Supplementary information

Table S1. Proportion of informal workers* by region, sex and urban status

Region	Rural		Urban	
	Male	Female	Male	Female
AD	85%	94%	49%	54%
AN	53%	37%	30%	11%
AR	75%	73%	45%	24%
AS	81%	41%	58%	36%
BR	88%	71%	70%	35%
CH	31%	21%	34%	26%
CT	89%	96%	47%	60%
DD	35%	15%	9%	5%
DL	52%	4%	35%	21%
DN	19%	38%	14%	55%
GA	31%	47%	40%	22%
GJ	79%	87%	45%	46%
HP	73%	92%	45%	47%
HR	71%	83%	45%	49%
JH	89%	91%	62%	51%
JK	73%	55%	51%	31%
KA	85%	88%	53%	44%
KL	69%	51%	62%	34%
LD	54%	9%	49%	5%
MH	82%	93%	42%	38%
ML	87%	88%	59%	30%
MN	80%	75%	64%	58%
MP	90%	95%	59%	55%
MZ	87%	87%	53%	45%
NL	60%	60%	35%	31%
OR	88%	88%	55%	47%
PB	75%	64%	47%	33%
PY	69%	48%	58%	17%
RJ	82%	95%	54%	52%
SK	75%	72%	53%	42%
TN	67%	81%	45%	44%
TR	81%	72%	58%	40%
UP	90%	88%	62%	50%
UT	75%	85%	51%	24%
WB	86%	77%	55%	48%
India	84%	88%	51%	44%

*Informal workers include own-account workers, casual workers and unpaid family workers
Source: Periodic Labour Force Survey (2017/18), author's calculation

Projection method

1. Replication of the multistate cohort-component projection

The base population. Any microsimulation model for demographic projection requires a comprehensive microdata set representing the starting population. We have built our base population from scratch, using the aggregated population by age, sex, region, type of residence, and education in 2010 from KC et al. (2018). It includes 35 states (including union territories) of India as per the geographical divisions from the 2011 census all classified as either rural or urban areas, which in total makes it 70 'regions'. Educational attainment contains 6 categories (e1-e6): 'No education', 'Incomplete primary', 'Complete primary', 'Lower secondary', 'Upper secondary', and 'Postsecondary'. The definition of variables and their categories is as follow:

agegr – Age group of.

0. 0-4;
5. 5-9;
10. 10-14;
…
100. 100+;

edu – Educational attainment / ***eduM*** – Education of the mother.

e1. No education;
e2. Incomplete primary;
e3. Complete primary;
e4. Lower secondary;
e5. Upper secondary;
e6. Postsecondary;

sex – Sex.

0. Male;
1. Female;

region – Region of residence.
(followed by *_rural* for rural parts and *_urban* for urban parts)
AD. Andhra Pradesh;
AN. Andaman & Nicobar Islands;
AR. Arunachal Pradesh;

AS. Assam;
BR. Bihar;
CH. Chandigarh;
CT. Chhattisgarh;
DD. Daman & Diu;
DL. Delhi;
DN. Dadra & Nagar Haveli;
GA. Goa;
GJ. Gujarat;
HP. Himachal Pradesh;
HR. Haryana;
JH. Jharkhand;
JK. Jammu & Kashmir;
KA. Karnataka;
KL. Kerala;
LD. Lakshadweep;
MH. Maharashtra;
ML. Meghalaya;
MN. Manipur;
MP. Madhya Pradesh;
MZ. Mizoram;
NL. Nagaland;
OR. Orissa;
PB. Punjab;
PY. Puducherry;
RJ. Rajasthan;
SK. Sikkim;
TN. Tamil Nadu;
TR. Tripura;
UP. Uttar Pradesh;
UT. Uttarakhand;
WB. West Bengal;

For each subgroup of population, the sample size of the base population represents 0.05% of the population size when that size is higher than 10,000. For groups with smaller populations, using the same sample rule might generate too few individuals, which would lead to less accurate forecasting results by increasing the Monte Carlo error. At the same time, the dataset would be too loaded if we were to include too many observations for groups that are very marginal (such as women aged 90 to 94 who have postsecondary education and live in a rural area of Dadra &

Nagar Haveli). We have thus decided that, for our purposes, the number of observations should decrease when the size of the population in the group shrinks: 40 cases for populations between 1,000 and 10,000, 30 cases for populations between 100 and 1,000, 10 for populations between 30 and 100 and 2 for populations lower than 30. The resulting dataset has 846,024 cases with an average population weight of 1,431.2 (S.D.=890.5).

Demographic and education components. The demographic and education modules of INDIMIC are based on assumptions sourced from the baseline scenario of the multistate model developed by KC et al (2018). Educational attainment matters for fertility and mortality, but not for migration. Before the threshold age of 15, the education of the mother is used for determining mortality rates. Internal mobility is modelled on the age- and sex-specific origin-destination matrix. In addition to internal mobility, the model allows for the reclassification of rural areas as urban. The model is closed, which means there is no international migration.

In this multistate projection, events are ordered as follows:

1. Mortality is applied with survival ratios by age, sex, education and region;
2. Education transition rates by age, sex, region and education are subsequently applied;
3. For those who survive, the domestic migration is then applied using age- and sex-specific rates from an origin destination matrix;
4. Births are generated with fertility rates by age, education, and region applied to the exposed population;
5. Finally, region-specific reclassification rates from rural to urban areas are applied.

Validation of results. In order to see if there was a systematic bias in the microsimulation model compared to the multistate model, we calculated the mean error and the mean absolute error in the projected population size in 2060 (Table S2). We disaggregated the population by the smallest possible comparable subgroups, these being the size of each age- ,sex-, education- and region-specific group. We also split results according to the population size of the subgroup. We can see that the accuracy of the projection is relatively good, with a mean relative error of 1%. Because of the stochastic nature of the microsimulation, the smaller the population is, the higher the error. Thus, although the mean absolute error when the population size of the subgroup is between 0 and 10,000 is much higher and reaches 4%, it corresponds to a gap of only -14 individuals on average (mean error).

Table S2. Error between the multistate and the microsimulation model

Population size of the subgroup	Mear error	Mean absolute error	Mean relative error
[0, 10,000[	-14	942	4%
[10,000, 50,000[	-373	5,308	-2%
[50,000, 100000[	-916	9,821	-1%
[100,000, ∞	-15,131	34,770	-2%
All	-3,173	9,122	1%

In figure S1 we compare the projected population by level of education between 2010 and 2060 from our microsimulation model to the outcome from the multistate. The microsimulation leads to very similar results, with a sharp increase of the population between 2010 to 2060 from 1.2G to almost 1.8G. Most of the increase will be in the population with an upper secondary and a postsecondary level. The population with no education will sharply decline.

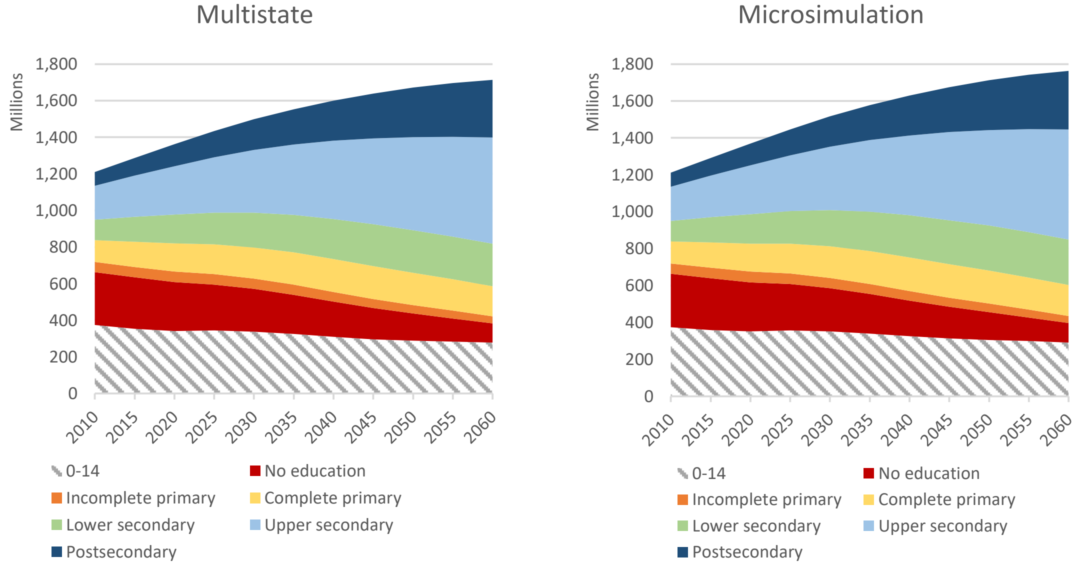

Figure S1. Comparison of projected population size of India by educational attainment from multistate model and from microsimulation, 2010-2060

In figure S2, we compare the projected age pyramid by education level in 2060 from both models.

In figure S3, we show the population size by region in 2060. Again, we can observe that the microsimulation produces similar results than the multistate projection, though the discrepancy becomes larger for regions with smaller population given the Monte Carlo error.

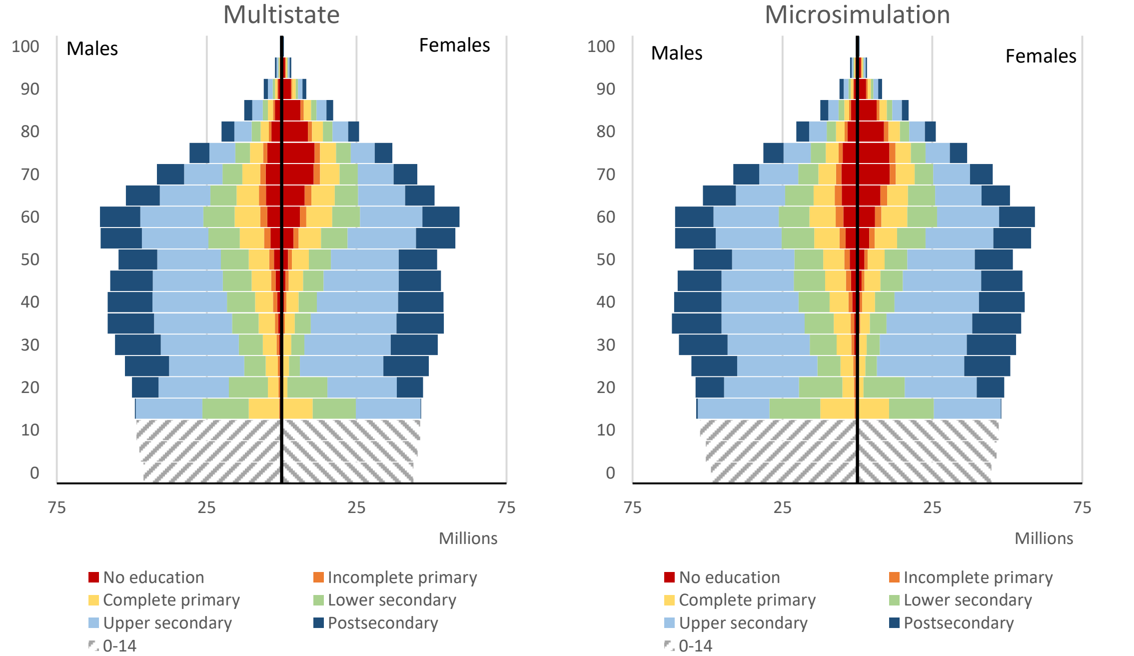

Figure S2. Comparison of the projected age pyramid in 2060 by education in India from multistate model and from microsimulation

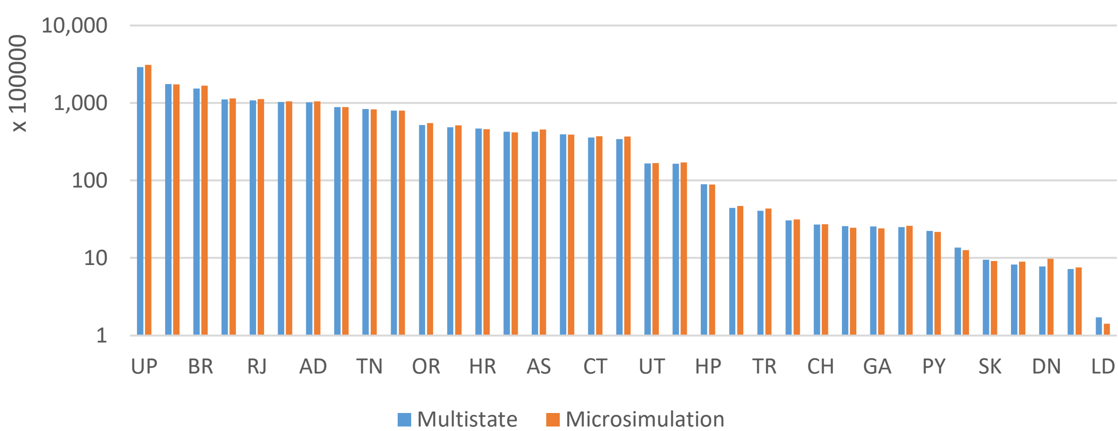

Figure S3. Comparison of the projected population size in 2060 by region, India, from multistate model and from microsimulation

Overall, the microsimulation replicates the multistate model outcomes quite well for broad aggregations, such as the population by age, sex, and education, and for subgroups with relatively large populations. However, for more specific subgroups with very small populations, for instance, the men aged 95-99 with a postsecondary education in an urban area of Dadra & Nagar Haveli, results may differ dramatically (183 in the multistate vs 0 in our run of microsimulation).

2. Adjustment and calibration for recent demographic estimates

Because of the adjustment in the base population, the projected population in our paper differs slightly from what was published in KC et al. (2018), in spite of the same demographic assumptions being used. The overall population trends are, however, similar, with a sharp increase in population between 2020 and 2060 from 1.3G to almost 1.8G (in our projection) compared to 1.7 in KC et al. (2018) and 1.65 as per the UN WPP 2019. Our projection leads to determining a higher population to that in KC et al. (2018) because of the age- and sex-specific adjustment in the base population. Indeed, although the total population size for the whole country is roughly the same, there is some under-reporting in KC et al. (2018) for younger age groups (in particular the 0-4) and over-reporting for older ones (see Figure S4). The source of the faster population growth in KC et al. (2018) and our projection compared to the UN WPP 2019 comes from the inclusion of more sources of heterogeneity in the fertility rates: the share of regions with higher fertility indeed increases slightly throughout the projection as a result of an increase in births, thus increasing the fertility for the whole country (KC et al. 2018).

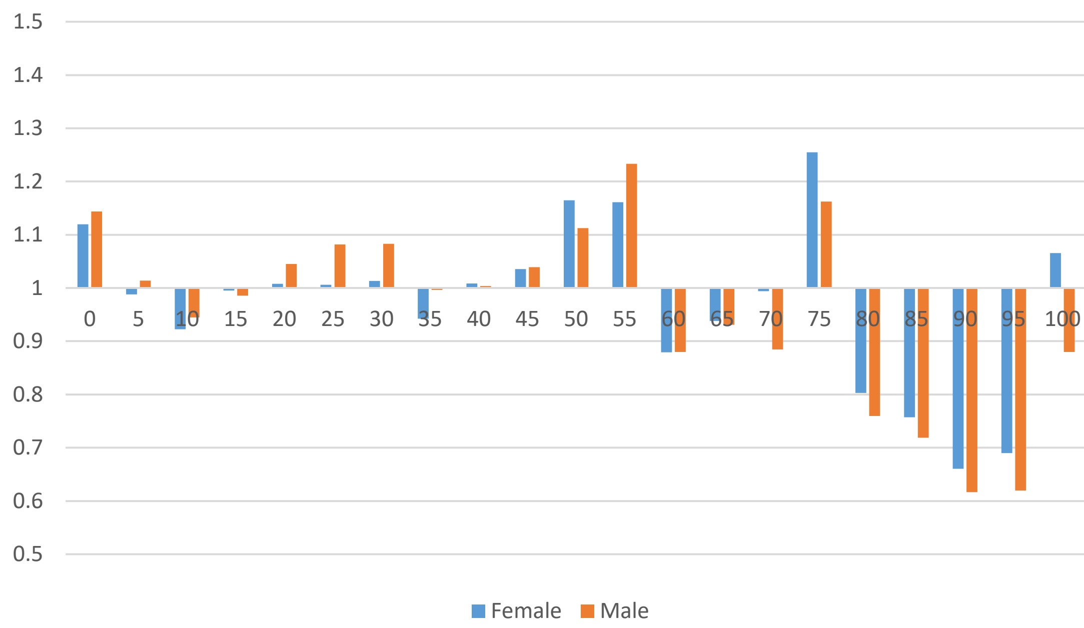

Figure S4. Adjustment factors by age and sex for the base population 2010

3. Implementation of the labour force participation module

Equation 3 from the main manuscript describes the model of labour force participation. The max-rescaled R-Square is 0.534 for the males' model (c-statistic=0.912) and 0.237 for the females' one (c-statistic=0.766). Complete parameters are presented in table S3. Table S4 shows predicted rates by sex and regions.

Table S3. Parameters from the logit regression (Eq.3) predicting the labour force participation status

Variable		Female		Male	
Intercept		-4.420	***	-5.935	***
EDU (ref=e3)	e1	0.393	*	2.850	***
	e2	0.921	***	2.567	***
	e4	-1.525	***	-4.366	***
	e5	-2.340	***	-6.058	***
	e6	1.088	***	-4.497	***
AGEGR		0.185	***	0.505	***
AGEGR*AGEGR		-0.002	***	-0.006	***
AGEGR*EDU	e1	0.000		-0.183	***
	e2	-0.027	*	-0.136	***
	e4	0.069	***	0.262	***

	e5	0.109	***	0.283	***
	e6	-0.009		0.215	***
AGEGR*AGEGR *EDU	e1	0.000		0.002	***
	e2	0.000		0.002	***
	e4	-0.001	***	-0.003	***
	e5	-0.001	***	-0.003	***
	e6	0.000		-0.003	***
YOUNG_KID		-0.324	***	N/A	
POSTSEC*YOUNG_KID		-0.390	***	N/A	
REGION (ref=WB_urban)	AD_rural	1.182	***	0.422	***
	AD_urban	0.336	***	0.206	**
	AN_rural	0.656		0.545	
	AN_urban	0.610		-0.182	
	AR_rural	-0.342		0.001	
	AR_urban	-0.339		-0.775	
	AS_rural	-0.580	***	0.594	***
	AS_urban	-0.410	**	-0.077	
	BR_rural	-1.906	***	-0.154	**
	BR_urban	-1.487	***	-0.398	***
	CH_rural	-0.761		-0.983	
	CH_urban	0.327		0.619	*
	CT_rural	1.830	***	0.526	***
	CT_urban	0.548	***	0.399	**
	DD_rural	0.221		0.397	
	DD_urban	-0.245		2.533	
	DL_rural	-2.124	**	0.703	
	DL_urban	-0.762	***	0.055	
	DN_rural	0.036		1.039	
	DN_urban	-0.374		1.327	
	GA_rural	0.757	**	0.386	
	GA_urban	0.822	***	-0.386	
	GJ_rural	-0.187	**	0.466	***
	GJ_urban	-0.400	***	0.214	**
	HP_rural	1.630	***	0.260	*
	HP_urban	0.201		0.469	
	HR_rural	-0.245	**	0.215	*
	HR_urban	-0.593	***	-0.060	
	JH_rural	-0.626	***	0.208	**
	JH_urban	-0.617	***	-0.150	
	JK_rural	-0.887	***	0.117	
	JK_urban	-0.196		-0.044	
	KA_rural	0.500	***	0.658	***
	KA_urban	0.146	*	0.029	
	KL_rural	0.432	***	-0.163	
	KL_urban	0.470	***	-0.423	***
	LD_rural	1.802		1.306	
	LD_urban	-0.162		-1.926	
	MH_rural	1.091	***	0.345	***
	MH_urban	0.041		-0.054	
	ML_rural	1.818	***	-0.120	
	ML_urban	0.785	**	-0.548	

MN_rural	0.182		-0.399	*
MN_urban	0.280		-0.602	*
MP_rural	0.884	***	0.678	***
MP_urban	-0.042		0.231	**
MZ_rural	0.446		-0.033	
MZ_urban	0.781	**	-0.435	
NL_rural	-0.308		-0.928	***
NL_urban	-0.113		-1.145	**
OR_rural	-0.200	**	0.638	***
OR_urban	-0.481	***	0.040	
PB_rural	-0.596	***	0.237	*
PB_urban	-0.260	**	0.330	**
PY_rural	-0.068		-0.431	
PY_urban	-0.059		-0.505	
RJ_rural	0.274	***	0.258	***
RJ_urban	-0.618	***	0.032	
SK_rural	1.319	***	0.077	
SK_urban	0.746		-0.373	
TN_rural	1.002	***	0.546	***
TN_urban	0.439	***	0.086	
TR_rural	-0.680	**	0.132	
TR_urban	-0.119		-0.407	
UP_rural	-0.873	***	0.385	***
UP_urban	-0.858	***	0.134	*
UT_rural	0.060		-0.157	
UT_urban	-0.666	***	-0.023	
WB_rural	-0.244	***	0.400	***
N	157638		163906	
Max-rescaled R-Square	0.237		0.534	
c-statistic	0.766		0.912	

Table S4. Labour force participation rate among the working age population (15-64) by region, 2020, India

Region	Women	Men	Total
AD	38%	84%	61%
AN	31%	87%	60%
AR	16%	79%	49%
AS	12%	86%	51%
BR	4%	76%	41%
CH	27%	88%	61%
CT	49%	85%	68%
DD	18%	93%	71%
DL	12%	82%	51%
DN	16%	88%	62%
GA	37%	81%	60%
GJ	17%	85%	53%
HP	47%	84%	66%
HR	15%	81%	51%
JH	12%	80%	47%
JK	12%	80%	48%
KA	27%	85%	57%
KL	27%	77%	51%
LD	23%	61%	41%
MH	31%	83%	59%
ML	50%	78%	64%
MN	24%	77%	50%
MP	31%	86%	59%
MZ	30%	81%	58%
NL	17%	70%	46%
OR	16%	86%	52%
PB	15%	85%	52%
PY	18%	76%	48%
RJ	22%	82%	53%
SK	44%	84%	65%
TN	33%	84%	59%
TR	15%	84%	50%
UP	10%	82%	47%
UT	19%	78%	49%
WB	19%	86%	53%
India	21%	83%	53%

The parameter for the binary variable YOUNG_KID accounts for a lower propensity to work among women who gave birth within the last 5 years. This parameter only affects women, since for men the decision to have a child does not impact their propensity to work (Gallaway and Bernasek 2002). This parameter (-0.324) would thus reduce by about 8.5 percentage points a participation rate that would otherwise have been 42%. The negative impact of having a young child is, moreover, much larger for women with postsecondary education than for other women (-0.324+-0.390). Finally, parameters show a strong heterogeneity among regions, and also higher participation rates in rural areas than in urban areas of the same region. Parameters thus range from -2.124 (NCT of Delhi, rural area) to 1.830 (Chhattisgarh, rural area) for women and from -1.926 (Lakshadweep, urban area) to 2.533 (Daman & Diu, urban area) for men.

Because of the availability of data used in the statistical model, this module does not take into account the past labour force participation of individuals. In other words, what is modelled is the probability of being in the labour force rather than the probability of entering and leaving the labour market. In consequence, the modelling can project reliable cross-sectional values, but does not allow longitudinal analysis as lives might well be inconsistent in how they play out.

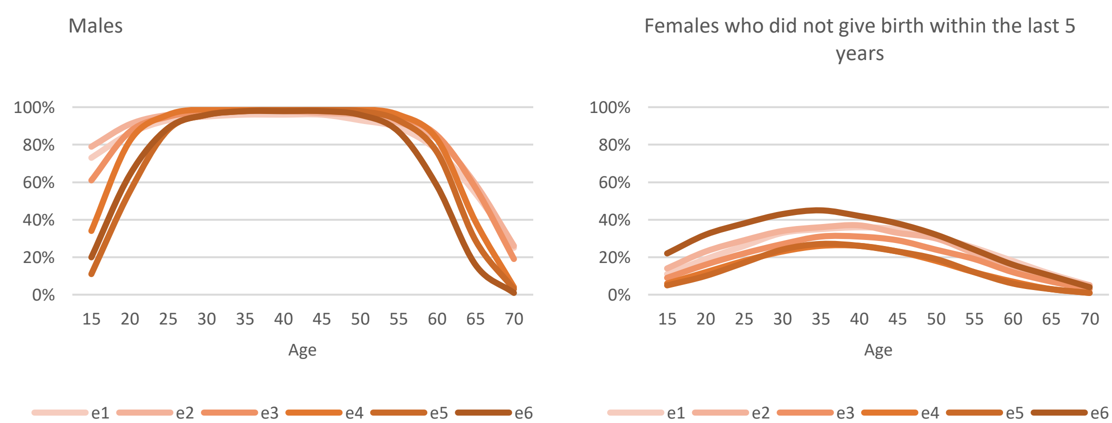

Figure S5. Predicted labour force participation rates from Eq.3 by age and education, India

In figure S5, we show the predicted rates from the regression model by age and education for both males and females (who did not give birth within the last 5 years). In males, rates are very high for everyone from 25 to 59 years of age; the education gap concerns mainly young and older adults, with lower rates for higher-educated ones. In other words, highly educated men enter the labour market later because they stay in school longer, and they also retire earlier, perhaps because they may be able to afford it by virtue of having had better jobs during their working years. In females, for their part, the pattern is very different. For all education categories and in all age groups, rates are 2 to 3 times lower compared to men. Furthermore, as has been observed in other studies (Chatterjee, Desai, and Vanneman 2018; Chaudhary and Verick 2014) the effect of education takes on a U-shape, with higher rates for both the highest and lowest categories.

Projected labour force participation rates

Labour force participation rates are, at an aggregated level, an outcome of the projection, as the inputs constitute parameters from logit regression used to calculate the rate at the individual level from a set of characteristics (age, sex, education, etc.). In the case of the Constant Rates Scenario, changes in the participation rate at the national level happen as a result of the change in the characteristics of the population over time. Figure S6 illustrates the ensuing labour force participation rate by gender among the population aged 15-74. For men (all scenarios), the rate is projected to be more or less stable, though with a slight decrease from 80% in 2020 to 76% in 2060, resulting from the expansion in postsecondary education which will mean delayed entry into the labour market.

As for women, when keeping parameters constant throughout the projection (Constant Rates Scenario), the rate also declines from 20% in 2020 to only 16% in 2060, which is in large part explained by the fast urbanisation of the country since women tend to work less in cities than in rural areas. The alternative scenarios yield very different outcomes. By 2060, the rate is 50% higher in the BestRegion Scenario and is multiplied by almost 4 in the Equality Scenario, reaching 30% and 76% respectively. In SI Figure S6, the evolution of projected rates is disaggregated by age.

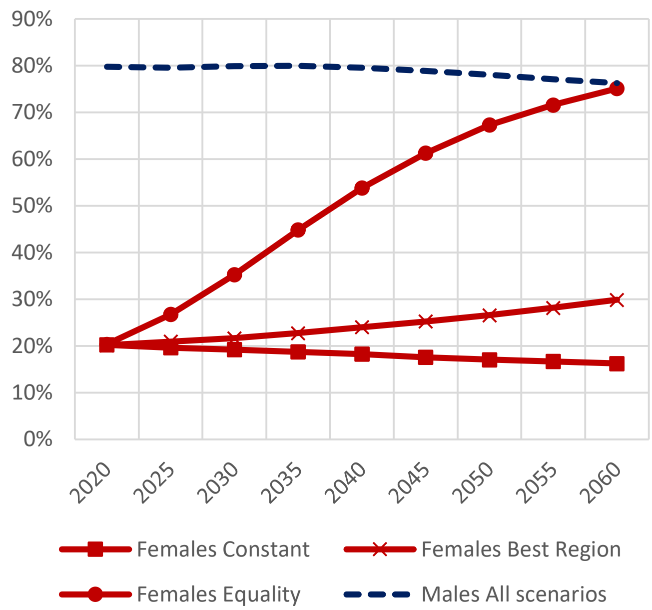

Figure S6. Projected labour force participation rate among the 15-74 year-old population by sex and scenarios, 2020-2060

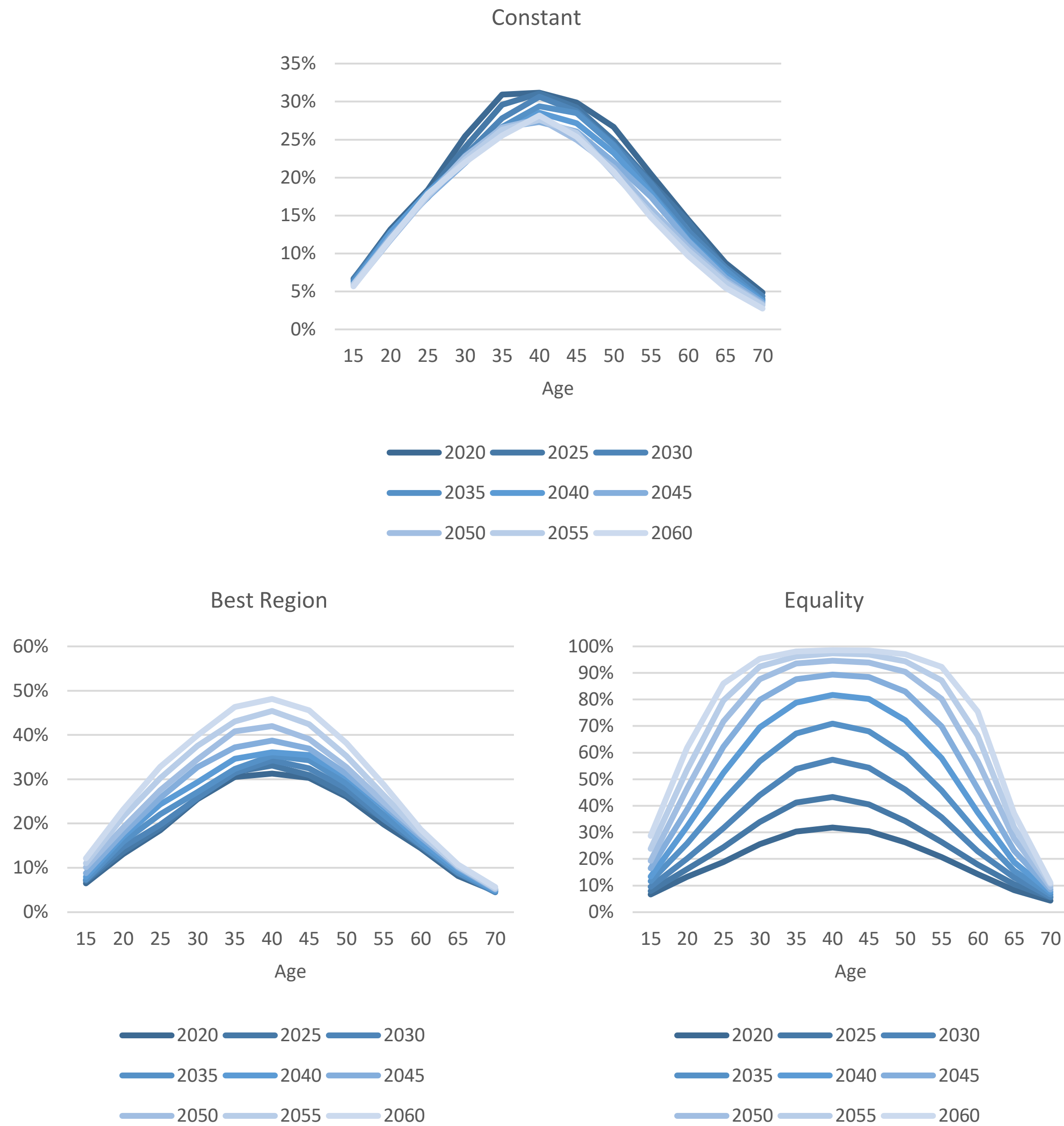

Figure S7. Projected labour force participation rates of women by age according to three scenarios, India

Results

Table S5. Outcomes of the constant scenario by region, 2020 and 2060, India

Region	2020				2060			
	Active	Inactive	LFDR	ADR	Active	Inactive	LFDR	ADR
AD	41,149,264	51,426,460	1.25	0.42	38,812,946	66,592,636	1.72	0.70
AN	218,900	242,404	1.11	0.34	253,987	396,438	1.56	0.67
AR	604,314	1,063,787	1.76	0.40	908,840	1,747,401	1.92	0.54
AS	12,210,839	23,517,861	1.93	0.49	15,654,049	30,001,977	1.92	0.55
BR	31,625,202	88,625,397	2.80	0.60	46,459,688	118,595,102	2.55	0.52
CH	636,956	739,536	1.16	0.32	1,104,486	1,642,520	1.49	0.58
CT	13,388,450	15,784,952	1.18	0.51	16,710,293	20,422,398	1.22	0.54
DD	215,008	165,290	0.77	0.28	395,832	413,848	1.05	0.57
DL	8,179,848	13,804,543	1.69	0.39	14,282,533	27,268,725	1.91	0.58
DN	247,397	282,548	1.14	0.39	473,084	647,460	1.37	0.54
GA	778,720	945,146	1.21	0.38	919,755	1,503,081	1.63	0.70
GJ	26,006,456	43,932,019	1.69	0.46	32,031,981	56,833,547	1.77	0.55
HP	3,653,650	3,958,304	1.08	0.43	3,720,821	5,171,599	1.39	0.65
HR	10,701,920	19,499,861	1.82	0.46	15,911,126	29,777,853	1.87	0.57
JH	12,061,905	25,961,511	2.15	0.53	16,821,323	34,261,241	2.04	0.52
JK	4,742,508	9,167,507	1.93	0.44	5,538,155	11,464,597	2.07	0.61
KA	27,688,391	40,278,425	1.45	0.44	28,404,036	51,208,641	1.80	0.64
KL	13,096,613	23,143,701	1.77	0.48	11,437,861	25,880,966	2.26	0.77
LD	27,774	51,040	1.84	0.37	46,594	92,414	1.98	0.63
MH	54,255,441	75,651,866	1.39	0.45	66,212,312	110,161,965	1.66	0.63
ML	1,544,145	1,875,590	1.21	0.49	2,125,613	2,557,775	1.20	0.48
MN	1,120,833	1,982,013	1.77	0.39	996,677	2,124,005	2.13	0.74
MP	33,576,028	50,427,129	1.50	0.52	45,510,935	68,433,705	1.50	0.52
MZ	488,454	714,842	1.46	0.40	498,984	798,378	1.60	0.71
NL	701,003	1,477,265	2.11	0.37	771,537	1,797,940	2.33	0.64
OR	16,963,969	29,400,257	1.73	0.47	18,791,388	36,627,986	1.95	0.58
PB	11,796,433	19,269,566	1.63	0.41	13,785,248	26,271,754	1.91	0.67
PY	516,659	973,771	1.88	0.42	607,607	1,495,485	2.46	0.68
RJ	28,396,427	52,484,372	1.85	0.54	40,961,718	71,158,650	1.74	0.53
SK	359,653	364,718	1.01	0.36	372,643	554,914	1.49	0.72
TN	33,492,111	45,025,263	1.34	0.43	29,800,108	54,841,228	1.84	0.72
TR	1,514,787	2,544,554	1.68	0.39	1,297,911	3,132,840	2.41	0.75
UP	71,938,846	159,553,789	2.22	0.56	104,089,652	205,693,778	1.98	0.52
UT	3,985,249	7,648,512	1.92	0.48	5,662,195	10,947,737	1.93	0.62
WB	38,760,279	61,376,193	1.58	0.41	35,807,647	69,173,747	1.93	0.62
India	506,644,432	873,359,992	1.72	0.49	617,179,565	1,149,694,331	1.86	0.58

Table S6. Outcomes of the BestRegion and Equality scenarios by region, 2060, India

Region	BestRegion			Equality		
	Labour force size	Difference (%) with the constant scenario	LFDR	Labour force size	Difference (%) with the constant scenario	LFDR
AD	40,653,788	5%	1.58	55,344,072	43%	0.90
AN	250,178	-1%	1.60	379,970	50%	0.93
AR	1,090,117	20%	1.37	1,384,037	52%	0.82
AS	18,092,092	16%	1.50	27,052,610	73%	0.70
BR	62,686,510	35%	1.64	91,569,738	97%	0.81
CH	1,183,254	7%	1.16	1,754,212	59%	0.62
CT	17,041,739	2%	1.19	22,134,410	32%	0.70
DD	430,401	9%	0.79	579,623	46%	0.43
DL	17,335,570	21%	1.41	22,961,700	61%	0.80
DN	566,725	20%	0.84	695,239	47%	0.48
GA	980,460	7%	1.55	1,318,287	43%	0.95
GJ	36,935,784	15%	1.41	51,710,556	61%	0.72
HP	3,945,058	6%	1.29	4,966,109	33%	0.82
HR	18,077,943	14%	1.49	25,299,270	59%	0.79
JH	19,940,677	19%	1.52	29,638,223	76%	0.75
JK	6,650,540	20%	1.60	9,317,352	68%	0.85
KA	30,735,372	8%	1.61	43,619,958	54%	0.84
KL	12,016,691	5%	2.05	16,379,797	43%	1.23
LD	45,256	-3%	2.42	57,822	24%	1.57
MH	69,764,499	5%	1.50	93,652,881	41%	0.86
ML	2,086,928	-2%	1.18	2,741,013	29%	0.75
MN	1,104,495	11%	1.81	1,554,456	56%	1.11
MP	48,441,977	6%	1.38	69,604,742	53%	0.67
MZ	485,125	-3%	1.69	685,841	37%	0.96
NL	864,405	12%	1.94	1,109,689	44%	1.17
OR	21,165,348	13%	1.58	31,525,291	68%	0.73
PB	15,886,698	15%	1.49	21,632,307	57%	0.81
PY	770,452	27%	1.86	1,035,127	70%	1.22
RJ	45,750,572	12%	1.44	64,206,149	57%	0.73
SK	415,165	11%	1.25	537,428	44%	0.82
TN	31,162,581	5%	1.72	42,940,870	44%	0.96
TR	1,495,413	15%	1.82	2,197,426	69%	0.96
UP	128,390,682	23%	1.43	181,249,781	74%	0.72
UT	6,242,618	10%	1.70	8,373,220	48%	0.95
WB	41,485,133	16%	1.54	59,691,318	67%	0.76
India	704,170,246	14%	1.51	988,900,524	60%	0.79

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