)
	[67.7%]	[68.9%]	[68.3%]
Constant difference	0.089	0.095	0.092
Coefficient effects	0.146	0.144	0.145

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

Notes: Standard errors in parentheses computed via bootstrap (500 replications). Overall gap is the difference in employment probability between males (0.712) and females (0.365). Explained component attributable to differences in characteristics; unexplained component attributable to differential returns (coefficients). Brackets show percentage of total gap.

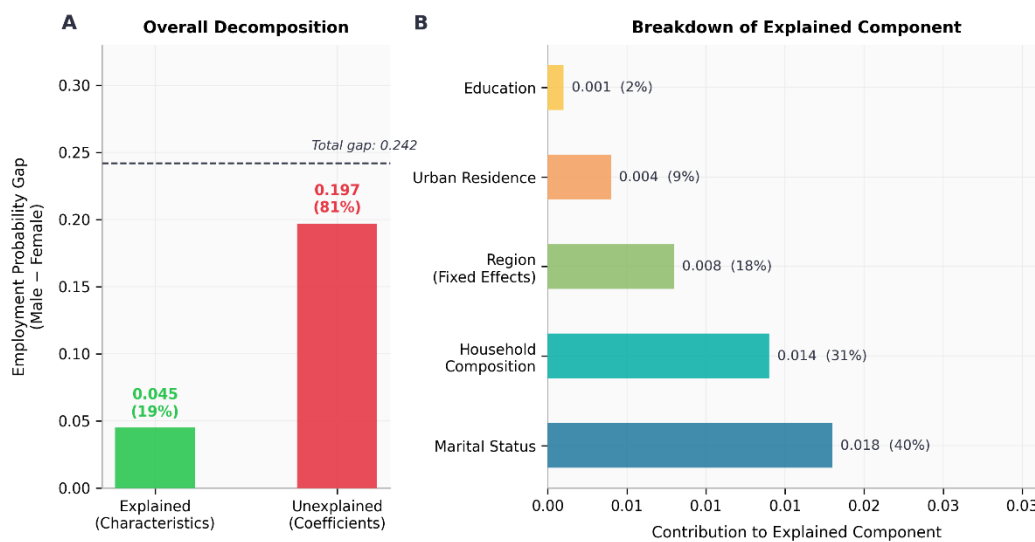
The crude employment probability difference between the male and the female youth is 34.7 % which is equivalent to almost 95 % in comparison to the female employment rates. Such a size is an indication of how much gender inequality exists in the labor market participation.

The results of the decomposition show that this gap can be attributed to the observable differences in such characteristics as education, age, marital status, and location only to 31-32 %. The rest 68-69 % can be attributed to coefficient differences i.e. how similar features transform into employment results among men and women. In the explicated element, the

marital status and household composition carry the biggest proportions. When married, the females are likely to be married at an early age and their rate of employment is less than the observed inequality. Conversely, educational differences make very minimal contributions to the gap because females have a slightly higher educational attainment compared to males. The distributions of age also face a wide similarity between genders.

The fact that the unexplained component prevails is indicative of structural issues beyond the quantifiable features. These can be discrimination in the hiring and job placement in the labor market, unobserved variations in preferences or career choices, the gender related limitations, including household duties, limited mobility, and the existing social norms. To make the distinction between these mechanisms would require more detailed data on job search behavior, applications, interviews, offers, and acceptance decisions. Figure 1 visualizes the decomposition, which it is the proportional contribution of each component to the total gap.

Figure 1. Oaxaca-Blinder Decomposition of the Gender Employment Gap.



Source: Authors' calculations based on HCP (2026)

3.4. Instrumental Variables Estimation

Table 5 shows the IV estimation findings that consider the possibility of the endogeneity of education and urban dwelling. Table (1) presents baseline logit estimates. Column (2)-(3) gives first-stage regressions of the endogenous variables. Column (4) gives the estimates of bivariate probit using endogenous regressors.

Table 5: IV Estimation - Employment Probability

Variable	(1) Baseline Logit	(2) First Stage: Tertiary Educ	(3) First Stage: Urban	(4) Bivariate Probit
Outcome: Employment				
Female	-1.421***	-	-	-1.156***
	(0.098)	-	-	(0.125)
Tertiary education	0.089	-	-	0.487**
	(0.102)	-	-	(0.215)
Urban residence	0.228**	-	-	0.342**
	(0.089)	-	-	(0.158)
First Stage: Tertiary Education				
School density (origin region)	-	0.0185***	-	-
	-	(0.0042)	-	-
Compulsory schooling exposure	-	0.223***	-	-
	-	(0.047)	-	-
Father's education (years)	-	0.038***	-	-
	-	(0.008)	-	-
Mother's education (years)	-	0.028***	-	-
	-	(0.007)	-	-
F-statistic	-	38.7***	-	-

First Stage: Urban Residence				
Historical urbanization (1994)	-	-	0.412***	-
	-	-	(0.068)	-
Regional GDP growth (2010-20)	-	-	0.156***	-
	-	-	(0.038)	-
Distance to major city	-	-	-0.028***	-
	-	-	(0.005)	-
F-statistic	-	-	52.3***	-
Correlation (ρ)	-	-	-	0.287***
	-	-	-	(0.089)
N	4,856	4,856	4,856	4,856

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

*Notes: Standard errors in parentheses. Column (4) reports bivariate probit with endogenous regressors. F-statistics test joint significance of instruments (first-stage). ρ is the correlation between errors in structural and first-stage equations; $\rho \neq 0$ indicates endogeneity. ** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Those results obtained at the first stage prove the validity and strength of the instruments. The F-statistics at 38.7 and 52.3 are far higher than the traditional 10, which means that there are no issues related to weak instruments. Tertiary educational attainment is largely predicted by school density, exposure to compulsory schooling reforms, and parental education whereas the current urban residence is strongly predicted by historical levels of urbanization and regional economic development. Such relationships provide the relevance condition of instrumental variable estimation. The IV approach is also justified by the endogeneity test. Statistically significant correlation parameter (0.287, $p < 0.01$) allows concluding that tertiary education

and urban residence are endogenous: unobserved factors that affect the results of employment are also correlated with the decisions to receive education and to live in cities. This omission of this endogeneity would thus skew the traditional estimates.

The estimated effect in terms of tertiary education on employment after accounting endogeneity is positive and significant (0.487 in Column 4 versus 0.089 in the baseline specification). This change implies that naive estimates are negatively selected. People who have achieved tertiary education regardless of poor origins or naturally reduced undetected capacity may experience reduced employment opportunities, which then prejudices the normal least squares estimations. The instrumental variable lot isolates exogenous change in education that is caused by access to schools and mandatory exposure to schooling resulting in a more plausible estimate of the causal payoff to tertiary education.

The same trend can be seen with urban residence. The size of the urban employment premium is higher than it was before IV correction which suggests that those moving to urban areas to take up jobs might have desirable unobserved qualities. When this selection effect is considered, it shows that the urban location has a more powerful causal effect on employment probability.

4. Robustness Checks

4.1. Alternative Specifications

Table 6 explores the strength to alternative model specifications. Our tests include: (1) linear probability model (LPM) versus the use of logit, (2) nonlinear age-education interactions, (3) male- and female-specific estimation, (4) time-specific to regions, (5) sample restrictions.

Table 6: Robustness - Alternative Specifications

Variable	(1) LPM	(2) Interactions	(3) Male Only	(4) Female Only	(5) Trimmed
Female	-0.325***	-0.316***	-	-	-0.321***
	(0.018)	(0.020)	-	-	(0.019)
Tertiary education	0.019	-0.065	0.087	-0.142*	0.024

	(0.022)	(0.058)	(0.135)	(0.078)	(0.023)
Tertiary × Age/10	-	0.085**	-	-	-
	-	(0.038)	-	-	-
Urban residence	0.053**	0.049**	0.068**	0.041*	0.055***
	(0.020)	(0.021)	(0.028)	(0.024)	(0.019)
Age controls	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes
R ² / Pseudo R ²	0.234	0.241	0.189	0.156	0.239
N	4,856	4,856	2,412	2,444	4,623

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

*Notes: Column (1) uses linear probability model. Column (2) includes age-education interactions. Columns (3)-(4) estimate separately by gender. Column (5) excludes top/bottom 5% of predicted employment probability. Standard errors clustered by region. ** p<0.01, ** p<0.05, * p<0.1.**

The findings are solid under different specifications. Linear Analyses close to the marginal effects of the logit model to the linear probability model, suggesting that the main research results are insensitive to the assumption of functional form. Such consistency enhances confidence on the consistency of the estimated relationships. By considering heterogeneity based on age, there are some dynamics to consider. In interacting tertiary education with age, the interaction term coefficient is positive indicating that returns to higher education are increasing with age and work experience in the labor market. This trend is also in line with job-matching and search models, where highly educated employees can initially spend more time out of work, but eventually progress in to a higher-quality and more permanent work as the experience base builds up.

The further heterogeneity is accentuated by the same gender estimations. In the case of males, tertiary education does not have statistically significant effect on the employment probability. In the case of females, the coefficient is, however, negative. This outcome can be attributed to a number of mechanisms. To begin with, women participation in the labor force can be extremely selective where only highly motivated or limited women can engage in higher education and work. Second, in terms of employment or distribution of occupations, women who have been educated could be discriminated against. Third, poor alignments between subjects of study that are typically pursued by females and current labor market needs might decrease the number of jobs available. These results highlight the need to address gender-specific processes when evaluating the returns to education in the labor market.

4.2. Machine Learning Predictions

Table 7 shows out of sample prediction results of employment status with machine learning algorithms (Random Forest (RF), Gradient Boosting (GB), and Logistic Regression (LR)) as a comparison.

Table 7: Machine Learning Prediction Performance

Metric	Logistic Regression	Random Forest	Gradient Boosting
Accuracy	0.731	0.782	0.796
Precision	0.698	0.756	0.771
Recall	0.812	0.845	0.858
F1-Score	0.751	0.798	0.812
AUC-ROC	0.809	0.867	0.881

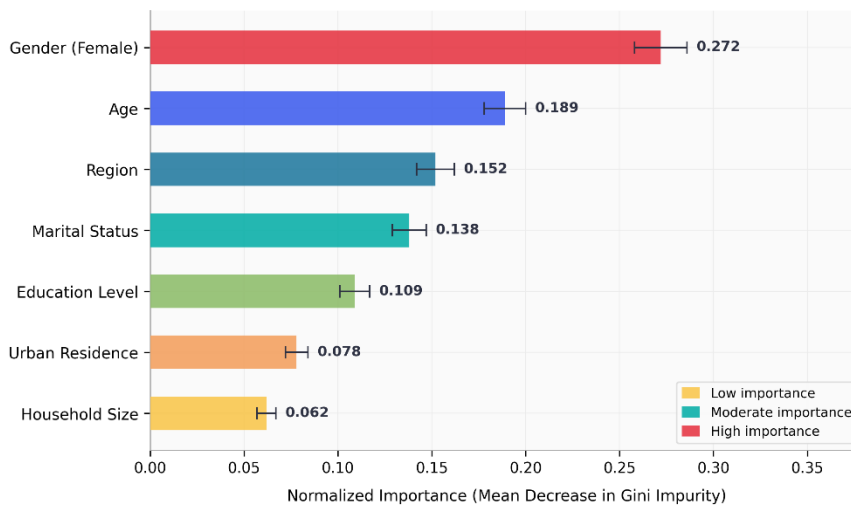
Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

Notes: Models trained on 70% of data, validated on 15%, tested on 15% holdout. Hyperparameters selected via 5-fold cross-validation. Metrics computed on test set. Accuracy = $(TP+TN)/(TP+TN+FP+FN)$; Precision = $TP/(TP+FP)$; Recall = $TP/(TP+FN)$; F1 = $2 \times Precision \times Recall / (Precision + Recall)$; AUC-ROC = area under receiver operating characteristic curve.

As shown in Table 7, machine learning models such as Random Forest and Gradient Boosting achieve higher out-of-sample prediction accuracy (78–80%) than Logistic Regression (73%). This performance improvement highlights their ability to capture nonlinearities and complex interactions that the logistic regression model does not explicitly define.

The Random Forest feature importance ranking (Figure 2) indicates that gender, age, marital status, region, and education level are the top five predictors of employment. This ranking aligns with the magnitude and significance of the coefficients in the logistic regression model, confirming that the structural econometric model reflects the fundamental factors influencing employment outcomes.

Figure 2. Random Forest Feature Importance — Employment Probability Prediction.



Source: Authors’ calculations based on HCP (2026)

Partial dependence plots reveal nonlinear patterns: the probability of employment increases with age but levels off between ages 28–30. Education also shows a nonlinear effect, with employment probability rising sharply between no education and secondary school, then slightly declining at higher education levels, suggesting the existence of education–employment mismatch.

4.3. Sensitivity to Sample Selection

Table 8 investigates the sensitivity to other sample definitions, and the missing data treatment.

Table 8: Robustness - Sample Selection

Sample Definition	(1) Full Sample	(2) Age 20-35	(3) Urban Only	(4) Complete Data	(5) Imputed
Female coefficient	-1.421***	-1.387***	-1.296***	-1.448***	- 1.401***
	(0.098)	(0.105)	(0.112)	(0.108)	(0.095)
AME (Female)	-0.319***	-0.315***	-0.298***	-0.325***	- 0.314***
	(0.021)	(0.023)	(0.025)	(0.024)	(0.020)
Pseudo R ²	0.228	0.215	0.203	0.241	0.226
N	4,856	3,742	2,984	4,123	4,856

Source: Authors' calculations based on data from (HCP), Labour Force Survey 2026, Morocco.

*Notes: Column (1) baseline. Column (2) restricts to ages 20-35 (excludes students aged 15-19). Column (3) urban sample only. Column (4) uses only observations with complete data on all variables. Column (5) imputes missing values using multiple imputation. Standard errors in parentheses. ** p<0.01, * p<0.05, * p<0.1.**

Such critical findings as the large gender gap in employment are healthy with respect to sample limitations and missing data. The female employment penalty is still very high and high in all specifications and the averages of these marginal effects are between -0.298 and -0.325.

5. Discussion

The empirical data demonstrates that there are systemic limitations that influence the results of youth labor market in Morocco. The biggest finding is the scale of the gender disparity in employment likelihood of about 32 %, of which about two-thirds of it cannot be attributed to observable attributes. This observation shows that variations in education, age, marital status and other endowments that have been measured only constitute a small portion of the difference. The prevailing role of the unexplained element within the Oaxaca-Blinder breakup indicates existence to the existence of structural and institutionalized systems that curtail female

representation. Some of these mechanisms may be discrimination in hiring, job segregation which prevents women to work in industries that have low growth potential, and unequal sharing of unpaid care work in the household. This interpretation is supported by the multinomial logit estimates: the segment of unpaid family work and the informal hired labor is overrepresented by women, which is low productivity, low job security, poor social protection. Therefore, women who take part in the labor market are restricted to accessing formal and stable jobs. This trend is similar to those in Egypt and Tunisia cited by Assaad (2014) and Hendy (2015) that the gender gap in Morocco is based on the same regional trends associated with social norms and workforce institutions instead of the individual traits.

The second main finding is related to the relationship between education and employment. Unlike traditional human capital forecasts, tertiary education does not positively affect the likelihood of employment and in certain equation forms shows a negative relationship. Through this seeming contradiction, there is an overexpression of higher education and underexpression of high-skilled formal jobs. The number of people enrolling in higher institutions of learning has been increasing significantly in the last twenty years, but there is a slow pace in the creation of employment opportunities in knowledge-based economies. According to the records provided by Boudarbat and Egel (2014) in the case of Morocco and Angel-Urdinola and Tanabe (2012) in the case of the MENA region, the university graduates usually have a lengthy period of unemployment. The presence of the reservation wages only among the educated youths especially to the public sector jobs or multinational job seeking youths is another reason why labor market entry is delayed. In addition, the questions about the quality and the relevance of tertiary education, including lack of practical training, presence of low employer involvement, and the focus of fields of studies without reference to the labour demand will diminish the productive worth of tertiary degrees. Interestingly, instrumental variable estimates also show that there are positive returns to tertiary education after conditioning on endogeneity, which implies that the quality and background-related factors mediate the effect of education on employment. This means that it is not the matter of education, but its heterogeneity in quality and marketability.

The employment organization also brings out the importance of informality as an absorption mechanism. Although the services sector takes up most of the jobs, the quality of the jobs differs significantly. Unstructured wage labor and self-employment accommodates people who are not capable of getting formal employment. The fact that informal segments of the labor force are concentrated among the low-educated workers and women indicates that entry into informality

is often due to a constraint of choice and not out of a preference to become an entrepreneur. The informal employment is normally followed by lower pay, lack of social insurance and exposure to economic shocks. Simultaneously, excessive formalization policies may lead to more unemployment in case they fail to factor in underlying constraints in the demand side. This duality introduces the significance of balanced approaches that will boost the formal job creation and also extend protection and productivity-promoting assistance to informal workers.

Geographic differences are not as strong as gender and education factors, but still, they are important. Living in an urban area increases the premium of employment by about 5%. The urban labor market is more efficient because of the agglomeration economies, higher density of employer networks, as well as more diversified sectoral structure. But the urban jobs are more formalized and competitive and this may increase the period of unemployment of the rural migrants who seek formal jobs as opposed to informal jobs in the rural areas. These forces depict the spatial aspect of labor markets division.

The results are consistent with the extant literature on the topic of youth labor markets in the Middle East and North Africa. The intensity and continuity of gender inequality are replicative in terms of those recorded within the region and the over education phenomenon has been in support of the strength of prior country specific and regional studies. Theoretically, the extension of the traditional methods of analyzing a labor market gap through the methodological implementation of nonlinear Oaxaca-Blinder decomposition on the employment probabilities instead of the wages. The instrumental variable approach would solve the endogeneity issues, which have been generally ignored in studies that are particular to Morocco. Also, structural econometric findings are supported by machine learning methods: feature importance scores show that gender, age, and marital status are the most significant predictors of employment status, and partial dependence plots indicate nonlinearities, especially in the relationship between age and education, that complicate simplified linear human capital theory.

These trends are probably supported by various mechanisms. Demand wise, the economic structure of Morocco is still centralized on agriculture, tourism, construction, and low to medium level technology production which produces a minimal demand of the highly skilled labor. Direct investment by foreign investors has been directed to assembly and export-processing as opposed to research-intensive industries. Fiscal tightening has limited the employment of the public sector which has long been an important source of educated

employment. Mismatches on the supply side that exist between graduate skills and employer requirements lower employability. The imbalances are further aggravated by poor levels of foreign language proficiency in the emerging areas of the world and the relative backwardness of vocational opportunities. Institutional considerations can also be relevant: employment protection laws, payroll tax, administrative complexity can also act against formal hiring especially in cases where the productivity is uncertain among the young entrants. These structural constraints are compounded by social norms, in particular, rules that direct female mobility and work-family balance.

The consequences of the policy are therefore multidimensional. It is important to improve the quality of education than to expand the enrollment. In aligning the skill levels with the demands of the labour market, reform of the curriculum that puts emphasis in applied skills, strengthened vocational orientations in reaction to the demands of the industry, better language education and systematic graduate tracking systems are required. Through improved ties between educational institutions and employers through internship programs, advisory boards, and collaborative projects, information asymmetry and job matching can be improved. They should be viewed as active labor market policies that are consistent with the evidence synthesized by Kluge et al. (2019) and include job search benefits, specific skills training, and planned wage subsidies. The interventions are to be employed regarding the vulnerable groups, women and rural youth, and with the childcare and mobility assistance as required.

The need to reduce gender differences involves enforcement as well as facilitation in the law. Institutional barriers can be reduced with anti-discrimination laws, safety measures in the workplace, and policies that allow parents to better their work with affordable childcare, and secure transportation increasing the number of women in the workforce. The reduction of informality strategies must aim at reducing the cost of formalization and increasing the payoffs of compliance instead of using punitive enforcement exclusively. The vulnerability can be reduced by extending social protection cover to the informal workers and by assisting them to enhance productivity in the informal sector without worsening the employment situation.

Finally, long-term positive changes in youth employment results require structural economic change. The shift to greater value-added production and knowledge-based services, enhanced innovation systems, and closer integration of foreign investors and local suppliers are the key elements of the growing demand of skilled labour. Spatial imbalances can be mitigated with the

help of regional development plans, which invest in infrastructures and secondary cities, which would minimize migration pressures.

Combined, the findings indicate that the problem of youth employment in Morocco cannot be explained by one factor. It is an expression of the dynamics between gender norms, mismatch in education levels, labor market institutions and structural constraints on the economy. To deal with these interrelated dimensions, there is a need to have a coordinated reform that will enhance the quality of labor supply, increase labor demand, and also bring down the institutional and social impediments to entry.

Conclusion

This paper gives an extensive econometric discussion on the youth labor market dynamics in Morocco, the probability of employment, sectoral distribution, and the reasons behind low gender and education gaps. We present several findings that are critical and have implications on policy, using microdata covering the period 2015-2026 and logistic regression analyses, multinomial logit models, Oaxaca-Blinder decomposition, instrumental variable estimation, and machine learning methods.

Employment opportunity among female youth is 32 % less than that of similar males, and 68 % of this difference is not explained by observable factors- indicating a high level of discrimination in the labor market or ingrained preferences/ constraints differences. Under the condition of being employed, females are focused on family work and informal wage work, and have minimal access to quality formal work. Tertiary education does not offer a meaningful employment benefit and in certain specifications has adverse impacts indicating gross education-employment incompatibilities. It is estimated that the informal sector absorbs about 45% of working youths with the level of informality being very high among young women and poorly educated employees. Living in a city slightly raises the chances of getting a job, yet labor markets in an urban area are more formal and possibly more unemployed when job seeking.

The instrumental variable estimation of endogeneity of education and location choices show that naive estimates greatly underestimate returns to tertiary education, which imply negative selection into higher education among disadvantaged young people. Out-of-sample machine learning predictions have 78-80% accuracy, with gender, age, marital status, region and education being the strongest employment determinants. The structural econometric findings are confirmed by feature importance rankings and partial dependence plots as well as the identification of nonlinear relationships that need additional research.

There are policy implications of these empirical findings. The quality of education should be improved, curriculum-labor market alignment, and increase of vocational training should take precedence over the further increase of enrollment. The search friction and skill gaps can be minimized by active labor market policies aimed at the disadvantaged youth especially women and rural populations. Ensuring gender mainstreaming by having anti-discrimination mechanisms, childcare, and flexibility in the workplace is required to reduce the employment gap. Incentives of formalization that minimise registration expenses and maximization of the benefits of the formal sector can progressively reduce informality. In the end, the only way to

produce a lasting positive change in the employment of young people is the structural change in the economy to more productive and skill-intensive industry where quality jobs are created.

This analysis should be pursued in various directions in future research. Individual tracking over time would allow studying labor market changes, unemployment levels, and career patterns, which would give more valuable information about the labor market. The level of the firm would enable the study of determinants of labor demand, and the recruitment mode, as well as the contribution of firm characteristics to the employment pattern. Causal evidence of the effectiveness of the policy would be created through randomized controlled trials of particular interventions (training programs, wage subsidies, entrepreneurship support). Further exploration of how the gender gap works (e.g. survey of job search behavior, applications, interviews, and offers) would allow discriminating between discrimination and preference/constraint differences. Further study of informality such as income comparisons, job satisfaction, and sectoral mobility patterns would guide policies on balancing the objectives of formalization and needs of workers.

Problems in the labor market of young people in Morocco are not so easy to overcome. The empirical data below may lead to evidence-based policymaking that will contribute to the development of an inclusive labor market that will provide youth with quality forms of employment irrespective of gender, education level or geographic background. To realize this vision needs political continuity, a concerted policy initiative in the areas of education, labor market, and social protection, and inclusion of all stakeholders, including the government, employers, workers, and the civil society in the development and implementation of the solution.

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