The urban gender premium in intergenerational mobility

Evidence from South Asia

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Intro

Motivation

- Developing countries tend to exhibit lower levels of social mobility (Narayan and Van der Weide, 2018).
- Spatial variation: Urban areas tend to be sources of economic opportunity, shifting social norms (Fafchamps and Shilpi, 2005; Bussolo et al., 2022).
- This might be particularly true for women.

Question: Do cities contribute to upward mobility in developing countries? Why?

Empirical challenge:

- Lack of linked parent-child income data makes estimating IGM a challenge$\rightarrow$ most work focused on developed countries (Chetty et al., 2014a,b).
- Parent-child linked data used for developing countries are educational data, which tend to be coarse, and no standardized measure of mobility was suitable for comparative analysis in these situations.
- Bottom Half Educational Mobility (μ_0^{50}) fills this gap.

Context: South Asia

- Rapid growth and urbanization: since 1990, urban population has grown by 380 million, likely underestimated (World Bank).
- Yet persistent socioeconomic and labor market inequities across multiple dimensions: gender, caste, religion (Munshi, 2019; Klasen and Pieters, 2015).
- Highest intergenerational rank persistence across the world (Narayan and Van der Weide, 2018).
- **But limited evidence on variation in mobility within the region**

This paper

We investigate the role of gender and urbanization in driving educational mobility, extending estimates from Asher et al. (2024) to all of South Asia.

Methods:

- Build harmonized microdata spanning 5.9 million South Asians across 7 countries.
- Match parent–child educational attainment from 39 nationally representative household surveys.
- Construct comparable location-specific mobility measures for boys and girls.

We identify the following empirical facts:

- Social mobility generally low across South Asia, though with heterogeneity.
- Urban mobility premium (UMP): social mobility higher in cities.
- Female urban mobility premium (FUMP): Women have higher UMP than men.

Methods

Data

Table 1: Datasets Harmonized for Analysis

Country	Survey Name	Years of Data	N: HH	Co-resident
Afghanistan	Afghanistan Living Conditions Survey	2013, 16	40607	Yes
Afghanistan	National Risk & Vulnerability Assessment	2008, 12	41404	Yes
Afghanistan	Income, Expenditure & Labor Force Survey	2019	18344	Yes
Sri Lanka	Household Income & Expenditure Survey	1991, 95, 2002, 06, 09, 12	95719	Yes
Nepal	Nepal Living Standard Survey	1995, 2003, 11	7316	Yes (exc. 2011)
India	India Human Development Survey	2012	38387	No
Bangladesh	Household Income & Expenditure Survey	2000, 05, 10, 16	75828	Yes
Bhutan	Bhutan Living Standards Survey	2003, 07, 12, 17	34415	Yes (exc. 2003)
Pakistan	Pakistan Integrated Household Survey	1991	4791	No
Pakistan	Pakistan Social & Living standards Measurement Survey	2006, 08, 10, 12, 14, 19	283426	Yes
Pakistan	Household Income & Expenditure Survey	2001, 04, 05, 07, 10, 11, 13, 15, 18	129906	Yes

Methods: sample selection

Requirement: Matched parent-child education pairs

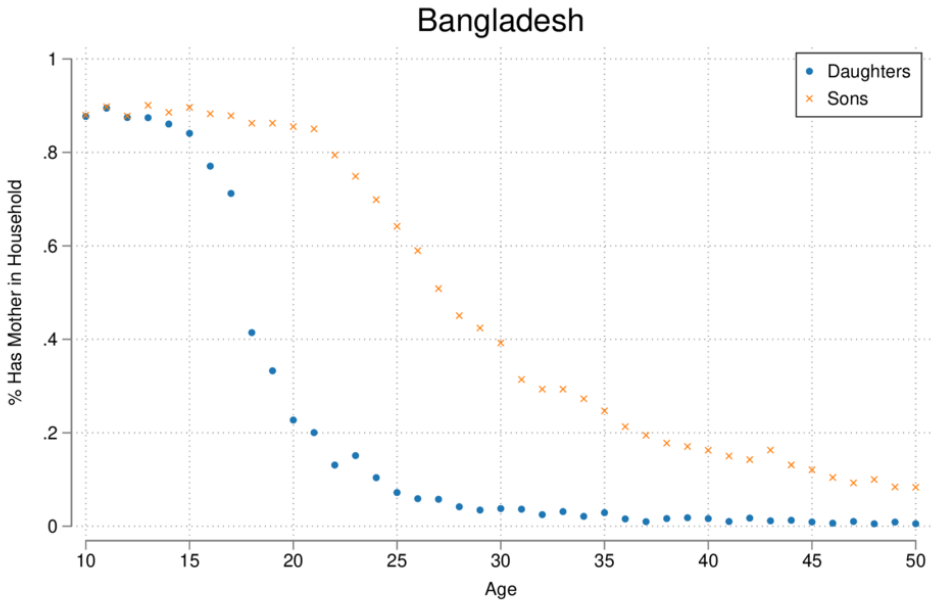
- In many datasets, we only observe parent-child pairs when they live together
- This results in bias if upwardly mobile children are more likely to stay or to exit

Our solution ⇒ Target ages when:

- Most children still at home
- Education attainment is stable: i.e. High–school for boys, Middle–school for girls

This solution works well for our countries Co-residence Women

Figure 1: Co-residence age: Bangladesh



Methods: estimating bottom-half mobility

Define bottom-half mobility (BHM) as $\mu_0^{50} = E[rank_{child}|rank_{father} \leq 50]$

- same focus and same range of the p25 measure used by Chetty et al $p25 = E[rank_{child}|rank_{father} = 25]$
- Random mobility, $\mu_0^{50} = 50$; no mobility, $\mu_0^{50} = 25$

Issue: partial identification of μ_0^{50}

- Since education distribution is discrete, one attainment category might cover the 50th percentile $\rightarrow$ *bounds* on μ_0^{50}

Estimation procedure:

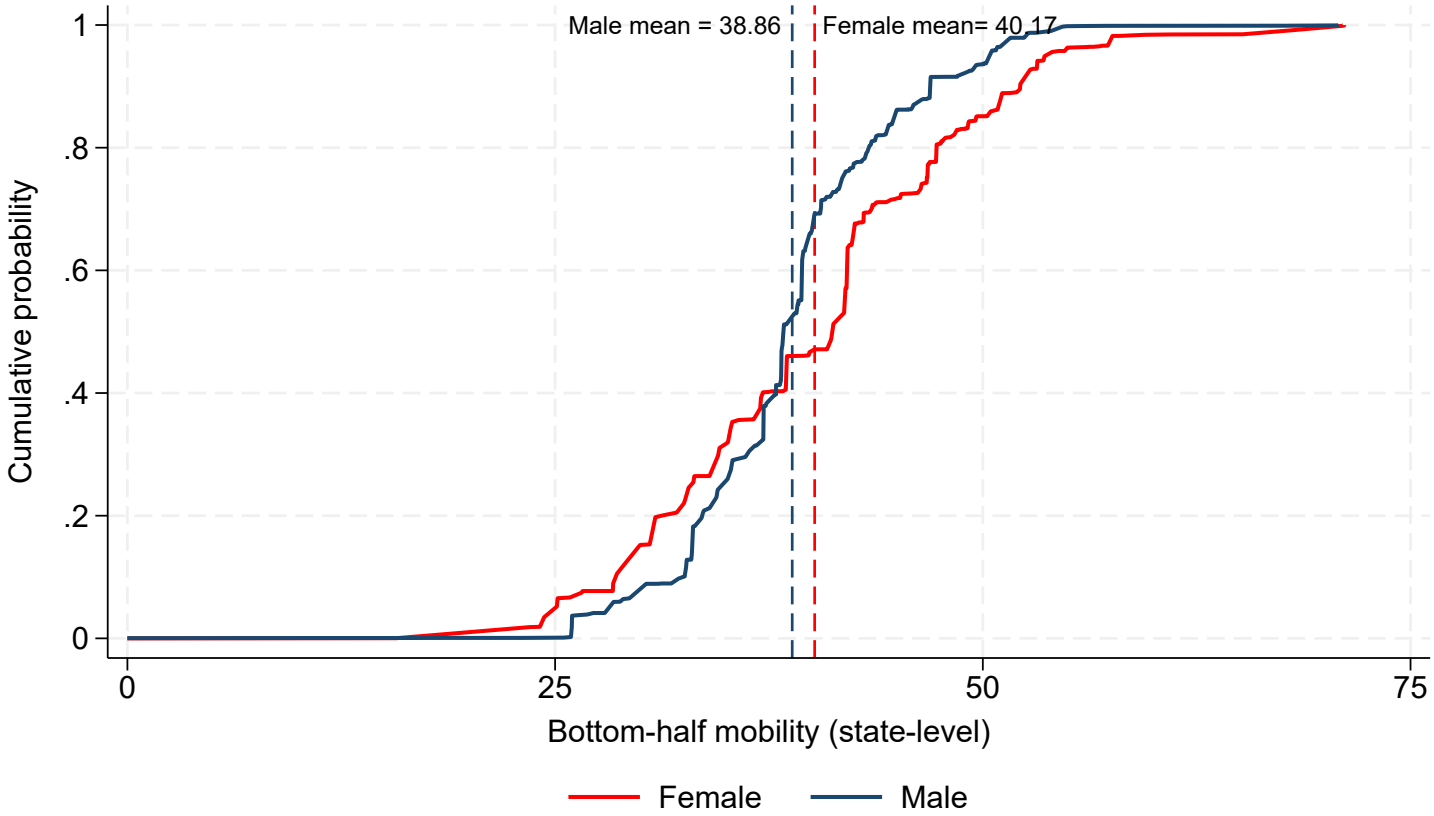
1. Standardize educational attainment into 6-group categorical variable.
2. Rank sons/daughters and fathers within country-birth cohort.
3. Calculate bounds on μ_0^{50}

Key assumption! Monotonicity of rank-rank function. Bounds example Education-consumption

Results

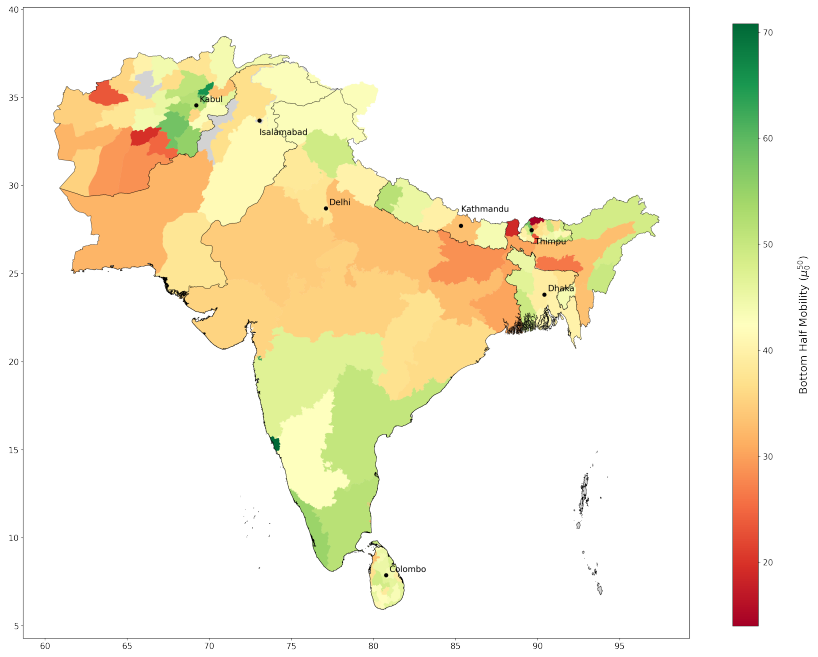
Bottom Half Mobility (BHM) in South Asia

Figure 2: Mobility distribution: state-level

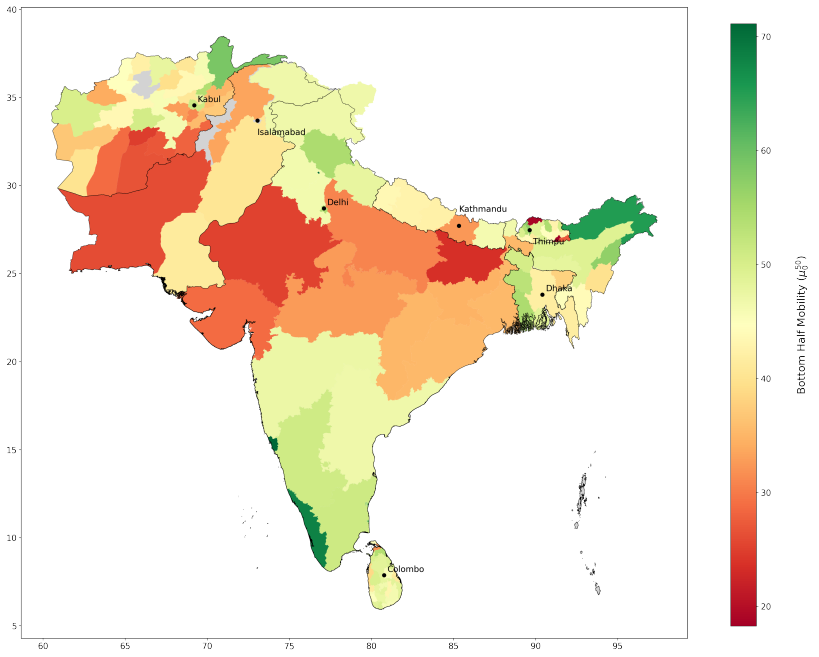


Cohort-level | Rank-rank estimates | Country-level

Mobility map: state-level



(a) Sons



(b) Daughters

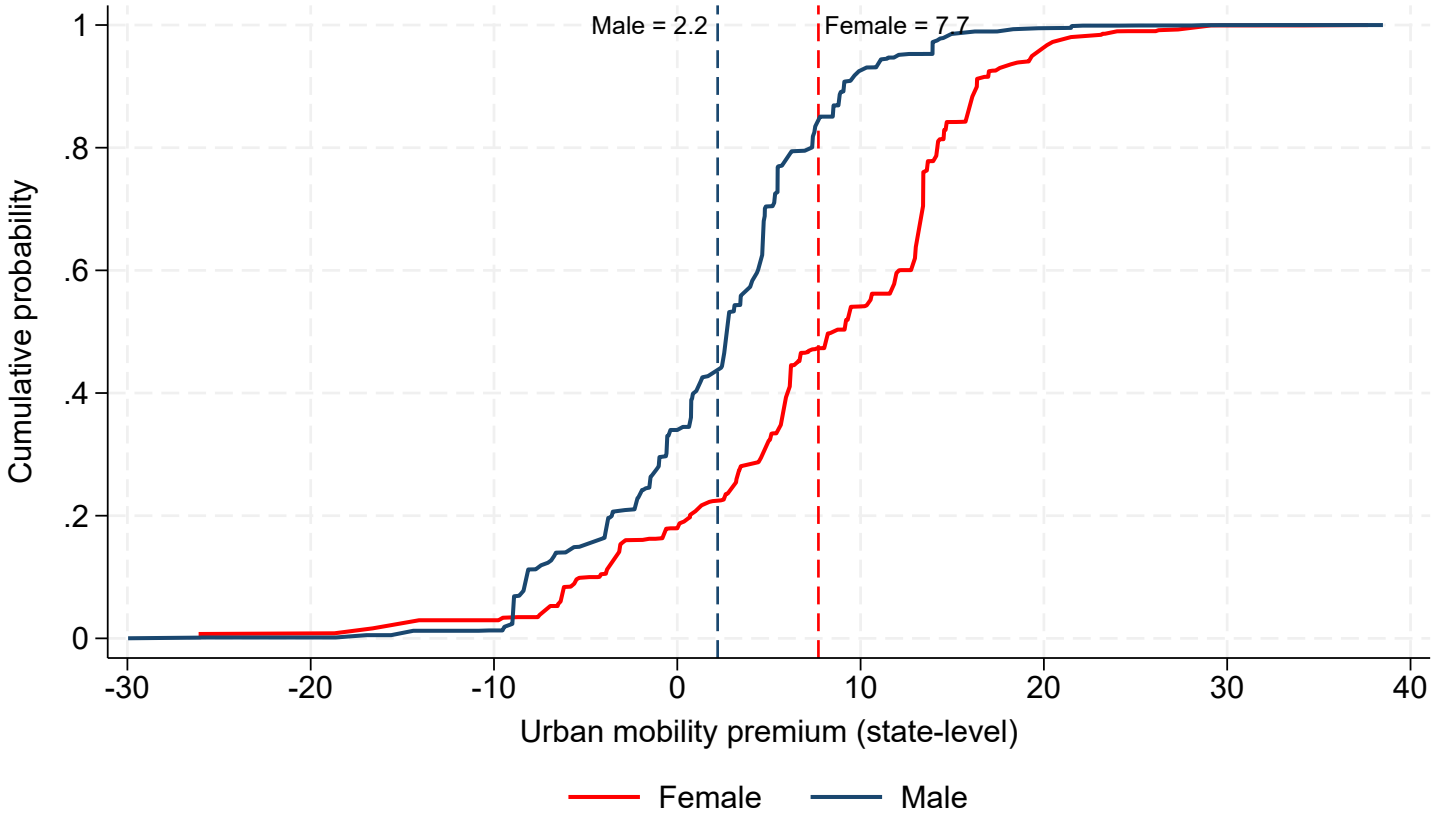
BHM & Urb Mobility Premium (UMP) — Country-level midpoint estimates

Table 2: Bottom half mobility

	Female			Male		
	Urban	Rural	UMP	Urban	Rural	UMP
Afghanistan	56.75	38.73	18.02	51.44	38.78	12.66
Bangladesh	42.97	45.38	-2.41	40.79	41.58	-0.80
Bhutan	57.50	45.31	12.18	58.99	44.34	14.65
India	47.52	34.91	12.61	40.40	36.98	3.42
Nepal	52.31	40.60	11.71	47.53	38.32	9.21
Pakistan	48.24	35.21	13.04	40.87	36.95	3.91
Sri Lanka	45.14	46.36	-1.22	45.68	43.50	2.19

The UMP

Figure 4: Urban mobility premium: state-level



Note: *Figure shows the cumulative distribution function of state-level urban bottom half mobility premia for men and women in South Asia. Sample is all cohorts since 1980. Distribution is weighted by state-level population. Vertical lines show average urban premia in bottom half mobility. Mobility estimates are taken at midpoints of bounds.*

Regression-based estimates of UMP

Table 3: Rank-level mobility regression

Mobility measure	Bottom-half				Top-half	Level
Sample	Male	Female	All			
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	3.610***	10.488***	6.725***	3.610***	8.457***	0.057***
	(0.508)	(0.565)	(0.399)	(0.508)	(0.384)	(0.010)
Female				-1.032**	-1.209***	-0.136***
				(0.446)	(0.361)	(0.009)
Urban × Female				6.877***	1.649***	0.099***
				(0.715)	(0.476)	(0.014)
Constant	38.121***	37.089***	37.639***	38.121***	54.292***	0.441***
	(0.294)	(0.345)	(0.229)	(0.294)	(0.283)	(0.006)
Observations	129280	97552	226832	226832	315297	226832
R^2	0.003	0.029	0.012	0.015	0.034	0.023

Note: Standard errors in parentheses clustered at the household level. Estimates are from a regression of child education outcomes (rank or level) on indicator variables for urban residence and female identity. Sample and mobility outcomes are indicated in table header. "Bottom-half" and "level" columns restrict the sample to parents in the bottom 50% of educational attainment, while top-half restricts to parents in the top 50%. Sample is all cohorts since 1980 pooled across seven South Asian countries. All estimates adjusted with cross-country sampling weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$$\text{child rank} = \alpha + \beta_1 \times \text{urban} + \beta_2 \times \text{female} + \beta_3 \times \text{female} \times \text{urban}, \quad \text{if parent rank} \leq 50$$

Drivers of FUMP

1) Returns to education

- Higher labor market returns to education for urban women may incentivize greater investment in education.
- In context with low FLFP, marriage market returns might also serve to incentivize educational investments.

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2) Social norms

- In places with less conservative norms, pre-existing social hierarchies are less likely to disproportionately constrain life outcomes for disadvantaged groups.

Drivers of FUMP

1) Returns to education

- Higher labor market returns to education for urban women may incentivize greater investment in education.
- In context with low FLFP, marriage market returns might also serve to incentivize educational investments.

2) Social norms

- In places with less conservative norms, pre-existing social hierarchies are less likely to disproportionately constrain life outcomes for disadvantaged groups.

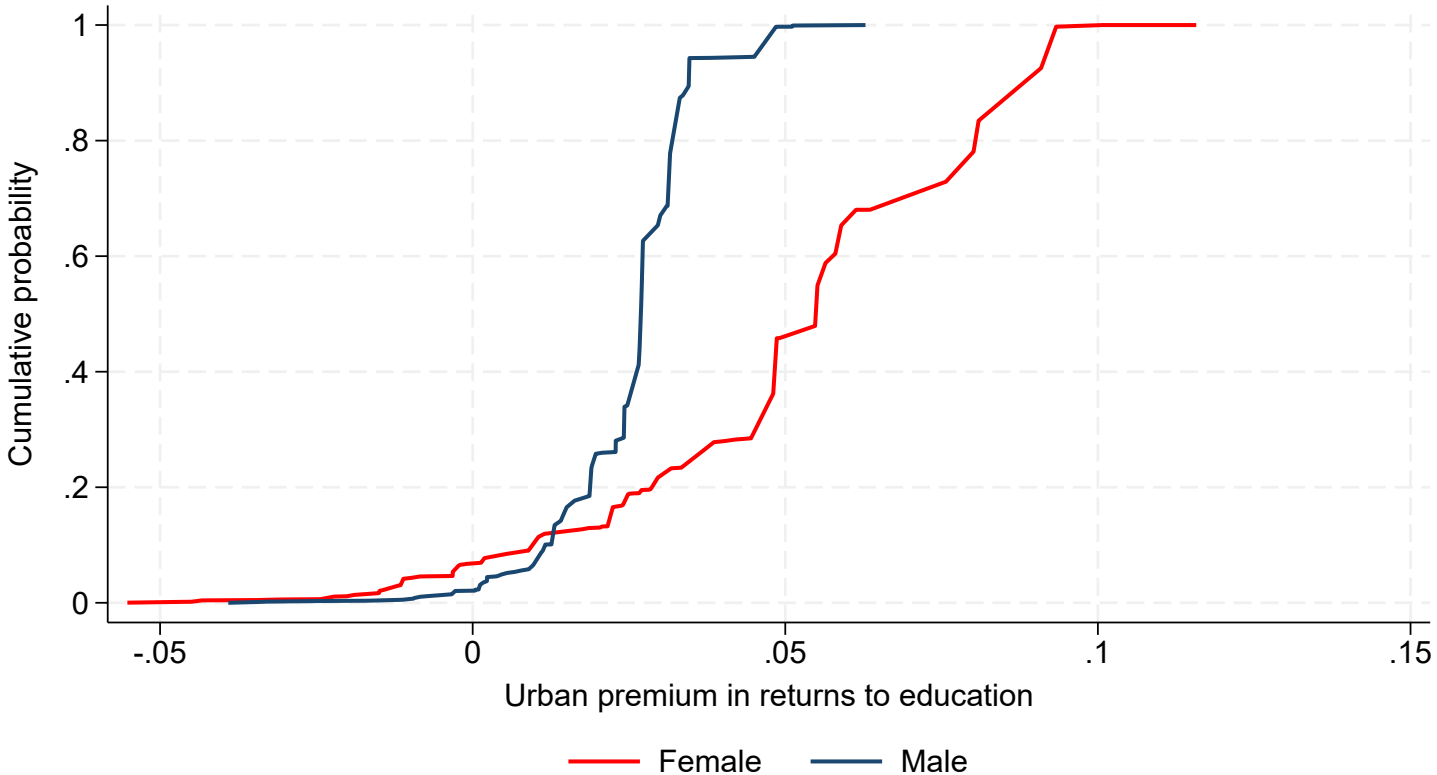
3) Income effects

- Higher incomes available in urban areas may increase educational investment, particularly for girls.

Note that in order to increase mobility, each of these explanations requires greater responses *by poor households*.

Returns to education: higher for urban women

Figure 5: Returns to education for men and women

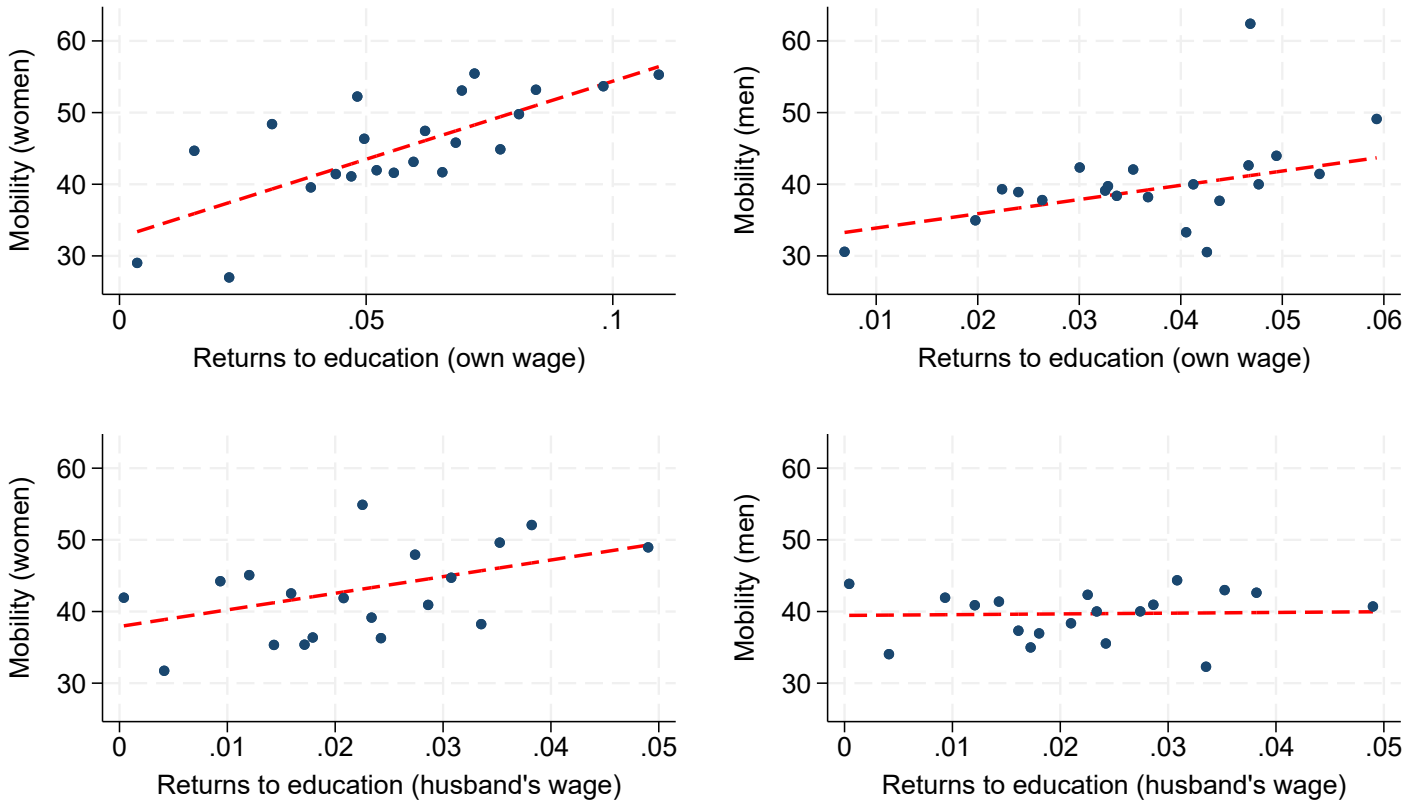


Cohorts since 1980, population weighted

Mincer regression

Returns to education: correlated with mobility

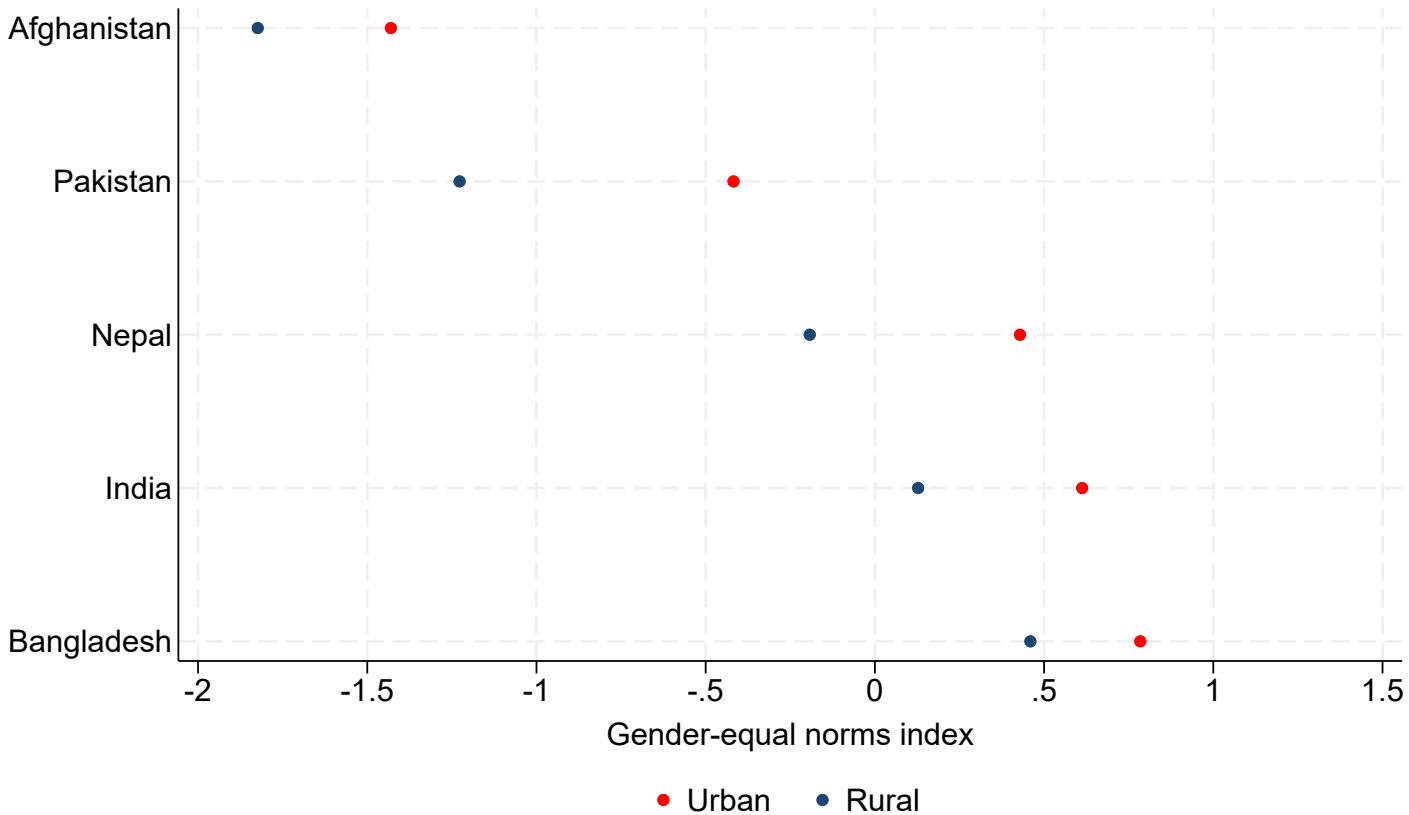
Figure 6: Mobility and returns to education



Regression test

Gender norms: looser in urban areas

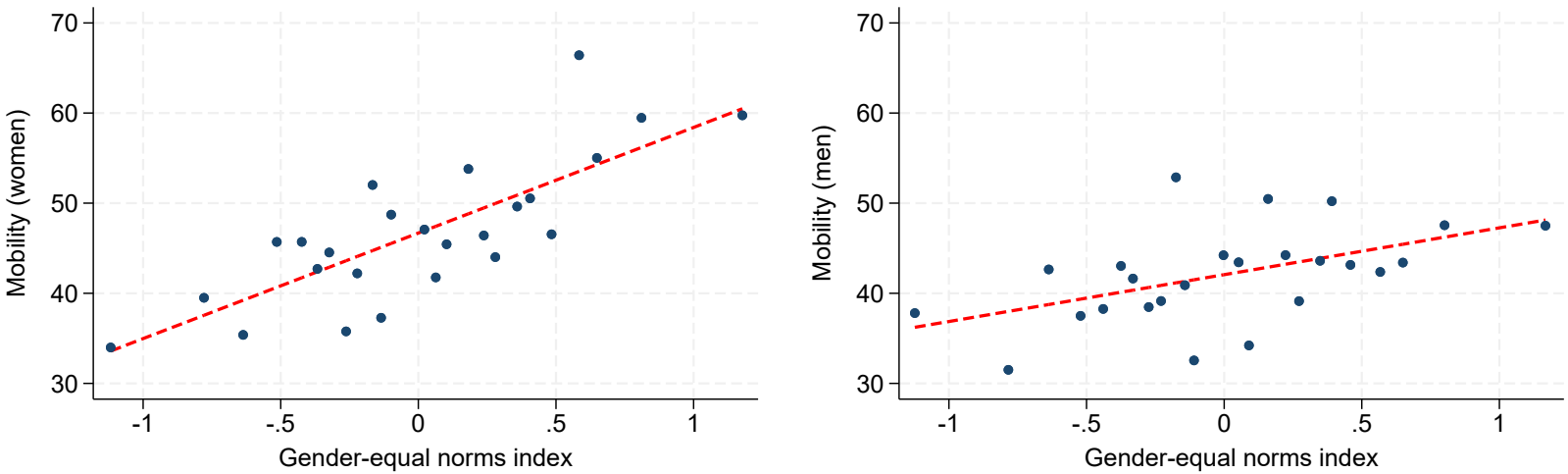
Figure 7: Urban and rural gender norms by country



Note: *Figure shows average values of the standardized gender-equal norms index in rural and urban areas across countries. The gender-equal norms index is averaged across the following dimensions: son preference, reproductive choice, justification of domestic violence, and household decisionmaking. Each of these index components is measured as the share of female DHS respondents agreeing with a gender-equal norm. The resulting index, which varies between 0 and 1, is standardized across sub-national units. All estimates are sample-weighted.*

Gender norms: correlated with female mobility

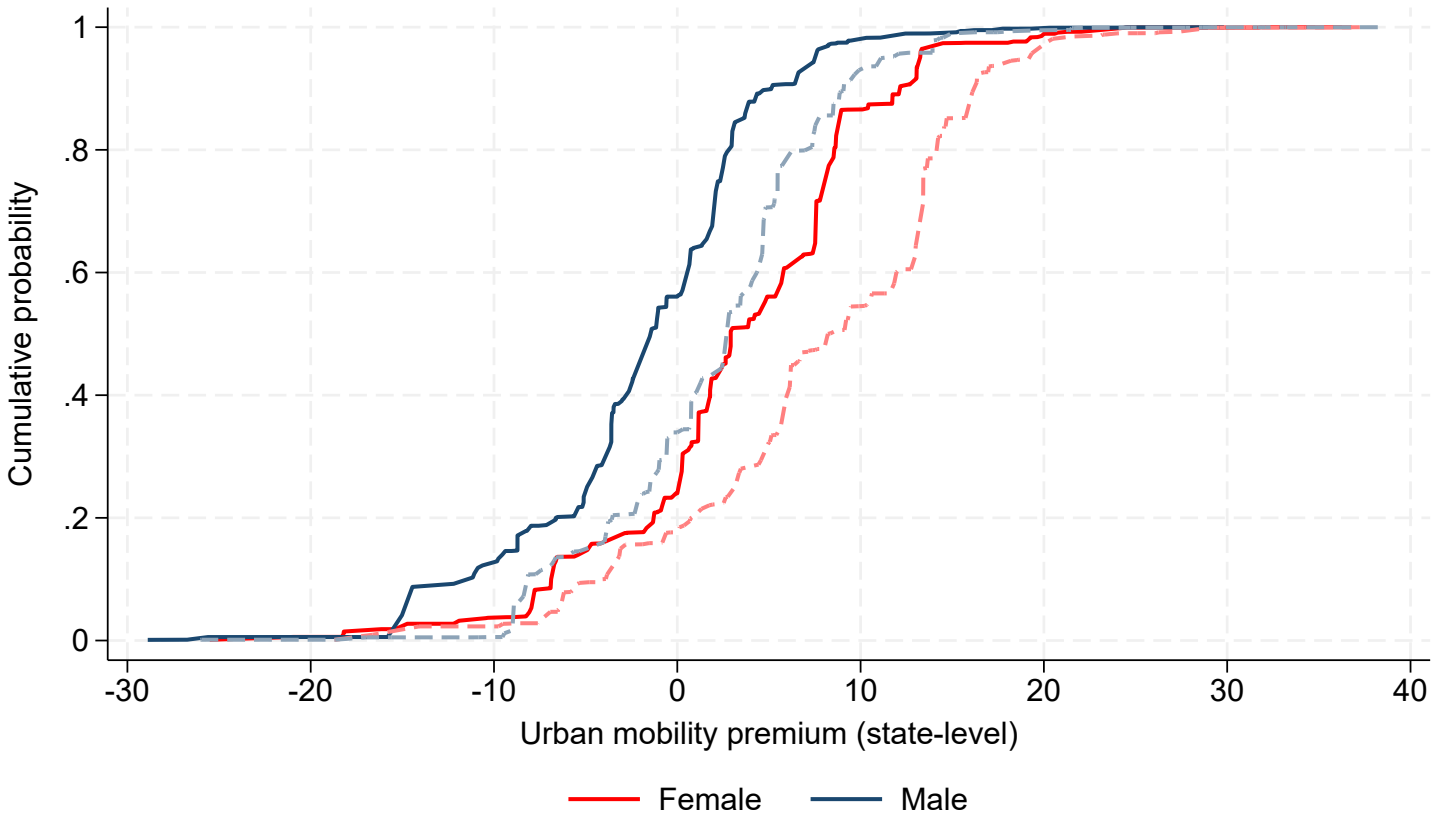
Figure 8: Mobility and gender norms



Regression test

Income effects

Figure 9: State-level UMP: Income-adjusted



Conclusion

- We introduce a comparable estimate of inter-generational educational mobility that can be constructed with standard household surveys.
- Mobility is low but spatially heterogeneous across South Asia.
- Women experience large mobility gains in cities.
- 65% of the FUMP is explained by returns to education and social norms.

UMP decomposition

Appendix

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Methods: bounds example

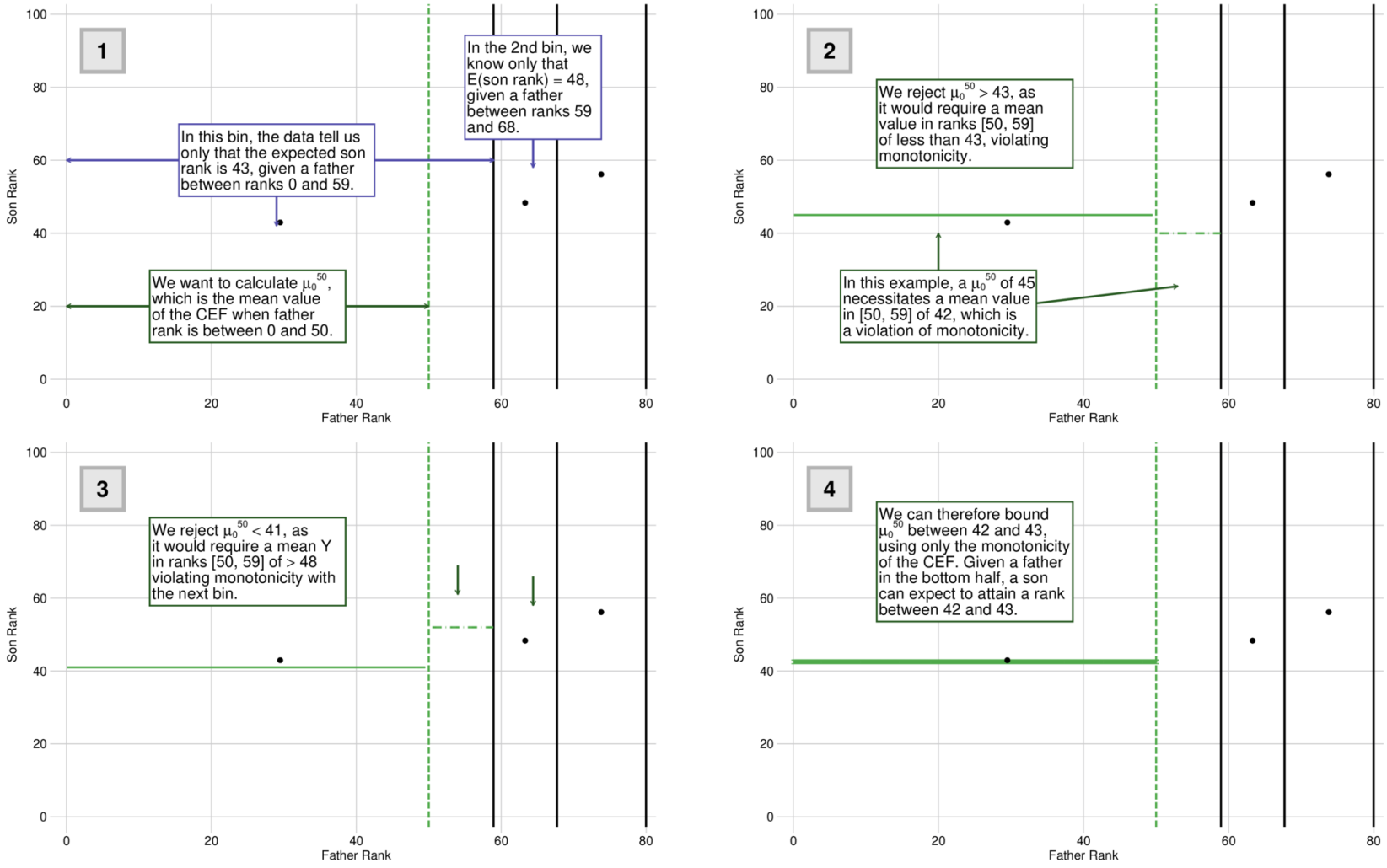

Figure A1: Calculating bounds on μ_0^{50}

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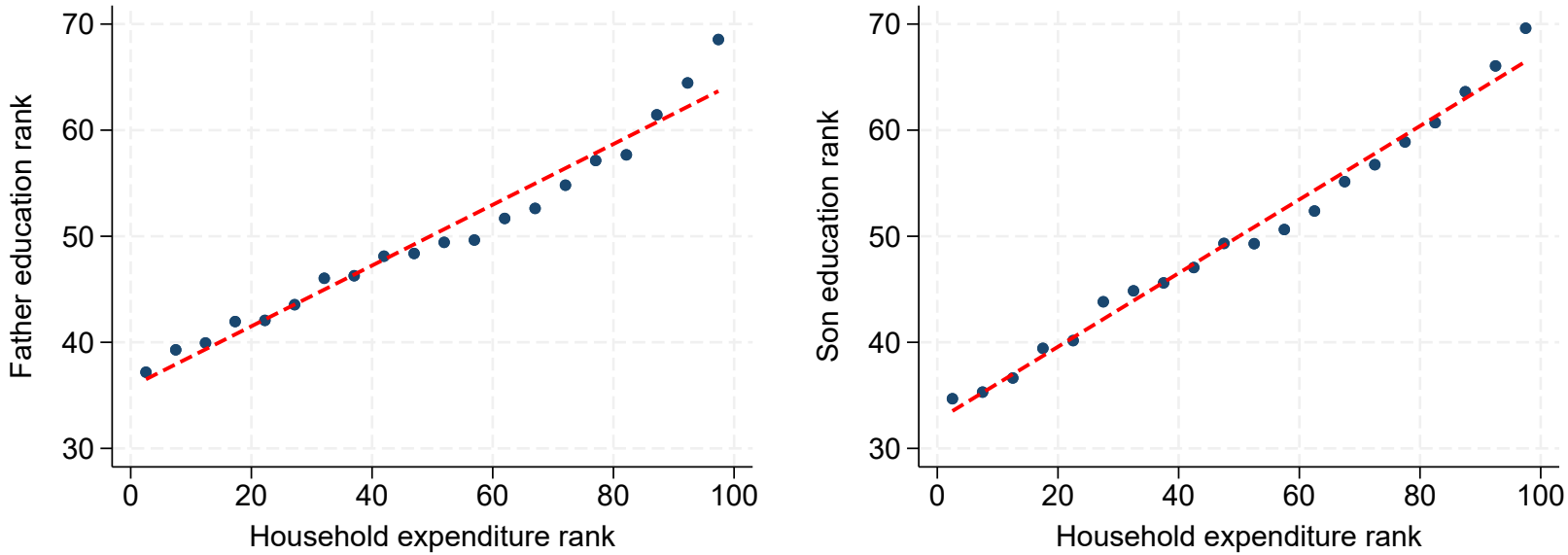
Education vs. consumption

Figure A2: Consumption-education rank-rank correlations



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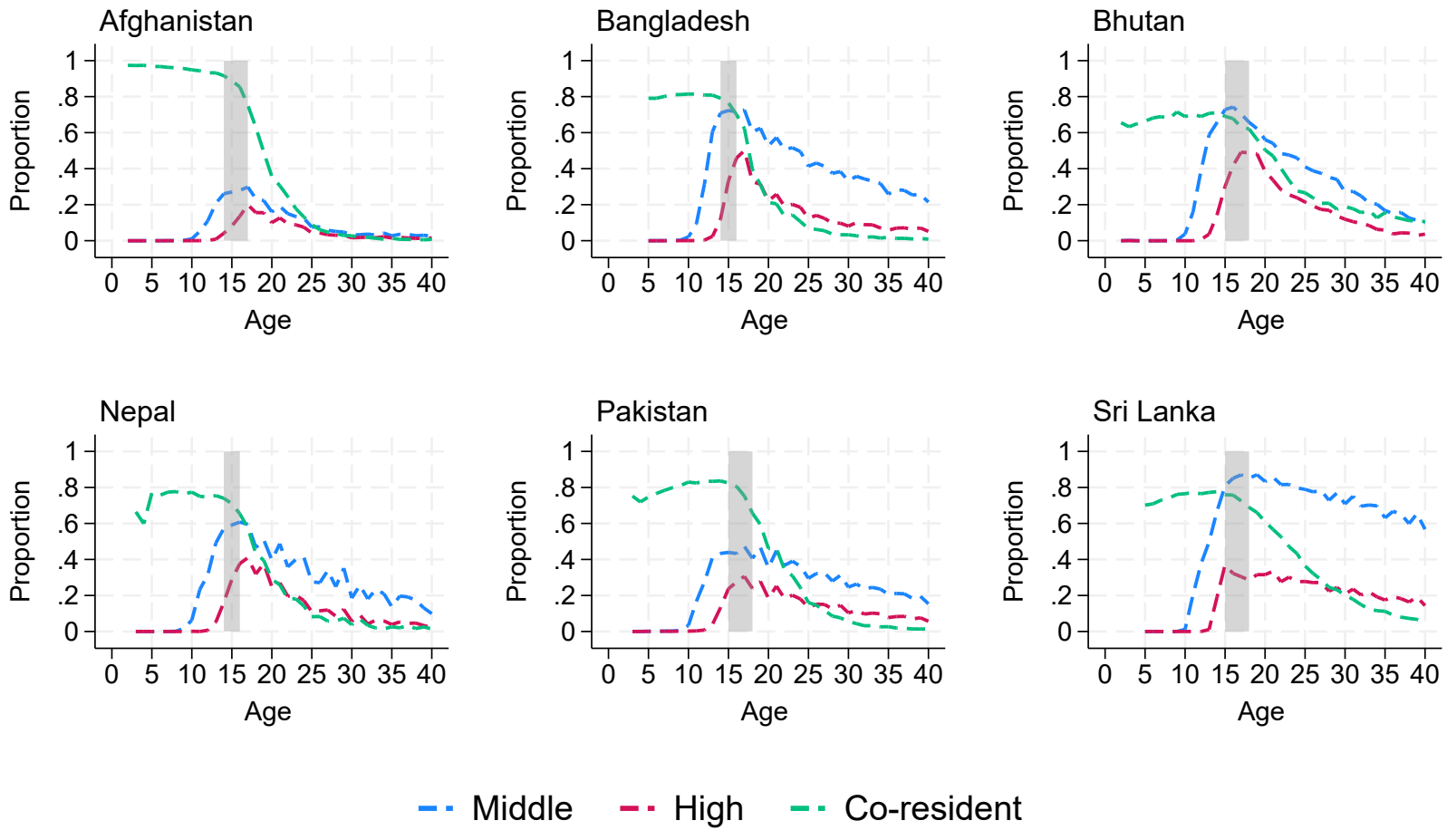
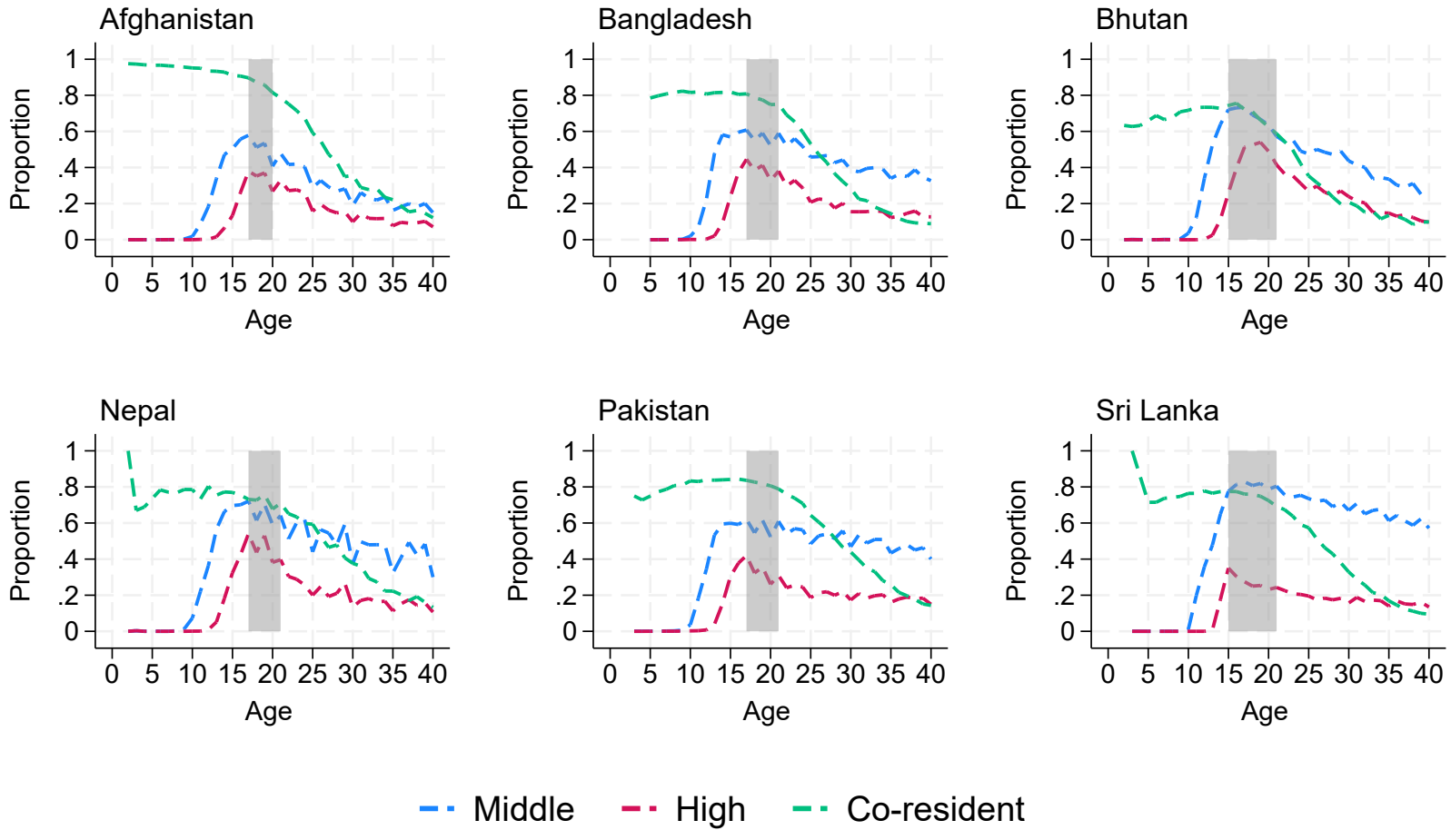
Coresidence: women

Figure A3: Coresidence and educational attainment: women



Coresidence: men

Figure A4: Coresidence and educational attainment: men



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Rank-rank regression

Table A1: Rank-rank mobility regression

Dependent variable	Child's education rank			
Sample	Male		Female	
	(1)	(2)	(3)	(4)
Father's education rank	0.482***	0.470***	0.440***	0.427***
	(0.006)	(0.006)	(0.006)	(0.006)
Predicted BHM	38.313	38.606	39.184	39.510
Observations	240617	240617	177950	177950
R^2	0.228	0.255	0.210	0.289
Cohort × State FE	No	Yes	No	Yes

Note: Standard errors in parentheses clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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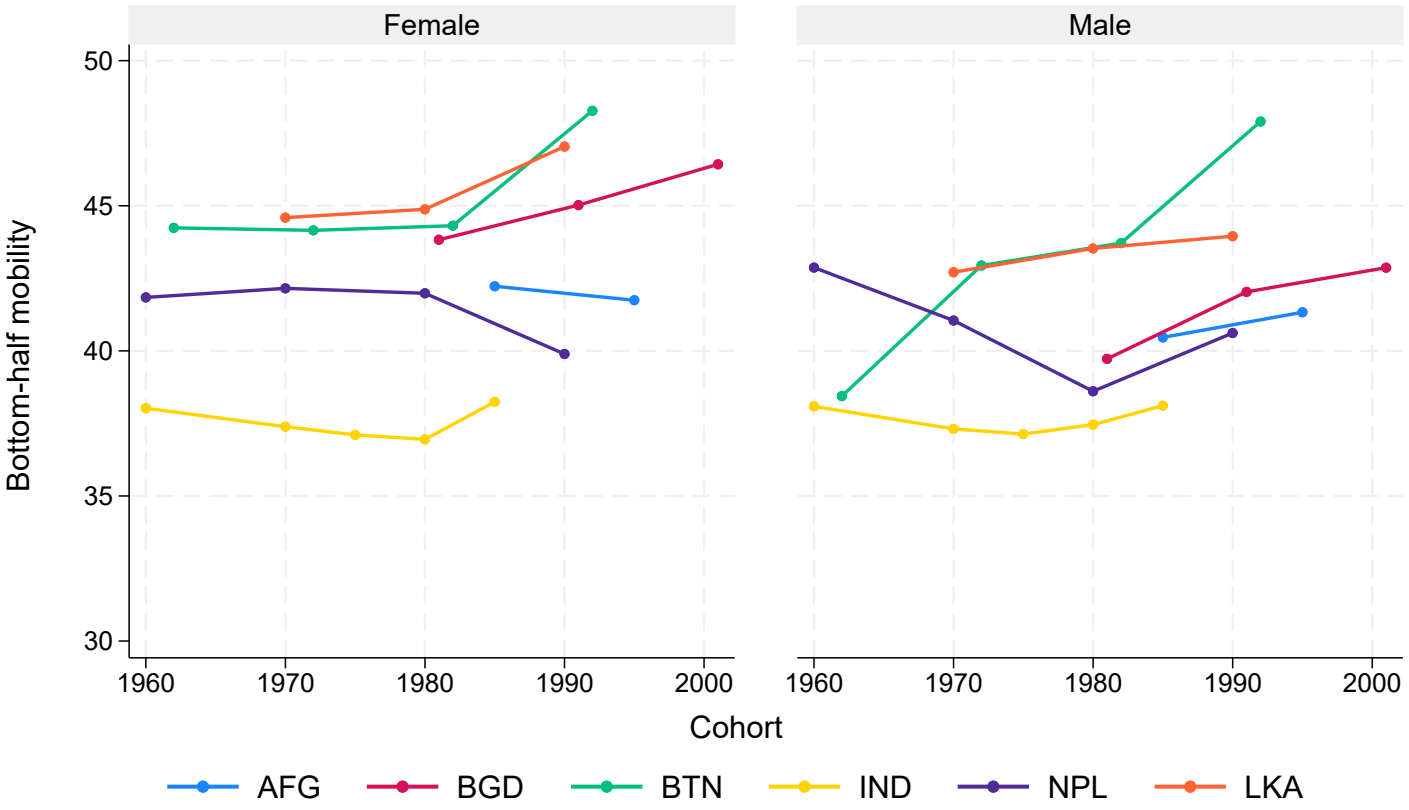
BHM by cohort

Figure A5: Cohort-wise mobility estimates: country-level



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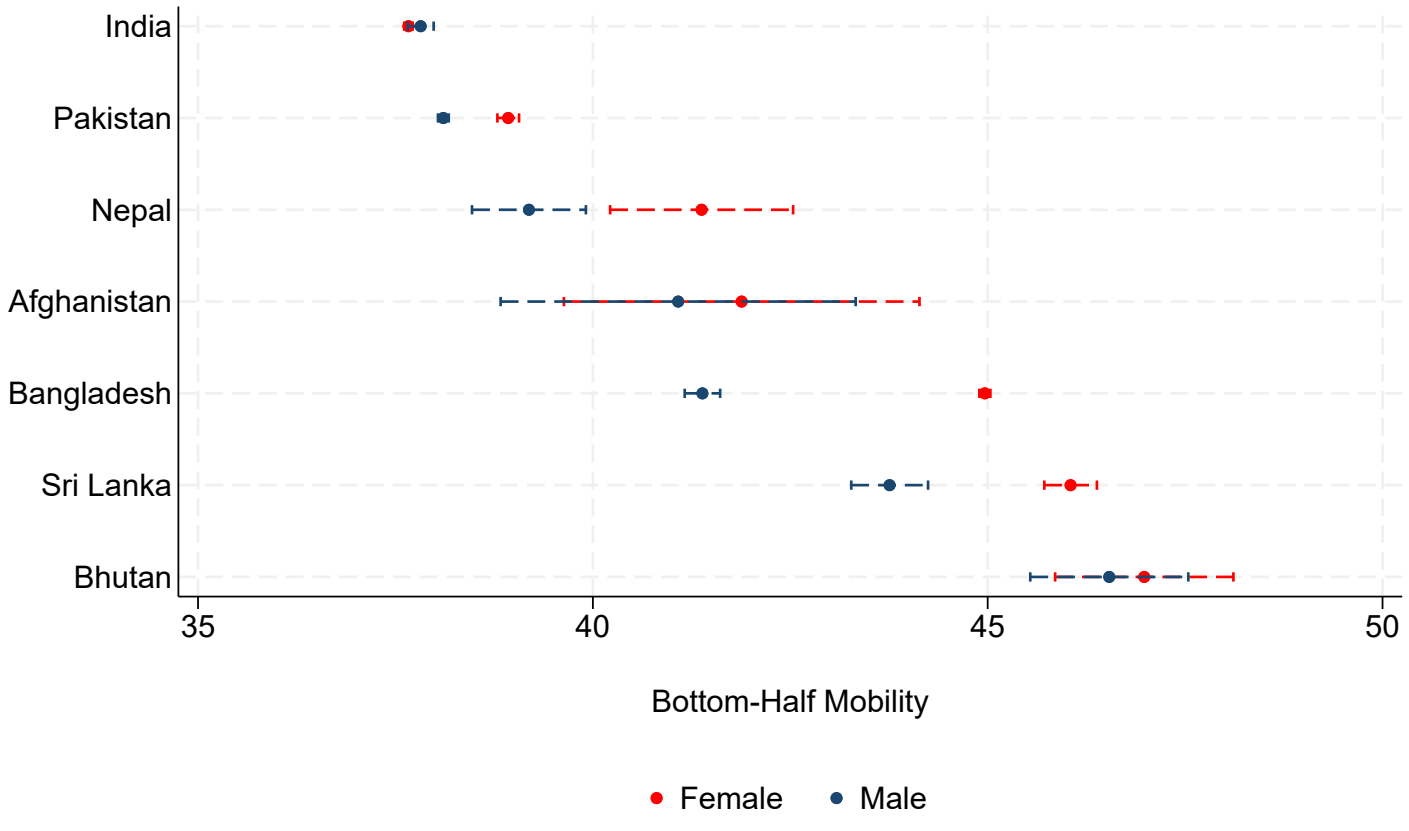
Country-specific BHM

Figure A6: Country-level BHM



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Rank-rank estimates of UMP

Table A2: Rank-rank mobility regression: UMP estimates

Dependent variable	Child's education rank				
Sample	Male	Female	All		
	(1)	(2)	(3)	(4)	(5)
Father's education rank	0.426***	0.449***	0.449***	0.435***	0.373***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.020)
Urban	12.529***	1.275	1.275	0.489	1.075
	(0.812)	(0.847)	(0.847)	(0.832)	(0.873)
Father's education rank × Urban	-0.066***	0.046***	0.046***	0.050***	0.041**
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Father's education rank × Female			-0.023	-0.017	-0.002
			(0.013)	(0.012)	(0.024)
Father's education rank × Urban × Female			-0.112***	-0.108***	-0.114***
			(0.017)	(0.017)	(0.018)
Father's education rank × Log per capita consumption					0.009***
					(0.002)
Father's education rank × Log per capita consumption × Female					-0.002
					(0.003)
Female UMP			9.603	8.712	9.715
Male UMP			2.423	1.735	2.096
Observations	177869	240617	418486	418486	397918
R^2	0.235	0.233	0.234	0.269	0.237
Cohort × State FE	No	No	No	Yes	No

Note: Standard errors in parentheses clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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Country-level midpoint estimates

Table A3: Bottom half mobility

	Female			Male		
	Urban	Rural	UMP	Urban	Rural	UMP
Afghanistan	56.75	38.73	18.02	51.44	38.78	12.66
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Regression-based estimates of UMP

Table A4: Rank-level mobility regression

Mobility measure	Bottom-half				Top-half	Level
Sample	Boys	Girls	All			
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	3.610***	10.488***	6.725***	3.610***	8.457***	0.057***
	(0.508)	(0.565)	(0.399)	(0.508)	(0.384)	(0.010)
Female				-1.032**	-1.209***	-0.136***
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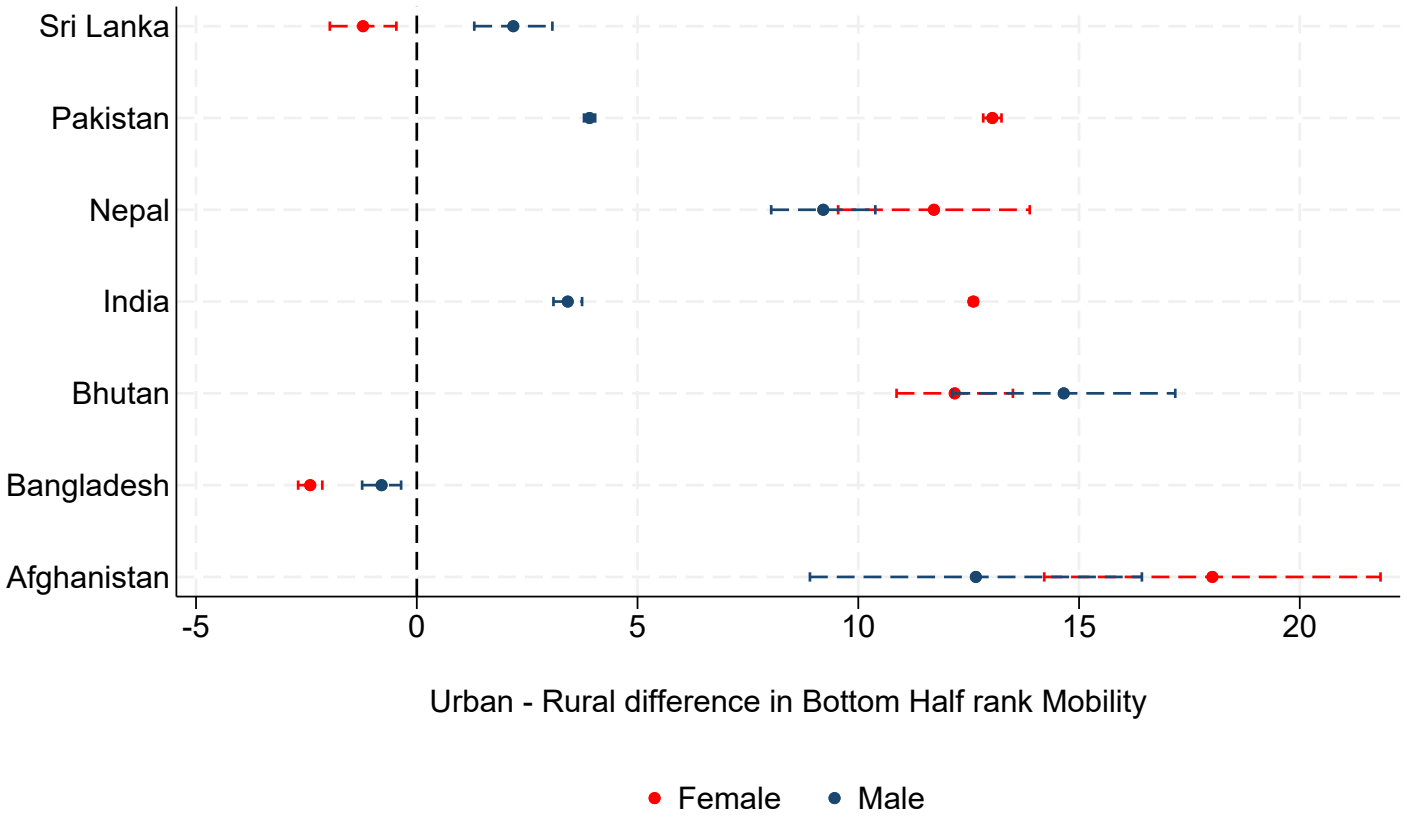
Country-specific UMP

Figure A7: Country-level UMP



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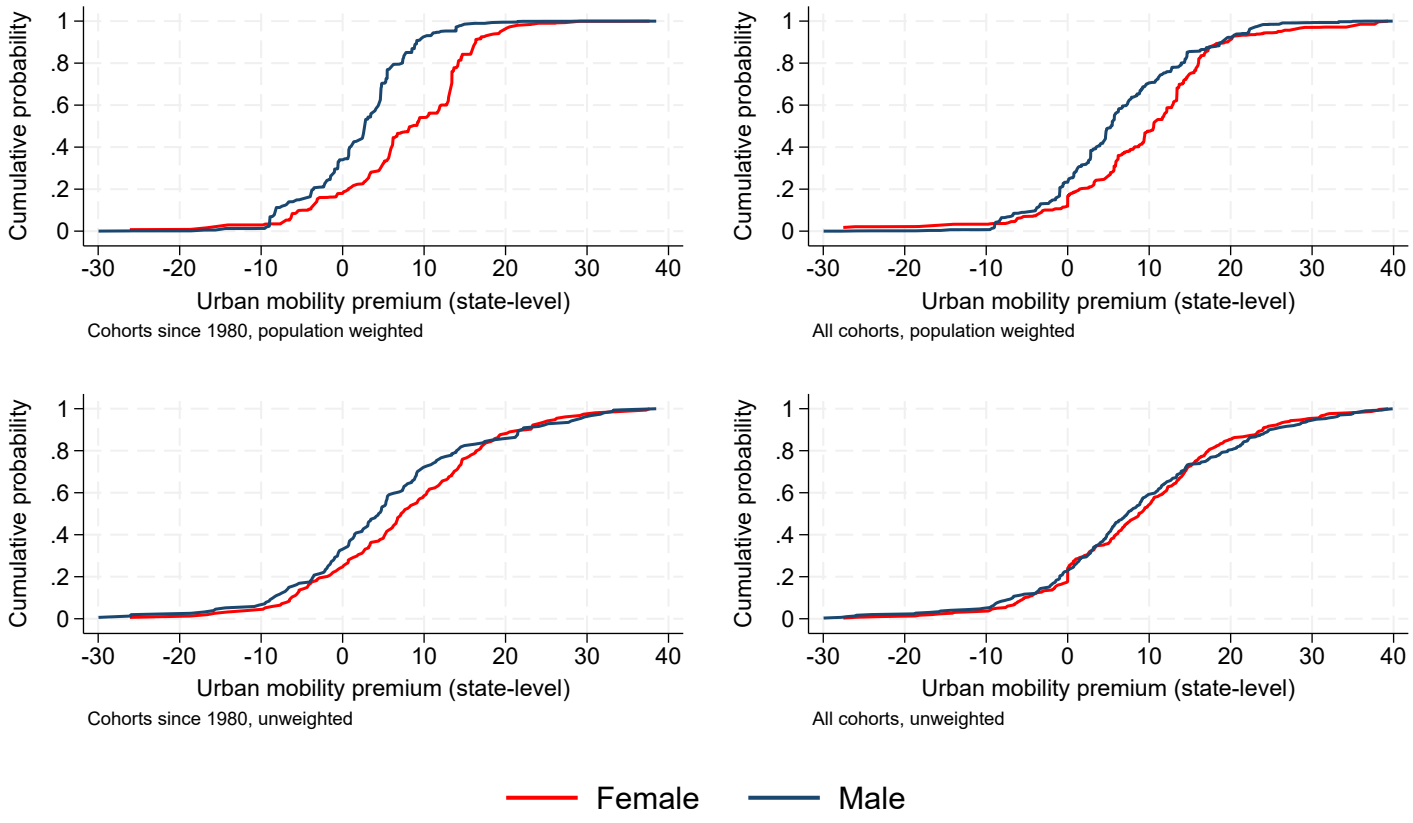
UMP robustness: specification

Figure A8: State-level UMP: Robustness to specification



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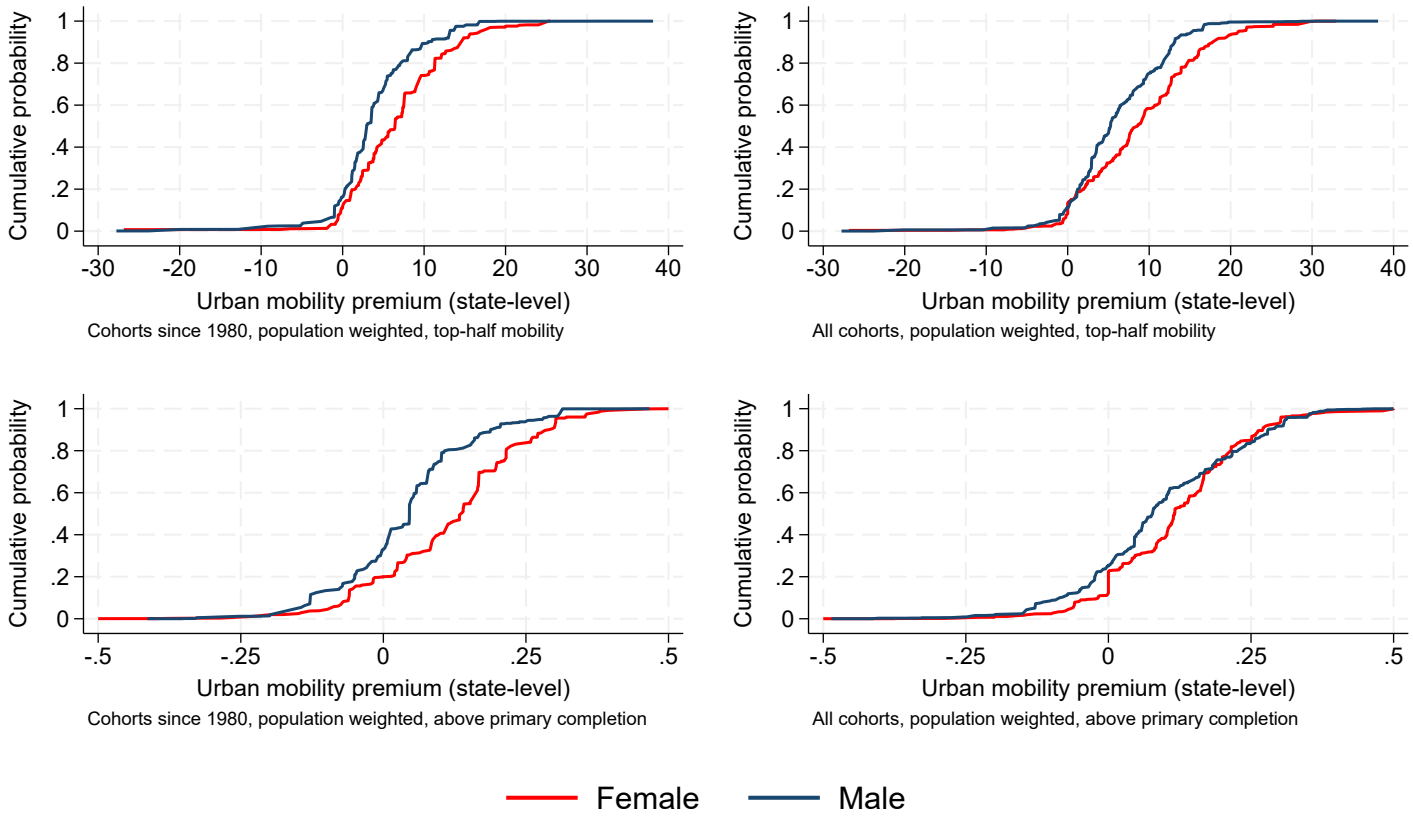
UMP robustness: outcome variable

Figure A9: State-level UMP: Robustness to outcome



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Mincer regression

Table A5: Mincer regression: returns to education

Dependent variable	Log own wage			Log husband's wage	
	(1)	(2)	(3)	(4)	(5)
Years of education	0.080***	0.069***	0.051***	0.036***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Years of education × Female		0.016***	0.007***		
		(0.000)	(0.001)		
Years of education × Urban			0.022***		0.018***
			(0.000)		(0.001)
Years of education × Urban × Female			0.017***		
			(0.001)		
Age FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Spouse age	No	No	No	Yes	Yes
Observations	2282207	2282207	2282207	1058529	1058529
R^2	0.660	0.690	0.707	0.661	0.679

Note: Robust standard errors in parentheses. Sample in columns (1)-(3) is all working-age (16+) adults in cohorts born since 1980 across six South Asian countries (no data for Bhutan), while sample for columns (4)-(5) is only married women. Wages measured as log daily wage in local currency units. All estimates adjusted with cross-country sampling weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$$\log(w_i) = \alpha + \beta_1 s_i + \beta_2 s_i \times \text{urb}_i + \beta_3 s_i \times \text{fem}_i + \beta_4 s_i \times \text{urb}_i \times \text{fem}_i +$$
$$\beta_5 \text{urb}_i + \beta_6 \text{fem}_i + \beta_7 \text{fem}_i \times \text{urb}_i + a_a + \delta_{sy} + \epsilon_i$$

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Estimation of mechanisms

Table A6: Bottom-half mobility by returns to education and social norms

Dependent variable	Child's education rank					
Sample	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Return to education	1.097**			1.076***		
	(0.445)			(0.293)		
Marriage market return to education		0.331			1.827*	
		(0.552)			(0.987)	
Gender-equal norms index			0.731			3.173***
			(0.894)			(1.042)
Constant	34.960***	38.261***	38.174***	34.025***	35.666***	36.312***
	(1.829)	(1.429)	(1.150)	(2.282)	(2.747)	(1.752)
Observations	126602	126602	119800	93667	93667	89591
R^2	0.004	0.000	0.001	0.027	0.010	0.011

Note: Standard errors in parentheses clustered at the state-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Back-returns Back-norms

Explaining UMP

Table A7: Bottom-half mobility by returns to education and social norms

Dependent variable	Child's education rank					
Sample	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	3.525***	0.920	1.900	10.536***	7.360***	2.771
	(1.061)	(0.996)	(1.564)	(1.608)	(1.653)	(2.326)
Expenditure rank		0.214***			0.236***	
		(0.024)			(0.020)	
Return to education			0.790			1.302***
			(0.707)			(0.284)
Gender-equal norms index			0.006			3.936***
			(1.053)			(1.365)
Share of UMP explained			0.461			0.737
Observations	112088	112088	112088	82215	82215	82215
R^2	0.003	0.050	0.005	0.030	0.086	0.053

Note: Standard errors in parentheses clustered at the state-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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