What drives female labor force participation? Comparable micro-level evidence from eight developing and emerging economies

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Motivation

- In the last two decades, in the developing world:
  - rising female education,
  - declining fertility,
  - economic growth,
- favorable background for rising FLFP rates everywhere.

Female labor force participation rates, age 15+

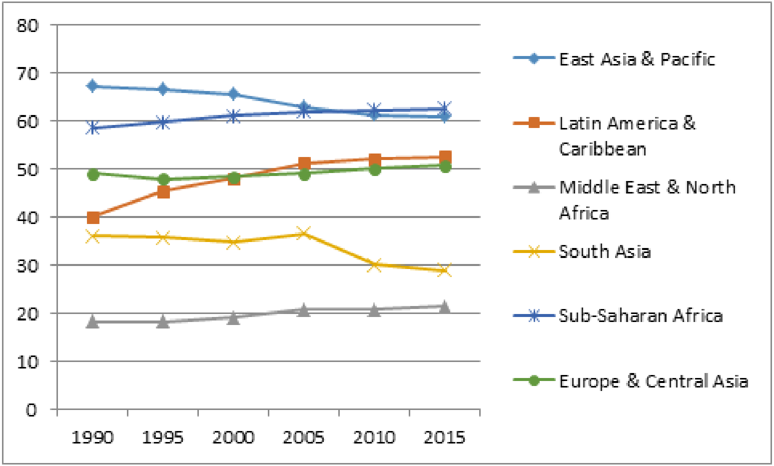


Figure 1: *Source:* ILO, modeled estimates

Puzzle

- Klasen and Pieters (2015) on India: *"Against this background, it is puzzling to see that the reported female labor force participation rate in urban India has stagnated at around 18 percent since the 1980s."*
- Schaner and Das (2016) on Indonesia: *"Why, in the face of so much change, has Indonesian women's labor force participation remained so stagnant?"*
- Majbouri (2018) on MENA region: *"Fertility and the Puzzle of Female Employment in the Middle East"*
- Gasparini and Marchionni (2015): in LA, slowdown in the growth of female labor supply since the 2000s
- etc...

What we do

We use comparable microdata from 8 low and middle-income countries, covering the period 2000–2014, to ask:

1. How are women's (and their households') characteristics associated with FLFP, and what are the key commonalities and differences across countries?
2. What drives FLFP changes over time *within countries*?
3. What explains differences in FLFP rates *between countries* and how has this changed over time?

How we do it

1. We estimate FLFP models for each country and year,
2. We decompose changes in FLFP over time for each country,
3. We decompose gaps in FLFP between countries.

Our contribution

- richer data than in cross-country analyses $\rightarrow$ heterogeneity across space and time,
- unified empirical framework $\rightarrow$ direct comparison between countries and over time,
- robust FLFP correlates over large samples and several periods.

Empirical model

- We follow the specification of Klasen and Pieters (2015):
- Population: married women of ages 25-54 living in urban areas.
- Probit model:

$$P(LFP_{ict}=1)=\Phi\left(\alpha_{ct}+\sum_{E}\beta_{ct}^{E}D_{ict}^{E}+\mathbf{X_{ict}}\gamma_{\mathbf{ct}}+\delta_{rct}\right), \quad (1)$$

Explanatory variables

- D^E_{ict}: woman's education attainment dummies.
- X_{ict} - individual and household level:
  - age, age^2,
  - ethnic or religious group,
  - per capita household income excluding the woman's earnings (log),
  - education attainment of household head,
  - at least one male household member has wage employment (dummy),
  - number of children 0–2, 3–5, boys 6–14, girls 6–14.
- δ_{rct} - region fixed effects.

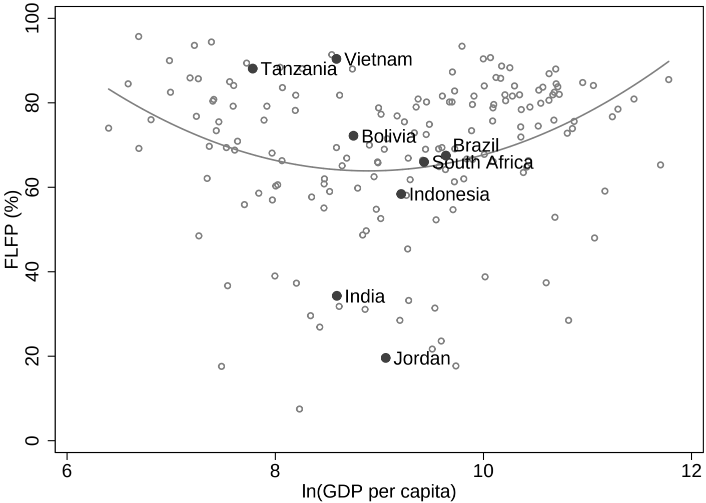
Interpretation

- reduced-form correlates,
- not causal, not structural (no own-wage effects),
- supply-side focus,
- (local) demand conditions captured by regional fixed effects.

Data

- Large scale repeated cross-sectional surveys for:
- Bolivia, Brazil, India, Indonesia, Jordan, South Africa, Tanzania, Vietnam,
- 32 surveys, $\sim$ 800,000 urban married women (prime-age),
- Period: roughly 2000-2014.

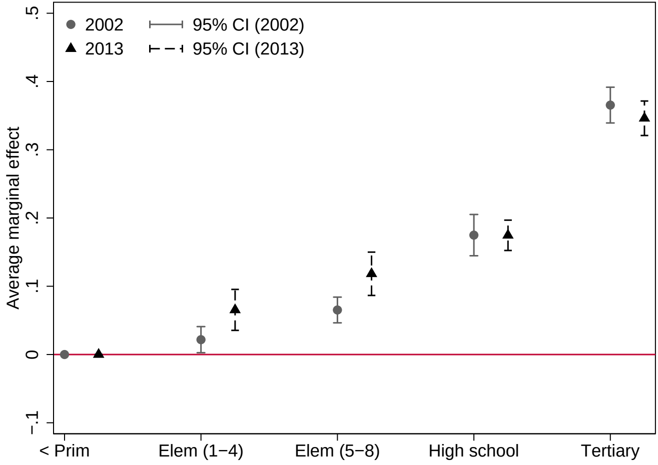
FLFP (prime-age) vs. income, 2014



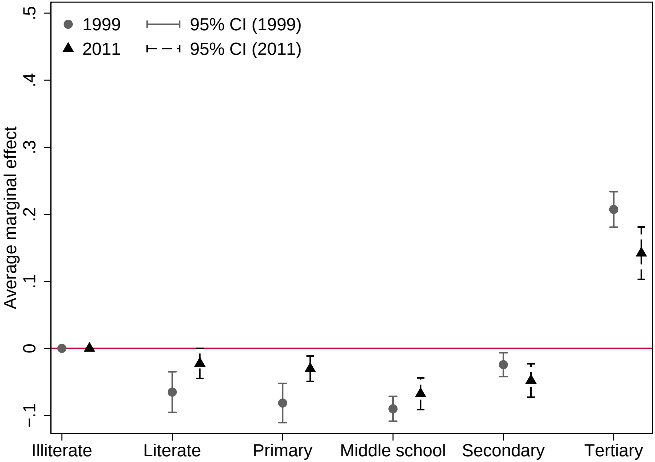
Result 1

- No universal relationship between a woman's education and her LFP status:
- strong, positive, and linear in Brazil and SA,
- U- or J-shape in India, Indonesia, and Jordan,
- Mixed in Bolivia, Tanzania, and Vietnam.

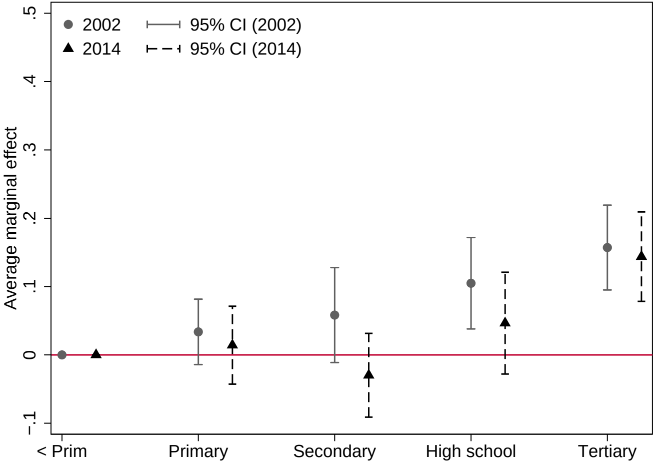
Average marginal effects of own education: Brazil



Average marginal effects of own education: India



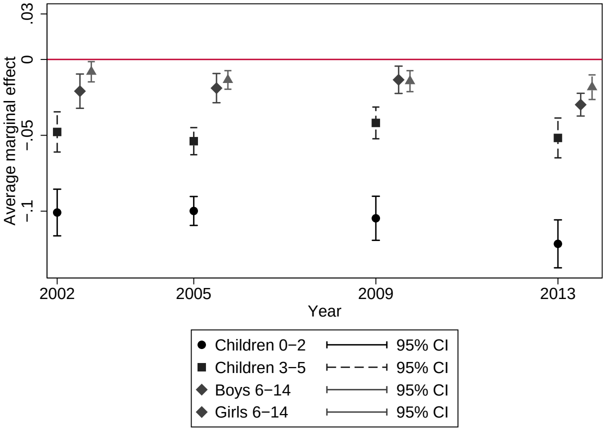
Average marginal effects of own education: Vietnam



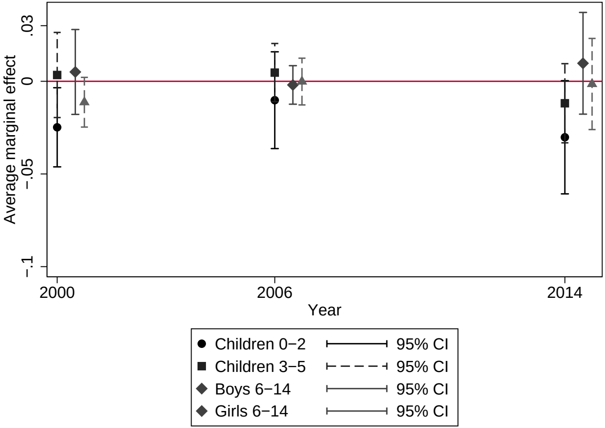
Result 2

- The negative effect of fertility is stronger in richer countries.

Average marginal effect of young children: Brazil



Average marginal effect of young children: Tanzania



Result 3

- Household circumstances lose their grip on FLFP in richest countries: Brazil and SA.
- Negative household income effects very strong in India, Indonesia, and Bolivia,
- Same for household head education.

Average marginal effect of log income: Indonesia

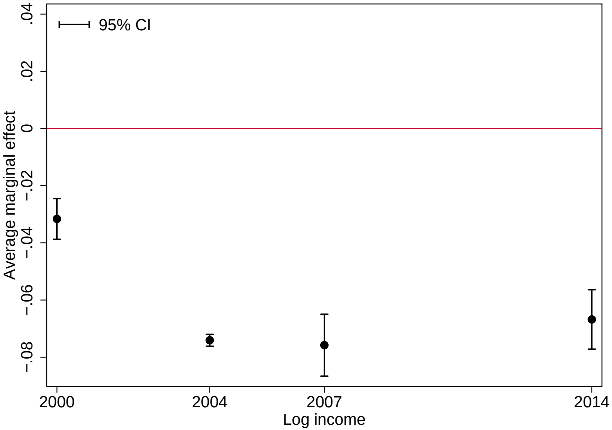


Figure 2: *Notes:* income is the household per capita earnings from main job excluding woman's own earnings

Average marginal effect of log income: South Africa

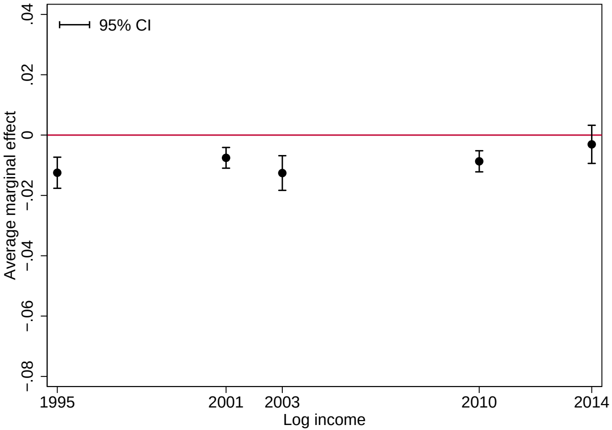


Figure 3: *Notes:* income is the household per capita earnings from main job excluding woman's own earnings

Robustness

Correlates are robust to:

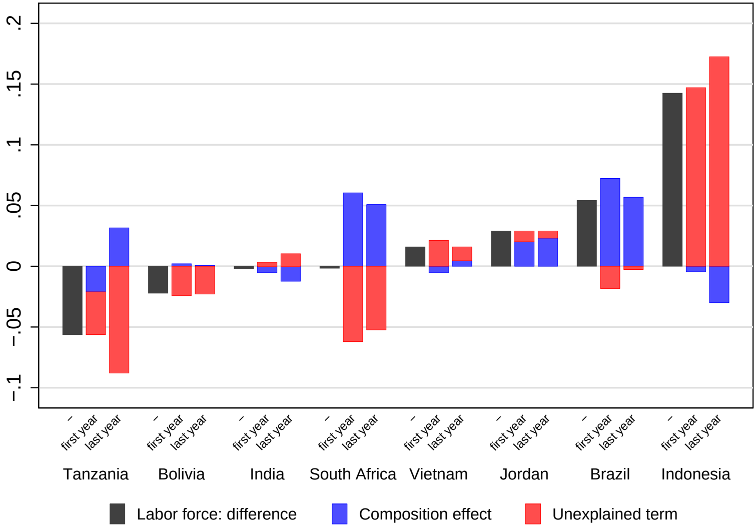
- PSU fixed effects (Brazil, Bolivia, SA, Tanzania),
- trends in marriage rates and urbanization,
- controlling for rural-urban migration directly (Tanzania) and indirectly (Brazil, Bolivia).
- Details

Within-country decompositions: results

Explained (composition effect) vs. unexplained (coefficients and unobservables) changes in FLFP:

1. composition effect explains FLFP changes relatively well in India, Brazil, and Jordan,
2. coefficients and unobservables account for most of the change in Bolivia, Indonesia, and Vietnam,
3. composition and unexplained term cancel each other out in South Africa,
4. results depend on the choice of coefficients in Tanzania.

Composition effect vs. unexplained term

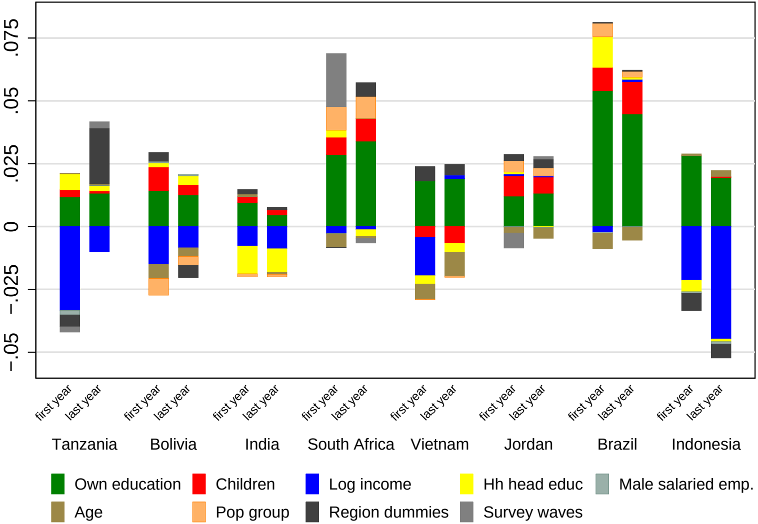


Within-country decompositions: results

Contribution of variable groups:

1. rising female education and falling fertility contribute positively everywhere,
2. but the magnitude of these contributions varies across countries,
3. in all but richest 3 countries (Jordan, SA, Brazil) positive education and fertility contributions are offset by rising household income,
4. other factors contribute only marginally.

Contribution of variable groups



Between-country decompositions

- Brazil's coefficients as reference,
- decompose FLFP gap of each country *viz a viz* Brazil,
- decompose gaps around 2000, and around 2014.

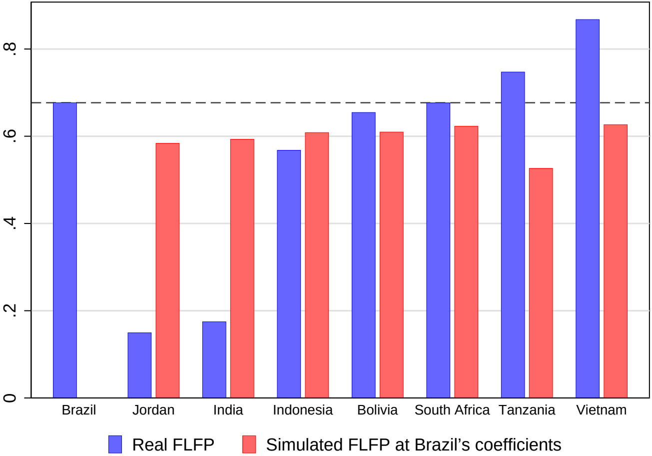
Between-country decompositions: results

1. covariates cannot explain FLFP gaps between countries,
2. for some countries, the composition effect even has the "wrong" sign,
3. coefficients and unobservables account for the bulk of FLFP variation between countries.

A thought experiment

- Imagine there is a single, fictional, labor market, where:
  1. all women face Brazil's coefficients and unobservables, irrespective of their country origin,
  2. but, otherwise, each woman has her own observable characteristics as given in the data.
- What would be the FLFP rates in this "Brazilian"-like market?

"Brazilian"-like labor market (c. 2014)



Conclusion

- Participation-returns to women's *own characteristics* and *family circumstances* differ substantially across countries,
- In fact, heterogeneity in returns to these characteristics explains most of the between-country differences in participation rates.

Policy message

- Economic growth alone or further improvements of women's labor market characteristics $\nRightarrow$ FLFP rates $\upuparrows$,
- *unless*: removal of barriers and constraints to female employment both at the household and at the labor market level in each country.

Thank you for your attention

Sample selection bias

- Sample composition effect due to trends in:
  1. urbanization rates
  2. marriage rates
- problem if selection into urban areas and marriage is correlated with labor force attachment.

Solution (following Blau and Kahn 2007):

- estimate parsimonious probit models to predict urban and marriage probabilities (age, age2, education, region, children)
- create "artificial" samples with constant urbanization and marriage rates by excluding the women with the lowest urban and marriage propensity.

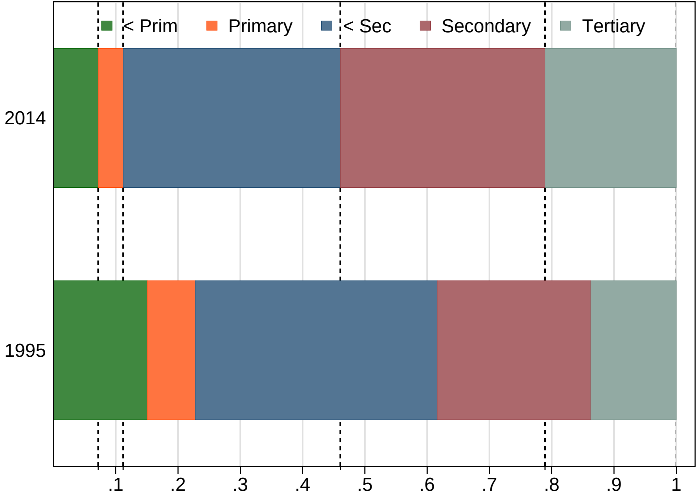
Selection bias in the education

- Massive expansion in education attainment in some countries,
- Rising education levels in our 25-54 group: more educated younger cohorts replacing less educated older cohorts.
- If the older cohorts were positively selected on education then, the decreasing AMEs for secondary and tertiary education could be due to a decline in this positive selection over time.

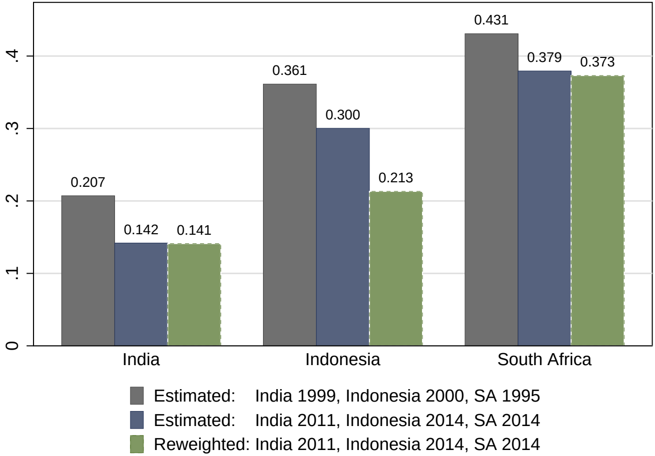
Our solution (following Klasen and Pieters 2015):

- Estimate an upper bound on this selection effect
- By weighting the AMEs of the first period by the changes in the distribution of education attainment

Distribution of educational attainment: example South Africa



Selection into education



return

Decomposition analysis for nonlinear models

- Fairlie's (2006) extension of the Oaxaca-Blinder decomposition analysis,
- Groups: A, B (two years, or two countries)
- Decomposition at group A's coefficients:

$$\overline{LFP}_B - \overline{LFP}_A \approx \left[\sum_{N_B} \frac{\Phi(X_B\hat{\beta}_A)}{N_B} - \sum_{N_A} \frac{\Phi(X_A\hat{\beta}_A)}{N_A}\right] + \left[\sum_{N_B} \frac{\Phi(X_B\hat{\beta}_B)}{N_B} - \sum_{N_B} \frac{\Phi(X_B\hat{\beta}_A)}{N_B}\right], \tag{2}$$

- Equally valid: decomposing at group B's coefficients.
- We show results using both coefficient vectors (A and B).