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Age-Specific Migration Schedules for India. Application of a Modified Rogers–Castro Model

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Abstract

The study models age-specific migration in India and selected states by estimating continuous, age-specific migration rates using limited data. A modified 7-parameter multi-exponential model based on the Rogers-Castro framework is used with non-linear optimization techniques to represent childhood and prime adult migration components. The model successfully replicated age-specific migration patterns for total and female population in India and in National Capital Territory (NCT) Delhi, and Uttar Pradesh. However, the model performed poorly for female migration in Maharashtra and failed to capture consistent male migration trends nationally. The present paper offers a refined approach to Rogers–Castro model to estimate age-specific migration. The findings offer a simplified yet insightful framework for migration modelling, suitable for population with limited or irregular data.

Introduction

Population dynamics are primarily driven by three fundamental demographic factors migration, fertility, and mortality. While fertility directly influences the size of younger age groups, the effects of mortality and migration are more complex, as they depend on age-specific patterns of change (Bourgeois-Pichat, 1951; Coale, 1956). Among these, migration plays a crucial role in redistributing the population across regions and is deeply associated with age, as different life stages correspond to varying migration intensities. Studying age patterns not only helps to understand migration behaviour within specific regions but also allows for comparison across countries and time periods. Previous studies have demonstrated that migration rates tend to be highest among young adults, followed by notable movement among children accompanying their parents, before declining during adolescence, peaking again around ages 25 to 30 due to employment and marriage-related moves, and gradually decreasing toward retirement (Rogers and Castro, 1981; Bell et al, 2002).

Despite significant advancements in migration research, challenges persist in estimating internal and international migration flows due to the lack of age- and sex-disaggregated data. Developed countries benefit from comprehensive administrative records and advanced survey methodologies, allowing for more precise migration

estimates. In contrast, developing countries struggle with under-registration and incomplete data coverage, leading to inconsistencies in migration statistics (Abel, 2013; Nowok et al, 2006; Raymer et al, 2013). Addressing these gaps, Rogers (1973) advanced indirect estimation techniques to derive age-specific gross migration rates from incomplete datasets. He developed the multiregional model life table, extending the Coale-Demeny life table to a multiregional population context. Building on this foundation, Rogers (1986) introduced a parameterised approach for estimating migration age profiles using labour-force data, demonstrating how model migration schedules encapsulate universal trends. Similarly, Nair (1985) developed methodologies to estimate period-specific place-to-place migration flows, crucial for understanding demo-economic relationships and forecasting subnational populations. Willekens (1994) further refined migration estimation techniques, bridging the gap between limited data and required migration statistics.

In the context of international migration estimation, Abel (2010) developed a methodology for generating comparable migration flow estimates across countries. Given that migration statistics often differ between sending and receiving nations due to variations in data collection methodologies, Abel's framework standardised these estimates for better international comparability. Wilson (2010) extended the standard migration model schedule to incorporate age-specific student migration, recognising a sharp increase in movement during the late teenage years due to higher education. To systematically analyse age-specific migration patterns, Rogers and Castro (1981) introduced the multi-exponential migration model, which provides a mathematical framework for modelling migration age profiles. They proposed a family of exponential functions with 7-, 11-, and 13-parameter forms, identifying key regularities in internal migration schedules. In recent years, further developments have improved the estimation of age-specific migration schedules. Studies by Bernard and Bell (2020) and Yeung, Alexander, and Riffe (2023) demonstrated that age-specific migration patterns exhibit remarkable regularity across countries and can be effectively estimated using spline-based or Bayesian approaches that quantify uncertainty. These advances underscore the importance of developing flexible models suited for data-scarce contexts such as India, where migration information remains limited to grouped census tables and infrequent surveys.

This study applies the Multi-Exponential Migration Model to 2011 Indian Census data to analyse age-specific migration patterns. Using exponential functions, it captures the underlying demographic behaviour of migration while refining estimation techniques and addressing data gaps. The research further evaluates how India's internal migration aligns with globally observed age-specific migration trends.

Data and Methodology

The present analysis is based on data on migration available from the 2011 population census in India. The decennial population census is the most abundant source of migration data in India. During the2011 population census, information was collected from all individuals about the place of last residence and individuals whose place of last residence was different from the place of enumeration are classified as in-migrants. The present analysis is confined to only those individuals whose duration of residence at the place of enumeration was 0–9. The age and sex-specific migration count is then used to

calculate the proportion of in-migrants for the total population and for males and females separately. The analysis has been carried out for India and for its three states – Uttar Pradesh, NCT Delhi, and Maharashtra.

Age-specific in-migration rate

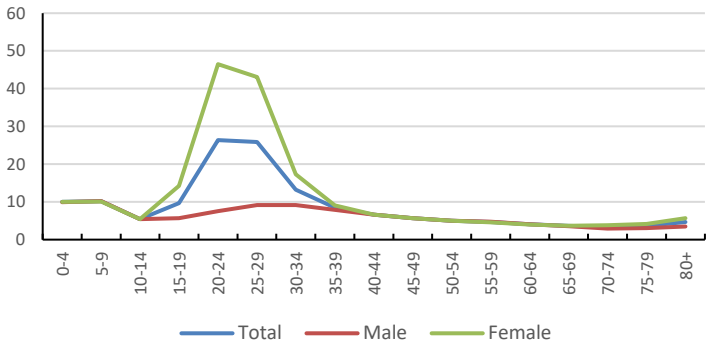
Table 1 gives the in-migration rates for India, Maharashtra, NCT Delhi and Uttar Pradesh by age for total population and separately for males and females. In India, 11 per cent individuals who were residing at the place of enumeration since last 10 years prior to the 2011 population census reported that their place of last residence was different from the place of enumeration. This proportion was more than two times in females compared to males. Among the three states, Maharashtra has recorded the highest female proportion of migration at 23.31 per cent for ages 0–4, while Uttar Pradesh recorded the lowest at 2.77 per cent for ages 10–14. In all the three states, the proportion of individuals whose place of enumeration was different from the place of last residence was higher in females compared to males.

Figure 1 also shows that age-specific in-migration rates differ markedly by sex and destination in the country and in the three states – Maharashtra, NCT Delhi and Uttar Pradesh. In the country and in all the three states, the female in-migration schedule is strongly concentrated in the young-adult ages, while the male in-migration schedule is comparatively flat. In India, the female in-migration rate rises from 5.4 per cent in population aged 10-14 years to 46.5 per cent in population aged 20-24 years and 43.1 per cent in population aged 25-29 years. The male in-migration rate, however, stays between 3-10 per cent in all age groups. The combined in-migration schedule, peaking at 26.4 per cent in population aged 20-24 years, therefore, follows the female pattern which is consistent with the evidence from the 2011 population census that marriage is the leading reason reported by female migrants, while work and employment are the dominating reasons among male migrants. In Maharashtra, the proportion of in-migrants was very high in the child population with little difference between male and female proportions suggesting household migration to major urban centres of the state. The relatively high proportion of male in-migrants in the age group 25-39 years reflect a strong labour component (Bhagat, 2009). Uttar Pradesh has the lowest in-migration rate among children but the highest in-migration rate in females aged 20-24 years which indicates that in-migration to the state is dominated by marriage-related movement of young women. NCT Delhi has the flattest profile, with total in-migration rates between 4.5-9.5 per cent and a modest female bump of around 14 per cent in the age group 25-29 years which suggests that in-migration in the state is spread across the life course for mixed employment, education, and family reasons. These contrasts show that age-specific in-migration rates reflect the importance of economic and social setting of the place of destination. The age-specific male in-migration rates in the country lack the characteristic bimodal structure typically captured by multi-exponential models. It appears that male in-migration in the country is often erratic and driven by diverse motives that are not clearly age-structured, thus making it unsuitable for parametric modelling. In contrast, female age-specific in-migration rates exhibit a well-defined age structure, with in-migration rate peaking prominently in the age group 15-40 years, largely due to marriage migration (Census of India, 2011). As such, modelling the total in-migration rate serves as a reasonable proxy, effectively capturing the dominant migration dynamics in the Indian context.

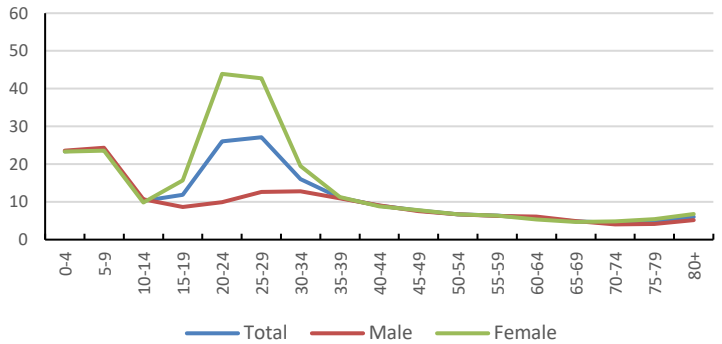
Table 1: Age-specific proportion of population whose place of last residence was different from the place of enumeration in India, Maharashtra, NCT Delhi and Uttar Pradesh, 2011.

Age	Proportion (per cent) of individuals whose place of last residence was different from the place of numeration											
	India			Maharashtra			NCT Delhi			Uttar Pradesh		
	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total	Male	Female
0-4	9.98	9.94	10.00	23.45	23.58	23.31	4.51	4.45	4.58	3.03	2.98	3.15
5-9	10.15	10.21	10.08	23.98	24.34	23.58	6.07	6.02	6.13	3.58	3.62	3.54
10-14	5.44	5.46	5.40	10.25	10.65	9.81	4.75	4.70	4.81	2.76	2.75	2.77
15-19	9.70	5.67	14.26	11.90	8.61	15.73	4.70	4.23	5.28	6.94	4.16	10.12
20-24	26.37	7.54	46.49	26.02	9.96	43.92	7.74	4.53	11.5	27.7	7.58	50.86
25-29	25.89	9.14	43.06	27.13	12.67	42.78	9.48	5.36	14.07	27.47	8.80	47.06
30-34	13.21	9.15	17.33	16.07	12.85	19.50	8.08	6.50	9.86	11.39	7.70	15.03
35-39	8.46	7.86	9.06	11.14	10.98	11.31	6.44	6.32	6.57	6.89	6.24	7.57
40-44	6.62	6.58	6.65	8.95	9.05	8.83	5.33	5.54	5.09	5.35	5.17	5.56
45-49	5.68	5.69	5.67	7.69	7.56	7.82	4.65	4.75	4.54	4.60	4.54	4.67
50-54	5.01	5.02	4.99	6.74	6.73	6.74	4.58	4.48	4.71	3.90	3.87	3.93
55-59	4.65	4.71	4.57	6.33	6.29	6.37	5.02	4.80	5.28	3.43	3.44	3.42
60-64	4.06	4.08	4.03	5.72	6.09	5.38	4.99	5.21	4.78	2.87	2.63	3.14
65-69	3.63	3.57	3.68	4.81	4.96	4.69	5.08	5.70	4.44	2.63	2.35	2.91
70-74	3.35	2.93	3.78	4.47	4.04	4.87	4.23	4.42	4.05	2.43	1.86	3.09
75-79	3.62	3.08	4.13	4.81	4.18	5.40	4.32	4.54	4.09	2.65	1.95	3.38
80+	4.63	3.46	5.66	6.05	5.17	6.81	4.87	4.57	5.15	4.49	2.38	6.74
All ages	9.13	6.19	12.43	13.76	11.51	16.38	30.67	25.47	37.01	6.64	3.12	10.67

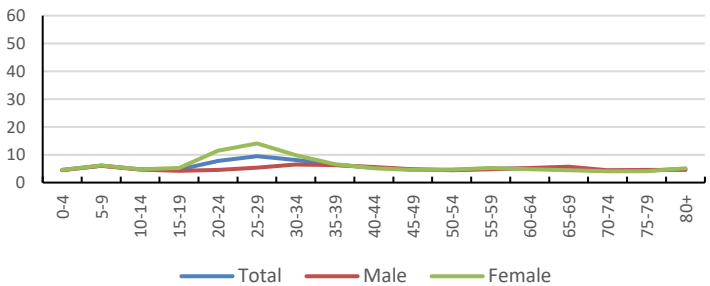
Remarks: All ages do not include those individuals whose age was not known.
Source: Authors.



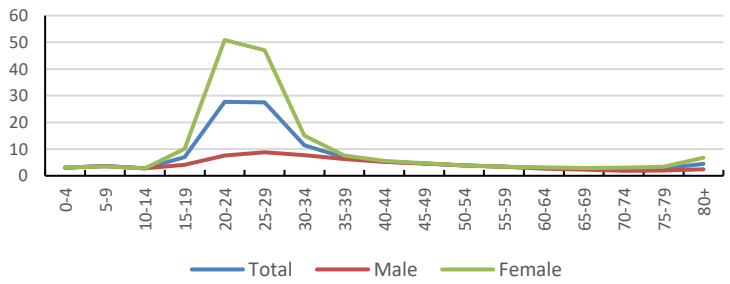
India



Maharashtra



NCT Delhi



Uttar Pradesh

The Model

The standard model migration schedule is the sum of five component curves (Rogers et al, 1990): migration intensity (M_x)= childhood curve + labour force curve + retirement curve +elderly curve + constant.

$$M_x = a_1 \exp(-\alpha_1 x) + a_2 \exp\{-\alpha_2(x-\mu_2) - \exp[-\lambda_2(x-\mu_2)]\} + \exp\{-\alpha_3(x-\mu_3) - \exp[-\lambda_3(x-\mu_3)]\} + a_4 \exp(\lambda_4 x) + c$$

The model includes 13 parameters, out of which 8 (α_1, α_2, μ_2, λ_2, α_3, μ_3, λ_3, and λ_4) define the shape of the migration profile, while the remaining 5 (a_1, a_2, a_3, a_4, and c) control the level or the magnitude. Adjusting the overall area under the curve of the model affects the level-defining parameters but does not alter the parameter defining shape.

The most prevalent form of the model is the 7-parameter reduced model, consisting of the first two components and a constant term. A substantial portion of the migration schedules are also aligned with an 11-parameter model which include a third component to represent a retirement-age peak. Some migration profiles, instead of featuring a retirement peak, display a continuous upward slope during the post-labour force years. These cases were modelled using a 9-parameter version, where the fourth component replaces the third. Additionally, in a study focused on elderly migration, Rogers and Watkins (1987) encountered patterns that exhibited both a retirement peak and a post-retirement upward slope, which required the use of the full 13-parameter model.

In this paper, we have modified the 7-parameter Rogers–Castro multi-exponential migration model for Indian migration pattern in which observed migration data do not exhibit a consistent pattern beyond the typical labour force retirement age. The modified model effectively captures migration dynamics during the pre-labour force and labour force phases while avoiding the added complexity of the full 13-parameter structure. In the traditional Rogers–Castro framework, the second component is labelled as the "labour force" component. However, in the Indian context, particularly for females, this peak, observed between ages 15 and 40 years, is overwhelmingly driven by marriage rather than employment. Therefore, while we retain the structural form and terminology of the "labour force" component for consistency, it should be more appropriately interpreted here as the prime adult migration component, representing the dominant peak of migration shaped by both economic and social (especially marriage) factors. The modified model is

$$M_x = a_1 \exp\{-\alpha_1(x-\mu_1) - \exp(-\lambda_1(x-\mu_1)\} + a_2 \exp\{-\alpha_2(x-\mu_2) - \exp(-\lambda_2(x-\mu_2)\}$$

$M(x)$ = Migration rate at age x.
a_1, a_2 = level of migration
α_1, α_2 = rate of descent of childhood and prime adult migration curve
λ_1, λ_2 = rate of ascent of childhood and prime adult migration curve
μ_1, μ_2 = age shift parameter

In the classical Rogers–Castro model, childhood migration is modelled as a simple exponential decay function $a_1 \exp(-\alpha_1 x)$, implying a monotonically decreasing migration rate with age among children. However, the grouped census data for the 0–4 age interval in India and its major states (e.g., Uttar Pradesh, NCT Delhi, Maharashtra) indicate substantial migration rates, suggesting that early-age movement is non-negligible and

cannot be fully captured by a purely declining curve. To accommodate this, we have adopted a more flexible childhood component $a_1 \exp\{-\alpha_1(x-\mu_1) - \exp(-\lambda_1(x-\mu_1)\}$, which allows for peaking behaviour and asymmetric decline during early life stages. This modification is empirically driven and demographically meaningful, as it reflects child migration often associated with family or household moves. The difference in the original model and the proposed model is shown in the figure 2.

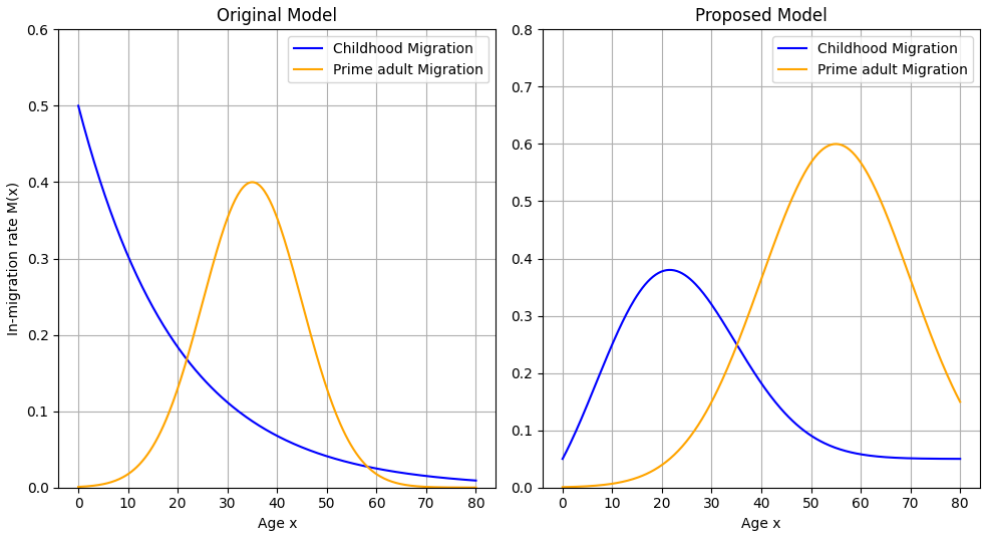


Figure 2: The original and the proposed model.
Source: Authors.

Smoothening of age data using cubic splines

The migration data sourced from the census are available in five-years age groups, whereas fitting a continuous model such as the multi-exponential function requires migration values for each specific age. To overcome this limitation, cubic spline interpolation was applied to convert age-grouped migration data into single-year age estimates. This approach helps to produce a continuous age profile necessary for accurate model fitting. Among various statistical approaches available, non-parametric methods such as cubic splines and kernel regression are used with demonstrated success in fertility (Moguerza et al, 2010), mortality (Peristera and Kostaki, 2005) and migration (Bernard and Bell, 2015). In comparative migration studies, Bernard and Bell (2015) assessed the effectiveness of cubic splines and kernel regression relative to traditional model migration schedules, finding that spline-based smoothing offers superior accuracy in capturing observed age-specific migration patterns.

In the present study, Python's scipy.interpolate module was employed for spline fitting, using CubicSpline function to estimate a smooth curve passing through each data point while ensuring continuity of the first and second derivatives across adjacent age intervals. This technique resulted in a continuous migration profile while preserving the demographic structure of the data. The selection of cubic spline interpolation to smooth grouped data was essential for continuous model fitting. Although splines can introduce

edge effects producing small or even negative estimates for the age group 0-4 years and ensure smooth and differentiable transitions between age groups, preserving the overall demographic pattern of migration. Alternative smoothing methods such as kernel regression, penalised B-splines, or Bayesian hierarchical approaches may alleviate boundary distortions, in which case the inclusion of a constant term could be justified both statistically and demographically. In the current context, however, the cubic spline's boundary behaviour, along with very low and unstable migration activity at extreme ages (specially 0-2 and 65+), warrants the exclusion of the constant term. This ensures a parsimonious and data-consistent model that avoids overfitting while maintaining stability in parameter estimation.

Parameter Estimation

Fitting of the model requires specification of initial parameter estimates which serve as starting values for the nonlinear optimisation algorithm. Choice of these initial values is important as initial values influence both convergence and quality of the model fit. As noted by Plane and Heins (2003), there is no universally optimal method for selecting the starting values for fitting the model. Researchers, therefore, must rely on informed assumptions, exploratory analysis, or prior empirical findings. Rogers and others (2005) have emphasised that the absence of standardised guidelines for selecting starting values often necessitates iterative calibration or trial-and-error approaches, which may not always generalise across different contexts.

In the present study, we have determined initial parameters for fitting the model through exploratory assessment of the spline-smoothed migration profiles and reference to the established literature. The visual inspection of smoothed curves guided the approximate placement and width of migration peaks, particularly during childhood and prime adult age group. Parameters such as modal age, amplitude, and rate of ascent and descent were chosen to reflect the observed trends in the data while accounting for the demographic plausibility.

Actual fitting was carried out using a nonlinear least squares optimisation approach which employs the Levenberg–Marquardt (LM) algorithm. This algorithm is an iterative method that estimates model parameters by minimising the sum of squares of the differences between observed values and values predicted by the model. We estimated a total of eight parameters – four each for the migration component corresponding to the amplitude, shape, location (modal age), and the rate of change. To enhance the convergence stability and minimise the computational time, the starting values were carefully selected to align with the expected patterns revealed by the spline-smoothed profiles.

It is important to emphasise here that the use of the cubic spline interpolation method may also introduce boundary effects, especially at the youngest and the oldest ages. It is, therefore, important that the parameter estimates of the model near the extremes are interpreted with caution so that the fitted model reflects the genuine migration patterns rather than spline-induced artefacts. An alternative to cubic spline interpolation is the Bayesian estimation which potentially improves parameter stability in boundary-sensitive cases. We have, however retained the nonlinear least squares framework for its computational efficiency, interpretability, and consistency with previous migration modelling research.

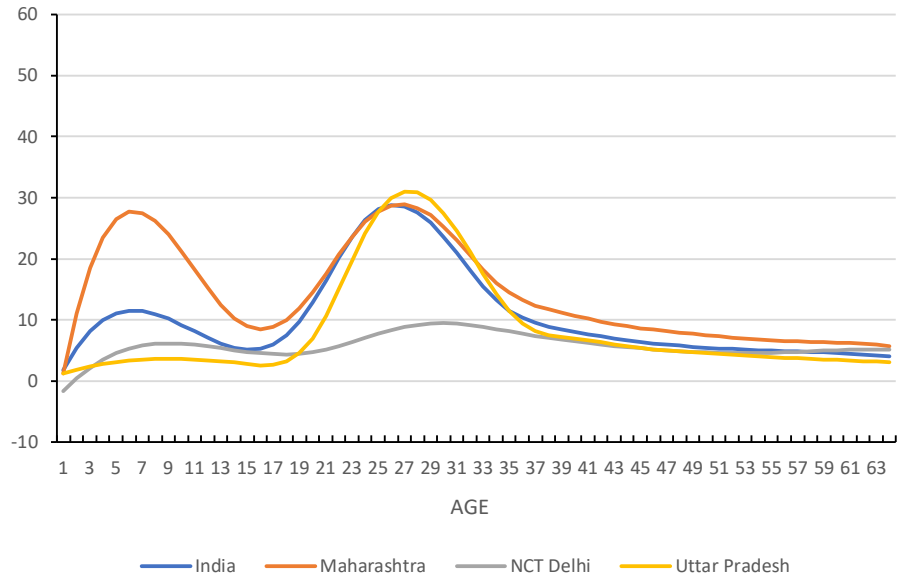


Figure 3: Smoothed age-specific In-migration rates in total population, 2011 – India, Maharashtra, NCT Delhi, Uttar Pradesh.
Source: Authors

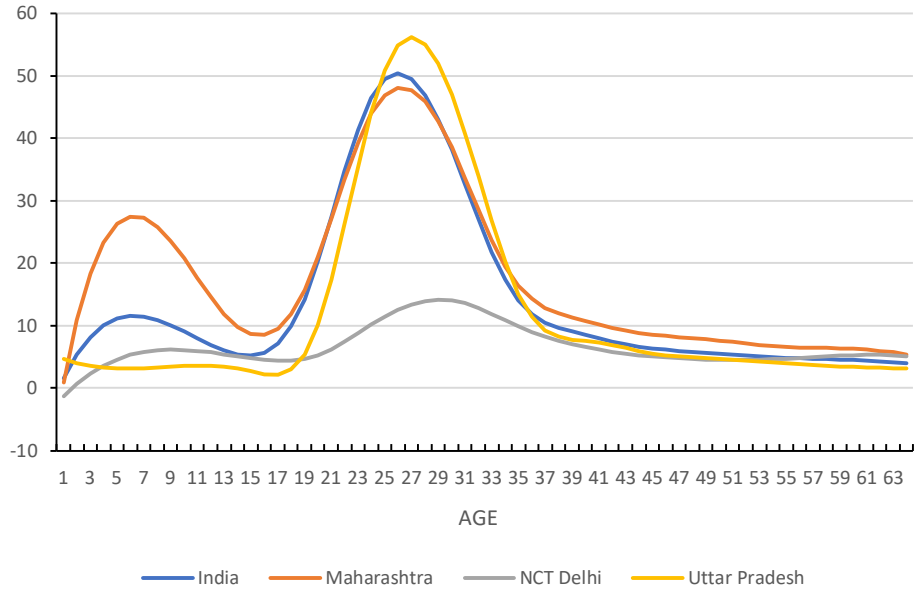
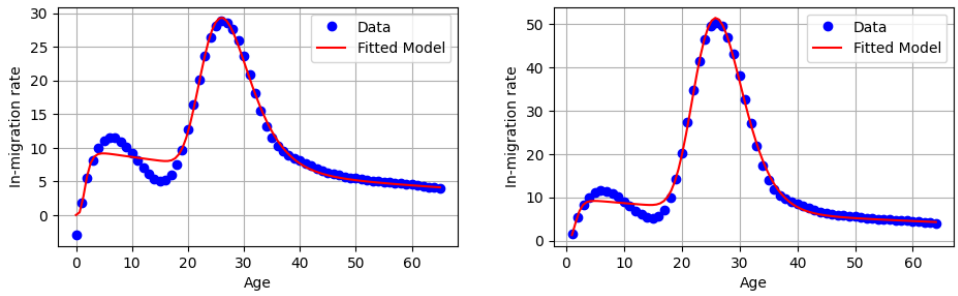


Figure 4: Smoothed age-specific In-migration rates in female population, 2011 – India, Maharashtra, NCT Delhi, Uttar Pradesh.
Source: Authors.

Results

The multi-exponential model was fitted to the age-specific in-migration rates of females and the total population. This approach ensures that the fitted curves capture the dominant and more regular age-specific trends, particularly the strong marriage-related peak in female migration which also shapes the total migration profile. The multi-exponential model is found to be fit for the observed In-migration rate data using the estimated parameters obtained through the nonlinear optimization procedure are substituted into the model equation to generate the fitted migration schedule. For each age X, the estimated migration rate is calculated by evaluating the model using the estimated parameters values of $a_1, a_2, \alpha_1, \alpha_2, \lambda_1, \lambda_2, \mu_1,$ and μ_2 for childhood and prime adult migration component for India and selected states in the proposed model. The fitted values represent the expected age-specific migration rates generated by the model and can therefore be compared with the observed migration rates. This comparison enables the assessment of the model's ability to reproduce the principal features of the age-specific migration pattern, including the childhood and prime adult migration peaks. Model performance is evaluated using goodness-of-fit measures, particularly the mean absolute percentage error (MAPE), which quantifies the difference between observed and fitted migration rates. Aim is to estimate parameters that describe the underlying components of migration behaviour, particularly the childhood and prime adult migration peaks. Figures 5 through 8 show fitted migration curves overlaid on smoothed in-migration rates. The visual alignment between modelled and observed values across supports the adequacy of the two-component exponential model in most cases.

For India, the fitted model reproduce the characteristic bimodal migration pattern, a minor childhood migration peak followed by a significant prime adult migration peak occurring between ages 20 and 30. This pattern is consistent across both the total and female populations, with excellent visual alignment and low MAPE values, reinforcing the robustness of the model. (Figure 5).

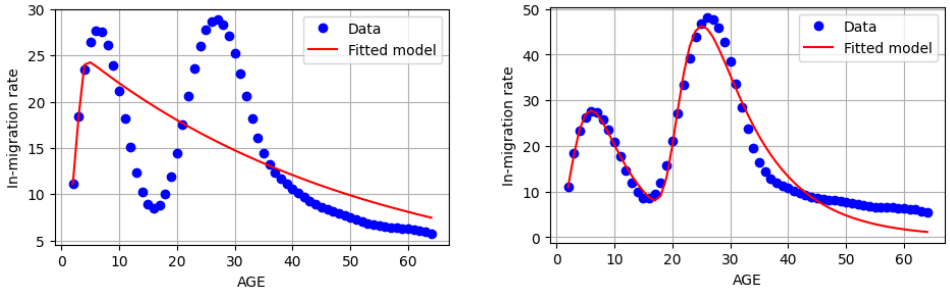


Total population Female population

Figure 5: Observed and fitted in-migration rates in India, 2011.
Source: Authors.

For Maharashtra, the model presents a more nuanced picture. For females, the fitted curve captures both early-age (childhood) and adult migration peaks. The childhood peak appears earlier and sharper than in other states, followed by a prominent adult migration surge around age 28 years. This trend reflects strong urban pull factors in the state, particularly in cities like Mumbai and Pune. The model shows a moderate MAPE,

indicating fair predictive reliability. However, for the total population, the model shows a noticeably poor fit. The observed in-migration rates feature two pronounced peaks, one in the early childhood and the other during the adulthood. However, the fitted curve fails to capture this dual-peak age-pattern of in-migration in the state. Instead, the model produces a flat and declining at pattern of in-migration that underestimates both peaks. This results in a high value of MAPE although it is still acceptable value (Figure 6).

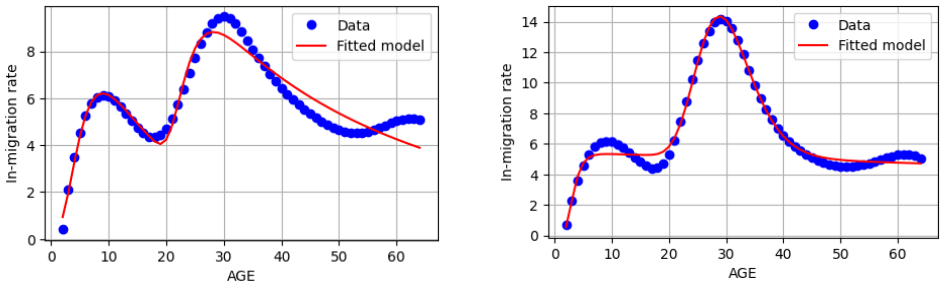


Total population Female population

Figure 6: Observed and fitted in-migration rates in Maharashtra, 2011.
Source: Authors.

The relatively poor fit in Maharashtra indicates that the age-specific in-migration schedule of the state may contain features that are not adequately represented by the two-component model. Maharashtra is a major migrant-receiving state, and migration to large urban centres may involve several overlapping processes, including employment-related movement and associated household relocation producing broader or multiple age-specific peaks rather than the simple structure assumed by the model. The poorer fit of the model, therefore, should be treated as the evidence that a two-component parametric specification may be insufficient to represent the complexity of migration in this setting. This suboptimal fit can be attributed to two main factors: 1) underlying complexity of female migration behaviour in Maharashtra which may not conform to the assumptions of the two-component model; and 2) sensitivity of nonlinear optimisation process to the selection of initial parameter estimates. As emphasised by Rogers et al (2005) and Plane and Heins (2003), inappropriate initial guess can lead the algorithm to converge to local minima, where estimated parameters may not fully capture the observed migration dynamics, particularly when multiple peaks exist in the data.

However, for NCT Delhi and Uttar Pradesh, the model provides a good fit to the observed age pattern of in-migration. In the NCT Delhi, the model slightly underestimates the childhood migration, particularly for females. The female in-migration peak in NCT Delhi occurs earlier than the national average – at around 22 years of age – highlighting the distinct urban migration dynamics in the state, which is driven, the most likely, by the early employment and education-linked in-migration. Model performance, however, remains strong as reflected by the low MAPE (Figure 7). In Uttar Pradesh, on the other hand, the in-migration rate peaks sharply around the age group 30–35 years. There is, however, noticeable disparity between total and female in-migration patterns, especially, in the prime adult age group. However, the model captures both magnitude and age distribution of in-migrants in the state with a high degree of accuracy as is reflected through the low value of MAPE (Figure 8).

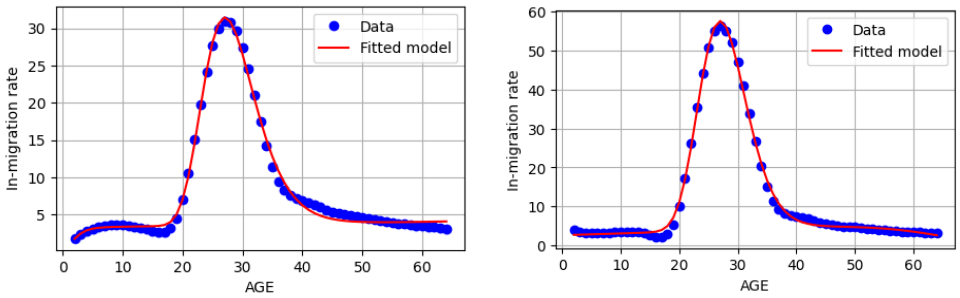


Total population Female population

Figure 7: Observed and fitted in-migration rates in NCT Delhi, 2011.
Source: Authors.

Parameter Estimates

The parameter values presented in Tables 2 and 3 have been reordered based on the value of μ to ensure demographic interpretability. Specifically, the component with μ falling within the expected age range for childhood migration (0–15 years) is labeled as the childhood component, and the one with μ in the range of prime adult migration (15–40years) is labeled as the prime adult migration component. This reassignment is necessary because the curve-fitting algorithm may assign components in arbitrary order during optimization.



Total population Female population

Figure 8: Observed and fitted in-migration rates in Uttar Pradesh, 2011.
Source: Authors.

The parameter estimates derived from the fitted multi-exponential models provide detailed insights into age-specific migration behaviour across India and selected states. These parameters like amplitude (a), decay (α), modal age (μ), and accentuation (λ) capture the intensity, shape, and timing of the two primary migration components for childhood and prime adult migration. Component assignments are based on the value of μ, which reflects the modal age of migration. Components with $\mu < 15$ are considered childhood migration peaks; those with $\mu \geq 20$ are considered labor force peaks. This reassignment ensures demographic interpretability when the optimization algorithm assigns parameter estimates inconsistently. Amplitude parameters (a) determine the height of each component and represent the intensity of migration. Higher values indicate a greater concentration of

migration at the respective peak age. Uttar Pradesh (total) shows a high prime adult migration amplitude (a_1=58.2), suggesting significant movement among working-age individuals. In Maharashtra, the amplitude for female childhood migration is particularly high (a_2 = 84.3), which may reflect concentrated early-age moves associated with family relocation or marriage-related migration. This elevated value supports the visual observation of a complex and overlapping pattern for females in Maharashtra.

Table 2: Parameter estimates for total population.

Region	Component	a	α	μ	λ	MAPE
India	Prime Adult component	38.58	0.39	33.44	0.139	9.48
	Childhood	9.68	0.01	1.51	1.39	
NCT Delhi	Prime Adult component	9.64	0.06	22.45	0.400	9.29
	Childhood	8.13	0.01	4.26	0.41	
Uttar Pradesh	Prime Adult component	58.21	0.31	30.53	0.171	10.29
	Childhood	3.24	-0.00	1.40	0.76	
Maharashtra	Prime Adult component	18.85	0.02	1.91	7.20	33.91
	Childhood	6.80	0.02	3.99	143.24	

Source: Authors.

Decay parameters (α) indicate how quickly migration declines after reaching its peak. Sharp post-peak declines are seen in some female labour components, such as α = 0.526 for Uttar Pradesh, suggesting migration in a narrow, concentrated age band. Broader, more gradual decline such as α = 0.013 for childhood migration in India suggest that children often move across a wider age range, likely accompanying family relocations, or school transitions.

Table 3: Parameter estimates for female population.

Region	Component	a	α	μ	λ	MAPE
India	Prime Adult component	37.96	0.39	33.50	0.13	9.19
	Childhood	9.62	0.01	1.71	1.84	
NCT Delhi	Prime Adult component	15.16	0.03	22.47	0.44	15.93
	Childhood	13.91	0.09	6.24	0.22	
Uttar Pradesh	Prime Adult component	5.15	0.52	40.07	0.11	11.75
	Childhood	7.26	-0.01	63.82	-0.11	
Maharashtra	Prime Adult component	57.86	0.15	21.79	0.41	24.14
	Childhood	84.27	0.10	3.55	0.36	

Source: Authors.

Accentuation parameters (λ) influence the steepness and symmetry of the migration curve near the peak. Steep increases followed by sharp declines are observed in the childhood migration of India (λ = 1.39) and NCT Delhi (λ = 0.41), indicating more abrupt transitions in younger age migration. In Maharashtra, an extremely high λ value of 143.2 for the childhood component (total population) likely reflects rapid early-age changes, possibly amplified by urban dynamics or model overfitting.

In the case of Uttar Pradesh (female), the model yields negative values for the decay (α_2) and accentuation (λ_2) parameters in the childhood component. While such negative estimates may appear counterintuitive. Since both parameters typically govern the decline and sharpness of migration rates this outcome is common in non-linear curve fitting. As

model convergence can sometimes lead to parameter estimates that are mathematically valid but demographically implausible, particularly when the initial guesses are far from optimal or when the migration curve lacks a well-defined second peak. Despite these values, the overall model still offers an acceptable visual and statistical fit, suggesting that the negative signs may reflect algorithmic compensation effects rather than meaningful demographic behaviour. Future modelling may benefit from imposing parameter constraints or refining the initial values.

In summary, these parameter estimates confirm consistent bimodal migration trends across India, UP, and NCT Delhi, while also exposing state-level variations particularly in Maharashtra suggesting the need for region-specific model adaptations. The relative alignment of modal ages and amplitudes across states reinforces the utility of multi-exponential models in capturing complex migration behaviour, though further refinement may be needed in contexts where overlapping motives and irregular migration timing distort classical age profiles

Discussion

We found that female migration in India is disproportionately driven by marriage migration, which is associated with a socially normed age at marriage and therefore produces a sharp, well-defined peak in the age schedule. Male migration, by contrast, reflects a mixture of education-related, employment-related, and circular or seasonal labour migration occurring across a wider and less consistently timed range of ages, without a single dominant life-course transition. This compositional difference is offered as the substantive explanation for the flatter, less clearly structured male age pattern relative to the female pattern and to exclude the male In-migration rate from modelling. The estimation procedure uses nonlinear least-squares optimization with the Levenberg–Marquardt algorithm. Since the modified Rogers–Castro model is nonlinear and involves several interdependent parameters, the estimation can be sensitive to the initial parameter values and convergence behaviour. Previous studies have also documented the need for suitable initial estimates and the possibility of nonconvergence or sensitivity to starting values when fitting Rogers–Castro migration schedules. In the present analysis, alternative initial parameter values were considered for the male schedule. However, the resulting fitted curves did not adequately reproduce the observed age-specific male in-migration pattern in a stable and substantively meaningful manner.

In contrast, the total and female In-migration rate patterns displayed stable bimodal shapes suitable for modelling, with the second major peak (prime adult migration) in this context largely representing marriage-related movements among females, while also incorporating employment-related mobility in the total population. This emphasizes on the need to interpret model components in line with socio-cultural realities rather than relying solely on their conventional demographic labels.

The fitted results confirm that a two-component multi-exponential model can effectively replicate age-specific migration trends in most Indian states, especially for the total population and female migration in India, NCT Delhi, and Uttar Pradesh. The model captures both the timing and intensity of early-life and prime adult migration, providing a

useful comparative framework. The proposed model is able to explain the age-migration relationship for Indian population in totality and well as its states and therefore can be used for other populations with similar migration patterns.

However, the poor fit observed for female migration in Maharashtra and the absence of a clear second peak in male migration highlight important methodological challenges. In such cases, model convergence can produce parameter estimates that are mathematically valid but demographically implausible, particularly when initial parameter guesses are suboptimal or when the true migration curve lacks the expected structure. This can further be explored using Bayesian estimation. A further limitation of the study lies in the dependence on decadal census data, especially in the case of India, which may mask short-term migration fluctuations, and the assumption that the two-component structure can adequately represent complex, overlapping migration motives such as simultaneous marriage and employment moves. These results point to the limitations of a one-size-fits-all approach and the importance of adapting models to region-specific migration dynamics and gendered migration motivations.

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Appendix Table 1: Smoothened in-migration rates for India and selected states using Cubic Splines:

Age	Uttar Pradesh		NCT Delhi		Maharashtra		India	
	Total	Female	Total	Female	Total	Female	Total	Female
1	1.18	4.69	-1.69	-1.31	1.17	0.91	1.77	1.65
2	1.80	4.03	0.41	0.67	11.10	10.92	5.44	5.40
3	2.31	3.57	2.12	2.30	18.43	18.29	8.13	8.15
4	2.73	3.29	3.48	3.59	23.45	23.31	9.97	10.01
5	3.06	3.15	4.51	4.58	26.44	26.27	11.06	11.10
6	3.31	3.13	5.26	5.31	27.70	27.48	11.51	11.54
7	3.48	3.19	5.76	5.79	27.52	27.24	11.44	11.44
8	3.58	3.30	6.03	6.07	26.18	25.84	10.95	10.92
9	3.61	3.42	6.13	6.18	23.98	23.58	10.15	10.09
10	3.58	3.54	6.07	6.13	21.21	20.75	9.16	9.07
11	3.50	3.60	5.90	5.97	18.17	17.67	8.08	7.98
12	3.37	3.59	5.65	5.73	15.13	14.61	7.02	6.92
13	3.20	3.47	5.35	5.44	12.39	11.90	6.10	6.03
14	3.00	3.21	5.04	5.12	10.25	9.81	5.43	5.40
15	2.76	2.77	4.75	4.81	8.94	8.62	5.11	5.19
16	2.55	2.24	4.52	4.55	8.48	8.49	5.27	5.68
17	2.58	2.10	4.37	4.39	8.84	9.55	6.00	7.15
18	3.14	2.97	4.33	4.42	9.99	11.91	7.44	9.91
19	4.50	5.44	4.43	4.69	11.90	15.73	9.70	14.26
20	6.94	10.12	4.70	5.28	14.49	20.97	12.80	20.31
21	10.58	17.31	5.14	6.23	17.50	27.10	16.42	27.41
22	15.03	26.15	5.72	7.45	20.63	33.43	20.16	34.70
23	19.73	35.46	6.38	8.81	23.57	39.26	23.61	41.34
24	24.13	44.09	7.07	10.20	26.02	43.92	26.36	46.49
25	27.70	50.86	7.74	11.49	27.73	46.86	28.09	49.48
26	29.99	54.85	8.32	12.57	28.67	48.07	28.80	50.38
27	31.00	56.15	8.81	13.41	28.86	47.70	28.61	49.44
28	30.84	55.06	9.18	13.96	28.34	45.89	27.61	46.92
29	29.63	51.93	9.41	14.19	27.13	42.78	25.89	43.06
30	27.47	47.06	9.48	14.07	25.29	38.56	23.59	38.16
31	24.52	40.85	9.39	13.58	23.03	33.66	20.92	32.65
32	21.08	33.88	9.17	12.81	20.58	28.53	18.13	27.03
33	17.52	26.82	8.85	11.87	18.18	23.66	15.47	21.76
34	14.17	20.32	8.48	10.85	16.07	19.50	13.20	17.33
35	11.39	15.03	8.08	9.86	14.43	16.42	11.49	14.09
36	9.44	11.43	7.71	8.99	13.23	14.29	10.29	11.91
37	8.21	9.29	7.36	8.23	12.34	12.88	9.47	10.52
38	7.51	8.21	7.03	7.59	11.68	11.97	8.90	9.66
39	7.14	7.77	6.72	7.04	11.14	11.31	8.46	9.06
40	6.89	7.57	6.44	6.57	10.64	10.71	8.05	8.51
41	6.61	7.27	6.18	6.17	10.16	10.15	7.65	7.98
42	6.29	6.87	5.94	5.82	9.71	9.64	7.28	7.48
43	5.95	6.41	5.72	5.54	9.31	9.20	6.93	7.04

Age	Uttar Pradesh		NCT Delhi		Maharashtra		India	
	Total	Female	Total	Female	Total	Female	Total	Female
44	5.63	5.96	5.52	5.29	8.95	8.83	6.62	6.66
45	5.35	5.56	5.33	5.09	8.63	8.55	6.35	6.37
46	5.13	5.26	5.16	4.92	8.36	8.34	6.12	6.14
47	4.97	5.05	5.00	4.78	8.12	8.16	5.91	5.96
48	4.84	4.90	4.86	4.67	7.90	8.00	5.74	5.81
49	4.72	4.78	4.75	4.59	7.69	7.82	5.58	5.67
50	4.60	4.67	4.65	4.54	7.47	7.61	5.44	5.53
51	4.47	4.54	4.58	4.52	7.26	7.38	5.31	5.38
52	4.32	4.39	4.54	4.52	7.07	7.14	5.20	5.24
53	4.17	4.23	4.53	4.56	6.89	6.93	5.10	5.11
54	4.03	4.08	4.54	4.62	6.74	6.75	5.01	4.99
55	3.90	3.93	4.58	4.71	6.62	6.62	4.94	4.89
56	3.78	3.80	4.65	4.82	6.53	6.54	4.87	4.81
57	3.68	3.68	4.74	4.95	6.46	6.48	4.80	4.74
58	3.59	3.58	4.84	5.08	6.39	6.43	4.73	4.66
59	3.51	3.50	4.93	5.19	6.33	6.37	4.64	4.58
60	3.43	3.42	5.02	5.28	6.26	6.29	4.54	4.48
61	3.34	3.35	5.10	5.32	6.17	6.16	4.42	4.37
62	3.25	3.29	5.14	5.31	6.05	5.98	4.30	4.26
63	3.14	3.23	5.14	5.22	5.91	5.73	4.17	4.14
64	3.02	3.18	5.10	5.05	5.72	5.38	4.06	4.03

Source: Authors

Appendix Table 2: Observed and expected in-migration rate using parameter estimates of the model for India and NCT Delhi.

Age	India				NCT Delhi			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
1	1.77	1.36	1.65	1.29	0.38	0.85	0.47	0.41
2	5.44	5.86	5.40	5.81	0.41	0.94	0.67	0.56
3	8.13	8.37	8.15	8.37	2.12	1.99	2.30	2.24
4	9.97	9.07	10.01	9.07	3.48	3.23	3.59	3.84
5	11.06	9.16	11.10	9.17	4.51	4.39	4.58	4.73
6	11.51	9.09	11.54	9.10	5.26	5.27	5.31	5.12
7	11.44	8.98	11.44	9.00	5.76	5.84	5.79	5.27
8	10.95	8.87	10.92	8.89	6.03	6.13	6.07	5.32
9	10.15	8.75	10.09	8.77	6.13	6.21	6.18	5.33
10	9.16	8.63	9.07	8.66	6.07	6.13	6.13	5.33
11	8.08	8.52	7.98	8.55	5.90	5.96	5.97	5.32
12	7.02	8.40	6.92	8.44	5.65	5.73	5.73	5.31
13	6.10	8.29	6.03	8.33	5.35	5.47	5.44	5.30
14	5.43	8.18	5.40	8.25	5.04	5.20	5.12	5.29
15	5.11	8.08	5.19	8.24	4.75	4.92	4.81	5.28
16	5.27	8.02	5.68	8.47	4.52	4.65	4.55	5.27
17	6.00	8.12	7.15	9.25	4.37	4.39	4.39	5.28
18	7.44	8.64	9.91	11.08	4.33	4.16	4.42	5.34
19	9.70	9.95	14.26	14.46	4.43	4.05	4.69	5.49
20	12.80	12.32	20.31	19.63	4.70	4.24	5.28	5.81
21	16.42	15.72	27.41	26.36	5.14	4.83	6.23	6.40
22	20.16	19.70	34.70	33.89	5.72	5.72	7.45	7.29
23	23.61	23.60	41.34	41.10	6.38	6.67	8.81	8.48
24	26.36	26.74	46.49	46.88	7.07	7.51	10.20	9.88
25	28.09	28.69	49.48	50.42	7.74	8.13	11.49	11.31
26	28.80	29.33	50.38	51.40	8.32	8.53	12.57	12.61
27	28.61	28.76	49.44	49.97	8.81	8.75	13.41	13.61
28	27.61	27.27	46.92	46.64	9.18	8.82	13.96	14.20
29	25.89	25.18	43.06	42.05	9.41	8.79	14.19	14.35
30	23.59	22.79	38.16	36.86	9.48	8.69	14.07	14.10
31	20.92	20.35	32.65	31.60	9.39	8.55	13.58	13.52
32	18.13	18.02	27.03	26.67	9.17	8.38	12.81	12.71
33	15.47	15.89	21.76	22.30	8.85	8.19	11.87	11.77
34	13.20	14.02	17.33	18.58	8.48	8.00	10.85	10.79
35	11.49	12.42	14.09	15.53	8.08	7.80	9.86	9.84
36	10.29	11.07	11.91	13.09	7.71	7.61	8.99	8.96
37	9.47	9.95	10.52	11.18	7.36	7.41	8.23	8.18
38	8.90	9.02	9.66	9.71	7.03	7.23	7.59	7.52
39	8.46	8.27	9.06	8.60	6.72	7.04	7.04	6.96
40	8.05	7.66	8.51	7.76	6.44	6.86	6.57	6.50
41	7.65	7.16	7.98	7.13	6.18	6.69	6.17	6.13
42	7.28	6.75	7.48	6.65	5.94	6.52	5.82	5.84

Age	India				NCT Delhi			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
43	6.93	6.42	7.04	6.30	5.72	6.36	5.54	5.61
44	6.62	6.14	6.66	6.02	5.52	6.20	5.29	5.43
45	6.35	5.91	6.37	5.81	5.33	6.05	5.09	5.30
46	6.12	5.72	6.14	5.64	5.16	5.90	4.92	5.19
47	5.91	5.56	5.96	5.50	5.00	5.76	4.78	5.11
48	5.74	5.41	5.81	5.39	4.86	5.62	4.67	5.04
49	5.58	5.29	5.67	5.29	4.75	5.49	4.59	4.99
50	5.44	5.18	5.53	5.20	4.65	5.36	4.54	4.95
51	5.31	5.08	5.38	5.12	4.58	5.23	4.52	4.92
52	5.20	4.99	5.24	5.04	4.54	5.11	4.52	4.89
53	5.10	4.90	5.11	4.97	4.53	4.99	4.56	4.87
54	5.01	4.82	4.99	4.90	4.54	4.87	4.62	4.85
55	4.94	4.75	4.89	4.83	4.58	4.76	4.71	4.83
56	4.87	4.68	4.81	4.77	4.65	4.65	4.82	4.82
57	4.80	4.61	4.74	4.70	4.74	4.55	4.95	4.80
58	4.73	4.54	4.66	4.64	4.84	4.45	5.08	4.79
59	4.64	4.48	4.58	4.58	4.93	4.35	5.19	4.78
60	4.54	4.41	4.48	4.52	5.02	4.25	5.28	4.77
61	4.42	4.35	4.37	4.46	5.10	4.16	5.32	4.76
62	4.30	4.29	4.26	4.41	5.14	4.06	5.31	4.74
63	4.17	4.24	4.14	4.35	5.14	3.98	5.22	4.73
64	4.06	4.18	4.03	4.29	5.10	3.89	5.05	4.72

Source: Authors

Appendix table 3: Observed and expected in-migration rate using parameter estimates of the model for Uttar Pradesh and Maharashtra.

Age	Uttar Pradesh				Maharashtra			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
1	1.45	1.32	3.80	2.35	8.25	7.65	8.52	8.43
2	1.80	1.72	4.03	2.74	11.10	11.10	10.92	10.93
3	2.31	2.42	3.57	2.78	18.43	18.43	18.29	17.90
4	2.73	2.84	3.29	2.82	23.45	23.45	23.31	23.55
5	3.06	3.07	3.15	2.87	26.44	24.38	26.27	26.81
6	3.31	3.19	3.13	2.91	27.70	23.90	27.48	27.74
7	3.48	3.26	3.19	2.96	27.52	23.42	27.24	26.94
8	3.58	3.29	3.30	3.01	26.18	22.96	25.84	25.09
9	3.61	3.32	3.42	3.05	23.98	22.50	23.58	22.74
10	3.58	3.34	3.54	3.10	21.21	22.06	20.75	20.23
11	3.50	3.35	3.60	3.15	18.17	21.62	17.67	17.78
12	3.37	3.36	3.59	3.20	15.13	21.19	14.62	15.51
13	3.20	3.38	3.47	3.25	12.39	20.77	11.90	13.46
14	3.00	3.39	3.21	3.30	10.25	20.35	9.81	11.63
15	2.76	3.40	2.77	3.38	8.94	19.95	8.62	10.04
16	2.55	3.44	2.24	3.55	8.48	19.55	8.49	8.70
17	2.58	3.57	2.10	3.98	8.84	19.17	9.55	8.01
18	3.14	3.98	2.97	5.01	9.99	18.78	11.91	9.05
19	4.50	4.98	5.44	7.16	11.90	18.41	15.73	13.06
20	6.94	6.96	10.12	11.05	14.49	18.05	20.97	20.00
21	10.58	10.17	17.31	17.05	17.50	17.69	27.10	28.33
22	15.03	14.49	26.15	25.04	20.63	17.34	33.43	36.05
23	19.73	19.43	35.47	34.25	23.57	16.99	39.26	41.80
24	24.14	24.22	44.09	43.38	26.02	16.65	43.92	45.14
25	27.70	28.12	50.86	50.99	27.73	16.32	46.86	46.26
26	29.99	30.60	54.85	55.90	28.67	16.00	48.07	45.65
27	31.00	31.48	56.15	57.54	28.87	15.68	47.70	43.87
28	30.84	30.88	55.06	55.97	28.34	15.37	45.89	41.37
29	29.63	29.09	51.93	51.79	27.13	15.06	42.78	38.49
30	27.47	26.53	47.06	45.90	25.29	14.76	38.56	35.48
31	24.52	23.57	40.85	39.22	23.03	14.47	33.66	32.49
32	21.08	20.53	33.88	32.52	20.58	14.18	28.53	29.61
33	17.52	17.64	26.82	26.36	18.18	13.90	23.66	26.91
34	14.17	15.02	20.32	21.05	16.07	13.63	19.50	24.39
35	11.39	12.74	15.03	16.71	14.44	13.36	16.42	22.08
36	9.44	10.83	11.43	13.30	13.23	13.09	14.29	19.96
37	8.22	9.26	9.29	10.73	12.34	12.83	12.88	18.03
38	7.51	8.00	8.21	8.85	11.68	12.58	11.97	16.28
39	7.14	7.00	7.77	7.52	11.14	12.33	11.31	14.70
40	6.89	6.22	7.57	6.59	10.64	12.08	10.71	13.27
41	6.61	5.62	7.28	5.96	10.16	11.84	10.15	11.97
42	6.29	5.17	6.87	5.55	9.71	11.61	9.64	10.80

Age	Uttar Pradesh				Maharashtra			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
43	5.95	4.82	6.41	5.27	9.31	11.37	9.20	9.74
44	5.63	4.56	5.96	5.10	8.95	11.15	8.83	8.79
45	5.35	4.37	5.56	4.98	8.64	10.93	8.55	7.93
46	5.13	4.24	5.26	4.91	8.36	10.71	8.34	7.15
47	4.97	4.13	5.05	4.86	8.12	10.50	8.16	6.45
48	4.84	4.06	4.90	4.81	7.90	10.29	8.00	5.82
49	4.72	4.01	4.78	4.77	7.69	10.08	7.82	5.25
50	4.60	3.98	4.67	4.72	7.47	9.88	7.61	4.74
51	4.47	3.96	4.54	4.67	7.26	9.69	7.38	4.28
52	4.32	3.95	4.39	4.61	7.07	9.50	7.14	3.86
53	4.17	3.94	4.23	4.53	6.89	9.31	6.93	3.48
54	4.03	3.94	4.08	4.44	6.74	9.12	6.75	3.14
55	3.90	3.95	3.93	4.34	6.62	8.94	6.62	2.83
56	3.78	3.95	3.80	4.22	6.53	8.76	6.54	2.56
57	3.68	3.96	3.68	4.08	6.46	8.59	6.48	2.31
58	3.60	3.97	3.58	3.92	6.39	8.42	6.43	2.08
59	3.51	3.98	3.50	3.74	6.33	8.25	6.37	1.88
60	3.43	3.99	3.42	3.55	6.26	8.09	6.29	1.70
61	3.34	4.01	3.35	3.34	6.17	7.93	6.16	1.53
62	3.25	4.02	3.29	3.11	6.05	7.77	5.98	1.38
63	3.14	4.03	3.24	2.88	5.91	7.61	5.73	1.25
64	3.02	4.05	3.18	2.62	5.72	7.46	5.38	1.12

Source: Authors