Post-apartheid trends in formal sector gender wage discrimination in South Africa: analysis through decomposition techniques

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Average formal sector real log(wage), by gender and race

Figure 1: African log (wage), 1996-2007, by gender

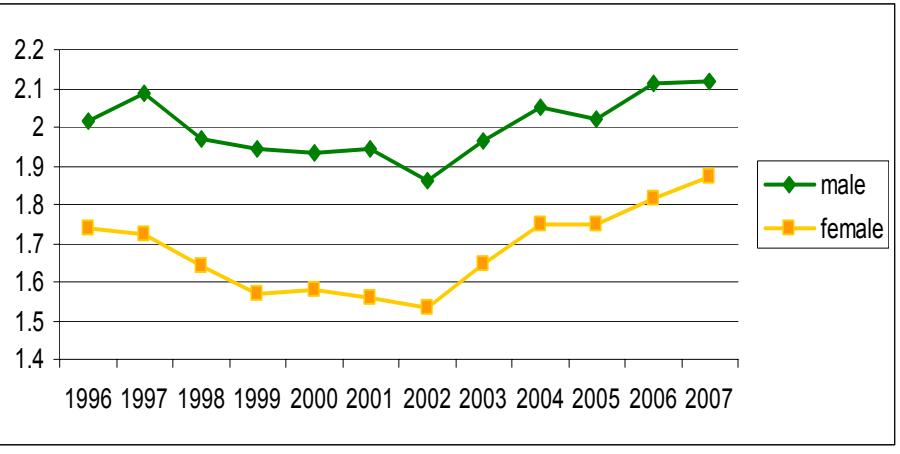


Figure 2: Coloured log (wage), 1996-2007, by gender

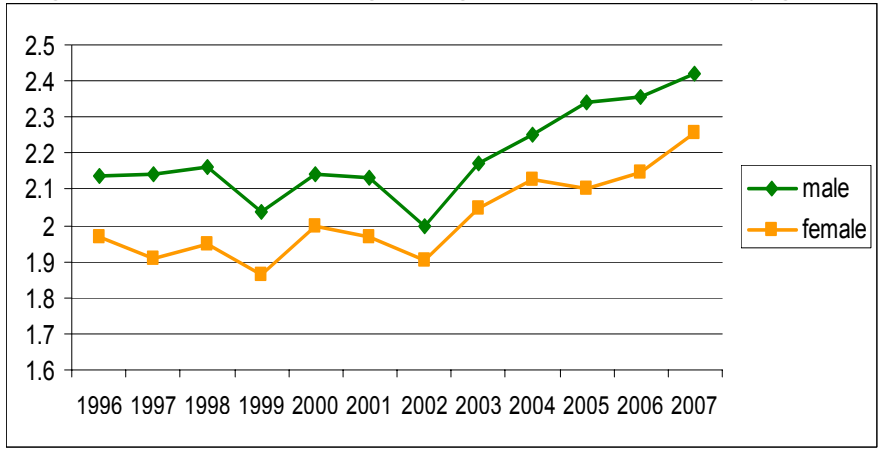


Figure 3: Indian log (wage), 1996-2007, by gender

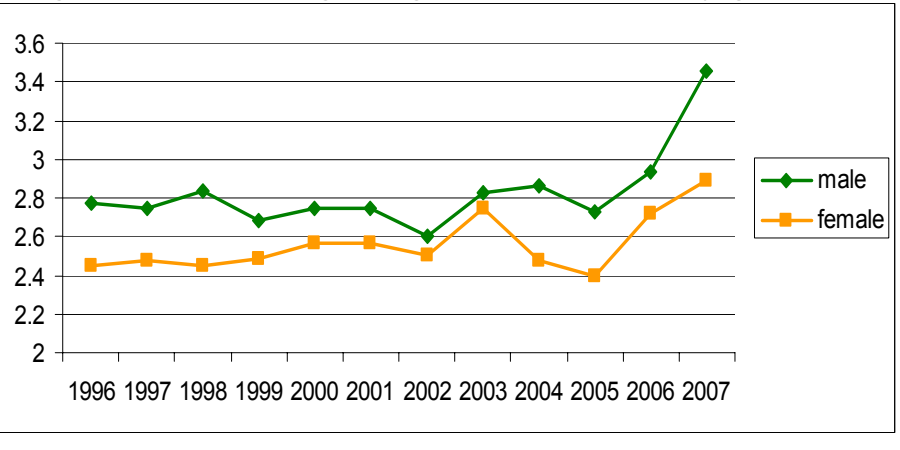
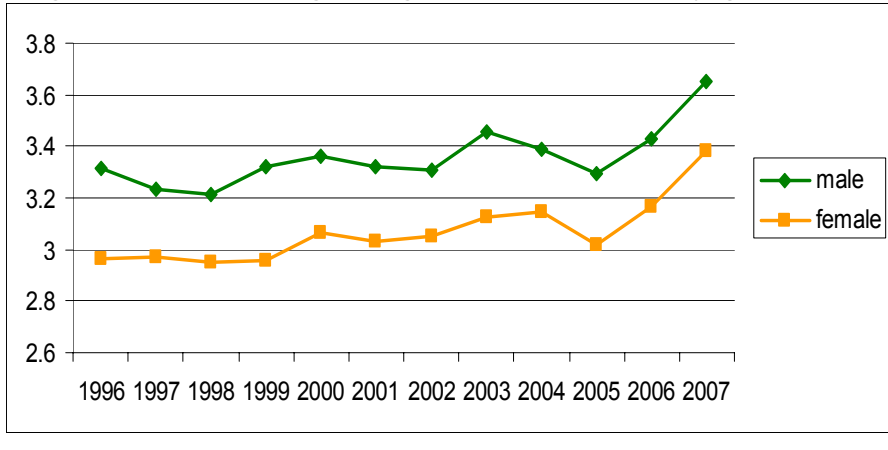
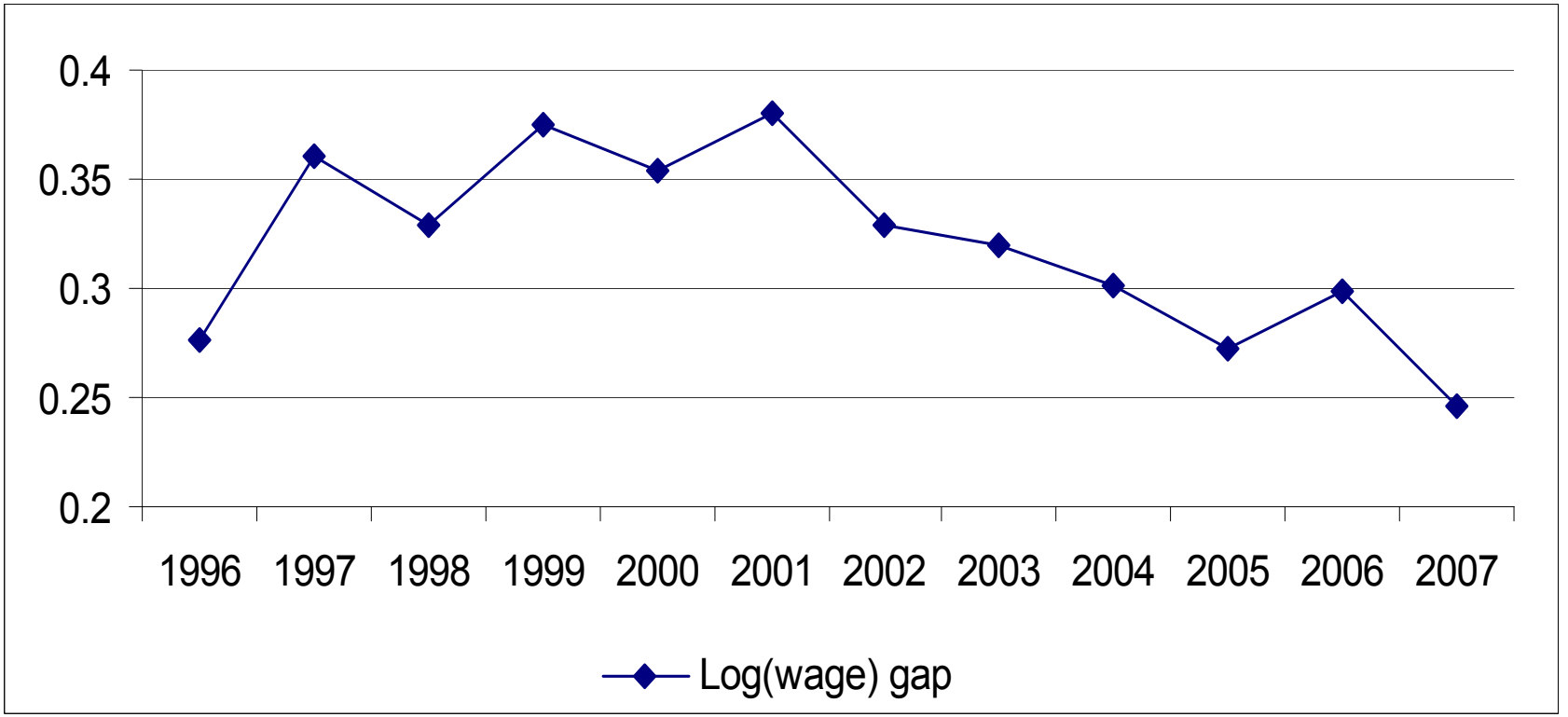


Figure 4: White log (wage), 1996-2007, by gender



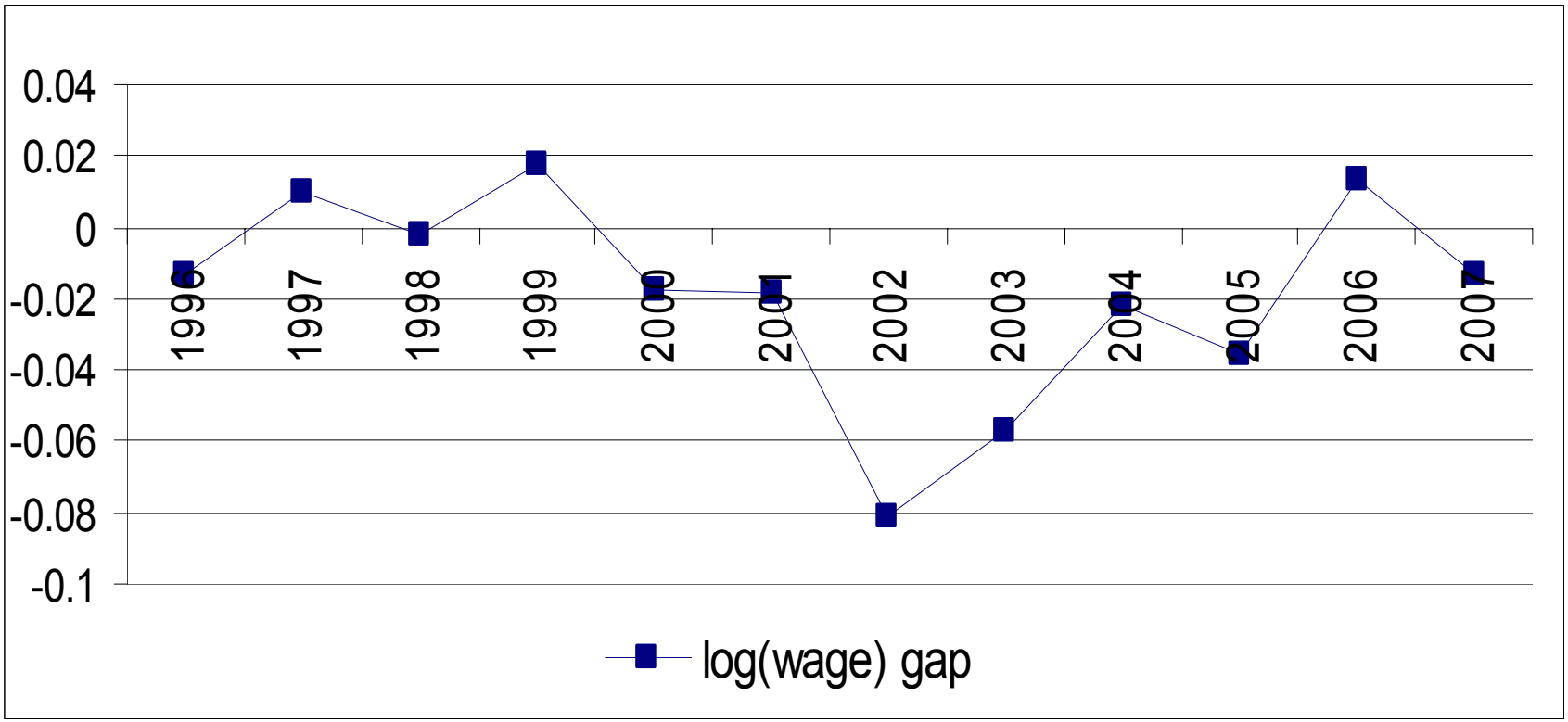
Notes: own calculations from OHS 1996-1999, LFS_2 2000-2007

Average African “formal” sector gender log(wage) gap



Notes: own calculations from OHS 1996-1999, LFS_2 2000-2007

Average African formal sector gender log(wage) gap (excluding domestic workers)



Notes: own calculations from OHS 1996-1999, LFS_2 2000-2007

Methodology: Oaxaca-Blinder decomposition

- Oaxaca and Blinder (1973) proposed to decompose the average wage gap into that part which can be "explained" by differences in observable characteristics, and that part which is "unexplained" by differences in returns to productive characteristics
- This study uses a more general form of the Oaxaca-Blinder decomposition using the coefficients from a pooled model (β*) as the non-discriminatory wage structure

$$lnW^m - lnW^f = \underbrace{\beta^*(X^m - X^f)}_{\text{Explained component}} + \underbrace{X^m(\beta^m - \beta^*) + X^f(\beta^* - \beta^f)}_{\text{Unexplained component}}$$

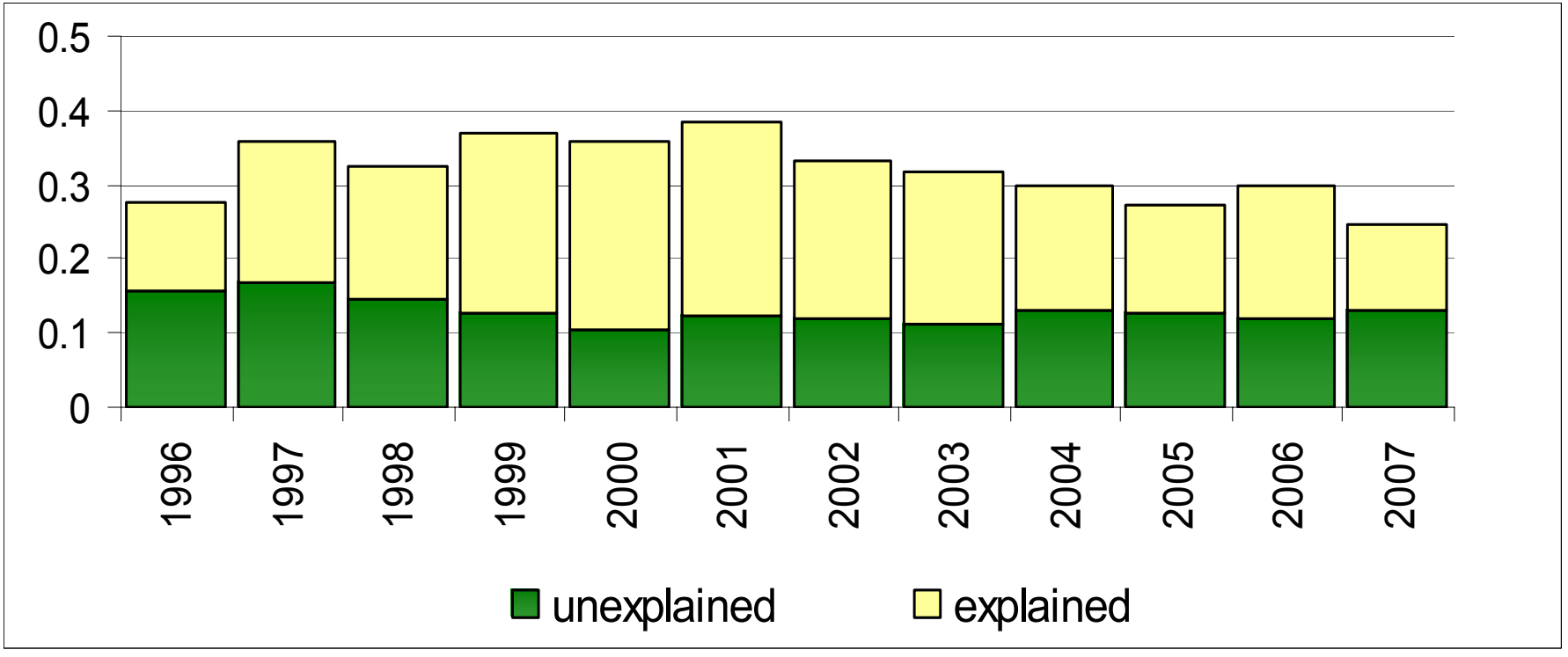
Selection in wage equations

- In the presence of sample selection, OLS estimation can lead to biased and inconsistent estimators (Oaxaca & Neuman, 2004)
- Number of methods are offered to allow for selectivity correction in OB decompositions
- In South African case, earnings functions need to be estimated in three phases (Ntuli, 2007)
- Most straightforward approach to adjusted for selection is to deduct the selection effects from the overall differential and then apply standard decomposition to adjusted differential (offered wage gap)
- Can alternatively incorporate the selection correction term into the decomposition and differentiate between direct and indirect gender discrimination (Mavromaras, 2003; Oaxaca & Neuman, 1998; application in SA context by Grun, 2004)

Data

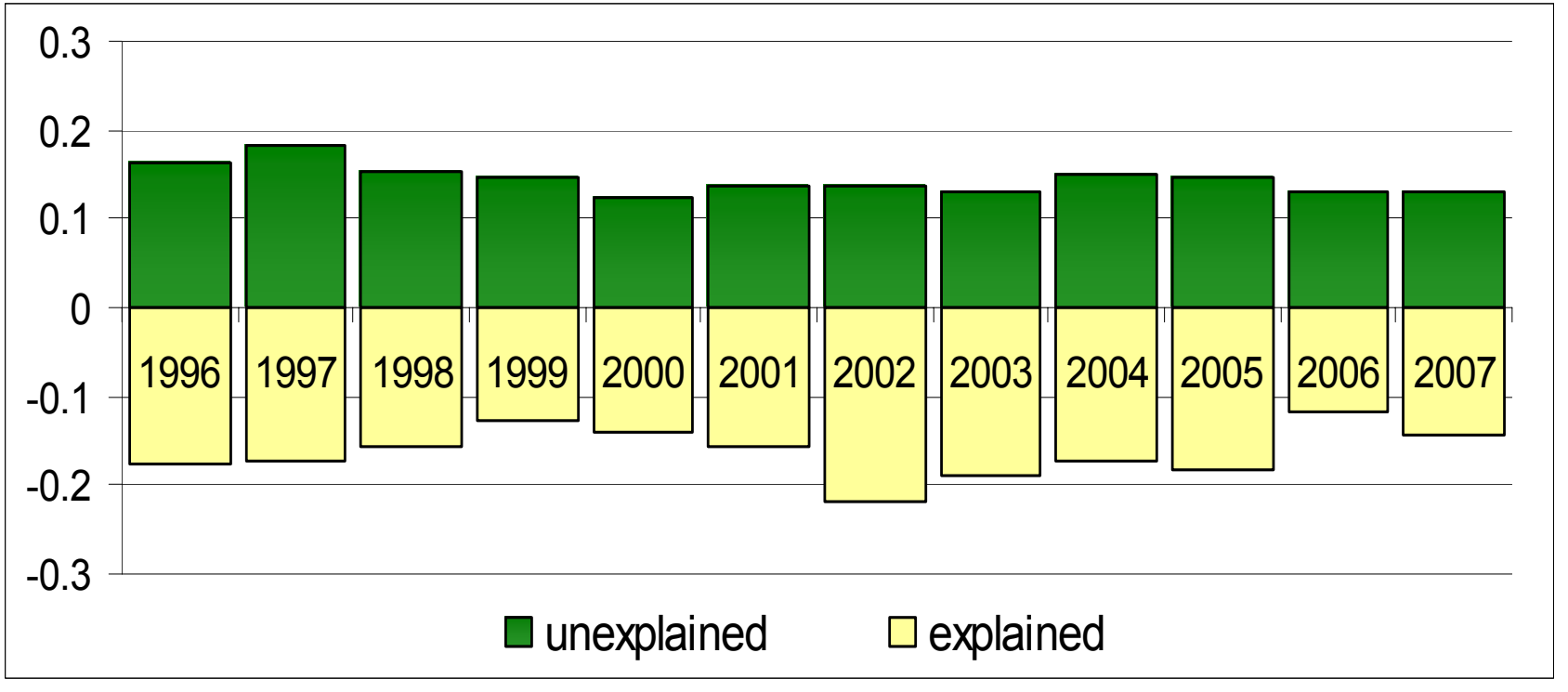
- Data obtained from September Labour Force Surveys (LFS_2: 2000 – 2007) and the October Household Surveys (OHS: 1996 – 1999)
- Exclusions were made for the self-employed, “outliers” (Burger & Yu, 2006), the informal sector and subsistence agriculturalists
- Sample design was taken into account in the estimation of all empirical models
- Regressors included in wage equations:
  - Education dummies
  - Age dummies
  - Tenure and tenure squared
  - Marital status
  - Children in the household
  - Union membership
  - Provincial dummies
  - Occupation and industry dummies (with public sector included)

Decomposition of average formal sector African gender log(wage) gap (1996 – 2007)



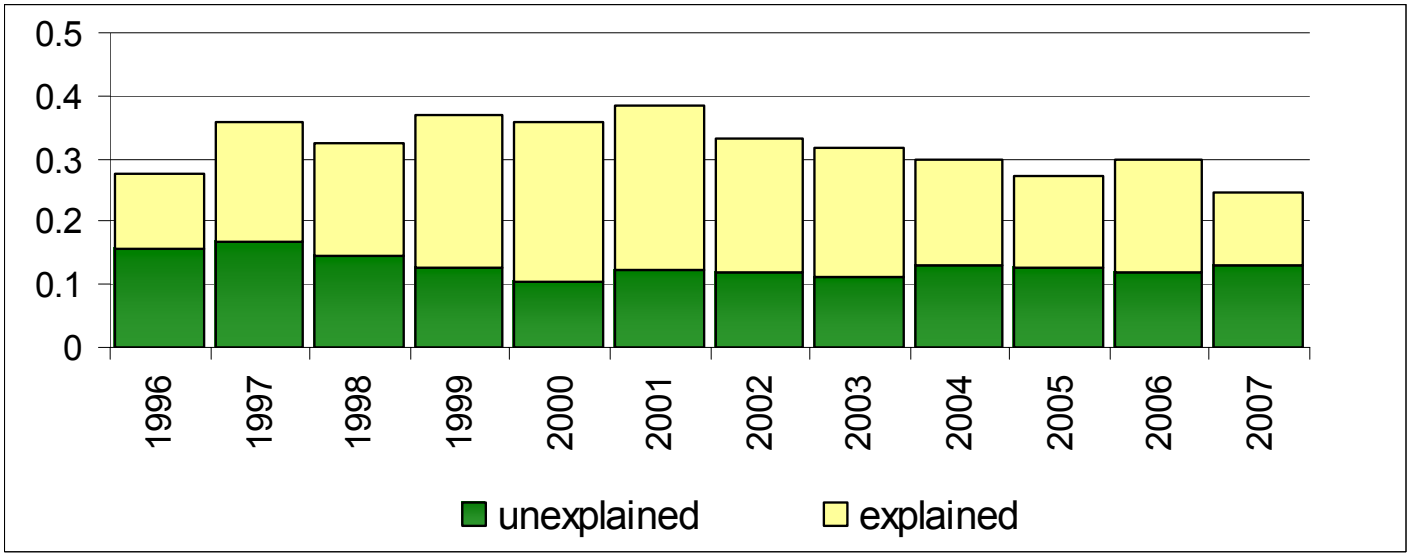
Notes: own calculations (OHS(1996-1999); LFS_2(2000-2007))

Decomposition of average formal sector African gender log(wage) gap (1996 – 2007) – excluding domestic workers



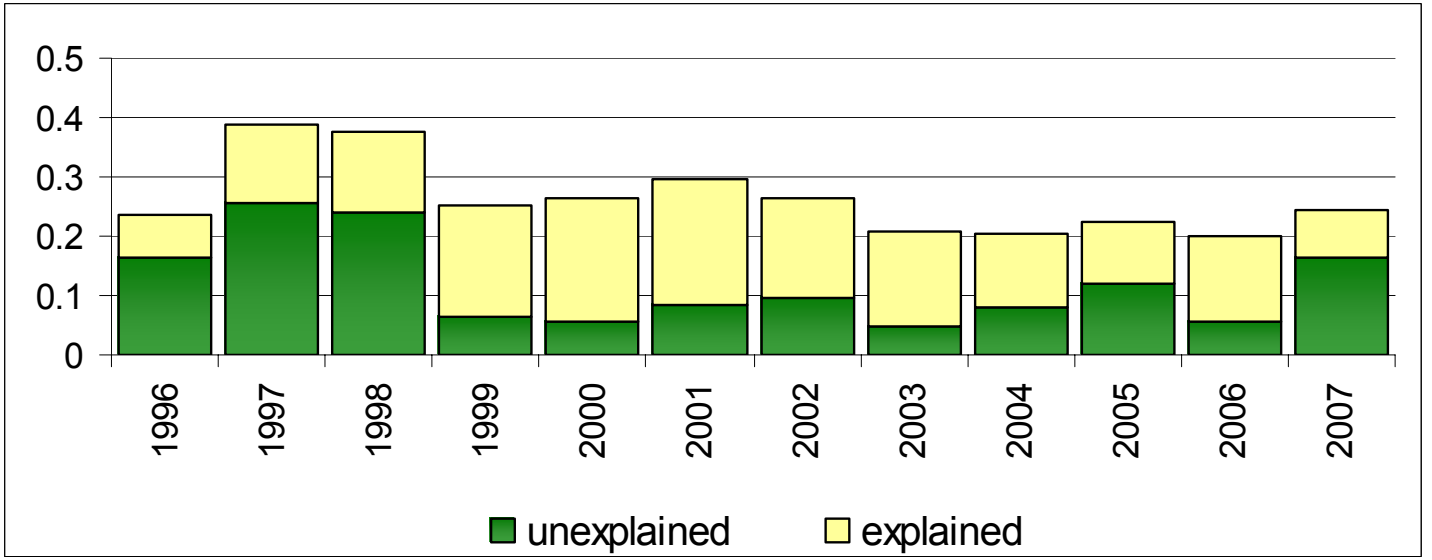
Notes: own calculations (OHS(1996-1999); LFS_2(2000-2007))

Unadjusted average African gender log(wage) gap



Notes: own calculations (OHS(1996-1999); LFS_2(2000-2007))

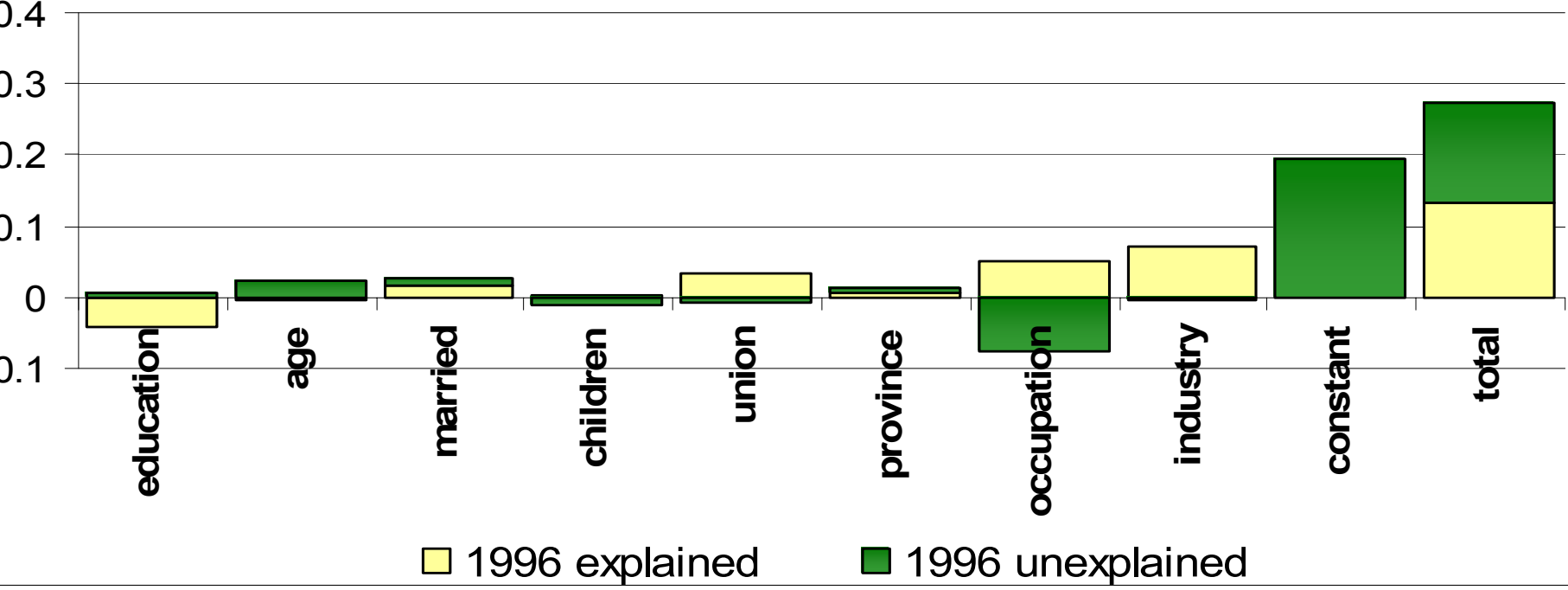
Selectivity-adjusted average African gender log(wage) gap



Detailed decompositions

- Detailed decomposition results for categorical predictors depend on the choice of reference group (Jones, 1983; Oaxaca & Ransom, 1999; Nielsen, 2000; Horrace & Oaxaca, 2001; Yun, 2005)
- Not critical for the explained part, but for the unexplained part, the base category not only alters the results for single dummy variables, but also changes the contribution of the categorical variable as a whole
- Simple solution proposed by Yun (2005):
  - Transform coefficient vectors on dummy variables so that deviations from the grand mean are expressed an the (redundant) coefficient for the base category is added

$$lnW = \alpha + \sum_{j=1}^{J} \beta_j + \sum_{l=1}^{L} C_l \beta_l + \sum_{j=1}^{J} \sum_{kj=1}^{Kj} D_{jkj} (\beta_{jkj} - \beta_j) + \varepsilon$$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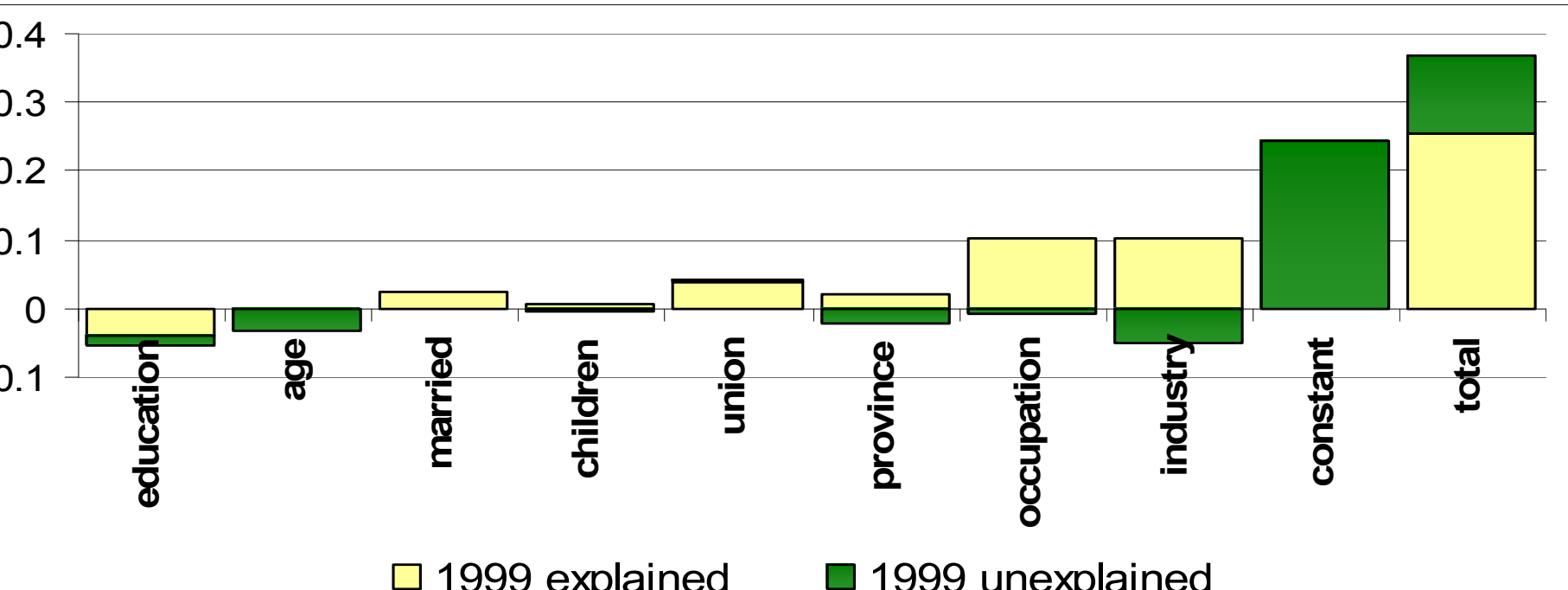
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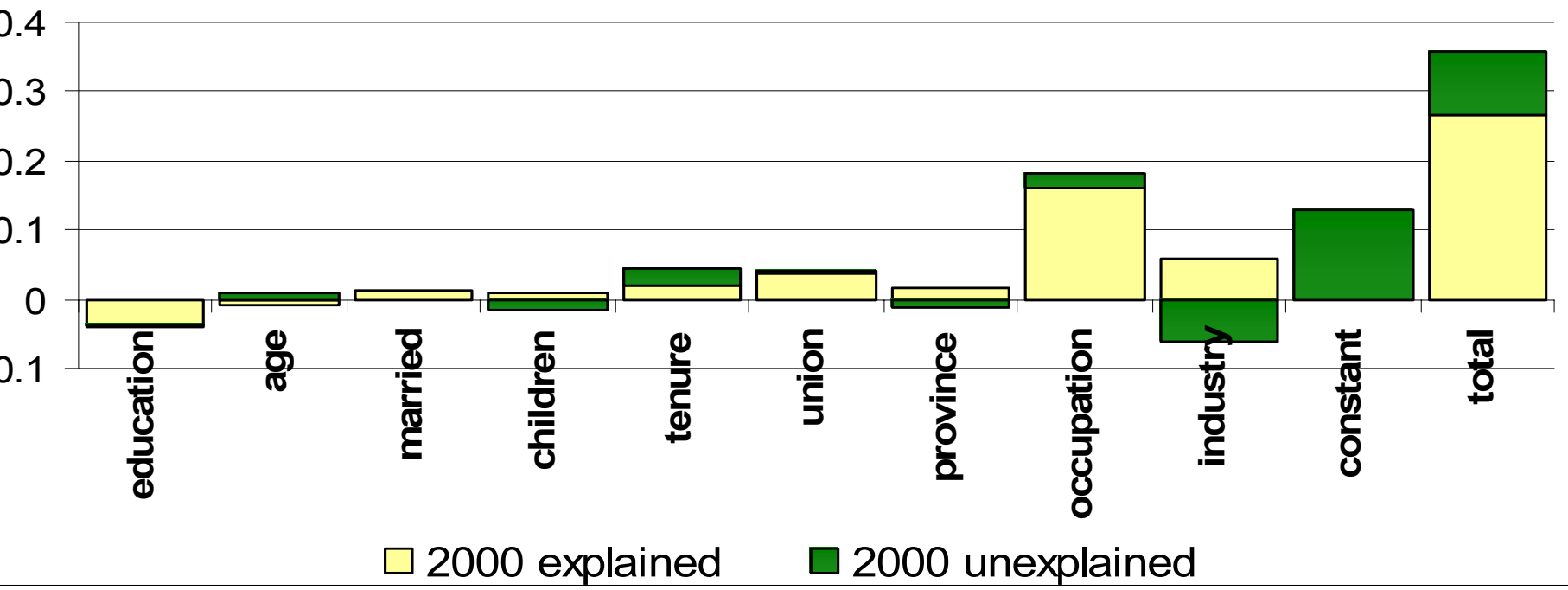
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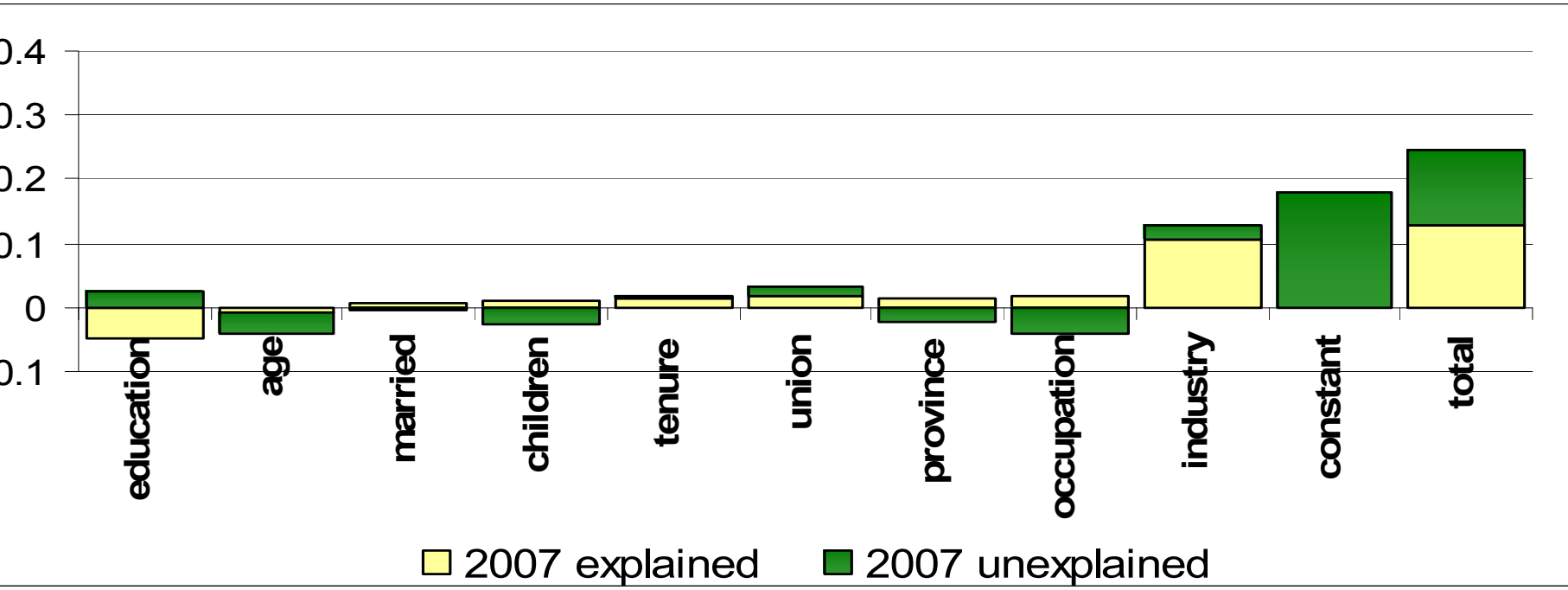
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2007 explained
2007 unexplained

Distributive approach: counterfactual distributions using quantile regression

- In general, studies measuring gender discrimination have virtually shared the same methodological assumptions
  1. "direct" gender discrimination exists if women do not earn equivalent wages as their male counterparts
  2. Wage differences can be estimated using wage regressions run separately for the male and female groups
  3. Discrimination is most commonly analysed using the average wage gap (the average wage discrimination experience)
- Research has begun to take the distributional aspect of gender discrimination into account
  - does the wage gap change across the wage distribution ("glass ceiling" or "sticky floor"), and
  - is the discrimination experience constant across the wage distribution

Extension of OB decomposition to quantile regression and counterfactual distribution

- Recent methodology to decompose wage gaps into:
  - Component based on differences in labour market characteristics
  - Component based on the difference in rewards that two groups receive for their labour market characteristics across the wage distribution (counterfactual distribution; Albrecht et al (2003), Machado and Mata (2005))

Methodology

- Quantile regression specifies the conditional quantile as a linear function of some control variables:

$$F^{-1}_{lnW}(\theta|X_i) = X_i'\beta_\theta$$

- Unlike in OLS regression where parameter estimates minimises the sum of squared errors, quantile regression estimation minimises the absolute sum of the errors from a particular quantile of the log wage distribution
- The distribution of the error term is left unspecified
- Standard errors are estimated by bootstrap methods (bootstrap 100 times)

Methodology

- Once the model parameters are estimated, Melly (2006) suggests a procedure to decompose differences at different quantiles of the unconditional distribution
- Because the conditional quantile function cannot be easily inverted to obtain the conditional distribution function, the unconditional distribution function is obtained by integrating over all quantiles and observations
- The counterfactual distribution is estimated by replacing the estimated parameters of the male distribution with those of the female distribution

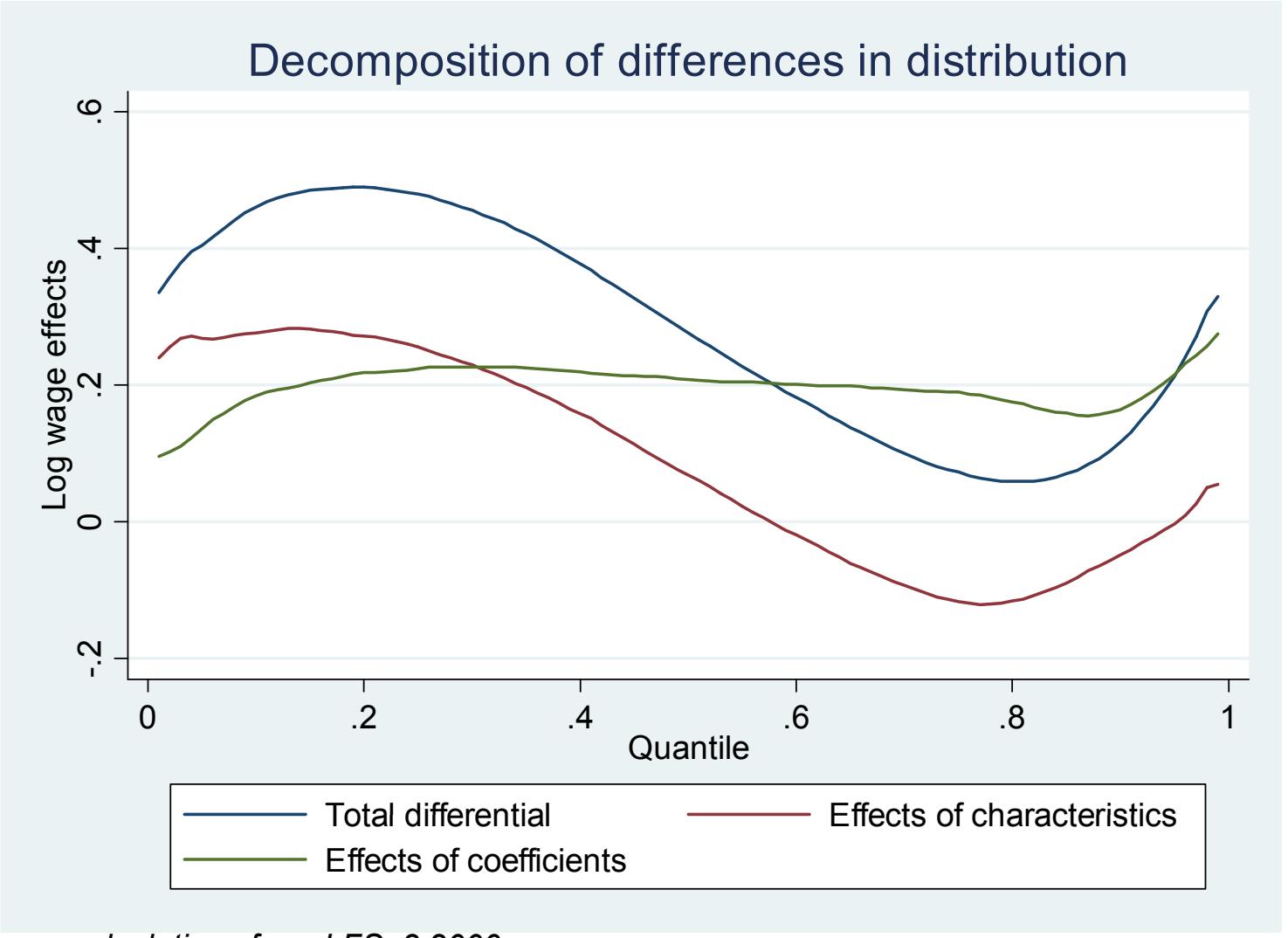
Methodology

- This gives us three wage distributions:
  1. The fitted female distribution $\beta_\theta^f X^f$
  2. The fitted male distribution $\beta_\theta^m X^m$
  3. The counterfactual distribution $\beta_\theta^m X^f$
- Therefore we obtain the generalized OB decomposition at each quantile as follows:

$$lnWm\theta - lnWf\theta = \beta_\theta^{m\prime}(X^f - X^m) + X^{f\prime}(\beta_\theta^m - \beta_\theta^f)$$

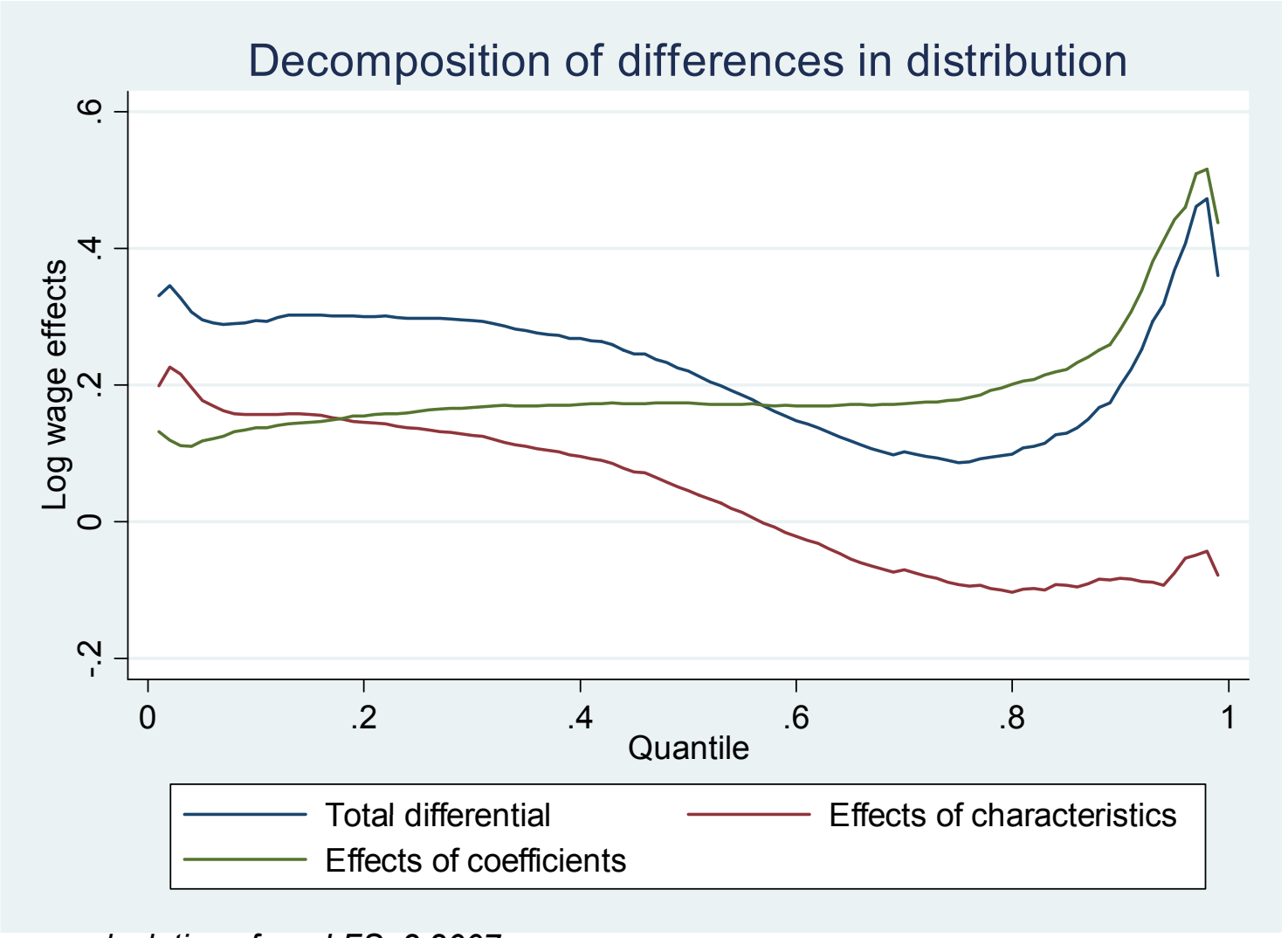
Results

Figure 1: Whole sample (formal sector & domestic workers) with male wage structure as non-discriminatory (2000)



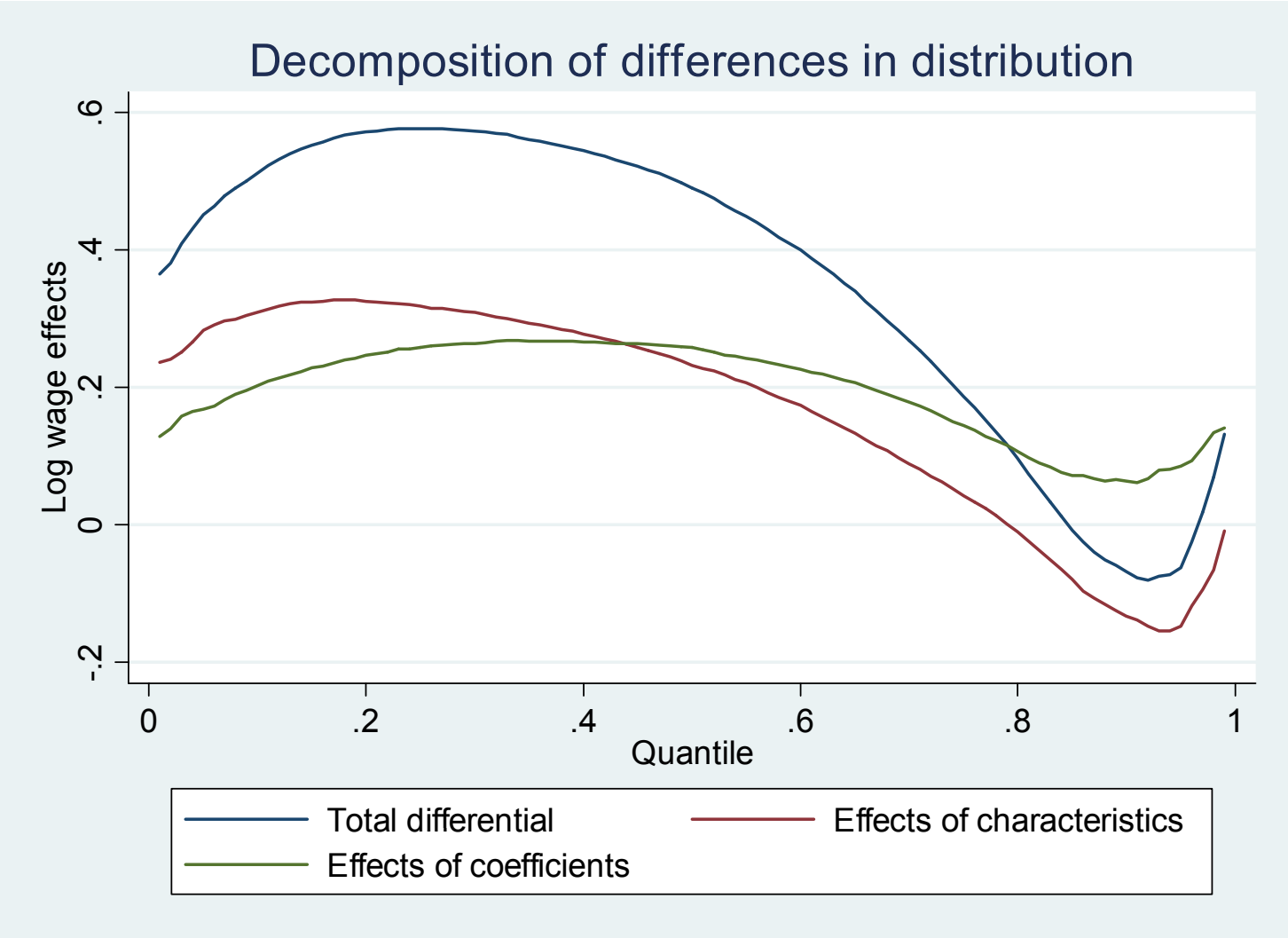
Results

Figure 1: Whole sample (formal sector & domestic workers) with male wage structure as non-discriminatory (2007)



Results

Figure 1: African sample (formal sector & domestic workers) with male wage structure as non-discriminatory (2000)



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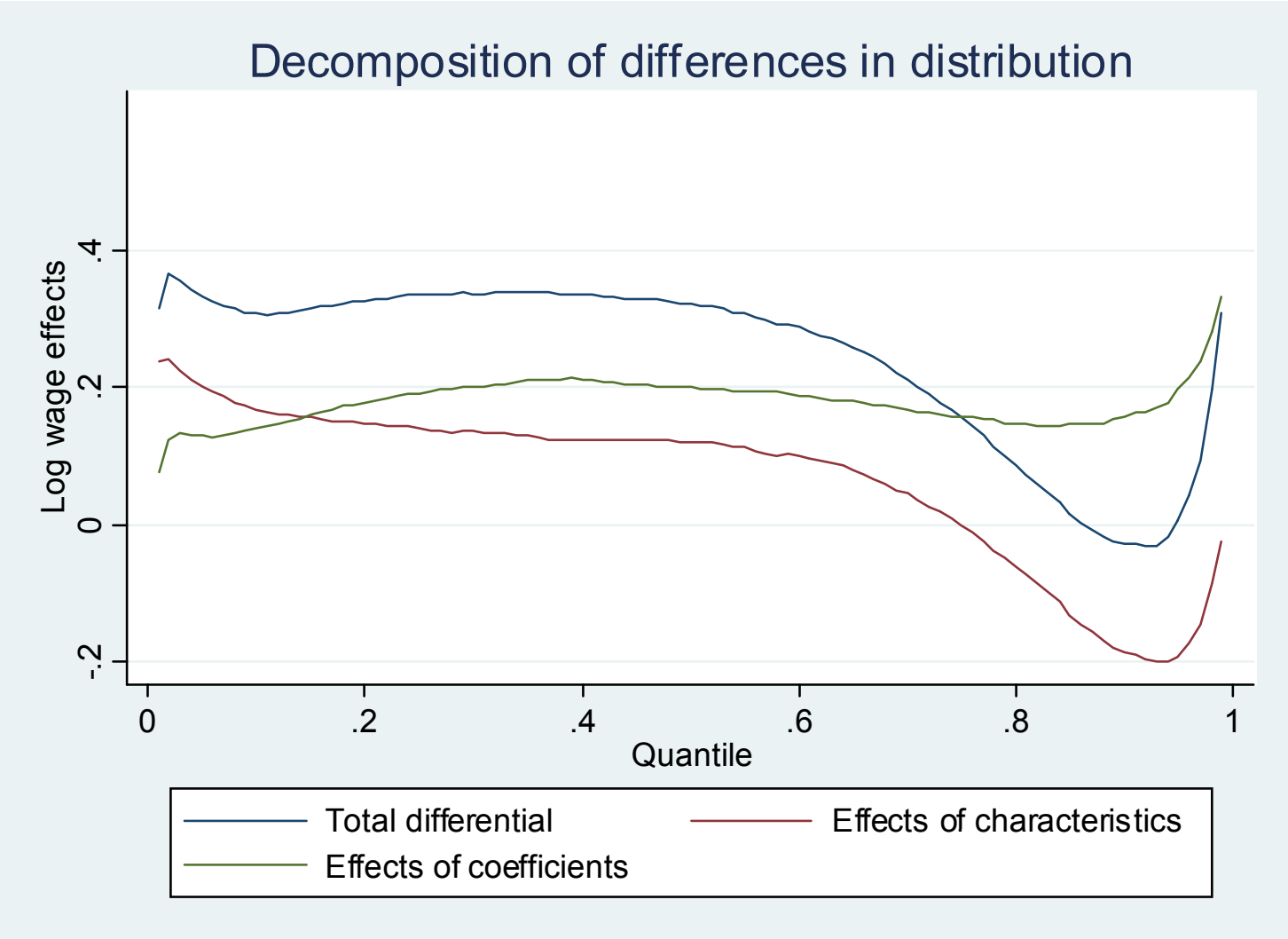
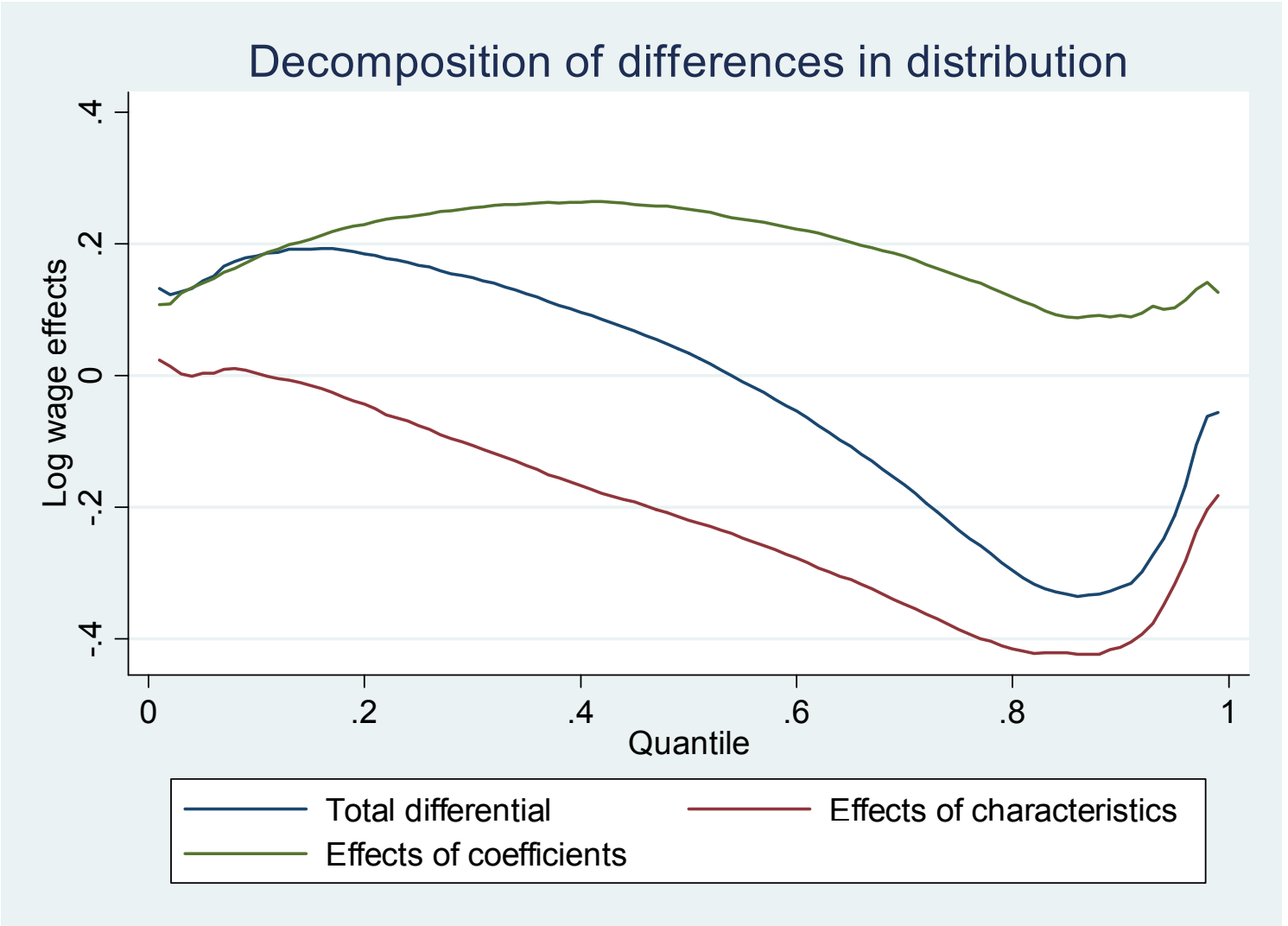


Results

Figure 1: African sample (excluding domestic workers) with male wage structure as non-discriminatory (2000)



Note:

Results

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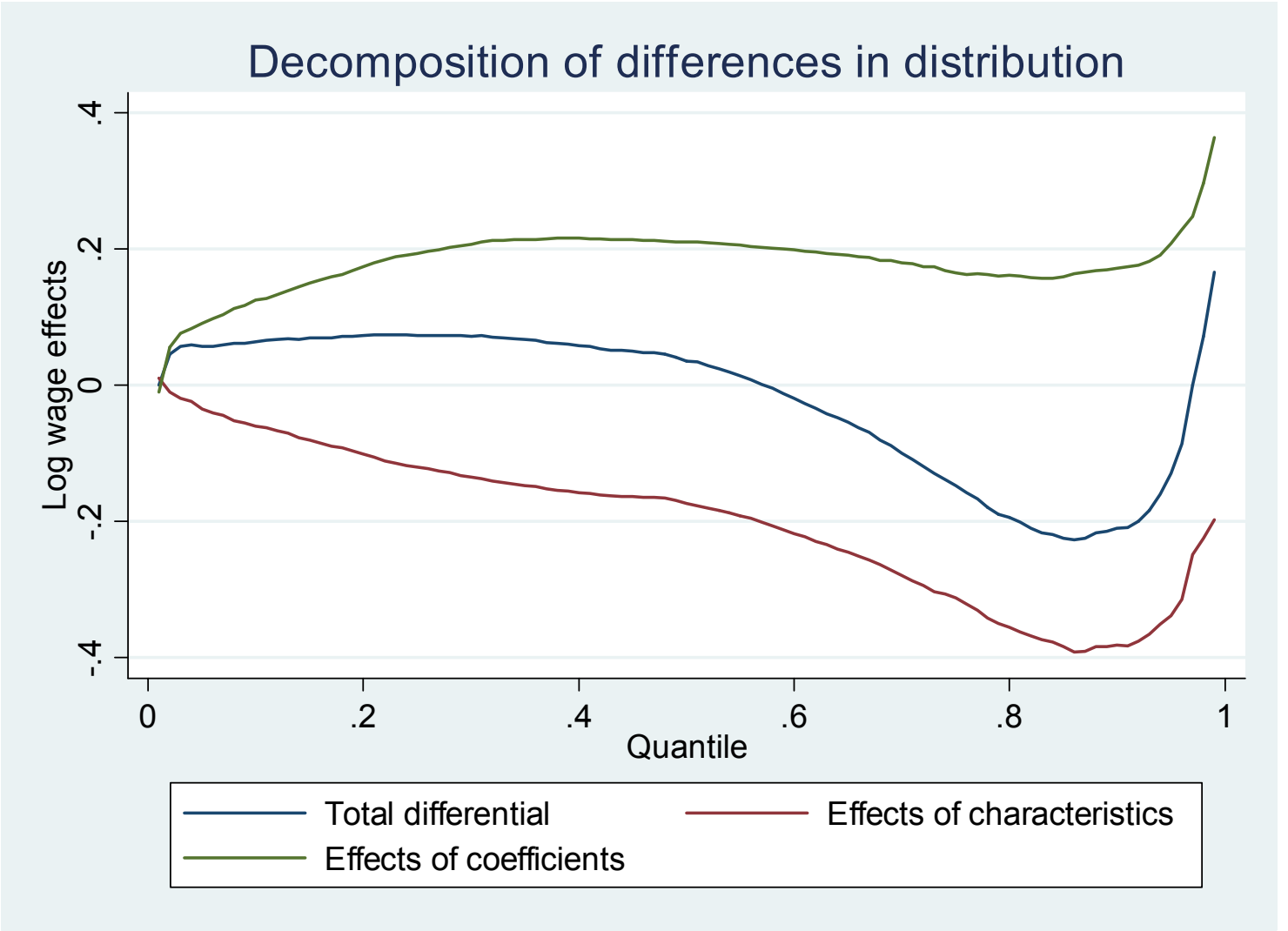

Note: