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Applied Multiregional Demography: Migration and Population Redistribution

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To all my grandchildren

Preface

My work in migration modeling and regional population dynamics and projections began in 1965, shortly after I had started to work on two reports for the California State Development Plan, as a member of the Center for Planning and Development Research at the University of California at Berkeley. I had never taken a course in demography, and at that time was a post-doctoral student in operations research, having just completed an advanced course on stochastic processes, which included lectures on Markov chains.

Those lectures motivated and shaped my efforts to introduce a *spatial* dimension to the demographer's non-spatial cohort-survival population projection model—efforts which culminated in the publication in 1966 of my first article on the subject in the journal Demography and in 1968 the publication of my first book: *Matrix Analysis of Interregional Population Growth and Distribution* (Rogers 1968).

Two years later, I moved to Northwestern University, and with the help of two superior doctoral students, Jacques Ledent and Frans Willekens, developed a formal demographic paradigm that I called multiregional demography. Soon thereafter, in 1975, my second book on population modeling: *Introduction to Multiregional Mathematical Demography* was published, and Willekens and I moved to Austria to join the International Institute for Applied Systems Analysis (IIASA), an East–West think-tank housed in a Habsburg palace, located just outside of Vienna, in a little town called Laxenburg. Shortly after, we were joined by Ledent and another graduate student of mine, Luis Castro, as well as a multinational collection of scholars who joined us for varying periods of time at IIASA to contribute to our work on multiregional demography. In 1983, I moved to the Institute of Behavioral Science (IBS) and the Department of Geography at the University of Colorado in Boulder where, with the help of another collection of my graduate students, I continued to carry out research on topics related to multiregional demography, focusing especially on various applications of that methodology, publishing my third, fourth, and fifth books on multiregional demography. In 1995, John Wiley and Sons issued my sixth book on this particular topic, *Multiregional Demography: Principles, Methods and Extensions*. Finally, in 2010 Springer published my book on the indirect estimation of migration, co-authored with my former Ph.D. students Jani Little and James Raymer.

Nathan Keyfitz's book *Introduction to the Mathematics of Population* in 1968 introduced me to uniregional mathematical demography and led me to generalize his results to the multiregional case. In 1977, he came out with a second book, entitled *Applied Mathematical Demography*, which showed how the models of mathematical demography, presented in his earlier book, could be used to find answers to commonsense questions that would be serviceable to those working on population and related matters, whether or not they cared to go deeply into the mathematics behind the answers. Following Keyfitz, I attempt to do something of the same for multiregional demography in this book, which I view as a capstone of my 50 years of research in multiregional demography.

Because over the past 50 years of published research I co-authored so many articles with my graduate students, not surprisingly, this book draws heavily on those collaborations. In particular, I received a great deal of help from and collaborations with first-rate students of different vintages, namely Luis Castro, Jacques Ledent, and Frans Willekens, who came to me at Northwestern in the early 1970s and then followed me to the International Institute of Applied Systems Analysis (IIASA) in Laxenburg, Austria. Then in the mid-1980s, during my early years at CU Boulder, I was helped by and collaborated with Alain Belanger, Jani Little, and John Watkins.

Finally, James Raymer, who began his graduate studies at Boulder in the mid-1990s, co-authored 16 papers with me over the next 20 years and made extraordinary contributions to the research reported in this book. All collaborators were essential to this book's development. I also had help over the years from a number of other former Ph.D. students of mine, namely Jennifer Woodward, Sabine Henning, and Lisa Jordan, and a few Masters students, particularly Kathy Gard, Cecile Hemez, Robin Taylor Wilson, and Junwei Liu. To all, my sincerest thanks; I couldn't have done it without you.

Other important sources of support were the various research grants I received from the National Science Foundation, the National Institute for Child Health and Human Development, and the National Institute of Aging, as well as a pilot grant from the Colorado University Population Center. Finally, I am thankful to have had the support of my institute directors both in Austria at IIASA (Roger Levien) and at the Institute of Behavioral Science (Dick Jessor and Jane Menken). Thanks also go to Rick Rogers, who followed me as Director of the IBS Population Program, for his support and valuable collaboration on our research project on active life expectancy in the 1990s, and for reviewing Chap. 7.

Finally, I wish to thank the various journal editors for permission to draw on my articles and to the large numbers of secretaries and staff members who collectively were indispensable in assisting with the completion of the final manuscript: Elisa and Samantha Elvove, Nancy Thorwardson, and Lindy Shultz, as well as to the two faculty members at CU Boulder with whom I co-authored several articles:

Professors Richard Rogers and Robert McNown. Professor James Raymer, at the Australian National University, and Jani Little, Director of IBS Computing and Research Services, both read this work in manuscript form, for which I am most grateful. Any remaining errors are mine.

Boulder, CO, USA Andrei Rogers
March 2015

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Acknowledgments

Many of the ideas and findings summarized in this book originally appeared in unpublished papers or in articles in journals. I am grateful to the various editors and publishers for permission to draw on materials contained in those essays. Specifically, parts of Chap. 1 first appeared in a 1996 article published in *Geographical Analysis* (Rogers 1996). Chapter 2 summarizes some of the material in yet another article in that same journal (Rogers 1990). Most of Chap. 3 is a revision of Rogers and Woodward (1988) in *Professional Geographer*. Chapter 4 presents results from an unpublished paper by Rogers and Raymer. Chapter 5 draws on another unpublished paper presented by James Raymer and me at last year's Annual Meeting of the Population Association of America (Raymer and Rogers 2014). Chapter 6 includes some of the results reported in Raymer et al. (2012), which appeared in the journal *Environment and Planning A* and ideas drawn from Rogers (1995) in *Mathematical Population Studies*. Chapter 7 is largely based on material that originally appeared in three articles, co-authored with Richard Rogers and Alain Belanger (Rogers et al. 1989; Rogers et al. 1990; Rogers et al. 1991) in the *Milbank Memorial Fund Quarterly, The Gerontologist, and Cahiers Québécois Démographie*, respectively. The author is grateful to these journals for permission to draw on the results presented in the cited articles.

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Contents

Chapter 1
Introduction: What Is Multiregional Demography?

Abstract This chapter sets the context, reviews the principal distinguishing features of the sub-field of multiregional demography, and identifies the key role played by migration. The next 6 chapters deal with applications of multiregional demography; the final chapter, Chap. 8, concludes the book with a renewed argument about the importance of proper model specification. Although the first few chapters deal with “closed” models that ignore international migration, “open” models with international migration are introduced in later chapters. [Readers unfamiliar with the models referred to in this monograph should consult Rogers (Introduction to multiregional mathematical demography. Wiley, New York, 1975 and Multiregional demography: principles, methods, and extensions. Wiley, Chichester, 1995)]

Keywords Multiregional demography · Uniregional demography · Migration age patterns

Formal demography is concerned with the mathematical description of human populations, particularly their structure with regard to age and sex, and the components of change, such as births and deaths, which occur over time to alter that structure. Accordingly, demographers have focused their attention on population *stocks* and on population *events*. Formal *multiregional demography* extends that focus to include the *flows* that interconnect and weld several regional populations into a multiregional population system. It, therefore, is concerned with the mathematical description of the evolution of human populations over time and across space. The trifold focus of such descriptions is on the *stocks* of human population groups at different points in time and locations in space, the vital *events* that occur among these populations, and the *flows* of members of such populations across the spatial borders that delineate the constituent regions of the multiregional population system.

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1.1 Modeling the Age and Spatial Dynamics of Multiregional Populations

Two principal features distinguish the multiregional from the uniregional perspective: the population being examined and the definition of rates of flow. The multiregional approach considers a population as an interacting system of subpopulations; the uniregional approach instead examines each regional subpopulation one at a time. Moreover, the multiregional approach employs migration/transition rates that are associated with the appropriate populations at risk to yield outmigration rates; the uniregional approach cannot do that because it considers only a single population at risk for both outmigration and inmigration, and therefore must rely on net or inmigration rates.

1.1.1 A Multiregional Perspective

A multiregional perspective in demographic analysis focuses simultaneously on several interdependent population stocks, on the events that alter the levels of such stocks, and on the gross flows that connect these stocks to form a system of interacting populations. The perspective deals with rates that refer to true populations at risk, and it considers the dynamics of multiple populations exposed to multiregional growth regimes defined by such rates. All of these attributes are absent in a uniregional perspective of growth and change in multiple interacting populations.

The fundamental difference between the uniregional and the multiregional approaches to population analysis may be depicted by the illustration set out in Fig. 1.1. Imagine a barrel containing a continuously fluctuating level of water. At any given moment, the water level is changing as a consequence of losses due to two outflows, identified by the labels "deaths" and "outmigration," respectively, and of gains introduced by two inflows labeled "births" and "inmigration," respectively.

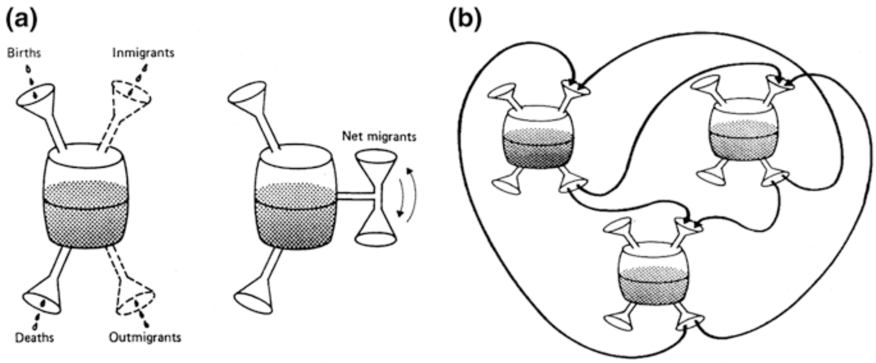

Fig. 1.1 Contrasting perspectives: uniregional versus multiregional models. **a** Uniregional model. **b** Multiregional model

If it is assumed that each barrel's migration outflow and its migration inflow, during a unit period of time, vary in direct proportion to the average water level in the barrel at that time, then the two flows may be consolidated into a single net flow (which may be positive or negative), and the ratio of this net flow to the average water level defines the appropriate rate of net flow. Such a perspective of the problem reflects a uniregional approach.

Now imagine an interconnected system of three barrels, say, where each barrel is linked to the other two by a network of flows, as in Fig. 1.1b. In this system, the migration outflows from two barrels define the migration inflow of the third. A uniregional analysis of the evolution of water levels in this would focus on the changes in outflows and inflows in each barrel, one at a time. A multiregional perspective, on the other hand, would regard the three barrels as a system of three interacting bodies of water, with a pattern of outflows and inflows to be examined as a simultaneous system of relationships. Moreover the multiregional approach would focus on outflows; hence the associated rates would always be positive, and they would refer to the appropriate "populations exposed to the possibility of migration."

To deal with the interlinkages that connect one population's dynamics to another's, the uniregional perspective generally must resort to the use of ad hoc procedures and unsatisfactory concepts such as the statistical fiction of the invisible net migrant. But does it really matter? What are the drawbacks of a view that ignores gross flows in favor of a focus on net changes in stocks? In what respects is a multiregional perspective superior to a regional one?

A focus on gross flows more clearly identifies the age and spatial regularities, illuminates the dynamics, and enhances the understanding of demographic processes that occur within multiple interacting populations. Distinguishing between flows and changes in stock reveals regularities that otherwise may be obscured; focusing on flows and changes into and out of a region-specific stock to expose dynamics that otherwise may be hidden; and linking explanatory variables to disaggregated gross flows permits a more appropriately specified causal analysis.

Net rates express differences between arrivals and departures as a fraction of the single population experiencing both. But net rates also reflect sizes of population stocks. For example, if the gross rates of migration between urban and rural areas of a nation are held constant, the net migration rate will change over time with shifts in the relative population totals in each area. Accordingly, one's inferences about changes in net migration patterns over time will confound the impacts of migration propensities with those of changing population stocks, hiding regularities that may prevail among the observed gross migration flows.

Gross flow data permit the construction of improved population projection models. It can be demonstrated that multiregional projection models based on gross flow statistics are superior to uniregional models in at least four respects. First, uniregional models can introduce a bias into the projections, and they can produce inconsistent results in long-term prognoses. Second, the impacts of changes in age compositions on movement patterns can be important, yet a uniregional perspective fixes these impacts at the start of a projection and thereby can introduce an additional bias into the projection. Third, multiregional projection models have a decisive advantage over uniregional models in that they alone can follow subpopulations over time. Thus they can produce disaggregated projections that are impossible to obtain with uniregional models. Finally, causal explanations brought forth by studies of population redistribution all too often have been founded on models of population dynamics that reflect inadequate statistical perspectives. For example, no reliable inferences about migration behavior can be made of the basis of cross-sectional tabulations of changing fractions of a population defined to be net migrants. Data on gross flows are essential, and increasingly it is being recognized that such data must be available in disaggregated form.

Disaggregation into subgroups allows one to study the diverse demographic behavior of heterogeneous populations exhibiting temporally dependent changing patterns. To the extent that their differing propensities to experience events and movements can be incorporated into a formal macrodemographic analysis, illumination of the aggregate patterns of behavior is enhanced. For instance, our understanding of migration is enriched by information on the degree to which such movements occur among those who have previously migrated. In generating such information, a multiregional analysis can identify, for example, how much of a change in levels of migration in a country can be attributed to "chronic" migrants as opposed to "first-time" migrants.

Typical age-specific patterns of in-, out-, and net migration rates are set out in Fig. 1.2. The data come from observed migration schedules. Note the effects of the netting out process: similar age patterns of directional migration give rise to totally different age patterns of net migration. To use the latter in a regression causal model, for example, would create misspecification.

Age patterns of gross migration rates are similar in profile because migration is related to the life course. Notice that the top age profile in Fig. 1.2b depicting migration to Florida exhibits a typical migration schedule with three sequences of rising rates, two of which occur at the elderly ages. The first rise is triggered by a move away from the *parental* home, a move that reflects the transition from adolescence to adulthood. Entry into the job or marriage markets, military enlistment, or university enrollment are all life course events that often generate migration. The first rise generally peaks at some age in the early twenties and then begins a monotonic decline until the start of the second rise around age sixty for males and earlier for females. The second upswing in the age pattern of migration reflects movement away from the *family* home, a move that if often motivated by amenity-oriented retirement migration. Finally, the third rise in the schedules occurs at around age seventy-five and is migration away from the *retirement* home, a move that often is a consequence of entry into dependent status and the onset of illness, disability, or the death of a spouse.

Rates of migration for children, start at a peak during the first years of life and drop to a low point around age ten. The age patterns of these rates for children usually mirror that of their parents, that is, the patterns of rates occurring some twenty-five or thirty years later.

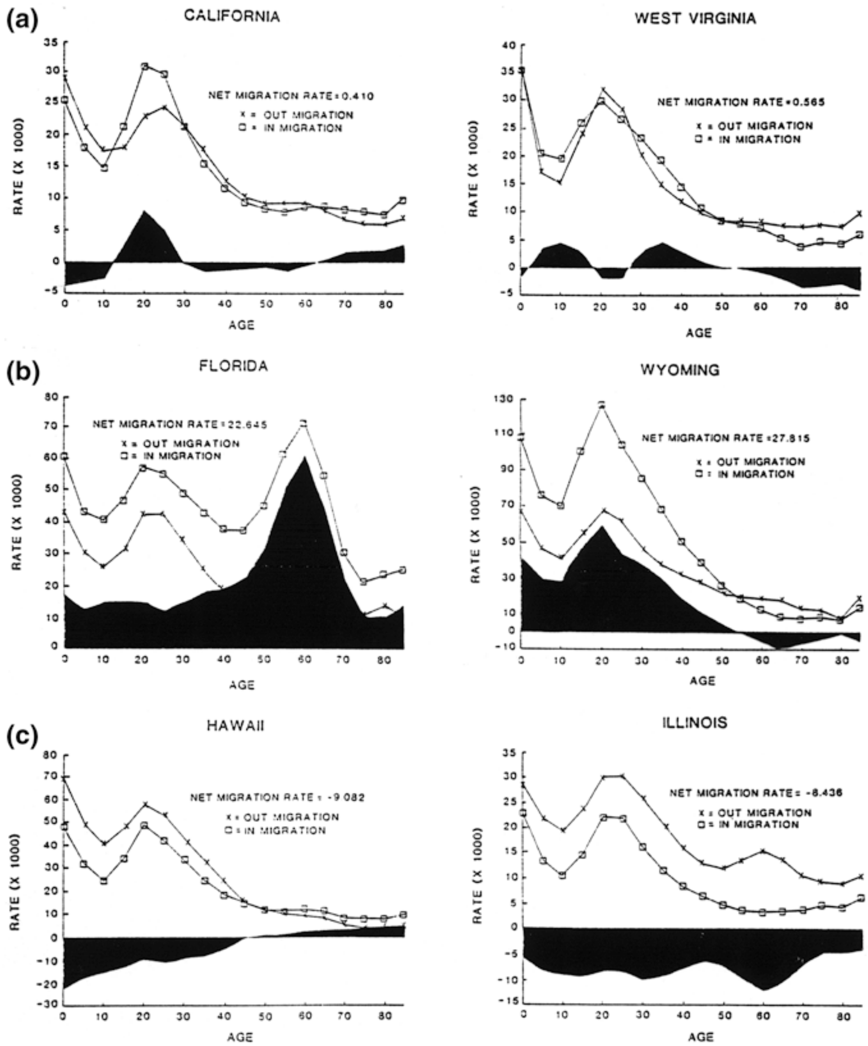

Fig. 1.2 Out-, in-, and net migration schedules for six U.S. states, 1975–1980. *Source* Rogers (1990). **a** Near zero net migration rate. **b** Positive net migration rate. **c** Negative net migration rate

Two classes of models are commonly used to examine how the growth and structure of a national multiregional population evolves from particular regimes of fertility, mortality, and migration: the life table model and the projection model. Both allow one to separate out the impacts, on population growth and structure, of the demographic processes prevailing at a particular moment, and of the age composition and spatial distribution of the national multiregional population at that moment (Rogers 1973a, b).

1.1.2 Multiregional Life Tables

The life table is a central concept in classical uniregional demography. Its use to express the facts of mortality in terms of survival probabilities and their combined impact on the lives of a cohort of people born at the same moment has been so successful that demographers generally think of population change with the life table as a natural starting point. The natural starting point for thinking about multiregional population change, therefore, is the multiregional life table. The multiregional generalization of the conventional uniregional life table posits a life table with multiple radices, one for each of the regional populations in the system and follows each birth cohort as it redistributes itself spatially and eventually leaves the system through death (and emigration, in instances of systems experiencing international migration).

Uniregional life tables are derived from a set of probabilities of surviving from one exact age to another. Multiregional life tables do that also, but keep track, not only of age, but also of region of residence. Estimates of the required input probabilities normally are developed from observed data on rates and/or conditional proportions surviving. The data are produced by an explicit or implicit *observational plan* that defines whether such data are prospective or retrospective in character, and whether they refer to individuals or to groups, to life history segments or to entire lifetimes, to the experiences of a cohort or to the events occurring during a particular period. To ensure consistency, the data may be adjusted by basic accounting identities that are embedded in a set of demographic accounts.

Important variation in estimation procedures arise as a consequence of differences in how migration is observed and measured. Counts of *moves* call for different estimation procedures than do counts of *movers*; therefore, migration data obtained from population registers require a different method for estimating transition probabilities than do migration data obtained from national censuses. In a multiregional life table, expectancies at each age, and also conditional age-to-age survivorship proportions (probabilities), are calculated. The former provide expected durations of residence in various regions; the latter may be entered into a projection model to generate expected future age- and region-specific population totals.

1.1.3 Multiregional Population Projections

Population projections are numerical estimates of future demographic totals and are often based on rates that are extrapolations of past and current trends. Such calculations are fundamental inputs to social and economic planning. They identify potential demographic futures, anticipate the needs that such futures are likely to create, and provide a basis for judging whether or not efforts should be launched to alter current population processes and trends.

The mechanics of multiregional population projection typically revolve around three basic steps. The first ascertains the starting age-region distributions and the age-specific regional schedules of fertility, mortality, and migration to which the multiregional population has been subject during a past period; the second adopts a set of assumptions regarding the future behavior of such schedules; and the third derives the consequences of applying these assumed schedules to the initial population stock.

The typical discrete model of multiregional demographic growth expresses the population projection process by means of a matrix operation in which a multiregional population, set out as a vector, is multiplied by a growth matrix that survives that population forward over time (Rogers 1975, 1995). The projection calculates the regional and age-specific survivors of a multiregional population of a given sex and adds to this total the new births that survive to the end of the unit time interval. As in the uniregional model, the survival of individuals from one moment in time to another, say five years later, is calculated by diminishing each regional population to take into account mortality and net migration. In the multiregional model, however, one needs to include both the decrement resulting from outmigration and the increment contributed by inmigration. In models "open" to international migration the decrement from emigration and the increment from immigration also need to be incorporated. Surviving children born during the five-year interval, migrate with their parents or are born after their parents have migrated, but before the time interval has elapsed. Finally, implicit in every multiregional projection matrix is a stable distribution across ages and regions, expressible in terms of age compositions and regional shares. Deviations from these compositions and shares, in the initial age-by-region distribution, ultimately disappear, but in the short to medium run they create fluctuations and disturbances in age profiles and in population allocations over regions.

1.2 Estimating the Age and Spatial Structures of Migration Flows

The estimation of migration from aggregate and incomplete data generally has been carried out with a focus on *net* migration and approximated by the population change that cannot be attributed to natural increase. Given data on population sizes at two points in time, and estimates of birth and death rates for the interval defined by those two points, net migration may be approximated by the difference between the observed population at the second point in time and the hypothetical projected population that would have resulted at that time if only natural increase were added to the initial population.

Methods for inferring *gross* (directional) migration streams have a more limited history and literature. In the early years, methods of indirect estimation were geared to particular missing data problems. Consequently, the methods had an ad hoc character (as do many methods of indirect estimation in demography). More recently, however, the indirect estimation of migration has relied on the use of models and on the theory of statistical inference to infer the relevant parameters from available data. Some describe age patterns of migration, while others describe spatial interaction patterns (Rogers et al. 2010).

1.2.1 Model Migration Schedules and Spatial Interaction Models

Recognizing that most human populations experience rates of age-specific fertility and mortality that exhibit remarkably persistent regularities, demographers have found it possible to summarize and codify such regularities by means of mathematical expressions called *model schedules*. Although the development of model fertility and mortality schedules has received considerable attention in demographic studies, the use of *model migration schedules* has played a more limited role, even though the techniques that have been successfully applied to treat the former can readily extended to deal with the latter.

Several studies of regularities in age patterns of migration, over the past some 45 years have demonstrated that the mathematical expression called the *multiexponential function* provides a remarkably good fit to a wide variety of empirical interregional migration schedules (Rogers and Castro 1981). That goodness-of-fit has led a large number of demographers and geographers to adopt it in various studies of migration all over the world.

Models that describe and predict the numbers of migrations between two regions by relating them to variables describing the characteristics of the origin, the destination, and the "friction" associated with their separation are often called spatial interaction models. The problem of fitting spatial interaction models has been approached from different perspectives over the past decades. First formulated as an analogy to Newton's law of gravitation, the resulting purely mechanical approach was revised by some 35 years ago, when geographers recognized that models developed in the field of discrete multivariate analysis could be applied to express spatial interaction patterns. Foremost among these models has been the log-linear model (Willekens 1983).

1.2.2 The Indirect Estimation of Migration from Inadequate Data

In countries with well-developed data reporting systems, demographic estimation, typically is based on data collected by censuses and vital registration systems. Demographic estimation in countries with inadequate or inaccurate data reporting systems, on the other hand, often must rely on methods that are indirect. For instance, the use of the proportion of children dead, among those ever borne by women 20–24 years of age, to estimate the probability of dying before age 2 is an example of indirect estimation. Such estimation techniques usually rely on model schedules (collections of age-specific rates that are based on patterns observed in various populations other than the one being studied) and select one of them on the basis of some data describing the observed population. The justification for such an approach is that age profiles of observed schedules of rates vary within predetermined bounds for most human populations. Rates for one age group are highly correlated with those of other age groups, and expressions of such interrelationships are the basis of model schedule construction.

Unlike fertility and mortality, which involve single populations, migration links two populations: the population of the origin region and that of the destination region. This greatly complicates its estimation by indirect methods. What this means in practical terms is that a focus on *age patterns* (as in the case of fertility and mortality) is not enough—one also must focus on *spatial patterns*. The imposition of observed regularities in both the age and spatial patterns of interregional migration to "discipline" inadequate data on territorial mobility holds great promise as a means for developing detailed age- and destination-specific migration flow data from inaccurate, partial, and even non-existent information on this most fundamental process underlying population redistribution.

Over the past two decades, a formal model-based approach to the indirect estimation of migration has evolved (Rogers et al. 2010). The formal approach suggests that rough estimates of interregional age-specific migration streams can be developed by indirect estimation methods applied to two age-region-specific population counts, disaggregated by region of births, and some auxiliary information obtained from historical data. For example, robust estimates have been obtained using infant migration data of a current period and regression relationships prevailing during an earlier period. Since children who have been born in region i, and who are, say, 0–4 years old at the time of the census and living in region j, must have migrated during the immediately preceding 5-year interval, we can obtain a "proxy" infant migration rate by "backcasting" them to their region of birth and then calculating their prospective propensity to migrate. Given their young age, and the fact that they were on average born 2½ years ago, it is unlikely that they experienced more than one migration. Regression equations and model migration schedules can be used to expand these child-migration levels and spatial patterns into the corresponding levels and patterns for every age.

1.3 Outline of the Rest of the Book

The organization of this book is straightforward. Chap. 2 focuses on model specification and uses a simple numerical illustration to show how net migration rates introduce a bias when used to represent the contribution of migration in a population projection of urban growth. Chap. 3 examines the question of whether it is migration or aging-in-place that contributes most to regional elderly population growth. Chap. 4 considers birthplace dependence in migration patterns and shows that return migration to region of birth generally exhibits higher levels and different spatial patterns than non-return migration. Chap. 5 carries this topic a step further by separating the foreign-born and the native-born populations, identifying the separate contributions made by each to regional elderly population growth. Chap. 6 addresses the issue of model performance in population projection efforts and accords special attention to the impact of uncertainty. Chap. 7 introduces regions that are status categories and demonstrates that the mathematical apparatus for tracing the demographic consequences of movements of people between regions (multiregional demography) is the same apparatus for modeling the transitions of people between statuses (multistate demography). Finally, Chap. 8 concludes the book with a return to its principal argument, namely, that incidence rates should be used in place of prevalence rates when modeling the growth and redistribution of several interacting populations.

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Chapter 2
Does Model Specification Matter?

Abstract Multiregional demography stresses the importance of identifying the proper flows to enter as numerators in constant coefficient account models, and of relating these numerators to appropriate denominators measuring population stocks. When applied in demographic definitional and structural equations, such procedures lead to correctly specified "incidence" rates and the subpopulations at risk of experiencing the changes brought about by these particular rates. In this context, models of the determinants and consequences of migration that rely on inmigration rates and net migration rates are misspecified. So too are models, for example, that rely on the "labor force participation rate." In both instances the denominators of the rates do not correspond to the subpopulations that are at risk of experiencing the events represented in the numerators. Demographic innumeracy produces a biased model.

Keywords Model specification · Net migration rates · Incidence rates · Prevalence rates · Urbanization

2.1 Introduction

The principal arguments of this chapter are developed with the aid of a prototype biregional baseline model with constant rates, and in which simple contrived numbers are used to demonstrate the arguments. (After all, most of us learned how to solve quadratic equations by using only integer numbers.) However, an empirical illustration is also included later in the chapter for completeness.

The baseline model is used to generate spatial population dynamics that are described by a set of conventional indices, measured over time until stability. Sections 2.2 and 2.3 focus on the *net migration rate* as a representation of spatial population flows, and show how that introduces a projection bias. Section 2.4 uses the concept of Simpson's Paradox to illustrate how the introduction of age-specific migration rates can produce counterintuitive reversals. Section 2.5 examines the

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proximate sources of urban population growth. Finally, Sect. 2.6 concludes the chapter with a discussion of the principal results and an assessment of their significance for the modeling of migration.

2.2 The Net Migration Rate: How It Creates a Projection Bias

Net changes in regional population stocks are often dwarfed by the gross migration flows that help to produce them, hiding the spatial dynamics that are at work; a modest net contribution to regional population growth by migration may be generated by large gross flows in both directions. Demographers generally focus on demographic rates rather than counts, because analyses based on rates are superior to those based on counts. Demographic rates exhibit strong age-specific regularities and temporal stabilities that a projection based on rates can exploit to generate events through demographic accounting identities; a projection based on a count of events ignores this information. Moreover, it is much easier to assess and interpret the reasonableness of results produced by forecasted rates. For instance, a set of one hundred numbers representing deaths by single year of age of decedent is not very informative; nor is a collection of thirty numbers representing number of births by single year of age of mother. Yet the meanings of the expectation of life at birth and the net reproduction rate implied by these two sets of numbers (both calculated using age-specific rates) are readily grasped, and unrealistic values for these two variables suggest possible sources of error in the data or in the forecasting procedure.

The net migration rate, m_j, for a particular region j is defined as the difference between the region's inmigration rate, i_j, and its outmigration rate, o_j. The outmigration rate is defined as a true rate because it divides the number of times that an event, outmigration, occurred during a year, say, by the number of persons exposed to the risk of experiencing that event. The inmigration rate, on the other hand, is a measure of *prevalence* rather than of propensity. It too has a numerator that is an occurrence count of a particular event, inmigration in this case, but its denominator is not a count of the number of persons that could have experienced the event. Rather, its denominator is the population in the region of destination that was at risk of experiencing the *outmigration* event. Since the net migration rate is the difference between a measure of prevalence and a true rate or propensity, its interpretation is necessarily ambiguous.

For each set of fixed outmigration rates, different spatial distributions of a population will give rise to different values of the net migration rate to a region. Also, for each fixed initial spatial distribution of a population, a given value of the net migration rate can be generated by a wide range of inmigration and outmigration rates; but the long-term implications for the geography of the population may be quite different. Thus one must be wary of cross-sectional comparisons of net migration rates of different regions as well as comparisons of such rates for the same region over time. In both instances the net migration rate will embody the influences of spatial population distribution along with those of movement propensities.

Consider, for example, how projections of urbanization might be carried out with uniregional (net migration) and multiregional (gross directional migration) models. In a uniregional model, the urban population is the central focus of interest and all rural-to-urban migration flows are assessed only with respect to the population in the region of destination, that is, the urban population. Changes in the population at the region of origin are totally ignored, with potentially serious consequences. For example, the rural population ultimately may be reduced to near zero levels, but a fixed and positive net migration into urban areas will nevertheless continue to be generated by the uniregional model.

To see the source of the problem more clearly, consider how the rural-urban migration specification is altered when a biregional model of urban and rural population growth is transformed into a uniregional model (Rogers 1990). Let urban population growth be described by the equation

$$P_u(t+1) = (1 + b_u - d_u - o_u)P_u(t) + o_v P_v(t) \tag{2.1}$$

Equation (2.1) states that next year's urban population total, $P_u(t + 1)$, may be calculated by adding to this year's urban population $[P_u(t)]$ the increment due to the excess of births over deaths, that is, urban natural increase $[(b_u - d_u)\ P_u(t)]$, the decrement due to urban outmigration to rural (v = village) areas $[o_u P_u(t)]$, and the increment due to rural-to-urban migration $[o_v P_v(t)]$.

Now, multiplying the last term in the Eq. (2.1) by unity expressed as $P_u(t)/P_u(t)$ transforms that equation into its uniregional counterpart

$$\begin{aligned} P_u(t+1) &= (1 + b_u - d_u - o_u)P_u(t) + o_v P_u(t) \\ &= (1 + b_u - d_u - o_u + i_u)P_u(t) \\ &= (1 + b_u - d_u + m_u)P_u(t) = (1 + r_u)P_u(t) \end{aligned} \tag{2.2}$$

where

$$\begin{aligned} i_u &= o_v \left[\frac{P_v(t)}{P_u(t)}\right] = o_v \left[\frac{1 - U(t)}{U(t)}\right], \\ m_u &= i_u - o_u, \end{aligned}$$

and U(t) is the fraction of the total national population that is urban at the time t. If all annual rates are assumed to be fixed in the biregional projection, then in the uniregional model i_u, and therefore also m_u, depend on U(t), which varies in the course of projection, thereby introducing a bias. The dependence of the urban net migration rate m_u on the level of urbanization at the time t means that m_u *must decrease as the level of urbanization increases.* Consequently, it seems inappropriate to use such a model to answer, for example, the question whether it is natural increase or net migration that is the principal source of urban population growth over time, as did Keyfitz (1980).

2.3 The Uniregional Fallacy and Bias

The notion that the spatial dynamics of a system of multiple interacting regional populations can be analyzed profitably by a set of *independent* uniregional models, which apply net migration rates to each regional population, dies hard. The biases and inconsistencies that are created by such decompositions of multiregional population projection models are generally ignored. Thus despite decades of published work on multiregional demography exposing the "uniregional fallacy," it is unfortunately still common to find articles in prominent journals that ignore this literature.

2.3.1 Aggregation Bias

Imagine, once again, a closed two-region population system consisting of an urban population, $P_u(t)$, and a rural population, $P_v(t)$. In its discrete-time formulation

$$\begin{aligned} P(t) &= P_u(t) + P_v(t) \\ &= (1 + r_u)^t P_u(0) + (1 + r_v)^t P_v(0) \\ &= (1 + r_u) P_u(t-1) + (1 + r_v) P_v(t-1) \end{aligned} \tag{2.3}$$

and

$$r(t) = U(t-1) r_u + [1 - U(t-1)] r_v \tag{2.4}$$

where, as before, $U(t) = P_u(t)/P(t)$ is the fraction urban at time t.

By definition, the urban growth rate, r_u, is equal to the birth rate, b_u, minus the death rate, d_u, minus the outmigration rate, o_u, plus the inmigration rate, i_u:

$$r_u = b_u - d_u - o_u + i_u. \tag{2.5}$$

If r_u is to remain constant, then the component rates on the right-hand side of the Eq. (2.5) must sum to a constant, and

$$P_u(t) = (1 + r_u)^t P_u(0) \tag{2.6}$$

Note that instead of a chained multiplication of one-year at a time, one can simply raise the quantity in the parentheses to the power t. But we have earlier shown that

$$i_u = o_v \left[\frac{P_v(t)}{P_u(t)} \right] = o_v \left[\frac{1 - U(t)}{U(t)} \right] \tag{2.7}$$

which means that i_u (and therefore r_u) *changes over time as urbanization proceeds*. Bias and inconsistency are therefore the probable result of viewing this biregional population system through a uniregional perspective. Changes in magnitude of migration flows may occur apart from changes in the propensity to move. A biregional perspective can be used to distinguish between changes in rates that reflect actual changes in propensity from changes in rates that are merely a consequence of changes in compositions. The uniregional perspective does not have this ability. To see this, assume a behaviorally fixed and totally *homogeneous* population in Eq. (2.5),

$$\begin{aligned} r_u(t) &= b - d - o + o\left[\frac{1 - U(t)}{U(t)}\right] \\ &= b - d + \left[\frac{1 - 2U(t)}{U(t)}\right]o = n + A(t)o \end{aligned} \tag{2.8}$$

and, similarly,

$$\begin{aligned} r_v(t) &= b - d - o + o\left[\frac{U(t)}{1 - U(t)}\right] \\ &= b - d + \left[\frac{2U(t) - 1}{1 - U(t)}\right]o = n + B(t)o \end{aligned} \tag{2.9}$$

where natural increase, $n = b - d$, $A(t) = [1 - 2U(t)]/U(t)$, and $B(t) = [2U(t) - 1]/[1 - U(t)]$.

Since all members of the population exhibit identical and constant behavior, one might expect both regional growth rates $r_u(t)$ and $r_v(t)$, to be identical and to remain fixed at the value of the natural increase rate $n = b - d$; but this will only occur either if (i) the two regional populations do not interact with each other via migration (that is, $o = 0$), or (ii) the entire population is currently experiencing stable growth, a condition that in this illustration can only arise if the two regional populations happen to be identical in size (that is, $U(t) = ½$, whence $A(t) = B(t) = 0$).

Unlike the case of the "perfect aggregation," total homogeneity is not a sufficient condition for "perfect deconsolidation," that is, for avoiding a bias in transformations of multiregional models to uniregional ones; indeed homogeneity is irrelevant and distributional stability is essential (Rogers 1969).

2.3.2 Decomposition Bias

The transformation of a multiregional model that describes interregional migrations between the constituent regions of the population system into the corresponding separate uniregional models can be viewed as a process of compensated decomposition in which net migration rates carry out the "compensation." Before such a transformation, the population of the *j*th region, $P_j(t + 1)$ for example, can be defined as

$$P_j(t+1) = (1 + b_j - d_j - o_j)P_j(t) + \sum_{i \neq j} o_{ij}P_i(t). \tag{2.10}$$

Denoting $1 + b_j - d_j - o_j$ by o_{jj}, and multiplying the last term in the equation by unity, in the form of $P_j(t)/P_j(t)$, gives

$$\begin{aligned} P_j(t+1) &= o_{jj}P_j(t) + \left[\sum_{i \neq j} o_{ij}\frac{P_i(t)}{P_j(t)}\right]P_j(t) \\ &= \left[o_{jj}(t) + \sum_{i \neq j} o_{ij}\frac{P_i(t)}{P_j(t)}\right]P_j(t) \end{aligned} \tag{2.11}$$

2.3.3 Numerical Illustration: A Simple Projection Model of Urbanization

The urban population of the Pacific island of Mora-Bora increased by three quarters last year ($r_u = \frac{3}{4}$), while the rural population grew by an eighth ($r_v = \frac{1}{8}$). At the start of the year the two populations were enumerated to be 16 and 32 thousand, respectively. During the course of the year a half of the rural population migrated to urban areas ($o_v = \frac{1}{2}$), while a fourth of the urban population moved to the rural areas ($o_u = \frac{1}{4}$). Given these rates and the initial populations, it is a simple matter to define the growth process that will project the island's biregional population forward two consecutive years. The island's population increases from 48 thousand to 64 thousand after a year, and then it grows to 82 thousand after the following year. The demographic accounting equations for the first year are:

$$\begin{aligned} P_u(1) &= [1 + (b_u - d_u) - o_u]P_u(0) + o_vP_v(0) \\ &= (1 - n_\text{u} - o_u)P_u(0) + o_vP_v(0) \\ &= (1 + 0 - \frac{1}{4})16 + (\frac{1}{2})32 = 28 \end{aligned}$$

and

$$\begin{aligned} P_v(1) &= o_uP_u(0) + (1 + n_\text{v} - o_v)P_v(0) \\ &= (\frac{1}{4})16 + (1 + \frac{1}{2} - \frac{1}{2})32 = 36 \end{aligned}$$

where n denotes the natural increase rate. Notice that the urban population is experiencing replacement level fertility, that is, $b_u = d_u$, and the rate of natural increase, n_u, is zero. The natural increase rate of the rural population is a half.

The above disaggregated model produces a projected evolution of the national population that is: 48, 64, 82, …. Notice that the corresponding consolidated uniregional model for the national total [that is, $P(1) = \frac{4}{3}P(0)$] leads to a *higher*, not lower, projected set of totals: 48, 64, $85\frac{1}{3}$,…. Hence, Keyfitz's (1977, p. 16) proof of a guaranteed overprojection by the more disaggregated model does not apply in this case.The above two fundamental equations define the biregional model. The corresponding uniregional models may be obtained by a compensated decomposition. In that event, the net migration rate for the urban region is

$$m_u = i_u - o_u = o_v \left[\frac{P_v(0)}{P_u(0)}\right] - o_u$$
$$= \frac{1}{2}[2] - \frac{1}{4} = \frac{3}{4}$$

and correspondingly,

$$m_v = -\frac{3}{8}$$

Thus

$$P_u(1) = 28 = [1 + 0 + \frac{3}{4}]16$$

and

$$P_v(1) = 36 = [1 + \frac{1}{2} - \frac{3}{8}]32$$

Similarly

$$P_u(2) = 49 = (\frac{7}{4})28$$

and

$$P_v(2) = 40\frac{1}{2} = (\frac{9}{8})36$$

The island's population after the initial "calibration" period is overprojected by seven and a half thousand people relative to the biregional projection, with the rural population's *underprojection* of two and a half thousand being over-compensated by the urban population's *overprojection* of ten thousand. Notice that the former was losing net migrants, whereas the latter was gaining net migrants.

Finally, consider the same growth process as before, but now imagine that the initial national population of 48 thousand is distributed equally among the two regions. Then the biregional projections give

$$P_u(1) = 30 = (\frac{3}{4})24 + (\frac{1}{2})24$$

and

$$P_v(1) = 30 = (\frac{1}{4})24 + (1)24$$

Similarly

$$P_u(2) = 37\frac{1}{2} = (\frac{3}{4})30 + (\frac{1}{2})30$$

and

$$P_v(2) = 37\frac{1}{2} = (\frac{1}{4})30 + (1)30$$

The relevant net migration rates now are $m_u = \frac{1}{4}$ and $m_v = -\frac{1}{4}$, and the corresponding uniregional projection becomes

$$P_u(1) = 30 = (\frac{5}{4})24$$

and

$$P_v(1) = 30 = (\frac{5}{4})24$$

Similarly,

$$P_u(2) = 37\frac{1}{2} = (\frac{5}{4})30$$

and

$$P_v(2) = 37\frac{1}{2} = (\frac{5}{4})30$$

Because the initial population has a stable initial distribution, perfect decomposition results. No bias is introduced by shifting to a uniregional model by means of compensated decomposition.

2.3.4 *The Simple Projection Model Expressed in Matrix Form*

Matrix algebra provides a compact and useful means for studying the demographic evolution of multiple interacting populations. Matrix notation makes the projection process more transparent, and matrix theory brings to demographic analysis results that have direct application to population questions. Expressing the population projection process in matrix form also leads to the derivation of results that would be virtually impossible to establish otherwise.

The reader should confirm that the simple biregional projection of Mora Bora's urban and rural populations, described in Sect. 2.3.2 may be expressed in matrix form as

$$\begin{bmatrix} 28 \\ 36 \end{bmatrix} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1 \end{bmatrix} \begin{bmatrix} 16 \\ 32 \end{bmatrix}$$

and

$$\begin{bmatrix} 39 \\ 43 \end{bmatrix} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1 \end{bmatrix} \begin{bmatrix} 28 \\ 36 \end{bmatrix}$$

Recall that the multiplication rule in matrix algebra is "row times column."

A more transparent picture of the evolution to stable growth may be obtained by focusing on another numerical illustration in which an urban population of 24 million each year sends a fourth of its population to rural areas and receives, in exchange, one-half of the rural population, which initially is also taken to stand at 24 million persons. Assume that a zero population growth regime prevails, such that the annual increment due to births, in each region, is exactly offset by the annual decrement due to deaths. Then we have that

$$\mathbf{G} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1/2 \end{bmatrix}$$

$$\{\mathbf{P}(t)\} = \begin{bmatrix} 24 \\ 24 \end{bmatrix}$$

and the projection to stability is

$$\{\mathbf{P}(t+1)\} = \begin{bmatrix} 30 \\ 18 \end{bmatrix} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1/2 \end{bmatrix} \begin{bmatrix} 24 \\ 24 \end{bmatrix}$$

$$\{\mathbf{P}(t+2)\} = \begin{bmatrix} 31\tfrac{1}{2} \\ 16\tfrac{1}{2} \end{bmatrix} = \begin{matrix} 3/4 & 1/2 \\ 1/4 & 1/2 \end{matrix} \begin{bmatrix} 30 \\ 18 \end{bmatrix} = \begin{bmatrix} 11/16 & 5/8 \\ 5/16 & 3/8 \end{bmatrix} \begin{bmatrix} 24 \\ 24 \end{bmatrix}$$

$$\{\mathbf{P}(t+3)\} = \begin{bmatrix} 31\tfrac{7}{8} \\ 16\tfrac{1}{8} \end{bmatrix} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1/2 \end{bmatrix} \begin{bmatrix} 31\tfrac{1}{2} \\ 16\tfrac{1}{2} \end{bmatrix} = \begin{bmatrix} 43/64 & 21/32 \\ 21/64 & 11/32 \end{bmatrix} \begin{bmatrix} 24 \\ 24 \end{bmatrix}$$

$$\vdots \qquad\qquad \vdots \qquad\qquad \vdots$$

$$\{\mathbf{P}(\infty)\} = \begin{bmatrix} 32 \\ 16 \end{bmatrix} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1/2 \end{bmatrix} \begin{bmatrix} 32 \\ 16 \end{bmatrix} = \begin{bmatrix} 2/3 & 2/3 \\ 1/3 & 1/3 \end{bmatrix} \begin{bmatrix} 24 \\ 24 \end{bmatrix}$$

Note that once the initial urbanization level of ½ grows to 2/3, it remains at that level forever. The population has achieved stable growth; each of its subgroups is increasing exponentially and at the same rate. Its urban and rural growth rates both are zero, and its stable distribution is forever fixed in the proportions 2/3 and 1/3. These two fundamental attributes of the process of projection to stability are augmented by a third; the independence of the stable growth results from the starting population distribution—a property of the process called "ergodicity."

That the stable or intrinsic growth rate and corresponding stable distribution are independent of the starting population distribution and depend only on the growth regime defined by the projection matrix, **G** may be illustrated by applying the same matrix to a different initial population distribution. For example the reader should confirm that

$$\begin{bmatrix} 34 \\ 14 \end{bmatrix} = \begin{bmatrix} 3/4 & 1/2 \\ 1/4 & 1/2 \end{bmatrix} \begin{bmatrix} 40 \\ 8 \end{bmatrix}$$

converges to the same stable state as was obtained before, and that the alternative projection matrix

$$\begin{bmatrix} 5/6 & 1/4 \\ 1/4 & 5/6 \end{bmatrix}$$

ultimately brings about a level of urbanization with half of the national population living in rural areas and growing at 25/3= 8.3 % per annum.

2.3.5 Bias: A Summary

Aggregating the separate projections of several *noninteracting* heterogeneous populations will give rise to a total greater than one that would be obtained by projecting the aggregate population at its average rate of growth at the outset (Keyfitz 1977, p. 16). Aggregation prior to projection introduced an aggregation bias that is guaranteed to be *negative*, giving rise to an underprojection relative to the consolidation of the corresponding disaggregated projection. The aggregation of noninteracting heterogeneous populations prior to projection, then, always produces an underprojection: the aggregate population never stabilizes, the aggregate rate of growth forever increases, and the population's composition varies continuously.

Does the same guaranteed *negative* bias also arise in the aggregation introduced by the consolidation of *interacting* heterogeneous populations? The answer is no. Rogers (1985), for example, offers an illustration of a positive aggregation bias which is introduced by the consolidation of the Swedish female population across four "regions" that are marital status categories. The consolidated projection, in this instance, produces an overprojection relative to the aggregation of the deconsolidated projection. So clearly, the answer in this situation is an ambiguous one; the aggregation bias can be positive or negative. This can be readily demonstrated by carrying out a projection across two time intervals with both the deconsolidated and consolidated models and then comparing the two projections, as in our simple numerical example. The aggregation of interacting heterogeneous multiregional populations prior to projection, it can be shown, produces either under- or overprojection: the aggregate population ultimately stabilizes and both its aggregate rate of growth and its composition become fixed.

What about decomposition bias? The separation of each region from the others in a multiregional system by means of a net migration rate form of compensated decomposition will always create a bias in the projected regional totals, except in the two relatively uninteresting cases of an interregionally immobile population or one that is experiencing stable growth. Because net migration rates confound movement propensities with populations stocks, the conditions for "perfect decomposition" turn out to be even more stringent that those for "perfect aggregation" (Rogers 1969). A particularly simple, yet pervasive, form of decomposition bias is the relative overprojection of the population experiencing net gains from migration and the underprojection of the corresponding population that is the net loser of migrants.

2.4 Netting Out the Age Patterns of Directional Migration Rates

Crude rates are weighted averages of age-specific rates, where the rates are the proportional shares accorded to each age group to reflect that group's relative size in the total population. For example, if one of two populations has a much older age structure (say, Sweden) than the other (for instance, Costa Rica), its crude death rate is higher than the corresponding rate in the other, even though its every age-specific death rate is lower than the corresponding rate in the other population. This counterintuitive reversal is an illustration of what demographers and statisticians call Simpson's paradox–an apparent contradiction of two statements that arises as a consequence of the stratification of the populations into two or more subgroups and the resulting reversal of the rank ordering of those populations on the variable of interest. Similar counterintuitive reversals may occur in comparisons of a wide array of demographic processes, including migration. The crude outmigration rate of one population may be higher than that of another, even though its every age-specific outmigration rate is lower than the corresponding rate of the other.

Most illustrations of Simpson's paradox have focused until recently on cross-sectional comparisons. The impacts of changes in the relative weights used in the averaging process typically have been examined across several populations at one moment in time. Vaupel and Yashin (1985) and others have broadened this perspective to include the demographic dynamics of selectivity and the impacts of the changes that they bring about in the relative weights themselves, over time. In this chapter, their perspective is widened even further, by focusing on *interacting* population subgroups linked by migration, and on the dynamic impacts that this linkage generates through its contribution of *increments* as well as decrements to each of these population subgroups. Because migration, unlike mortality, say, is a repeatable event that directly affects two populations (origin and destination) the spatial population dynamics that it creates may introduce counterintuitive demographic consequences, some of which apparently have not been studied either empirically or theoretically (Rogers 1992).

Imagine a population of a million people in Country A and another of the same number in Country B. During the course of a year, ten thousand individuals die in the former and nine thousand die in the latter. A comparison of the mortality regimes prevailing in the two countries suggests that mortality is higher in Country A (1.0 % against 0.9 %).

Suppose that the population of Country A is equally divided among Young and Old people, half-a-million being in each age group. Country B, on the other hand has a younger age composition, with 70 % of its population being in the Young age group. Suppose, further, that of the thousand deaths in Country A a quarter occurred among the Young, whereas in Country B the corresponding total was 4.2 thousand. Then the age-specific death rates in Country A were 0.5 % among the Young population and 1.5 % among the Old, both lower than the corresponding percentages for Country B: 0.6 and 1.6 %, respectively. A comparison of these percentages indicates that mortality is *lower* in Country A at each age. The cause of this apparent contradiction with our earlier finding is the relatively younger age composition of Country B. Since crude rates are weighted sums of the constituent disaggregated rates, the relatively heavier weight accorded to the death rate of the Young population in Country B lowered its aggregate crude rate with respect to Country A:

$$Country\,A : 0.5(0.5\,\%) + 0.5(1.5\,\%) = 1.0\,\%.$$
$$Country\,B : 0.7(0.6\,\%) + 0.3(1.6\,\%) = 0.9\,\%$$

What is true of crude mortality rates is, of course, also true of crude outmigration rates and, therefore, of crude net migration rates. Assume that the above figures now refer to emigration from one country to the other. The aggregate flows then reveal that Country B gains a thousand net migrants from the exchange. This total results from the combination of a net loss of Young people (−1.7 thousand) and a net gain of Old people (+2.7 thousand). *Thus Country B gains net migrants, even though its rates of emigration are higher at each age than those of Country A.* This compositional artifact could possibly be a contributing factor to the counter-intuitive directional behavior of *net* interstate migrants that puzzled David Plane (1988, p. 10) who observed that in recent years something like two-thirds of all the net interstate streams of migration in the United States point in the direction of the lower average wage state.

But, of course, another contributing factor also could have been the decomposition bias introduced by a net migration perspective. Consider, for example, *identical* Young-Old age compositions of a half and a half, say, and the same directional age-specific emigration rates. But now assume that Country A has twice the population of Country B, say two million to Country B's one million. Then,

$$Country\,A : 0.5(0.5\,\%) + 0.5(1.5\,\%) = 1.0\,\%.$$
$$Country\,B : 0.5(0.6\,\%) + 0.5(1.6\,\%) = 1.1\,\%.$$

During the course of a year, then, twenty thousand individuals emigrate from Country A and only eleven thousand leave Country B. The result is that Country B shows a positive *net* migration rate of 0.9 %, while Country A exhibits a corresponding negative rate of 0.45. *And Country B gains net migrants once again, even though its rates of emigration are higher at each age than those of Country A.*

Our numerical illustration also clearly reveals how similar age profiles of gross migration rates may be hidden in the corresponding age profiles of net migration rates. For example, the age-specific immigration rates for Country A in the first illustration are

$$i_A(Y) = 0.6(\frac{7}{5}) = 0.84\,\%,$$
$$i_A(O) = 1.6(\frac{3}{5}) = 0.96\,\%,$$

and for country B they are

$$i_B(Y) = 0.5(\frac{5}{7}) = 0.36\,\%,$$
$$i_B(O) = 1.5(\frac{5}{3}) = 2.50\,\%.$$

Hence the corresponding net migration rates are

$$m_A(Y) = 0.84 - 0.5 = +0.34\,\%,$$
$$m_A(O) = 0.96 - 1.5 = -0.54\,\%,$$
$$m_B(Y) = 0.36 - 0.6 = -0.24\,\%,$$
$$m_B(O) = 2.5 - 1.6 = +0.90\,\%.$$

Figure 2.1 sets out these age-specific patterns of migration and illustrates how the netting out of similar age patterns of gross migration rates gives rise to totally different corresponding age patterns of net migration rates. Note that merely reversing the Young-Old proportional relationship between the two nations, totally reverses the corresponding age pattern of net migration rates.

Net migration rates are often viewed as crude indices that reflect differences in propensities of movement. But as we have seen, net migration rates also reflect the relative sizes of population stocks. The consequence for age patterns of migration rates is the disintegration of a well-established regularity in age profile. To see this, imagine a migration exchange between two neighboring regions of a biregional system, regions i and j, say, that initially contain populations of equal size, $P_i = P_j$, say. Assume that the gross migraproduction rates (the areas under the migration schedules) are equal to unity in both directions, and that the age profile of both flows is that of the top age profile in Fig. 2.2. Under these conditions, the net migration rate in region i is zero at all ages, as shown by the dotted line in Fig. 2.3. At each age, the number of migrants from region j to region i exactly equals the number in the reverse direction, and the equality also holds for the corresponding rates.

Now imagine that because of higher fertility and immigration levels, say, one population in region j grows more rapidly than the other, such that it becomes

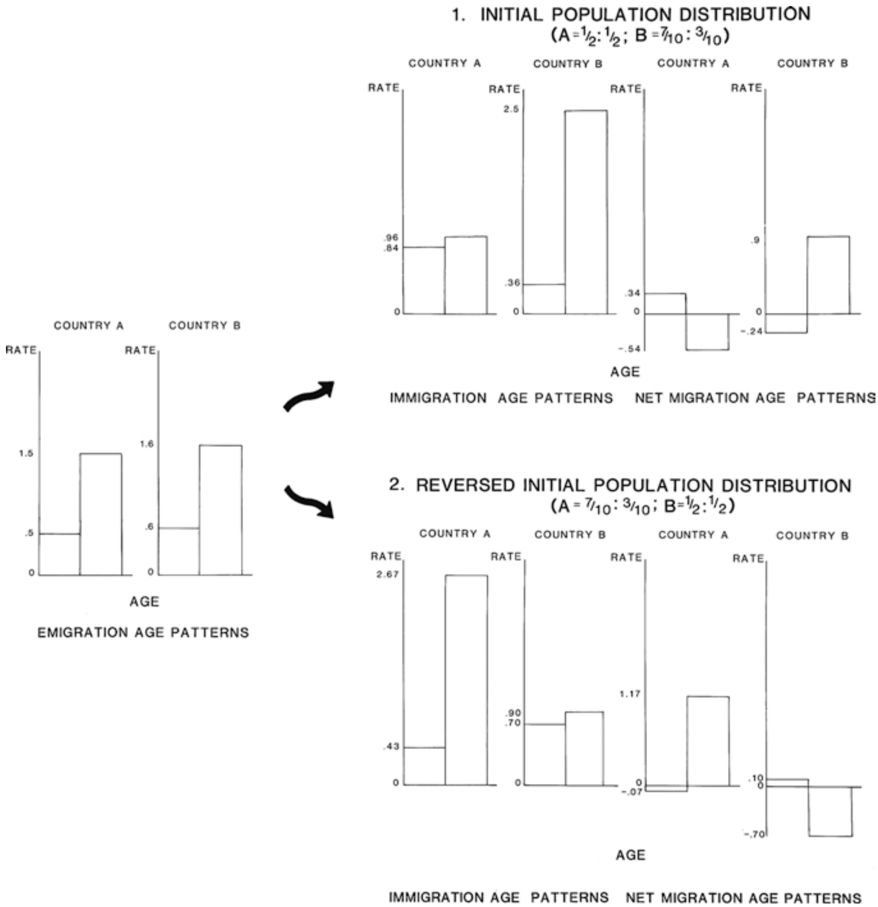

Fig. 2.1 Netting out the age patterns of directional migration rates: I. Two age groups. *Source* Rogers (1990)

twice as large as its neighbor, that is, $P_j = 2P_i$. Assume that the propensities to migrate in both directions and the associated age profiles remain the same as before for all ages of x. Then the resulting net migration rate schedule of one region becomes that of the solid line in Fig. 2.2, that is, the "standard" profile with a gross migraproduction rate of unity. We also include the corresponding net migration rate schedule when $P_j = P_i/2$ (the broken line in Fig. 2.2).

The three net migration schedules in Fig. 2.2 all reflect the same pair of gross migration schedules. In each instance the propensity to migrate in the two directions is the same, and so is the age profile. Yet the net migration rate for region i, say, varies directly with the relative sizes of the two populations, that is, with the ratio P_j/P_i. The net rate is zero at all ages when the ratio is unity, positive at all ages when the ratio exceeds unity, and negative at all ages when the ratio falls

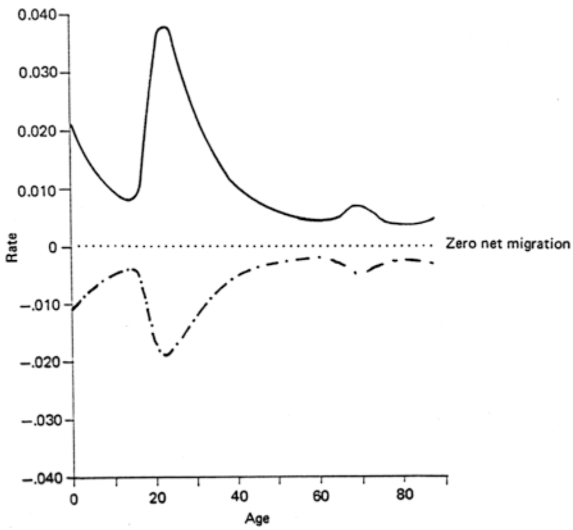

Fig. 2.2 Netting out the age patterns of directional migration rates: II. Eighty age groups. *Source* Rogers (1990)

short of unity, in the latter two instances following the age profile of the migration schedule standard. Thus, in this illustration, net migration once again depends on relative populations sizes; the effects of flows are confounded with the effects of changes in stocks.

Because net rates confound flows with changes in stocks, they hide regularities that prevail among gross flows. Although the latter tend to always follow the conventional age profile, the former exhibit a surprisingly wide variety of shapes, a few of which appeared earlier in Fig. 1.2.

2.5 The Proximate Sources of India's Urban Population Growth: Mostly Migration or Mostly Natural Increase?

2.5.1 Introduction

The urban population of India increased by 3.7 % a year during the late 1960s and early 1970s. The urban growth rate, r_u, was the outcome of a birth rate b_u of 30 per 1000, a death rate d_u of 10 per 1000, an inmigration rate i_u of 27 per 1000, and an outmigration rate o_u of 10 per 1000 (Rogers 1982, 1985). Expressing these rates on a *per capita* basis leads to the fundamental identity

$$\begin{aligned} r_u &= b_u - d_u + i_u - o_u \\ &= 0.030 - 0.010 + 0.027 - 0.010 \\ &= 0.037 \end{aligned}$$

The corresponding identity for the rural population was

$$\begin{aligned} r_v &= b_v - d_v + i_v - o_v \\ &= 0.039 - 0.017 + 0.002 - 0.007 \\ &= 0.017 \end{aligned}$$

The total national population of India in 1970 was about 548 million, of which roughly 109 million (20 %) was classified as urban. Multiplying this latter total by the urban growth rate gives 109(0.037) = 4.03 million as the projected *increase* for 1971. An analogous calculation for the rural population gives 7.46 million for the corresponding projected increase in the rural population. These changes imply, for 1971, an urban population of 113 million, a rural population of 446 million, and a rate of national population increase of

$$r. = 0.20r_u + 0.80r_v = 0.021$$

What would be the immediate contributions of net migration and natural increase to urban population growth if rates either of net migration or of natural increase were suddenly to drop to zero? This reveals that urban natural increase in 1970 India contributed 0.020/0.037 = 0.54, or just over a half of the urban population growth rate. But this is a static cross-sectional view that ignores the evolution of the changing contributions of migration and natural increase to urban growth *over time*. The long-run impacts of current patterns of natural increase and migration on urban population growth and urbanization levels can only be assessed by population projection. And, according to Keyfitz (1980), the results indicate that migration is the principal contributor at first, but then is overcome by natural increase. Following Keyfitz, imagine a hypothetical population, initially entirely rural, that experiences the annual national rate of natural increase of r., say, and a net rural outmigration rate of m_v. Then the projected evolution of the rural populations should follow the path defined by

$$P_v(t) = (1 + r. - m_v)^t P_v(0)$$

whereas that of the national population exhibits the path set by

$$P.(t) = P_u(t) + P_v(t) = (1 + r.)^t P.(0).$$

Clearly, one can obtain $P_u(t)$ as a residual.

On the Indian data, this gives the following *uniregionally* projected totals for, say, 1980:

$$\begin{aligned} P_v(10) &= (1 + 0.021 - 0.005)^{10} 439 = 515 \text{ million} \\ P.(10) &= (1 + 0.021)^{10} 548 = 665 \text{ million} \end{aligned}$$

and

$$P_u(10) = P.(10) - P_v(10) = 665 - 515 = 150 \text{ million}$$

Once again, notice that instead of a chained multiplication of one-year at a time, one can simply raise the quantity in the parentheses to the tenth power.

Alternatively, one could project the urban and rural populations at their own rates of growth instead of the national, and then obtain the latter population by simple addition. In this event,

$$P_u(10) = (1 + 0.037)^{10} 109 = 157\,\text{million}$$
$$P_v(10) = (1 + 0.017)^{10} 439 = 520\,\text{million}$$

and

$$P.(10) = P_u(10) + P_v(10) = 157 + 520 = 677\,\text{million}$$

or 12 million more persons than in the previous projection for India as a whole. Continuing on with the latter equation to the target year 2000, say, gives an urban population of 324 million and a corresponding rural population of 728 million for the uniregional specification. Clearly, model specification matters.

A uniregional perspective must rely on the notion of *net* migration. An immediate consequence of such a perspective in this application is an ultimate and total urbanization, that is India's initial urbanization level of U(0) = 20 % in 1970, is headed toward an ultimate level of 100 %. And, correspondingly, the *absolute* contribution of urban net migration *must*, of necessity tend toward zero in the long-run… a somewhat problematic situation for an analysis that seeks to answer the question of whether it is net migration or natural increase that contributes most to urban population growth over time.

2.5.2 The Problematic Net Migration Rate

Recall the crude rates listed earlier to specify the corresponding biregional components-of-change model

$$P_u(t+1) = (1 + b_u - d_u - o_u)P_u(t) + o_v P_v(t) \tag{2.12}$$

$$P_v(t+1) = (1 + b_v - d_v - o_v)P_v(t) + o_u P_u(t) \tag{2.13}$$

where, for example,

$$\begin{aligned} P_u(1971) &= (1 + 0.030 - 0.010 - 0.010)109 + (0.007)439 \\ &= 113.0\,\text{million}\,\textit{persons} \end{aligned} \tag{2.14}$$

and

$$\begin{aligned} P_v(1971) &= (1 + 0.039 - 0.017 - 0.007)439 + (0.010)109 \\ &= 446.5\,\text{million}\,\textit{persons} \end{aligned} \tag{2.15}$$

Projecting to the target year 2000 with the *biregional* model defined by Eqs. (2.14) and (2.15) produces different future population totals than before: an urban population of 285 million and a corresponding rural population of 753 million, for a grand total of $P(2000) = 1.038$ billion.

2.5.3 A Disaggregation by Age

Having examined the sources of urban growth in India—first using the uniregional and then the biregional model, with both models ignoring age and both assuming a fixed rate of natural increase, n_u, and fixed outmigration rates, o_u and o_v, we saw that, because the level of urbanization U(t) increased over time, the urban *net* migration rate, $m_u(t)$ was certain to decline over time, thereby guaranteeing that the *relative* contribution of migration to the urban growth rate would decline as well. A more realistic model is needed, one that allows natural increase to decline also. Introducing age-specific rates is a first step in that direction.

To illustrate the problematic nature of the net migration rate, consider next a *biregional* (and still closed to international migration), constant-coefficient, baseline projection to the target year 2000, say. Such a projection of India's urban and rural total population growth, using the *age-specific* rates of 1970 in Appendix B of Rogers (1985), projects a total urban population of 291 million and a corresponding rural population of 760 million.

The introduction of age favors migration as a contributor to urban growth. In the Indian illustration it increases migration's *ultimate* (stable growth) contribution threefold. In other illustrations it can reverse the ranking itself, making migration the principal source of urban growth (Rogers 1985, p. 75). What accounts for this reversal?

The disaggregation by age does not change the pattern of evolution of the aggregate urban net inmigration rate, $m_u(t)$. In the Indian illustration it declines sharply from its initial level. But now the aggregate rate of natural increase no longer remains constant, dropping from 2 to 1.5 %. The cause of this decline in the aggregate rate is, of course, the gradual aging of the population and the associated shifts in its age composition. This shift alters the relative weights with which the fixed age-specific rates are consolidated to form the aggregate crude rates. The result is an increased relative contribution of net migration as a source of urban population growth, a consequence apparently of the fact that, as with mortality (but not with fertility), the risks of migration are experienced by individuals of all ages.

In conclusion, it appears that the principal effect of introducing age composition into the fixed-rate projection model is to decrease the aggregate rate of natural increase over time, while slowing down the decline of the urban net migration rate. Because these two contributors to urban growth now can exhibit different rates of decline over time, their relative importance as sources of urban growth also can change.

2.6 Discussion and Conclusion

Much of literature on aggregate, cross-sectional behavioral models of internal migration continue to exhibit a curiously ambivalent position with regard to the measurement of geographical mobility. This ambivalence is particularly surprising because it stands in striking contrast to the corresponding studies of mortality and fertility, which often devote considerable attention to measurement problems.

Models that seek to explain patterns of net migration are founded on inadequate perspectives. Net migration rates confound movement propensities with relative population stock levels. They hide well-established regularities in the age pattern of geographical mobility. They can lead to misspecified explanatory models, and they make it virtually impossible to consider properly the impacts of important violations of the basic assumptions underlying many spatial demographic studies: homogeneity, stationarity, and temporal independence.

Gross migration stream (multiregional) models, on the other hand, more realistically depict the phenomenon being modeled (since there are no net migrants). The rates they use to represent directional movements are linked to the populations at risk of moving and therefore measure true propensities of migrating (a feature that net migration rates lack). Gross migration models can generate changes in migration streams that arise out of changes in the sizes of the various populations at risk of moving (something that net migration models cannot do since they only consider the size of the destination population). And, finally, gross migration models permit their users to keep track of important population attributes such as places of birth and places of former residence, a feature that for example, allows one to differentiate the migration rates of return migrants from those of nonreturn migrants.

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Chapter 3
The Proximate Sources of Regional Elderly Population Growth: Mostly Migration or Mostly Aging-in-Place?

Abstract Changes in the elderly population of a region arise from net migration and net aging-in-place (the number of persons becoming elderly minus elderly deaths). This chapter shows that the relative contributions of these two sources of change vary over time, as the numbers of elderly outmigrants, inmigrants, deaths, and people aging into the elderly population fluctuate. Elderly populations growing mostly from net migration generally exhibit different demographic and socioeconomic characteristics than do those that grow mostly, or indeed entirely, from net aging-in-place. This is because elderly non-migrants generally exhibit different attributes than do elderly outmigrants, and because the latter often also have different attributes than do elderly inmigrants.

Keywords Elderly Population Growth · Aging-in-Place · Net Migration

Concerns about an aging population in the United States will continue to increase over the next several decades as fertility rates remain low, life expectancies increase, and the large Baby-Boom cohort continues to age. Evidence of an aging population was already apparent in the United States by 1980, when 11 % of the total national population was 65 years of age and older. By 2025, this percentage could increase to about double that number. Projected rates of growth for the elderly population, that is, those aged 65 and older, reveal a distinctive nonlinear trend. The rates were at a low point at the end of the century as a direct consequence of the low birth rates 65 years ago (Fig. 3.1). The growth of the elderly population will continue to increase until the Baby Boom cohort completely exits the elderly age groups.

Changes in the elderly population of a region arise from net elderly migration and net aging-in-place (the number of people becoming elderly minus elderly deaths). The contributions of these of these two sources of change vary over time as the numbers of elderly inmigrants, outmigrants, deaths, and the people aging into the population fluctuate. Changes in the numbers of elderly may be dominated by either net migration or the net aging-in-place. These two sources of change should be identified, because an elderly population that grows due to migration

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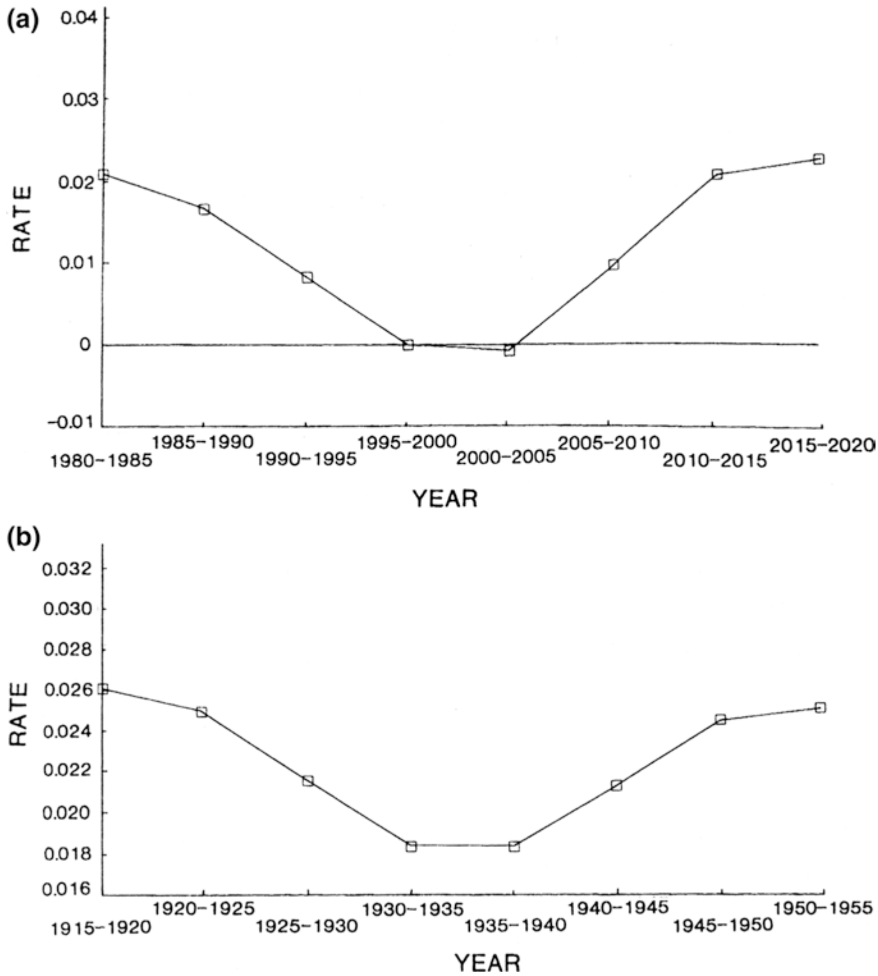

Fig. 3.1 Annual rates of elderly population growth and of births in the United States **a** (*top*) Elderly growth rates, 1980–2020 **b** (*bottom*) Birth rates, 1915–1955. *Source* Rogers and Woodward (1988)

may have very different socioeconomic and demographic characteristics than an elderly population that has primarily aged in place.

3.1 Introduction: An Aging Population

Historically five states have played a major role in the redistribution of the elderly US population with Florida, California, and Arizona as the three principal destination states, and New York and Illinois as the primary origin states for aged migrants. Elderly interstate migrants tend to be younger, better educated, healthier, and wealthier than the elderly nonmigrants. Migrants are predominantly white and more likely to be married than their nonmigrant counterparts. Trends in the previous selectivity patterns will continue to receive a positively selected group of older people and the social and economic characteristics of these migrants may have important consequences for the public health and social service demands.

Although migration plays an important role in the changing geography of the elderly, typically only about 5 % of the elderly change their state of residence. Aging-in-place must therefore be the more important factor fueling elderly population growth. The aging-in-place population is generally older, less healthy, more disabled, and poorer than are the elderly interstate migrants. A shrinking tax base and an aged population, with many dependent on local service institutions, is the likely result. States in which the elderly population grows mostly by net migration, however, may benefit from the expenditures of retirement pensions that increase local demands for retail goods and services, without adding significant demands to the collective public welfare burden or to the pressure for social services for the aged. The Older Americans Act, however, allocates federal funds for state run programs on the basis of the number of people aged 60 and over, without reference to the differences in the average socioeconomic characteristics of the elderly residents in the states. Thus principal origin states, such as New York, may be "short changed" compared to important destination states, such as Florida. Therefore, both sources of growth of the elderly population should be examined jointly in studies of the policy impacts of the changing interstate geography of the elderly.

This chapter develops a method that quantifies the changing sources of elderly population's growth over time. It differs from past research on the sources of population change over time in that it adopts a truly dynamic multiregional perspective. The projected components of such growth are quantified to assess their implications for the future interstate geography of the U.S. elderly population. The method is illustrated for the five states prominent in the interstate migration of the elderly.

3.2 Methods of Analysis

Recall the balancing equation introduced in Chap. 2. In a population "closed" to international migration, future population five years hence, say, is equal to the present population total P(t) plus the net contribution over the time interval made by births (B), deaths (D), inmigrants (I) and outmigrants (O):

$$P(t+5) = P(t) + B(t) - D(t) + I(t) - O(t) \tag{3.1}$$

Equation (3.1) is applicable to each five year age group except the first, the population of which is defined simply as the number of births surviving to the end of the time interval within which the babies were born. For all other age groups "births" are the new entrants into that age group. Aggregating the populations in all age groups beyond the age 65 relates the elderly population at time t + 5 to the population alive at time t. For the elderly population in such an expression, all components in Eq. (3.1) refer to the population aged 65 and over, for which the "births" now denoting the "new elderly," that is, the number of people into 65–69 year age group, say, during the five-year time interval. Note that the *P*s refer to a population stock at a moment in time, whereas the other variables denote totals for a time interval, *t* to *t* + 5, say.

The contributions of net aging-in-place and net migration to elderly population growth in a five-year time interval can be determined from Eq. (3.1).

$$\begin{aligned} P(t+5) - P(t) &= [B(t) - D(t)] + [I(t) - O(t)] \\ &= \text{Net Aging-in-place} + \text{Net Migration} \end{aligned} \tag{3.2}$$

The total change is thus apportioned to the two sources of change. The calculations can be carried out for all projected time intervals.

Over a specific time interval, the number of people aging into the projected elderly population, the number of elderly inmigrants and of elderly outmigrants, can be calculated by applying observed age-specific survivorship proportions to the appropriate age-specific population totals.

The number of people who age into an elderly population in the time interval t to t + 5, say, can be found by the multiplication:

$$P_{ii}(65-69) = P_i(60-64)s_{ii}(60-64)$$

where P_i(60–64) is the number of people in region *i* who are 60–64 years of age at time *t*; s_{ii}(60–64) is the 60–64 year old survivorship proportion for the people living in region *i* who survive and stay in region *i* from *t* to *t* + 5, and P_{ii}(65–69) is the number of people entering the aged 65–69 population in region *i*, of those who were aged 60–64 in region *i* at time *t*.

Elderly outmigrants can be determined by applying the appropriate age-specific survivorship proportion for region *i* to the appropriate age-specific elderly population:

$$P_{ij}(70-74) = P_i(65-69)s_{ij}(65-69)$$

where s_{ij}(65–69) is the survivorship proportion for people moving from region *i* to region j and becoming 5 years older; P_i(65–69) is the age-specific population in region *i*; and P_{ij}(70–74) is the corresponding total number of age-specific outmigrants who move from region *i* to region *j* and survive the five year period. The total number of elderly outmigrants can be found by summing all elderly age groups.

Age-specific survivorship proportions and populations aged 60 and over are used to calculate the number of elderly inmigrants. The 60–64 year olds are included in this equation, because this group survives to be 65–69 years of age and joins the elderly population in region *i*:

$$P_{ji}(65-69) = P_j(60-64)s_{ji}(60-64)$$

where $s_{ji}(60–64)$ is the age specific survivorship proportion for people moving from region j to region i; $P_j(60–64)$ us the age-specific population in region j at time t; and $P_{ji}(65–69)$ is the number of age-specific migrants from region j to region i over the five year interval. Total elderly inmigrants can be found by summing age-specific inmigrants for each elderly age group, i.e., the total elderly population for each projection period is obtained by summing the projected age-specific populations from ages 65 to 90 and above.

The analysis can profitably be extended a step further to comprehend more fully the individual contributions of net aging-in-place and of net migration to the growth of the elderly population. The growth rate of elderly population, $g(t)$, over the five-year time interval is the sum of the associated net aging-in-place rates, $n(t)$, and the net migration rates, $m(t)$, calculated by dividing all terms in Eq. (3.2) by the initial population, $P(t)$:

$$\begin{aligned} g(t) &= \frac{P(t+5) - P(t)}{P(t)} \\ &= \frac{[B(t) - D(t)]}{P(t)} + \frac{[I(t) - O(t)]}{P(t)} \\ &= n(t) + m(t) \end{aligned} \tag{3.3}$$

The corresponding average annual growth rate of the elderly is then given by:

$$r = \frac{1}{5} \ln \left[\frac{P(t+5)}{P(t)} \right] = \frac{1}{5} \ln \left[1 + g(t) \right]$$

and since

$$P(t+5) = \left[1 + g(t) \right] P(t) = (1+r)^5 P(t) \tag{3.4}$$

In Eq. (3.3) both n(t) and m(t) refer to a five-year time interval. To estimate the corresponding one-year rates, x and y, say, assume that the relative proportional relationships in Eq. (3.3) also hold for each single year from t to t + 5, whence

$$\frac{g(t)}{r} = \frac{n(t)}{x} + \frac{m(t)}{y} \tag{3.5}$$

where

$$r = x + y \tag{3.6}$$

$$x = \left[\frac{n(t)}{g(t)} r \right] \tag{3.7}$$

and

$$y = \left[\frac{m(t)}{g(t)} \right] r \tag{3.8}$$

Thus, x is the average annual net aging-in-place component and y is the average annual net migration component that together define the average annual growth rate, *r*.

3.3 Results

Decomposing the projected annual growth rates of the elderly populations of Arizona, California, Florida, Illinois, and New York, using the above procedure, yields the observed and projected evolution of the net aging-in-place and net migration components set out for the nation in Fig. 3.1 (top) and for the five states in Fig. 3.2.

The patterns of change of the net aging-in-place contribution to elderly population growth over the projection period are similar in all five states (Fig. 3.2a). The profiles closely mirror the national V-shaped pattern. The contribution of net aging-in-place to the total elderly growth rate is largest for California over the entire projection period, and smallest for Florida over much of the 40-year period. All states except California exhibit periods of negative net aging-in-place during the period. Negative net aging-in-place occurs when the number of elderly deaths exceeds the number of people aging into the elderly population. Florida shows negative net aging-in-place for part of the period. Arizona, Illinois, and New York show approximately ten years of negative net aging-in-place. The specific periods of net aging-in-place vary among the four states. However, each of them has negative net aging-in-place during the 1995–2005 decade, when the small cohort of Depression babies of the 1930s entered the elderly population.

Patterns of elderly net migration rates vary considerably among the five states (Fig. 3.2b). The profile over time of the elderly net migration component is nearly a straight line for California, Illinois, and New York; California's remain positive over the entire projection period. Arizona and Florida exhibit large initial positive net migration components that decrease until the end of the century and then level off. The projected result is from a constant coefficient multiregional projection.

An examination of the combined effects of net aging-in-place and net migration reveals the influence that each has on the overall growth rate of a state's elderly population. Growth of the elderly population in Florida, for example, is dominated by net migration over the entire projection period. A comparison of the net migration component (Fig. 3.2b) with the total elderly growth rate (Fig. 3.3) for Florida reveals that from 1990 to 2005 the net migration contribution exceeded the total annual elderly growth rate. Elderly migration is expected to continue to be important to the growth of the elderly population in Florida. Net migration also is the principal source of elderly population growth in Arizona until the 2010–2015 period, when net aging-in-place became the dominant source of growth. California's elderly population growth is dominated by net aging-in-place over most of the period (Fig. 3.3).

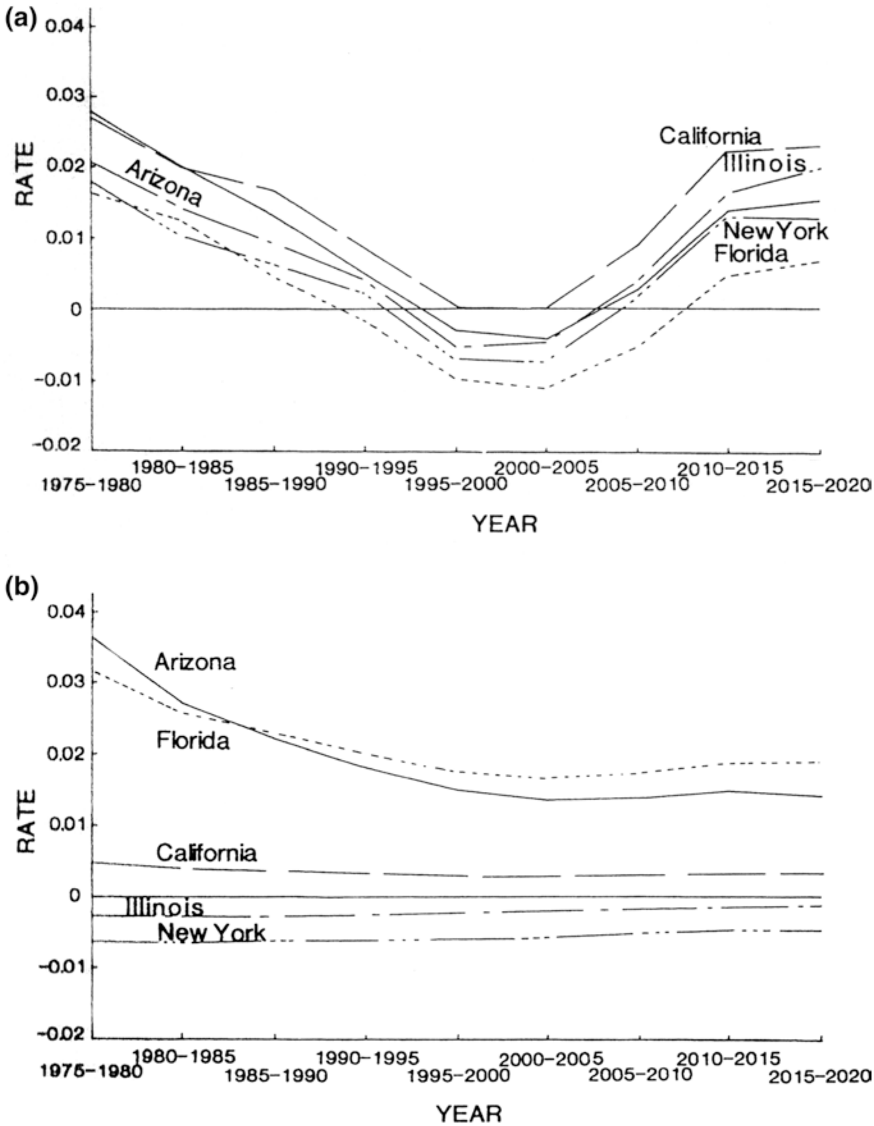

Fig. 3.2 Decomposition of the annual growth rate of the elderly population in five key U.S. states: 1975–2020 **a** (*top*) Net aging-in-place rate **b** (*bottom*) Net migration rate. *Source* Rogers and Woodward (1988)

So, the evolution of the growth rate of the elderly population in each state resembles that of the nation, but each state's curve is suitably positioned to reflect the contribution of the net migration component. Variations among the projected rates are substantial. Arizona's elderly growth rates range from an initial high of 4.7 % to a low of 0.9 % around the turn of the century and then a subsequent high

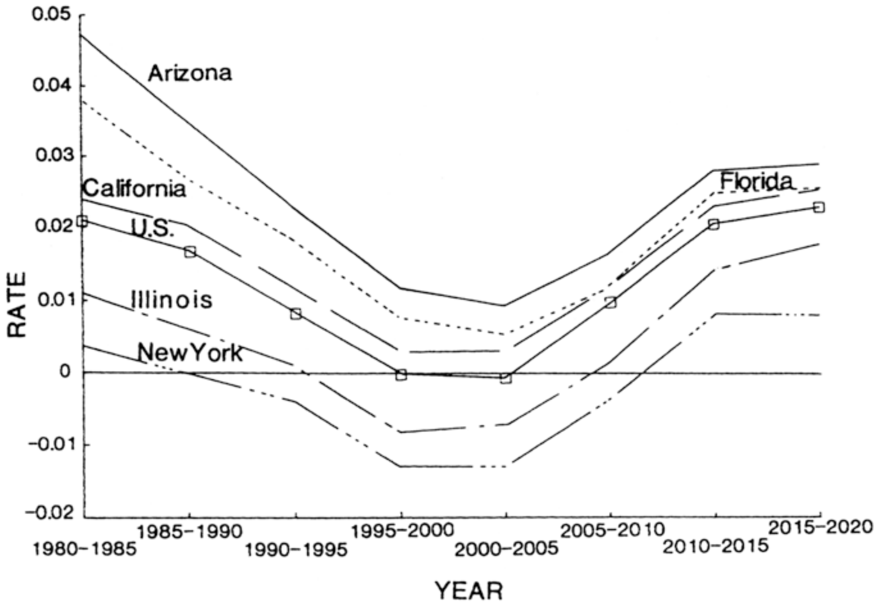

Fig. 3.3 Projected annual growth rate of the elderly population in the United States and five key states: 1980–2020. Source Rogers and Woodward (1988)

of 2.9 % at the end of the projection period. The corresponding rates for New York are 0.4, −1.3 and 0.8 %, respectively. The ranges for the remaining three states lie inside of these two extremes.

3.4 Discussion and Conclusion

The sources-of-growth method presented in this chapter contributes to current elderly research in two major ways. First, it allows a researcher to determine how much each of the two sources of growth contributes to the total elderly growth rate. The method also allows the researcher to examine the components of elderly population growth over time, illuminating the temporal and regional variations in the two sources. Our illustrations of the sources-of-growth method show that the growth of the elderly population in Arizona and Florida will be dominated by a migrant population that is more likely to have more money, be in better health, and be more independent than its elderly nonmigrant counterparts. These qualities may be beneficial for Arizona and Florida, because the elderly inmigrants will increase demands for retail goods, and they probably will not have high demands for jobs and public health social services in the near future.

Illinois and New York probably will continue to lose many of their wealthier and healthier elderly. Communities experiencing outmigration of elderly are left with a population comprised of many dependent on local service institutions. Therefore, during periods of positive elderly population growth in these states, that growth will be dominated by a net aging-in-place population that can be expected to have higher demands for public health and social services than do the elderly populations in Arizona and Florida.

Although the net migration component is negative over all years in Illinois and New York, these states will continue to receive elderly inmigrants, primarily return migrants from the "amenity states." Return migrants are typically older, with lower incomes, and in poorer health than the migrants moving to the amenity states. Therefore, return migrants could further increase the needs and demands for public services in Illinois and New York.

The elderly populations in Illinois and New York are also affected by the outmigration of the younger population. These states have been principal origin states for general migrants. Not only are they losing their wealthier and healthier elderly, they may also continue to lose a large portion of their younger population. The outmigration of both subpopulations may decrease the tax base and thereby limit the funding available for needed services.

Differences in demands for services between states are not revealed by simply examining the total projected growth rates for the elderly populations, however. Were this the case, Florida's and California's large and quickly growing elderly populations would have relatively equal per capita demands for services in the future. By examining the sources of elderly population growth in each state, however, and by considering the socioeconomic and demographic differences among elderly migrants and nonmigrants, a more accurate conclusion about future service demands between states can be obtained. Thus, the sources-of-growth method contributes to the current methodological apparatus of formal population geography and is an important tool for assessing future state service needs in the nation.

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Chapter 4
Origin Dependence: Does Birthplace Specificity in Migration Rates Matter?

Abstract Migration is usually more than a one-time event in the lives of most migrants, and scholars of migration histories have repeatedly found that the previous migration experiences of individuals significantly influence their subsequent migration patterns. Individuals who have migrated before are more likely to do so again, and to destinations that they have visited earlier in life. Among the most important of these regional dependencies are to their birthplaces. This chapter refers to this influence as a special case of origin dependence, and focuses on its most important consequence, which is that the migration propensities of persons returning to their region of birth are significantly higher than those of the average individual, and that they also differ in their fundamental age profiles. Consequently, the introduction of origin dependent outmigration rates into multiregional life tables and population projections produces a substantial impact on life measures and projected regional totals.

Keywords Birthplace specificity · Return migration · Origin dependent summary measures

4.1 Introduction

A common finding in social science research is that the evolution of each individual's life course is shaped by that person's attributes at birth or childhood. Such initial "endowments" include social class, levels of family income and education, race and, for human geographers interested in issues related to migration and spatial population dynamics, *location of birth*.

This chapter focuses especially on the most important consequence of the locational influence of origin dependence, which is that the migration propensities of persons returning to their region of birth are substantially higher than those of the average individual, and that they also differ in their age profile.

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This chapter begins with a brief discussion of definitions and calculations, issues of measurement and specification, and age patterns of migration. This is followed by a brief exposition of the construction of origin-dependent multiregional life tables and migration life histories drawing on an application based on U.S. census data. Finally, the chapter ends with a review of the principal argument and a conclusion.

4.2 Origin-Dependent Migration Streams: Primary, Return, and Onward Flows

4.2.1 Definitions

The simplest illustration of birthplace-specific migration flows is set out in Fig. 4.1. For the 1985–1990 interval, for example, the two U.S. macro-regions: the *North* (comprised of the Northeast and Midwest) and the *Southwest* (comprised of the South and the West) constitute the biregional system; hence, there are no onward migrants: migrants are either leaving or returning to the macro-region of birth. About 3670 + 1022 = 4692 thousand persons migrated from the Northeast and Midwest (North) to the South and West (Southwest) during the preceding

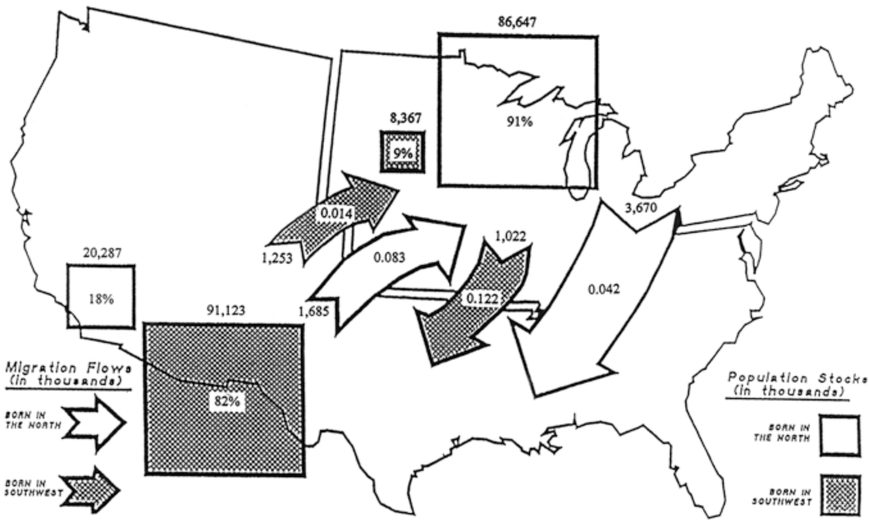

Fig. 4.1 Birthplace-specific migration outflows: Biregional example, U.S. 1985–1990. *Source* Rogers and Raymer (unpublished)

five year interval (and survived there to report that move). Of those leaving the North, 1022 thousand were Southwestern-borns returning to their region of birth, and the remaining 3670 thousand were Northern-borns leaving their region of birth. Since the Southwestern-born population living in the North in 1985 (and surviving to report it in 1990) totaled 8367 the *conditional* probability of *return* migration to the Southwest was 0.122. Analogously, the conditional probability of *primary* migration out of the North, calculated as the quotient of 3670 to 86,647, was 0.042. Thus the ratio of return to primary outmigration probabilities from the North was 2.9; the corresponding ratio from the Southwest was 6.0. The resulting conclusion is inescapable: probabilities of return migration were several times as high as the corresponding primary migration probabilities. The conditional primary migration probability out of the North was about three times that out of the Southwest (0.042 vs. 0.014), and the conditional return migration probability of the Southwestern born was about one-and-a-half times that of the Northern born (0.122 vs. 0.083). Figure 4.2 illustrates the age-specific schedules, which show comparable differences, but by age.

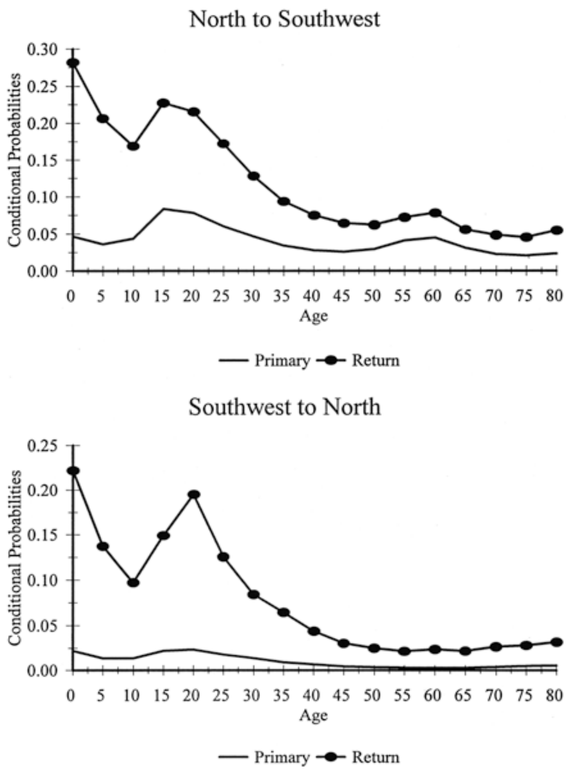

Fig. 4.2 Birthplace-specific migration age patterns: Biregional example, U.S. 1985–1990. *Source* Rogers and Raymer (unpublished)

4.2.2 Fundamental Calculations

Disaggregating the above two macro-regions into their constituent Census Bureau Regions of Northeast, Midwest, South, and West adds the third type of migration stream consisting of *onward* migrants. If birthplace-specificity is retained, three distinct categories of migrants arise: (1) persons leaving their region of birth: *primary* migrants; (2) persons returning to their region of birth: *return* migrants; and (3) persons moving neither from nor to their region of birth: *onward* migrants. Such categories have in the past been used to successfully differentiate the patterns of motivations of return migrants from those of non-return migrants. The arithmetic underlying such calculations becomes considerably more intricate as the number of regions is increased. Moreover, the size of the areal unit influences the relative values of probabilities.

Consider the 1,603,751 migrants moving from the Northeast to the South; 1,216,170 were Northeastern-born primary migrants, 262,102 were Southern-born return migrants, and the remaining 125,479 were Midwestern- and Western-born onward migrants (Table 4.1, the South column). Dividing each of these flows by

Table 4.1 Primary, return, and onward migrants by region of birth: 1985–1990

Birthplace	Residence in 1985 age 0+	Residence in 1990				
		Northeast	Midwest	South	West	Total
Northeast	Northeast		196,845	1,216,170	328,882	1,741,897
	Midwest	*104,326*		**98,778**	**43,969**	247,073
	South	*373,282*	**70,341**		**111,329**	554,952
	West	*160,569*	**32,037**	**109,849**		302,455
	U.S.A.	638,177	299,223	1,424,797	484,180	2,846,377
Midwest	Northeast		*94,936*	**90,654**	**42,448**	228,038
	Midwest	195,792		1,147,230	702,016	2,045,038
	South	**66,137**	*583,488*		**178,520**	828,145
	West	**36,885**	*362,617*	**170,765**		570,267
	U.S.A.	298,814	1,041,041	1,408,649	922,984	3,671,488
South	Northeast		**26,775**	*262,102*	**36,777**	325,654
	Midwest	**30,958**		*370,392*	**70,905**	472,255
	South	292,059	473,966		575,246	1,341,271
	West	**31,622**	**58,486**	*388,443*		478,551
	U.S.A.	354,639	559,277	1,020,937	682,928	2,617,713
West	Northeast		**11,291**	**34,825**	*61,177*	107,293
	Midwest	**12,844**		**56,014**	*130,105*	198,963
	South	**28,820**	**52,251**		*256,946*	338,017
	West	110,666	205,141	383,712		699,519
	U.S.A.	152,330	268,683	474,551	448,228	1,343,792

the corresponding birthplace-specific 1985 population at risk of moving, gives the following three conditional migration probabilities from the Northeast to the South:

1. 0.0323 for primary migration,
2. 0.1096 for return migration, and
3. 0.0758 for onward migration.

Their simple sum does not give the corresponding aggregate non-birthplace-specific probability of 0.0385. This is because what is needed instead is their *weighted* sum, in which the weights reflect the share of the total population living in the Northeast that is at risk of primary (Northeastern-borns), return (Southern-borns), and onward migration (Midwestern- and Western-borns). Since these shares were, respectively, 90.29, 5.74, and 3.97 % of the total Northeast population in 1985, the appropriate weighted sum takes the form:

$$\begin{aligned} p_{NE,S}(\text{total}) &= (0.9029)0.0323 + (0.0574)0.1096 + (0.0397)0.0758 \\ &= 0.0385 \end{aligned} \tag{4.1}$$

Thus we see that the total conditional probability of migration from the Northeast to the South (that is, 0.0385) can be expressed as an appropriately weighted sum of the underlying primary, return, and onward migration probabilities. But one also could direct the focus of the analysis more on the types of outmigrants, without considering destination-specificity. For example, one could augment the above decomposition of the Northeast to the South migration flow with the corresponding decompositions of the other two Northeast migration flows (that is, those directed to the Midwest and the West). This would produce the following conditional probabilities:

	Northeast to midwest	Northeast to south	Northeast to west	Northeast total
Primary	0.0052	0.0323	0.0087	0.0463
Return	0.0793	0.1096	0.1333	0.1033
Onward	0.0134	0.0758	0.0221	0.0600
Weighted sum (total)	0.0079	0.0385	0.0113	0.0577

All row sums and all column sums are the result of weighted summations in which the weights reflect the shares of the total population that are accounted for by the relevant "at risk" subpopulations. Equation (4.1) illustrates an example of a weighted column sum calculation. Equation (4.2), below, offers an example of a weighted row sum calculation in which the weights reflect the proportional distribution of those living in the Northeast but born in one of the other three regions:

$$\begin{aligned} p_{NE.}(\text{return}) &= (0.2957)0.0793 + (0.5909)0.01096 + (0.1134)0.1333 \\ &= 0.1033 \end{aligned} \tag{4.2}$$

a number that appears in percentage form in the lower right panel of Table 4.2.

Table 4.2 Conditional probabilities [×1000] of primary, return, and onward outmigration by region: 1935–1940, 1955–1960, 1965–1970, 1975–1980, and 1985–1990

Migration by type	Region	1935–40	1955–60	1965–70	1975–80	1985–90
Primary	Northeast	12.8	37.0	38.4	53.4	46.3
	Midwest	27.8	45.0	40.4	48.5	44.2
	South	21.3	37.0	31.4	22.5	22.8
	West	11.9	23.6	31.7	27.4	26.7
	U.S.A.	20.6	38.1	35.9	37.9	34.5
Return	Northeast	58.2	86.8	77.7	111.5	103.3
	Midwest	52.0	91.1	90.3	96.7	85.8
	South	83.8	136.2	131.5	97.9	92.8
	West	36.2	62.5	73.4	69.4	69.1
	U.S.A.	52.6	87.4	90	88.9	84.3
Onward	Northeast	24.7	51.0	47.7	67.0	60.0
	Midwest	24.7	41.6	43.5	47.8	44.5
	South	40.0	64.3	57.3	44.7	38.8
	West	13.8	24.1	33.1	30.9	33.3
	U.S.A.	23.3	39.9	43.1	43.1	40.2

Finally, Eq. (4.3) below, shows how the weighted sum of the three probabilities in the last column (primary, return, and onward) yields the aggregate conditional probability of the total outmigration from the Northeast:

$$\begin{aligned} p_{NE.}(\text{total}) &= (0.9029)0.0463 + (0.0971)[0.1033 + 0.0600] \\ &= 0.0577 \end{aligned} \tag{4.3}$$

4.2.3 A Historical Time Series

The disaggregation of the aggregate national patterns of primary, return, and onward inmigration and outmigration among the four Regions in the United States for the five censuses shows a complex mosaic (Table 4.2). The percentages of primary inmigrants coming into the Northeast, Midwest, and West declined over time, whereas in the South they remained much the same. Among the corresponding patterns of outmigration, the Midwest and South regions had smaller proportions of primary outmigrants over time. In the Northeast, the proportions remained relatively stable, whereas in the West they increased. The net results of all these patterns were negative net primary migration for the Northeast and Midwest, essentially zero for the South, and positive for the West.

The patterns for return inmigration were generally the reverse: the proportions increased in all regions except the South. For return outmigration they increased in the South, decreased in the West, and stayed relatively constant in both the Northeast and Midwest. The net results here were the reverse of those for primary migration: positive net return migration for the Northeast and Midwest, essentially zero for the South and negative for the West. Finally, the percentages of onward inmigration and outmigration showed similar patterns, generally increasing slightly over time (except during the 1935–1940 period in the West). The net results of these patterns were essentially zero net onward migration for the Northeast and Midwest and slightly negative net migration for the South and West.

The conditional probabilities of outmigration and inmigration further illuminate the observed structure of migration flows. For example, historical probabilities of return outmigration have been many times higher than those of primary migration. Examining again the conditional probabilities in Table 4.2, one finds that, over the past five decades, regional return outmigration probabilities have ranged from a high of 136.2 per thousand to a low of 36.2 per thousand, and in all but two instances they have been two to four times as high as the corresponding primary outmigration probabilities (Fig. 4.3).

Most interregional migrants are persons who have moved before. Consequently, a disaggregation that reflects their prior mobility experiences can answer fundamental questions that clarify the dynamics of migration. For example, do particular regions grow because they are able to attract a significant number of the natives of other regions, or because they send out relatively few of their own natives? Are regions that attract a disproportionately large number of return migrants ones with high conditional inmigration probabilities, or are they simple unable to attract many persons other than their own natives?

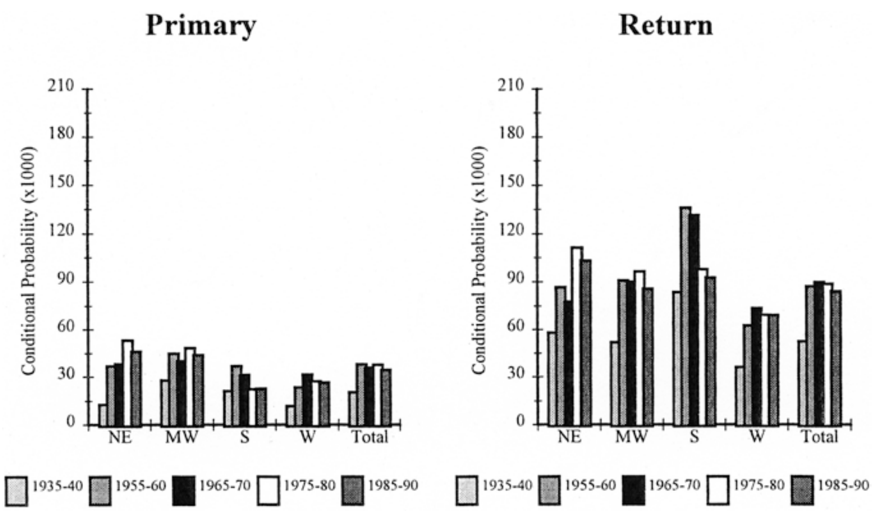

Fig. 4.3 A history of primary and return migration outflows across five censuses. *Source* Rogers and Raymer (unpublished)

4.3 Return Migration: Measurement and Spatial Dynamics

If the migration patterns of return migrants are significantly different from those of non-return migrants, then an incorporation of such differentials in spatial processes can sometimes produce surprising and illuminating results. This is illustrated next by considering two questions of interest to migration researchers.

4.3.1 The Positive Correlation: Why Do Attractive Regions Lose so Many Migrants?

A number of studies have consistently identified a strongly positive correlation between rates of outmigration and inmigration across different regions. This seems paradoxical to economic demographers because the aggregate data on migration are expected to reflect opportunities that motivate migration. Thus attractive regions (i.e., those with attractive opportunities) should draw a sizable numbers of inmigrants, while at the same time retaining many of their own residents. Less attractive regions should exhibit the reverse pattern. Consequently, the expected correlation between inmigration and outmigration rates should be negative; yet it turns out to be positive. Why?

Several explanations have been put forward in the literature. For example, it has been argued that regional populations growing as a consequence of large flows of inmigrants tend to become more migration prone and therefore more likely to lose their members to other regions. Others have argued that a region's attractive (economic) opportunities have a much smaller impact on its residents than on the residents of other regions. Still others have argued that a region's attractions may draw inmigrants at the same time that they repel some of its residents. Patterns of primary and return migration offer yet another explanation.

Attractive regions that draw a large number of primary outmigrants from other regions accumulate a sizable pool of potential return outmigrants. Since this population at risk of returning home typically exhibits much higher than average probabilities of outmigration, one finds that its growth generates a corresponding growth in outmigration levels.

Consider, once again, the *biregional* population system illustrated earlier in Fig. 4.1. According to the preference index proposed by Liaw and Rogers (1999), the Southwest region has been the more attractive region, and therefore it has accumulated a higher number of *non-local-borns* (i.e., persons born elsewhere) than has the North. With a total population that is 21.3 % larger than that of the North, it nevertheless exhibits a non-local-born population that is more than twice the size of the North's (its non-local fraction is 18 % compared to the North's 9 %). Consequently, even though both of its birthplace-specific conditional outmigration probabilities are significantly lower than the North's (0.014 compared with 0.042, and 0.083 compared with 0.122) the much larger non-local fraction weights the lower return migration probability so as to create the surprisingly high aggregate conditional *outmigration probability* out of the Southwest of 26 per thousand:

$$\begin{aligned} p_{SW.}(\text{total}) &= 0.18(0.083) + (1 - 0.18)(0.014) \\ &= 0.026 \end{aligned} \tag{4.4}$$

The North's much higher probabilities give it a corresponding aggregate conditional outmigration probability that is slightly more than twice as large:

$$\begin{aligned} p_{N.}(\text{total}) &= 0.09(0.122) + (1 - 0.09)(0.042) \\ &= 0.049 \end{aligned} \tag{4.5}$$

4.3.2 Origin Dependence and the Vintage Effect: Are the Elderly More Likely to Return Home?

Do people exhibit a greater tendency to return to their region of birth after reaching retirement age than before? Some scholars believe that they do (Serow 1978; Serow and Charity 1988). Others have argued that they do not (Rogers 1990). The answer depends on the index used to assess the relative importance of the return flow. If that index contrasts the relative size of return migration in the migration streams of the elderly to that of the non-elderly (Serow 1978) then its definition as a *prevalence* rather than an *incidence* measure ensures that a compositional bias will be introduced into the comparison.

The numerical size of return migration clearly depends on the number of persons living outside of their region of birth. The higher that number, the higher will be the numerical value of the return flows. And regions with a relatively recent period of settlement, such as the West, will have relatively fewer such older persons living "away from home" and will be populated by relatively more people whose birthplace was elsewhere. This latter feature is very evident in states such as California, which in 1980, for example, was found to have only 20.3 % local-borns among its elderly population, while New York and Illinois, on the other hand, showed comparable percentages of 76.6 and 68.9 %, respectively (Rogers 1990).

The regional "vintage" effect will influence the value of any index that relates return migration levels to the corresponding levels of total migration. Thus, Serow's (1978, p. 288) conclusion that return migration is more important in the migration flow of the elderly than in the total migration flow may be partly a consequence of the particular spatial distributions of the two populations rather than an indication that elderly persons are more prone to return "home" than are non-elderly.

The general mobility level of the non-elderly, for return as well as non-return migration, is about twice as high as that of the elderly. To develop an appropriate comparison that answers the above question regarding elderly return migration, one should, first, focus on probabilities (incidence measures) and not on relative sizes of flows (prevalence measures). Second, to avoid the vintage effect one should not contrast directly the return migration probabilities of elderly people to those of non-elderly (or total) persons, but rather one should contrast the return migration propensities of elderly persons with those of their non-return (or total) propensities. That contrast when compared to the corresponding such contrast among non-elderly (or total) persons should indicate whether the elderly are more likely to return home than are the non-elderly (or the total population). Such comparisons may be examined using data such as are set out in Table 4.3.

In Table 4.3 we discover that the ratios of return to non-return (or in this case total) migration probabilities of elderly persons are uniformly greater than unity and range from 0.8 to 4.7. For the non-elderly (or, more exactly, in this case total population once again) the corresponding range is from 1.3 to 3.4. And, of particular interest to us, a comparison of the two sets of ratios reveals that, with two exceptions in the 1965–1970 migration data, *the elderly ratio is never the larger of the two ratios*. There is, therefore, no indication that elderly persons are more prone than non-elderly persons to return "home" to their region of birth.

In conclusion, research on return migration patterns has shown that those returning "home" after retirement make up a significant component of total elderly migration streams but not of the aggregate migration streams for the population at large. Past research also has suggested that elderly persons are more likely to return home than are the non-elderly (Serow 1978; Serow and Charity 1988). Further study, however, has shown such a conjecture to be false (Rogers 1990). When the ratios of return to total migration propensities toward region of birth are compared for the elderly and the general population: the ratio for the elderly is almost never higher than the one for the general population. The conclusion suggested by this that elderly persons are not more likely to return home than are the non-elderly.

Table 4.3 The significance of return migration among elderly and nonelderly [total] persons: ratios of return to total conditional outmigration probabilities: 1935–1940, 1955–1960, 1965–1970, 1975–1980, and 1985–1990

Region	1935–1940	1955–1960	1965–1970	1975–1980	1985–1990
A. Elderly (age 60+) migration					
Northeast	2.9	1.4	1.0	1.1	1.2
Midwest	0.8	1.2	1.5	1.2	1.1
South	3.0	2.6	4.7	2.4	2.1
West	0.9	0.9	1.7	1.0	1.0
U.S.A.	1.4	1.2	1.7	1.2	1.1
B. Total migration					
Northeast	3.4	1.9	1.6	1.7	1.8
Midwest	1.6	1.6	1.7	1.6	1.5
South	3.2	2.7	2.7	2.4	2.2
West	1.3	1.3	1.2	1.3	1.3
U.S.A.	2.0	1.7	1.7	1.6	1.7

4.4 Multiregional Life Tables: Migration Histories

4.4.1 Multiregional Life Tables and Origin Dependence

Imagine following a hypothetical cohort of 100,000 babies, born in the South say until they all have died: some in the South, others in the Northeast, Midwest, or West. Assume that these babies are continuously exposed to the risks of migration, and also of dying, according to the regional migration and mortality schedules of a particular period. Decrementing this age-specific population to take into account departures from the South (due to death or to outmigration) and, at the same time, incrementing it to account for return inmigration flows entering the South, generate a series of regional population stocks and interregional migration flows that together define the life history of that Southern-born synthetic cohort. With that life history one can calculate such useful measures as the life expectancy at birth of a Southern-born baby, expressed as a sum of region-of-residence-specific components of that total. Such a disaggregation, calculated using migration data provided by the 1990 census, for example, reveals that a Southern-born baby could at that time have expected to live, on average, 76.0 years with 55.3 years of that total to be lived in the South (Table 4.4). The quotient of these two numbers, i.e., $55.3/76.0 = 0.73$, is known as that region's *retention* expectancy.

The above numbers for South were calculated without an introduction of origin-dependence into the analysis. Doing so would increase the value of the state's retention expectancy because of the influence of the higher than average probabilities of return migration. Origin-dependence acts to reduce the numbers of years lived outside of an individual's region of birth. This is clearly evident in Table 4.4, in which the life expectancies are presented calculated both with and without origin-dependent probabilities. Note the significantly larger retention expectancies that are associated with the origin-dependent version. For example, according to

Table 4.4 The impact of origin dependence on life expectancies [in years], United States: 1955–1960 and 1985–1990

Period	Region of residence at census	Regional life expectancies							
		Origin independent				Origin dependent			
		NE	MW	S	W	NE	MW	S	W
1955–60	Northeast	48.6	3.6	5.2	3.7	56.7	1.5	2.8	1.0
	Midwest	5.2	45.7	8.6	7.8	2.7	54.2	5.5	2.2
	South	10.0	10.3	46.8	10.6	5.6	4.6	55.1	2.6
	West	6.0	10.4	8.5	47.8	4.5	9.9	5.5	64.4
	Total	69.7	70.0	69.1	69.9	69.6	70.1	69.0	70.2
1985–90	Northeast	48.8	3.5	5.0	4.2	58.1	1.5	2.0	1.2
	Midwest	4.9	50.1	8.0	7.7	2.1	59.8	3.5	2.7
	South	16.6	14.6	55.3	13.3	11.8	8.7	66.5	5.2
	West	6.0	8.3	7.8	51.5	4.2	6.6	3.9	67.7
	Total	76.3	76.5	76.0	76.6	76.2	76.6	75.9	76.9

the 1985–1990 data, almost 11 (66.5–55.3) years are added to the years expected to be lived in the South in the origin-dependent calculation, and the retention expectancy associated with the Southern-born population, which was 0.73 in the origin-*independent* life table increased to 66.5/75.9 = 0.88 in the origin-*dependent* version. Note that the same additional number of years to be lived in the South also differentiate the 1985–1990 life expectancy from that of 1955–1960, a dramatic increase when compared to those calculated for the other three regions.

4.4.2 Migration Life Histories

Life table measures are derived from information about the life histories of synthetic regional birth cohorts. Such life histories are generated by applying age-specific probabilities of dying and out-migrating to the regional radices, which may be set any number, say 100,000. These synthetic origin dependent aggregate life histories of 100,000 babies born in one of the four regions allow one to calculate several summary measures from multiregional life tables of the U.S. population calculated using migration data reported in the 1960 and 1990 censuses: mean ages of outmigrants, probabilities of surviving to age 60 in each region, and life and mobility expectancies (Table 4.5). All of these measures derive from the region-specific expected number of survivors at exact ages from 0 to 85 (not shown).

The mean ages set out in Table 4.5 reveal the following findings: (1) that of the three groups, primary migrants in general exhibit the youngest mean ages while onward migrants show the oldest, (2) that the mean of ages of migrants leaving the Northeast and Midwest are older than those of migrants leaving the South and West, and (3) that migrants in 1990 were a few years older in average age than migrants in 1960.

The probabilities of surviving from birth to age 60 also are illuminating. They show that the general increase of about 6 years of life expectancy from 1960 to 1990 produced a corresponding increase of about 10 % in the survival probability to age 60. Moreover, the probabilities identify two significant shifts in regional destination preferences. First, the probability of survival in the region of birth increased dramatically (from 0.572 to 0.726) in the South—a consequence both of the decline in death rates and the emergence of the South as an attractive region of destination. The growing attraction of the South also sharply increased the corresponding probabilities of non-Southern-born babies living in the South at age 60: from 0.081 to 0.177 for the Northeast, from 0.063 to 0.128 for the Midwest, and from 0.026 to 0.069 for the West.

The second significant shift over the 30-year period is the decline in the Midwest to West migration and a corresponding increase in Midwest to South migration—a shift that produced a corresponding drop in the birth-to-60 probability from 0.159 to 0.104.

Table 4.5 Summary measures from origin dependent multiregional life tables of the U.S-born population: 1960 and 1990

Region of residence	Region of birth							
	1960				1990			
	Northeast	Midwest	South	West	Northeast	Midwest	South	West
A. Mean age of primary, return, and onward outmigrants by region								
Primary	24.2	24.0	20.7	15.0	29.7	27	22.9	18.9
Return	26.0	25.0	23.9	25.8	29.2	29.6	27.3	29.3
Onward	28.5	28.0	26.5	27.1	30.2	30.7	29.4	31.2
Total	24.9	24.6	22.1	23.0	29.7	27.9	25.7	26.2
B. Probability of surviving from birth to age 60 in each region								
Northeast	0.599	0.02	0.041	0.011	0.590	0.020	0.026	0.014
Midwest	0.039	0.554	0.078	0.025	0.029	0.618	0.047	0.032
South	0.081	0.063	0.572	0.026	0.177	0.128	0.726	0.069
West	0.072	0.159	0.082	0.732	0.066	0.104	0.056	0.754
Total	0.791	0.797	0.773	0.794	0.862	0.870	0.855	0.870
C. Life expectancies at birth (in years)								
Total	69.6	70.1	69.0	70.2	76.2	76.6	75.9	76.9
D. Mobility expectancies at birth (in percent)								
Northeast	81.5	2.1	4.1	1.4	76.2	1.9	2.6	1.6
Midwest	3.9	77.3	8	3.1	2.8	78.1	4.6	3.5
South	8.1	6.5	79.9	3.7	15.5	11.4	87.6	6.8
West	6.5	14.1	8.0	91.8	5.5	8.6	5.2	88.0
U.S.A.	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Finally, the mobility expectancies at birth presented in Table 4.5 also reflect the shifts described by the survival probabilities—for example, the South's retention expectancy increases from 79.9 to 87.6 % over the 30 years, while the percentage of a Northeastern-born baby's lifetime that is expected to be lived in the South grows from 8.1 to 15.5 %.

4.5 Discussion and Conclusion

Researchers on migration have increasingly interpreted geographical mobility as more than a one-time event in the lives of most people. They have shown that migration begets migration. This perspective has elevated the relative importance of previously observed migration patterns of individuals as variables in explanations of currently observed migration patterns. The role of migration away from and toward the place of birth has, in particular, received considerable attention. The migration propensities of people returning to their region of origin are considerably higher than those of the average individual (and they differ in age profile).

Consequently, the introduction of origin-dependent migration rates into multiregional demographic models produces a significant impact on life table measures and population projections.

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Chapter 5
The Foreign-Born and the Native-Born: Are Their Elderly Migration and Settlement Growth Patterns Different?

Abstract This chapter illustrates a general method for analyzing the demographic processes that contribute to population growth and distribution in a multiregional population system that is "open" to international migration. The method incorporates a historical perspective that can be used to trace dynamic population processes as they evolve over time and space. It uses an open multiregional projection model framework for identifying the contributions to regional growth rates made by each of the principal demographic components of change: fertility, mortality, outmigration, inmigration, emigration, and immigration. At the same time, the method recognizes the importance of disaggregating the native-born and foreign-born populations. Publically available data and indirect estimation techniques are used to develop the inputs for the projection model, with which the regional population changes are reconstructed for each five-year period between 1950 and 1990. Regional growth rates for the native-born and foreign-born populations are partitioned into the separate demographic components of change, and the projection model also identifies the separate contributions made by each of the sub-populations. This allows a direct comparison of the impacts of immigration with those of native-born contributions effected through internal migration and natural increase.

Keywords Immigration · Foreign-borns · Native-borns · Sources of growth

The multiregional projection is normally used in a prospective mode, forecasting the likely future populations of a multiregional system. However, it also can be used in retrospective mode, to analyze the past population dynamics that produced current age-specific regional population totals, for example, the evolution of today's regional elderly populations disaggregated into native and foreign-born numbers. In either case, it needs as inputs data on the components of change: births by age of mother, age-specific deaths, internal and international migration flows. This chapter begins with models in a retrospective mode to trace the evolution of the elderly regional populations of the U.S. from 1950–2010, continues on with migration patterns, and concludes with a discussion of the sources of regional population growth.

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5.1 Introduction

The U.S. population is aging rapidly and an increasing fraction of the older adults are immigrants, many of whom arrived relatively recently. A recent report produced by the Center for an Urban Future (Gonzalez-Rivera 2013), and summarized in the New York Times (August 13, 2013), focuses on the need to take steps to plan for this growing, rapidly diversifying population, pointing out that not enough attention is being paid to this particularly vulnerable subset of seniors.

What the article and the report ignore is the influence of age and date of entry of the immigrants. Obviously, those immigrants who entered long ago and have assimilated are likely to exhibit quite different degrees of vulnerability than the relative newcomers. Grouping the various cohorts together and referring to all of the U.S. foreign-borns as immigrants creates its own form of diversity.

The CUF (Center for an Urban Future) report states that the foreign-borns are one of the fastest growing population subgroups in the city of New York. Is this the case nationally and regionally? Have the internal elderly migration patterns of the foreign-borns shown a sharp difference with the corresponding migration patterns of the native-borns? How significant have been the differences on regional population growths? What have been the relative contributions of migration, aging-in-place, and immigration? How have the contributions of the foreign-born differed from those of the native-born?

To examine such questions and some of the more important underlying population dynamics, one needs to have assembled available census data, indirectly estimated missing data (such as emigration flows), and built a multiregional cohort-survival model of the U.S. population, focusing especially on the evolution of the foreign-born elderly population during the last half of the 20th century and paying particular attention to the sources-of-growth of that population.

The CUF report focused on internal migration and did not consider the usually more significant contribution of "aging-in-place" to elderly migration growth and settlement patterns. This chapter does and asks whether it was migration or aging-in-place that was driving regional elderly population growth during the last half of the 20th century.

These questions and their answers constitute the core of this chapter. It first introduces a disaggregation of the U.S. population into foreign-born and native-born subpopulations, because of the differences in their respective migration patterns. But before addressing the above questions, it is useful to describe the historical immigration context within which the principal demographic processes took place. This part of the chapter, then, is followed by a description of the models used, and an analysis of the obtained results.

5.2 Historical Context, Data, and Models

5.2.1 Historical Context

The elderly population of the United States has assumed ever larger shares of the total national population during the past century. Whereas, persons 60 years and older constituted about 6 % of the national population in 1900, they accounted for over 16 % of that population at the century's end. Driving this March toward an older population have been the remarkable increases in average life expectancy (from 47 years in 1900 to 76 years in the year 2000), and corresponding decreases in the birthrate (from 32 per thousand to about 15 per thousand).

The temporal pattern for the foreign-born elderly population during this same period, however, has been quite different. The 20th century began with immigrants accounting for 31 % of the elderly (60+ years) population and for 14 % of the total U.S. population (Rogers and Raymer 2001). It ended with these two percentages taking on close to identical values: about 12 and 13 %, respectively. The dynamics that have produced this evolution over the past century are particularly interesting because of particular immigration laws passed by the federal government over the past century—laws which collectively have influenced immigration numbers and compositions (Fig. 5.1).

Recognizing that many of the old immigration laws were outdated, Congress passed the Immigration and Nationality Act of 1952 and Amendments to it in 1965 and 1976. These were followed in the 1980s and 1990s by the Immigration Reform and Control Act (IRCA) of 1986, the Immigration Act of 1990, and the Illegal Immigration Act of 1996. These pieces of legislation produced rather dramatic demographic consequences for levels of immigration, age structures, and spatial patterns of settlement. Figure 5.2 presents the changes in national age composition over time that arose partly as a consequence of the changes in the regional immigration levels over time and spaces. (The regional age distributions, too numerous to exhibit here, generally show the same profiles.) Figure 5.3 exhibits the changing regional geographies of the elderly foreign-born and native-born populations.

For the first 90 years of the 20th century, the growth rate of the elderly foreign-born population in the United States was lower than that of the elderly native-born population (Fig. 5.4b). Indeed, between 1950 and 1990, the elderly foreign-born population actually declined in size and exhibited a negative growth rate for almost 30 years. Only in the 1990s did the elderly foreign-born population begin to exhibit higher annual growth rates than its native-born counterpart, a consequence of the immigration reforms of 1965 and the relative low fertility levels of the native-born population during the Depression years.

The impacts on the elderly foreign-born population of contracting or expanding levels of immigration have tended to be felt some thirty years later. Whereas the impacts of contracting and expanding levels of fertility on the elderly native-born

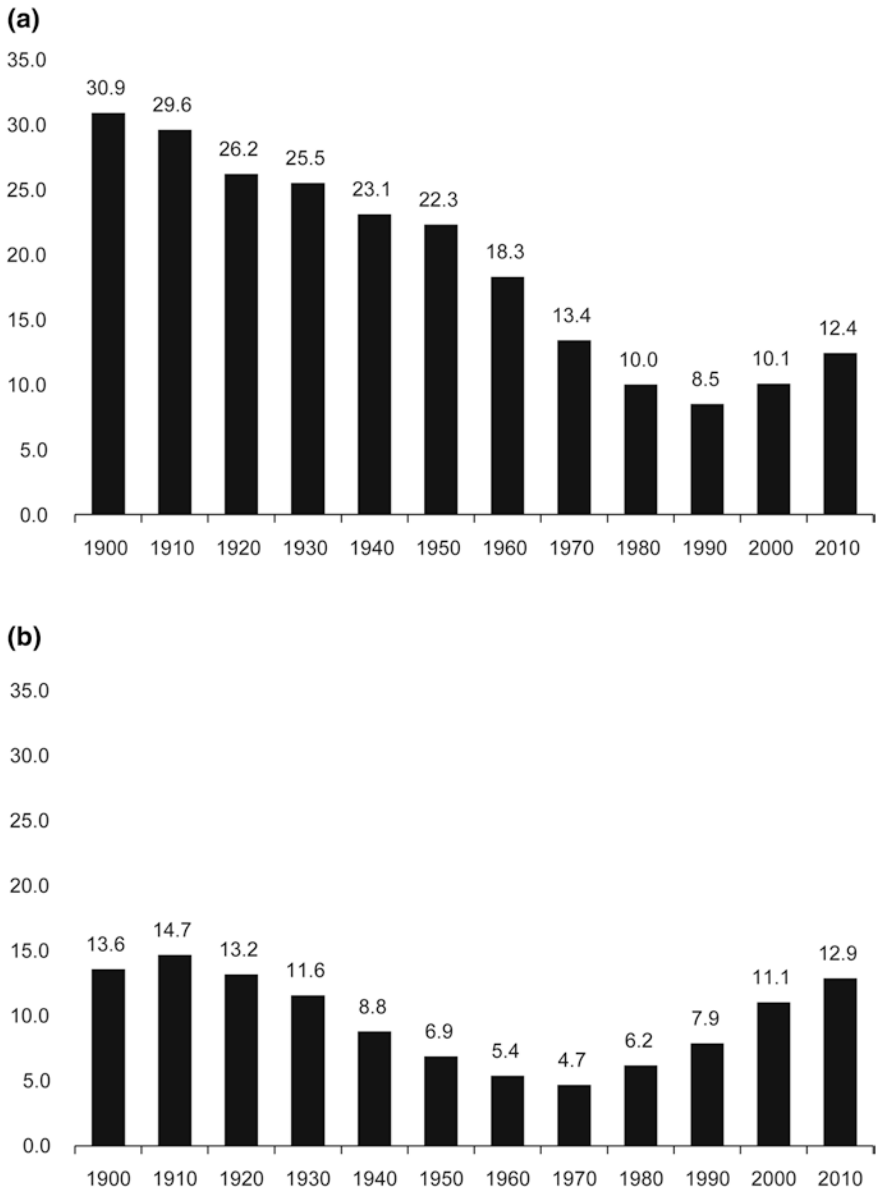

Fig. 5.1 Percentage foreign-born of **a** elderly (age 60+ years) and **b** total (age 0+ years) U.S. populations: 1900–2010. *Source* Raymer and Rogers (2014)

population become manifest some sixty years later. Thus the dramatic drop in the elderly foreign-born growth rates that began in the 1950s occurred roughly thirty years after the Immigration Act of 1924, and the increases in elderly foreign-born growth rates that occurred during the 1990s happened some thirty years after the

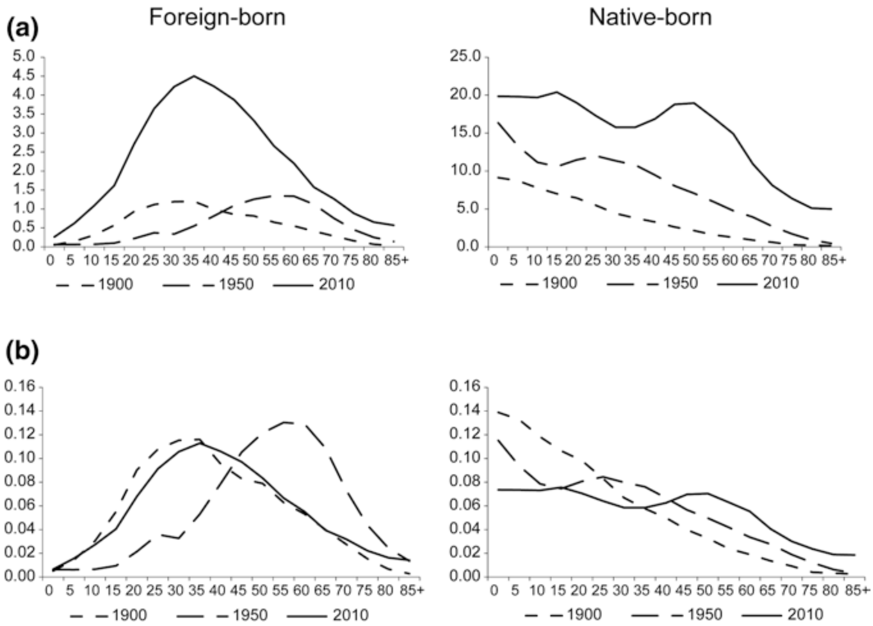

Fig. 5.2 Age compositions by nativity: 1900–2010. **a** Millions, **b** proportions. *Source*: Raymer and Rogers (2014)

Immigration and Nationality Act Amendments of 1965. Among the elderly native-born, however, growth rates fell to near zero in the early 1990s, sixty years after the very low birth rates of the Depression era.

In addition to the differences by nativity observed for the elderly population in the U.S., substantial regional variations also developed over time (Fig. 5.5). The elderly foreign-born populations of the South and West regions increased in size during the entire 20th century. Moreover, the South showed no major declines in annual growth rates between 1940 and 1970, such as occurred in the other three regions.

In contrast to the elderly foreign-born population, the elderly native-born population grew at a relatively stable rate until the 1980s, at which point the rates began to decline. Indeed, the elderly native-born populations in the Northeast and Midwest were smaller in the 1990s than they were in the 1980s. The relatively high rates of growth of the elderly native-born populations in the West and of the elderly foreign-born populations in the South arose partly as a consequence of the relatively small initial populations in those two regions during the first half of the century.

The race/ethnic composition of the U.S. immigrants was significantly altered by the immigration reforms introduced by Federal legislation passed in 1965. A major feature of the Immigration Nationality Act Amendments of 1965 was that the number of immediate family members of U.S. citizens eligible for immigration was no longer subject to numerical limits. A consequence of this provision

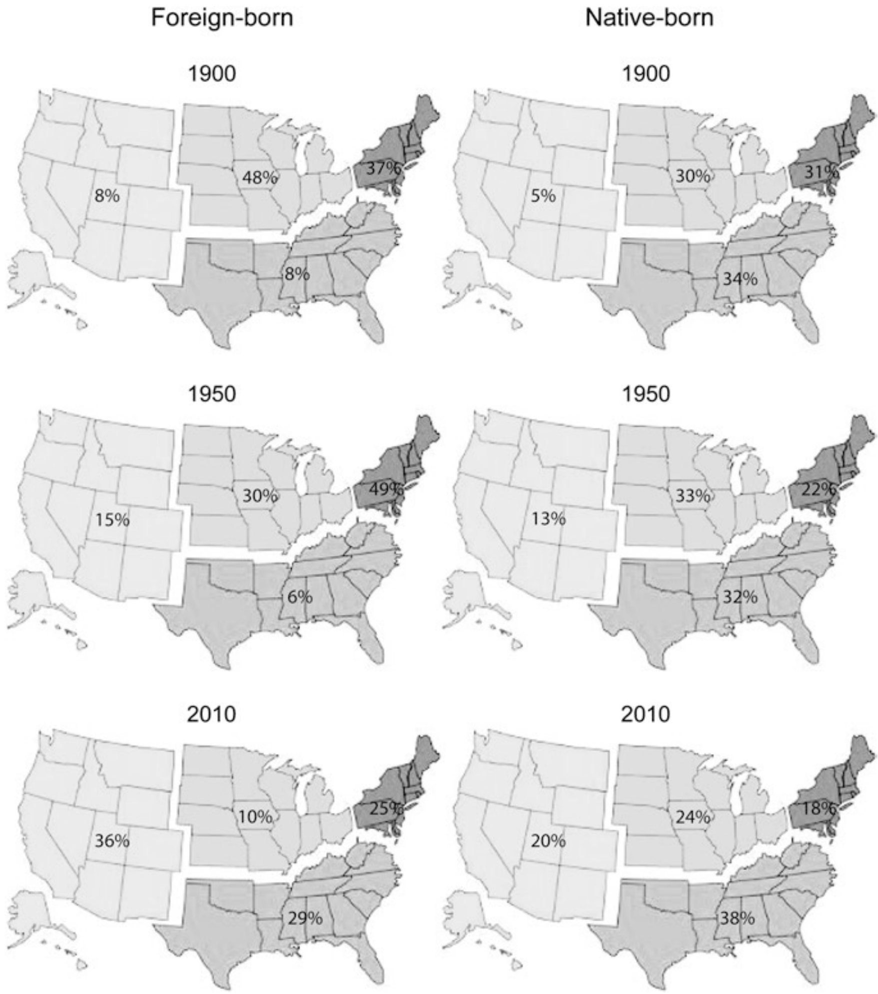

Fig. 5.3 Spatial concentrations: Percentage distributions of elderly (age 60+ years) foreign-born and native-born U.S. populations, by region: 1900, 1950, and 2010. *Source* Raymer and Rogers (2014)

was a dramatic increase in immigration from Asian to Latin American countries. With this increase came a sharp decrease in immigration from Europe and Canada. Whereas almost two-thirds of all immigrants to the United States during the 1950s originated in these two countries, by the 1990s, their contribution dropped to 14 %. At the same time, Asia, which contributed only 6 % in the 1950s, increased its share to 44 % in the 1980s, and immigration from Latin America increased from 26 % in the 1950s to 40 % in the 1960s, a share that it has maintained since then.

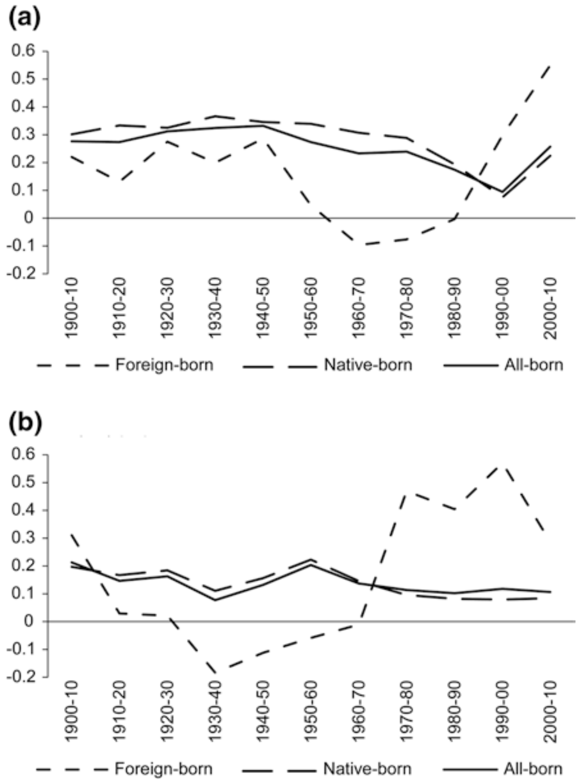

Fig. 5.4 Decadal **a** elderly (age 60+ years) and **b** total (age 0+ years) growth rates by nativity: 1900–2010. *Source* Raymer and Rogers (2014)

5.2.2 Data and Models: Identifying the Sources of Elderly Population Growth, 1950–1990

The 1940 Census was the first national census count to report origin-destination-specific migration flow data for the United States. Already by that time, elderly migrants were moving to the Sunbelt and exhibiting the two major national "elderly migration sheds" identified by Friedsam (1951, p. 238), with "migration to the Pacific region coming in large part from west of the Mississippi and most of that to the South Atlantic coming from east of the Mississippi."

Elderly migration patterns since the 1940 census most often have been studied using the question regarding the respondent's location of residence five years earlier. (The sole exception was the 1950 census, which adopted a one-year interval instead so as to avoid the immediate post-World War II period of readjustment.) In Rogers and Raymer (2001) these data were used to study the elderly migration patterns in the periods 1955–60, 1965–70, 1975–80, 1985–90, and 1995–00. The migrants in each of the time periods were reallocated back to their regions of origin of five years earlier. Thus, the at-risk population of migrating from any region is the population that lived their five years earlier. A younger age threshold

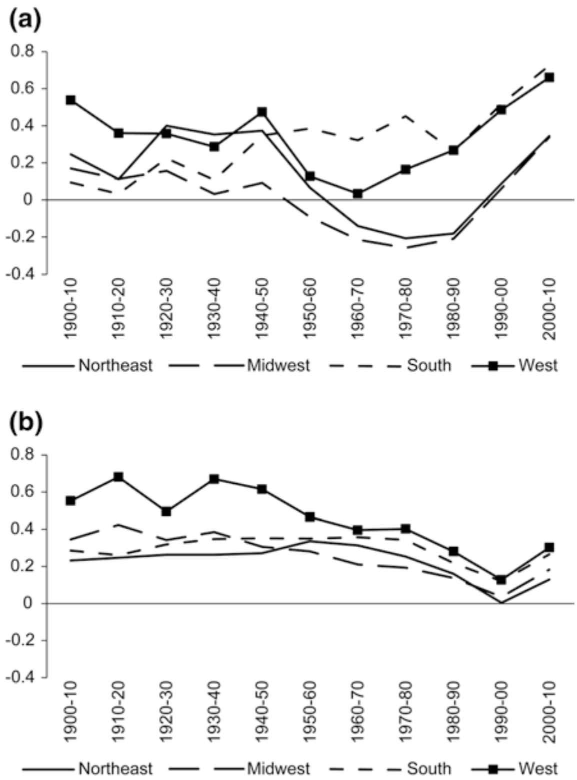

Fig. 5.5 Decadal regional elderly (age 60+ years) growth rates by nativity: 1900–2010. **a** Foreign-born, **b** native-born. *Source* Raymer and Rogers (2014)

was adopted to define the elderly population, namely, 60 years and over, instead of the more conventional 65 years and over. This, first, increased the sample size; second, recognized that most married men, who migrate at retirement, take along a younger wife; and, third, acknowledged the trend toward earlier retirement.

The elderly population was disaggregated into native-born and foreign-born subpopulations by separating those who were born in the United States and its territories (or born abroad to at least one American parent) from those who were not. For the projection exercises the necessary input data on mortality, fertility, and migration were obtained from the standard Vital Statistics and Census Bureau sources. Where necessary, (e.g., the case of emigration) conventional methods of indirect estimation were adopted. For details, the reader should consult Rogers et al. (1999), Rogers and Raymer (2001), and Raymer and Rogers (2014).

To identify in greater detail the demographic sources of regional increases or decreases in the elderly population, the reconstruction of the regional demographic dynamics of the elderly foreign-born and native-born populations in the United States from 1950 to 2010 were reconstructed. These estimated dynamics help to answer a number of interesting questions about the evolutions of these elderly populations during the last half of the 20th century. An "open" multiregional projection model framework was used to identify the contributions to regional population growth made by each of the principal demographic components of change: fertility, mortality, international migration (immigration and emigration), and internal migration (inmigration and outmigration). An earlier study (Rogers et al. 1999) describes this framework in some detail and uses it to illuminate the demographics of the total (not elderly) U.S. multiregional population. This chapter updates that work by including more recent data, obtained from the 2000 Census and the 2010 American Community Survey.

With data drawn largely from the U.S. Census Bureau's published and unpublished records, including various Public Use Microdata Sample (PUMS and IPUMS) files of the Censuses of Population, an empirical multiregional projection model was developed that begins with the population counts for each age group in each region that are reported by a decadal census at time t, and then survives that population forward five years at a time. The projection model accounts for emigration by combining emigration rates with death rates to make use of the standard methods for decrementing the population in a multiregional life table. In addition, the open multiregional projection model is adapted to simultaneously project the foreign-born and native-born population total. That is, the foreign-born population generates births, but these births are treated as increments to the first age group of the native-born population in each region.

The population projection represents the age- and period-specific fertility, mortality, emigration, and internal migration processes of the foreign-born population and the immigration distribution represents the foreign-borns entering the country during the period. But the projected population distribution is not the true foreign-born population because it includes the foreign-born contribution to native-born births. One therefore needs to extract the foreign-born births from the appropriate region-specific element of the projected population distribution that represents the first age group in each region and then to increment the appropriate elements of the native-born population to include the contributions of these births contributed by the foreign-born population. Of course, this problem does not appear if the evolution of only the elderly population is of interest. The "birth" component then becomes the "aging-in" component, i.e., total births are replaced in the accounting equation by the number of persons aging-into enter the first elderly age group, i.e., those becoming 60 to 64 years of age during the 5-year time interval. For example, consider the growth of a region's elderly population from t to t + 1. This growth can be expressed in the following manner:

$$P(t+1) = P(t) + A(t) - D(t) + I(t) - O(t) + IM(t) - EM(t) \tag{5.1}$$

where P represents the total elderly regional population, A the numbers of total persons aging-into the elderly population, D the numbers of total persons dying out of the elderly population, I the inmigration from the other regions in the system, O the outmigration from the region in question to the other regions, IM the immigration component, and EM the number of emigrants. The last four terms identify the contribution of net migration, whereas the difference between A and D defines the contribution of net aging-in-place.

Equation (5.1) describes total regional population growth as a summation of the initial population and the increments and decrements contributed by the principal demographic sources of growth. Each nativity-specific population is treated separately. However, one difference in the two accounting equations needs to be noted. To describe the growth of the elderly *native-born* population in each region, the I and E components are set to zero by assumption, because of the relatively insignificant contributions made by these two components to the growth of that population. Thus, we have

$$P_{NB}(t+1) = P_{NB}(t) + A_{NB}(t) - D_{NB}(t) + I_{NB}(t) - O_{NB}(t) \tag{5.2}$$

Equation (5.2) may be contrasted with the corresponding accounting equation for the foreign-born population, which retains the immigration and emigration components:

$$P_{FB}(t+1) = P_{FB}(t) + A_{FB}(t) - D_{FB}(t) + I_{FB}(t) - O_{FB}(t) + IM_{FB}(t) - EM_{FB}(t) \tag{5.3}$$

The numbers that correspond to each source of growth, except for *EM* and *IM*, may be obtained in the process of projecting the population distribution forward and then identifying and summing over the appropriate elements.

5.3 What Drives Regional Elderly Population Growth: Migration or Aging-in-Place?

5.3.1 Have Interregional Elderly Migration Patterns Changed?

Consider the temporal patterns of interregional elderly migration described in Tables 5.1 and 5.2. Three principal findings are indicated: (1) that the levels increased, at the national scale, for interregional migration; (2) that before the 1985–90 period, the percentages of elderly persons migrating to the South from the other three regions had been steadily increasing, and (3) that after identifying the net migration contributions made by these changing migration patterns (see Table 5.2) one notes that over the 1985–90 period the migration patterns did not deviate sharply from pre-1980 trends, as argued by Golant (1990). At the national scale, interregional migration levels held steady, falling between 2.4 and 2.7 % over four succeeding censuses. With the exception of the South, generally the same pattern was exhibited by each of the other three regions—a peak in 1975–80 and not thereafter.

The Northeast's peak was especially pronounced, and according to Fig. 5.6, it appeared in both the elderly foreign-born and native-born migration patterns. In general, elderly foreign-born outmigration flows from the four Census Regions over time exhibited different levels from those of the elderly native-born outflows. For example, they seem to have been more reluctant to leave the West, and it was

Table 5.1 Percentage elderly (60+) regional residents who migrated to particular regional destinations in the US: 1955–60 to 1995–2000

Origin region	Destination region					
	Period	Northeast	Midwest	South	West	Total
Northeast	1955–60		0.27	1.97	0.5	2.75
	1965–70		0.24	2.46	0.48	3.18
	1975–80		0.22	3.32	0.69	4.23
	1985–90		0.23	3.25	0.54	4.01
	1995–00		0.22	3.06	0.55	3.83
Midwest	1955–60	0.21		1.66	1.26	3.13
	1965–70	0.17		1.84	1.11	3.12
	1975–80	0.15		2.14	1.16	3.45
	1985–90	0.15		1.93	0.91	2.98
	1995–00	0.15		2.07	0.95	3.18
South	1955–60	0.40	0.61		0.47	1.48
	1965–70	0.40	0.58		0.39	1.36
	1975–80	0.42	0.54		0.48	1.44
	1985–90	0.44	0.64		0.50	1.58
	1995–00	0.49	0.62		0.56	1.68
West	1955–60	0.19	0.76	0.69		1.65
	1965–70	0.20	0.76	0.82		1.78
	1975–80	0.21	0.68	1.06		1.95
	1985–90	0.23	0.67	1.04		1.94
	1995–00	0.23	0.64	1.16		2.03
Total	1955–60	0.20	0.35	1.16	0.66	2.37
	1965–70	0.20	0.35	1.31	0.56	2.42
	1975–80	0.21	0.35	1.53	0.63	2.71
	1985–90	0.22	0.39	1.42	0.52	2.56
	1995–00	0.26	0.39	1.38	0.54	2.56

Source Raymer and Rogers (2014)

not until after 1975 that their corresponding levels from the South declined below the national level. But, in the aggregate, their national levels always exceeded the corresponding levels for the elderly native-born population.

5.3.2 *The Proximate Sources of Regional Elderly Population Growth*

A country's elderly population is not distributed evenly across a nation's territory. Geographic concentrations of elderly persons arise at destinations with high amenities, as elderly migrants move across longer distances in search of amenity-rich

Table 5.2 In-, Out-, and net-migration patterns of the US elderly (60+) population, by region and nativity: 1955–60 to 1995–2000

Period	Region	Foreign-born migrants			Native-born migrants			All-born migrants		
		In	Out	Net	In	Out	Net	In	Out	Net
1955–60	Northeast	7	40	−33	25	81	−56	32	121	−89
	Midwest	9	31	−21	46	125	−79	55	156	−100
	South	45	9	36	140	55	85	185	64	121
	West	27	6	19	81	31	50	105	37	68
1965–70	Northeast	8	47	−38	31	121	−90	39	167	−128
	Midwest	8	25	−17	61	156	−95	69	181	−112
	South	52	9	43	209	70	139	261	79	182
	West	20	7	13	92	46	46	112	53	59
1975–80	Northeast	10	55	−45	45	204	−159	55	259	−204
	Midwest	9	23	−14	81	210	−130	90	233	−144
	South	59	15	44	335	108	226	394	123	271
	West	24	9	15	138	76	62	162	85	77
1985–90	Northeast	9	42	−33	61	245	−185	69	287	−218
	Midwest	7	17	−11	114	216	−102	121	233	−113
	South	49	14	36	392	150	242	441	164	277
	West	19	11	8	143	98	45	162	109	53
1995–00	Northeast	16	56	−40	104	319	−215	120	375	−225
	Midwest	15	25	−10	164	321	−156	179	346	−167
	South	70	28	42	560	248	312	630	276	354
	West	32	23	8	221	162	60	253	185	68

Source Raymer and Rogers (2014)

communities with sunnier and warmer climates and recreationally diverse environments. But such concentrations also arise as a consequence of net aging-in-place—the “natural increase” component of elderly population change that is the numerical difference between pre-elderly persons and who remain in the region and enter the first elderly age group there (i.e. elderly “births”) and elderly persons who die during the unit time interval.

Earlier, this chapter set out a multiregional projection model that is “open” to international migration streams and that is responsive to historical changes in each demographic process. The output of that model permits a contrast between the foreign-born and native-born contributions to population growth. To do this one needs to add together their respective components of growth and obtained the total for each region. To simplify the presentation of the analysis, the growth components for each pair of adjacent five-year periods have been added together to describe the historical growth by decade. For a particular region, such as the Northeast, say, over a given decade, for example from t to $t + 1$, total elderly population growth, $G_{NE}(t, t + 1)$, can be partitioned as follows:

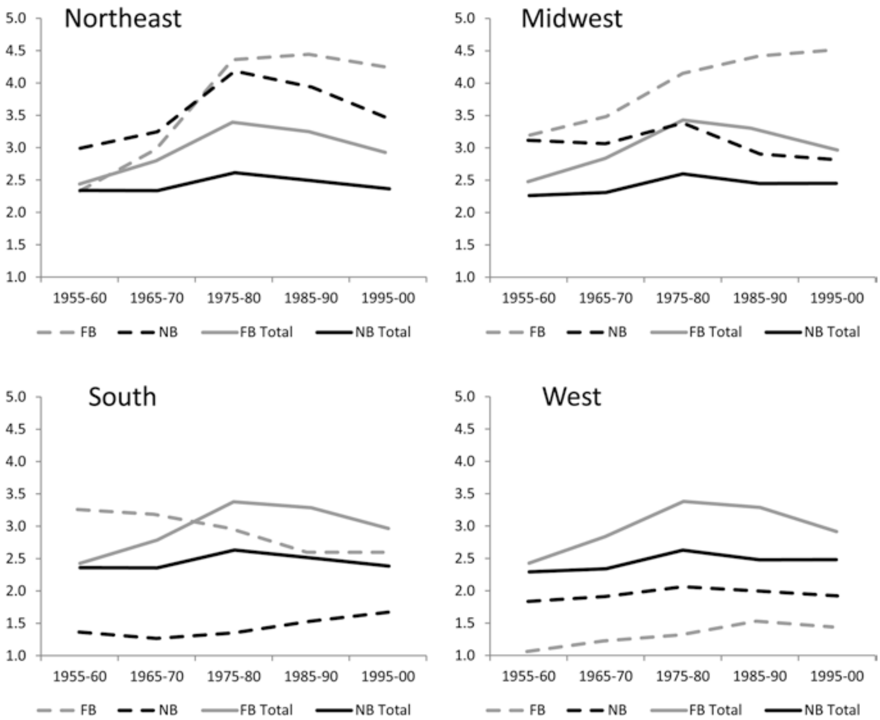

Fig. 5.6 Percentage of elderly (age 60+ years) and total (age 0+ years) residents migrating to a different region by nativity: 1955–1960 to 1995–2000. *Source* Raymer and Rogers (2014)

$$G_{NE}(t, t+1) = \{\text{Foreign-Born Contribution}\} + \{\text{Native-Born Contribution}\}$$
$$= P_{FB}(t+1) - P_{FB}(t) + \{P_{NB}(t+1) - P_{NB}(t)\} \tag{5.4}$$

$$= \{(A_{FB}(t) - D_{FB}(t)) + (I_{FB}(t) - O_{FB}(t)) + (IM_{FB}(t) - EM_{FB}(t))\}$$
$$+ \{(A_{NB}(t) - D_{NB}(t)) + (I_{NB}(t) - O_{NB}(t))\} \tag{5.5}$$

$$= \{\textit{FB}\text{ Net Aging-in-Place} + \textit{FB}\text{ Net Internal Migration} + \textit{FB}\text{ Net Immigration}\}$$
$$+ \{\textit{NB}\text{ Net Aging-in-Place} + \textit{NB}\text{ Net Internal Migration}\} \tag{5.6}$$

In Eq. (5.5) the foreign-born contribution is disaggregated into the net aging-in-place, net internal migration, and net immigration components. Each of the net components is calculated as the difference between the respective incremental and decremental contributions. The native-born disaggregation is dealt with in a similar way, but the net immigration component is set to zero by assumption. The results of such a decompositional analysis for the elderly foreign-borns are illustrated in Fig. 5.7.

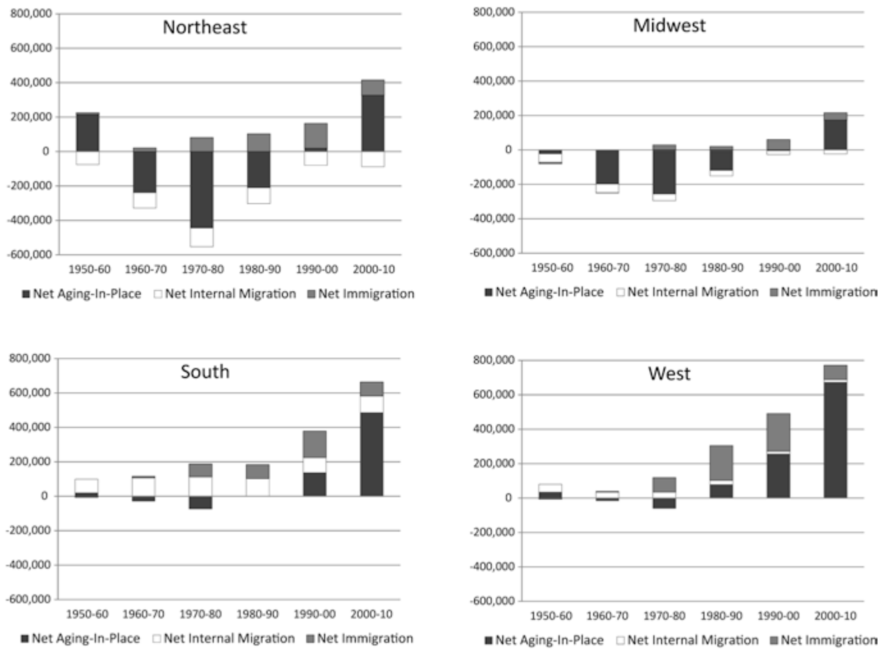

Fig. 5.7 Components of decadal foreign-born elderly population change. *Source* Raymer and Rogers (2014)

The three demographic components illustrated in Fig. 5.7 changed in relative importance over the 1950–2010 period and across the four regions. Except in the Midwest, aging-in-place was the dominant positive contributor to growth in the South and West since the 1990s, and mostly a negative contribution in the Northeast and Midwest (except in the 2000–2010 interval). Net internal migration was largely a positive contributor in the South and West and a negative one in the Northeast and Midwest. Its role, however, was a relatively modest one compared to the other two components (except in the South). Finally, immigration's contribution was always a positive one, but it did not begin until the 1970s, and affected the Midwest's elderly foreign-born population very little. Overall, the most important recent component of change was aging-in-place; its influence on the growth or decline of the regional elderly foreign-born populations was a significant one.

Although a multiregional "sources of growth" projection model was used to identify the importance of both positive and negative contributions to the evolution of regional populations during a past period, it may also be used to generate counterfactual scenarios that allow one to calculate the contribution made by immigration to the growth of the United States total national population, along the lines followed by Passel and Edmonston (1992). Their procedure can be adapted to carry out the same calculations for elderly regional populations over the period 1950–2000. For an example see Rogers and Raymer (2001) and Raymer and Rogers (2014).

5.4 Discussion and Conclusion

During the last half of the 20th century, the elderly population in the United States experienced many changes as a consequence of shifts in internal migration propensities, declines in mortality and fertility levels, and fluctuations in immigrations flows. These changes have led a number of scholars to study the underlying population dynamics. Some have focused on internal migration patterns. Others have analyzed the significance of the other important component of the dynamics: aging-in-place. Still others have examined the impacts of immigration. All three were considered in this chapter, leading to several interesting conclusions.

First, on the subject of changing internal elderly migration patterns, little evidence exists that the 1980s heralded a break with the past trends and introduced a new migration spatial structure, as was argued by Golant (1990), for example. An analysis of the data shows no evidence of such a break and, if one did occur earlier, then a return to past trends came surprisingly quickly. Indeed, if a mild break were to be identified, it likely would be the 1975–80 period and not later.

If migration trends did not change significantly, what drove the demographics of elderly growth and redistribution? Using available data, indirect estimation techniques, and a multiregional projection model, one can reconstruct elderly population changes for each five-year period between 1950 and 2010, for the four U.S. Census regions. In carrying out this reconstruction, historical elderly regional growth rates maybe partitioned in several ways. First, these rates maybe decomposed to separately identify the contributions of the foreign-born and native-born populations. Second, total regional growth rates for each of the four decades were decomposed into increments and decrements that were attributable to the foreign-born and to the native-born populations. This then permits an assessment of the importance of the three sources of elderly population growth, and analysis of the data reveals that the driving force behind the changes was net aging-in-place.

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Chapter 6
Multiregional Population Dynamics and Projections: Do Simple Models Outperform Complex Models?

Abstract During the past 70 years, the U.S. Bureau of the Census has been producing population projections that over time have become both methodologically more sophisticated and demographically more detailed. Yet this added complexity has not invariably led to increased accuracy. This chapter reviews some of the debate on the simple versus complex modeling issue and links it to questions of model bias and distributional momentum impacts. It introduces a probabilistic time series dimension to the projection exercise, and it focuses on a three-region illustration. Finally, it outlines how parameterized model schedules and projection models may be adopted to provide a strategy for simplifying models with a large number of variables that come with the adoption of age-specific rates.

Keywords Simple versus complex projection models · Probabilistic projections · Model migration schedules

6.1 Introduction

Inventories and projections of human populations are a necessary input for most planning activities. First, populations are the clients whose welfare the planning efforts are designed to improve. Second, they are a primary resource used to produce the goods and services that lead to higher levels of welfare. Third, they consume resources that could be used elsewhere and contribute to the environmental degradation that is evident everywhere.

The "complex" cohort-component method, used (in various implementations) by the Bureau since 1945, has become the dominant population projection model used virtually everywhere, because it takes advantage of the built-in momentum of age structure effects. It is this age momentum, for example, that created the concern about the expected rising growth rate of the 65 year and older population as

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the Baby Boomers continue to join the elderly population. However, despite this advantage over simple aggregate exponential growth models, Long (1987) of the Bureau found that little correlation existed between methodological innovation and the accuracy of the resulting projections. Apparently, the constant growth scenario, in the majority of cases, did as well or better than the more complex models in predicting future total growth rates and population projections.

6.2 The Problematic Model Assessment Procedure

The debate over projection performance considers the advantages held by complex cohort-component models over the corresponding simple models derived by aggregation or decomposition, and examines the past record of official projections. Since assessments of model performance in the literature are expressed in terms of such ill-defined words as simple, complex, naive, sophisticated, crude, and elegant, it becomes necessary to clarify the issue of assessment from the start.

6.2.1 The Assessment of Model Performance

Most assessments of the performance of alternative models have focused on the differences between observed population totals and growth rates and those predicted by the particular models being evaluated. All efforts focus on the difference between the average annual growth rate implied by the projection and the one subsequently observed. Such a statistic has the virtues of being independent of population size and of the length of the projection interval, whereas the difference between the absolute numbers of people depends on population size, and percent error doesn't take into account the length of the time period over which the projection is carried out.

Keyfitz (1981) studied the average annual growth rates of some 1100 projections, developed by different agencies, at different times, and for different countries. Comparing the ex-post performance of these projections, generated by cohort-component methods, with that of the corresponding projections produced by the simple exponential growth model, he concluded that the former models outperformed those based on simple geometric increase. Stoto (1983), on the other hand, examining many of the same projection efforts, and also focusing on the same indicator of accuracy, came to the opposite conclusion.

What accounts for the opposite conclusions reached? Both scholars adopted the same indicator of accuracy. But Keyfitz used a fixed base period of five years (1950–1955) and focused on the root-mean-square error, whereas Stoto adopted a "floating" base period, which at times was a five-year base period and at other times a ten-year period, and he focused on the standard deviation as the indicator of accuracy. Although these differences are unlikely to totally explain the opposite conclusions reached, they undoubtedly had a significant impact and illustrate the need for a fair competition, or tournament, in which a common set of procedures are applied throughout, particularly with regard to the choice of length of base period and of the error index. Beaumont and Isserman (1987, p. 1005), for example, found that the accuracy of a projection could be affected as much by the choice of length of base period as by the choice of method.

Observed ex-post forecast errors, of course, depend not only on the projection methodology used, but also on the particular historical periods selected for examination. As John Long pointed out, Census Bureau projections have had difficulties in anticipating periods of rapid rises or rapid falls in fertility. The first 25 years of Census Bureau forecasting activity, corresponding to the "Baby Boom" and the following "Baby Bust" produced projections (made before 1955 and between 1966 and 1970) that were uniformly worse than the models with the simple assumption of constant growth rates. However, projections made by the Bureau for 1955 through 1966 and after 1970 were generally better than the projection with the simple models (Long 1987).

The accuracy of the Census Bureau's national population forecasting efforts apparently has improved during the past decades. One wonders how much of this improvement is due to improved projection methods and how much is due to the decreased variability in the components of change?

If a population is experiencing close to stable growth, then even the simplest model will perform about as well as complicated alternatives in forecasting that population's evolution. To conclude in such instances that simple models outperform complex models obviously is not a rigorous test. And to accord this performance the same weight as one in which the assessment involved a population experiencing an unexpected baby boom is unfair. Obviously one needs a way of introducing the dimension of "degree of difficulty" into each assessment. In diving competitions, the degree of difficulty for a swan dive is considerably lower than for a double somersault. The assessment of the diver's performance is weighted by that degree of difficulty. Perhaps an analogous weighting should enter assessments of forecasting performance.

6.2.2 When Simple Models Outperform Complex Models

The simple growth models used by Keyfitz (1981), Stoto (1983), and others are general in nature and could be used as readily to project national incomes or automobile sales. They do not take advantage of an important attribute of human populations, namely, that individuals age one year at a time. And they do not consider that fundamental demographic events and associated accounting identities that underlie population change. How is it, then, that in short-run projections they often produce reasonable results and, on a number of occasions, results that are more accurate than those produced by more complex age-specific extrapolative models, which are built on the basic demographic accounting relationships familiar to us all?

Studies of the accuracy of past Census Bureau population forecasts present a clear message: simple models have outperformed complex models at major turning points in U.S. demographic trends. For example, the forecasters did not anticipate the Baby Boom, and after it began they expected it to continue. Thus their early forecasts were too low and their later ones were too high.

At times of relative stability in demographic trends, on the other hand, the more complex (cohort-component) models outperformed the simple models. For example, during the relatively stable periods of high fertility following 1957 and 1963 and of low fertility following 1974, 1976, and 1982, the Bureau's complex models outperformed the simple models. The reduced variability in fertility rates allowed the cohort-component method to take advantage of its ability to incorporate age momentum effects by tracing the impacts of changing age compositions in the childbearing ages on aggregate fertility levels.

It appears, then, that complex models have outperformed simple models in times of relative stable demographic trends, when the degree of difficulty has been relatively low, and have been outperformed by simple models in times of significant unexpected shifts in such trends, when the degree of difficulty has been relatively high. Why has this been so? One would expect the opposite to have been the case.

Why, for example, should it be easier to forecast changes in the evolution of the annual aggregate growth rate, which by definition is a function of the basic components of demographic change, than to forecast the underlying changes in the evolution of those components? Moreover, in the assessments carried out by Keyfitz (1981) and Stoto (1983) no trend extrapolation of the aggregate growth rate was carried out. In each instance an *average* across the preceding five or ten-year base period was adopted and assumed to remain fixed across the forecasting period. This suggests the following conjecture: when simple models have outperformed complex models, it has been a consequence of a serendipitous averaging of aggregate trends during times of relative demographic instability.

Because an average growth rate is more conservative in its growth impact than is an extrapolation of past trends (whether increasing or decreasing), its use generally leads to a lower error for times that experience a turning point. For example a simple projection in 1945 of the future U.S. population, using the average fertility regime that prevailed during the preceding five years, would underproject that population less than one based on an extrapolation of the decline. Conversely, a similar projection exercise carried out a dozen years later would find the simple model overprojecting the U.S. population less than the one based on an extrapolation of the Baby Boom fertility. However, since neither the proponents of simple or complex models can anticipate such changing times, it behooves a public provider of forecasts, such as the Census Bureau, to "expect the unexpected," adopt the complex model, and strive to improve the quality of the input assumptions, rather than resort to simple growth models, even in those few situations that only need an accurate forecast of *total* population.

Of course, most uses of population forecasts require accuracy for subgroups of the total population. Plans for future schools and of future nursing homes, after all, depend on forecasts of different population subgroups. And in such efforts, cohort-component models generally outperform simple growth models.

Finally, the accuracy of a forecast is not the only dimension on which forecasting models should be judged. Long (1987) suggests the additional dimensions of face validity, internal consistency, and level of detail. Face validity refers to the reasonableness and "believability" of the model and assumptions that were used to generate the forecast. Internal consistency refers to the inclusion in the modeling process of accounting mechanisms for ensuring that standard demographic identities are satisfied. And, of course, level of detail refers to the disaggregations needed to satisfy the particular needs of the users of the forecasts. All three point to the desirability of age-sex disaggregated cohort-component models.

Simplifying complex models is an art. Regrettably, relatively few research studies have addressed the issues surrounding this activity. As a result, few "rules-of-thumb" have been developed to aid professional demographers entrusted with the task of regularly issuing population forecasts. What is clear from the limited research findings now available is that the process of simplifying a demographic projection model comes with a price in the form of bias and absence of some built-in momentum effects.

6.2.3 Simplifying Complex Models and the Loss of Built-in Momentum Effects

Shrinking a large complex extrapolative model in order to simplify it typically involves the two processes of *aggregation* and *decomposition*. The former reduces the scale of a model by a consolidation across population subgroups, time intervals, and spatial units. The latter partitions the total population system in order to exploit the possibility of treating parts of the system separately from the rest. The use of age-specific net migration rates in place of the corresponding origin-destination-specific migration rates would be a prime example of decomposition. Consolidating net migration rates into a single *crude* rate would be an example of aggregation.

Since net-migration-based representations produce a decomposition bias, and because simple exponential growth models must adopt that form of specification, it is difficult to understand why such simple models should outperform the more complex multiregional cohort-survival models that deal with migration *flows*, except for reasons related to the serendipitous cancellations of errors.

Age specific rates of demographic events vary in a predictable way. The current age distribution of a population tells us about demographic changes that were experienced in the past, as well as those that are likely to occur in the future. The likely future changes are commonly referred to as age momentum effects.

A particularly powerful illustration of the projection impact of age momentum effects occurs when the age distribution of a rapidly growing population is favorable to further increase. Whenever an initial population distribution differs from the stationary distribution that would arise were the current fertility regime to immediately drop to bare replacement level, a "momentum" is associated with that population's projection, its magnitude defined by the ratio by which the ultimate stationary population exceeds the current one. Typically, if the initial age distribution is that of a "young" population whose high fertility level is assumed to immediately drop to bare replacement level, then population growth will nevertheless continue on for some time (about 60–70 years) before zero population growth (i.e., stationarity) is achieved.

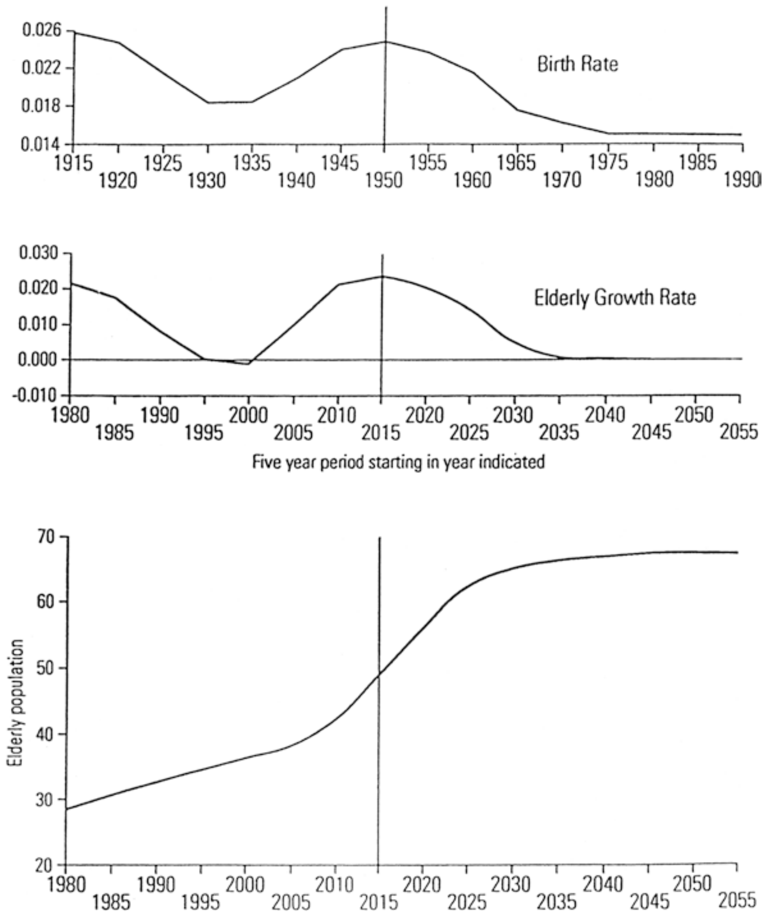

Fig. 6.1 Past birth rates, elderly growth rates, and the temporal evolution of the elderly population in the United States: 1980–2060. *Source* Rogers (1989)

An analogous result holds with respect to an initial divergence from the stationary spatial distribution. For example, India's urban population would continue to grow for several generations, even if fertility levels throughout India were miraculously to drop immediately to bare replacement levels. Age momentum would be one source of continued growth; spatial momentum, in the form of continued rural-to-urban migration, would be another. Age momentum and spatial momentum effects are suppressed when an aggregation across all age groups and a decomposition of all regional subpopulations are carried out simultaneously. Simple exponential growth models, therefore, carry no momentum impacts in their forecasting applications, and the loss of that impact can produce serious biases which contribute to inaccurate forecasts. Consider, for example, the problem of projecting the U.S. elderly population with simple and complex models. The 66-year-old population of next year will consist of the survivors of this year's 65-year-olds, who were 64-years-old last year, 63-years-old the year before that, and, of course, who were born 65 years ago. Figure 6.1 reflects this relationship between today's elderly and yesterday's births in its plot of the curve of crude birth rates from 1915 onward and the corresponding curve of the elderly population's annual growth rate 65 years later, i.e., from 1980 onward, including a projection to 2020. Not surprisingly, the latter curve is almost a perfect mirror image of the former. Cohort component models have such a relationship embedded in their formal dynamics, simple exponential growth models do not. Thus the former will anticipate the forthcoming turning point in the elderly growth rate, whereas the latter will not.

6.3 Multiregional Population Projection Models with Uncertainty: An Example

6.3.1 Introduction

Although population futures are uncertain, some forecasted futures are more likely outcomes than others. To identify these, statistical agencies increasingly are bracketing their projected population futures with "low" and "high" values. More recently, they have issued ranges of possible outcomes, along with the probabilities associated with each forecasted value for the variables of interest.

A number of models and procedures have been put forward in the literature on probabilistic forecasting but the general absence of reliable time series data on migration often have forced analysts to adopt uniregional specifications with a focus on time series analysis of fertility and mortality rates, supplementing them with rather crude estimates of future migration patterns. An exception is the explorative study carried out by Raymer et al. (2012), in which vector autoregressive (VAR) models were used to forecast future rates of birth, death, and directional outmigration for the three macroregions of England's national territory.

There are a number of ways to specify subnational population projection models. Raymer et al. (2012) focus on four: (a) the simplest possible projection model that relies totally on the evolution of the annual growth rate, (b) the components-of-change growth model that breaks down the annual growth rate into its components birth, death, and *net* migration rates, (c) the same components-of-change growth model but with the net migration rate replaced by the corresponding in- and outmigration rates, and (d) the multiregional model with three regions and only destination-specific outmigration rates and no inmigration rates. Three more alternatives are added to "open-up" the model to international migration. The three options are *net* international migration rates, immigration and emigration rates, and immigration *counts* along with emigration rates.

6.3.2 A Three-Region Projection Model of England's Subnational Population Growth and Distribution: 1976–2008

Consider the three-region map of England that is set out in Fig. 6.2. Data obtained from the Office for National Statistics for the years 1976–2008 revealed that the North's population stayed around 14.6 million during that period, the 1976 Midlands population grew slightly from 9.0 to 9.8 million in 2008, and the population of the South increased from 23 to 26.9 million over the same periods (Raymer et al. 2012).

Recall the simplest uniregional aggregate population projection model of a region's total number of residents, first defined in Chap. 2, Eq. (2.6):

$$P_i(t+1) = (1 + r_i(t))P_i(t) \tag{6.1}$$

This aggregate population projection model, in its multiregional version, first appears in Chap. 2 as a two-region illustration that in matrix form is expressible as:

$$\{\mathbf{P}(t+1)\} = \mathbf{G}(t)\{\mathbf{P}(t)\} \tag{6.2}$$

where $\mathbf{G}(t)$ is the growth matrix that survives and grows the vector of regional populations at time t into the corresponding vector at time $t+1$.

This model can be expanded to include flows of international migration. Of the three ways of accomplishing the latter, examined in Raymer et al. (2012), only the third option is considered here: immigration is introduced as a count, whereas emigration appears as a rate in the diagonal elements of the growth matrix $\mathbf{G}$. Thus Eq. (6.2) then becomes

$$\{\mathbf{P}(t+1)\} = \mathbf{G}(t)\{\mathbf{P}(t)\} + \{\mathbf{I}(t)\} \tag{6.3}$$

Fig. 6.2 Map of regions in England. *Source* Raymer et al. (2012)

6.3.3 Forecasting Uncertainty in Component Rates

Two important issues need to be addressed in any effort to generate multiregional population forecasts:

> First, one must consider the spatial correlation between component rates across regions. Second, one must develop a parsimonious method of modeling and forecasting a larger number of migration rates. (Gullikson 2001, p. 2).

The first issue is addressed next. The second issue is dealt with in Sect. 6.4, when a disaggregation by age is introduced via parameterized model schedules.

Table 6.1 Correlations among crude regional demographics rates, 1976–2008

		B			D			O				
		N	M	S	N	M	S	N-M	N-S	M-N	M-S	S-N
B	M	0.99										
	S	0.82	0.83									
D	N	0.52	0.52	*0.03*								
	M	0.50	0.49	*0.06*	0.98							
	S	0.48	0.48	*−0.01*	0.99	0.97						
O	N-M	−0.53	−0.53	*−0.08*	−0.57	−0.46	−0.56					
	N-S	*0.33*	*0.31*	*0.32*	0.37	0.44	0.35	0.37				
	M-N	−0.56	−0.53	*−0.11*	−0.61	−0.51	−0.61	0.82	*0.09*			
	M-S	−0.47	−0.47	*−0.18*	−0.40	−0.35	−0.39	0.86	0.50	0.64		
	S-N	*−0.12*	*−0.09*	*0.16*	*−0.26*	*−0.16*	*−0.28*	0.45	*0.14*	0.79	*0.25*	
	S-M	−0.40	−0.39	*−0.01*	−0.59	−0.52	−0.61	0.77	*0.21*	0.83	0.66	0.73

Birth (B), death (D) and destination-specific outmigration (O) rates
Note: *Italics* = not significant at 0.05 level; *N* North, *M* Midlands, *S* South
Source Raymer et al. (2012)

The three-region model of England's population exhibits significant correlations among the demographic variables that are the inputs to a probabilistic population projection. Not all of the correlations were significant. Raymer et al. (2012) elected to include the correlations among the regional rates of each demographic component, as well as between the separate components of migration. The correlations among other demographics variables, birth rates, and death rates were not included because they exhibited weak associations and no clear patterns (Table 6.1).

Once the future uncertainties in the demographic components of change were established, the analysis turned to the problem of how to account for them over time and across regions.

Simulations of the results from the models fitted to the crude rates were used to quantify the future uncertainty in the forecasts based on the historical patterns in the demographic components. The projection models were initially closed to international migration to simplify the exposition. The effects of international migration were added later on.

In the familiar multiple regression model, the variable of interest is predicted by a linear combination of predictor variables. In an autoregressive model (AR), the predictor variables are past values of the variable of interest. Vector autoregressive models (VAR) allow for more than one evolving variable and may be used to introduce linear dependencies among multiple time series, e.g., correlations. In the three-region example presented in this section, vector autoregressive (VAR) time series models were used to account for correlations both over time and across regions. An AR model of order 1, denoted AR(1), is defined as

$$y_t = \mu + \beta y(t-1) + u_t \tag{6.4}$$

where y denotes a particular demographic rate, t denotes time period, μ represents the mean level of the process, β is the autoregressive coefficient representing the correlation between observations $y(t)$ and $y(t-1)$ and $u(t)$ is assumed to be independently normally distributed with zero mean and constant variance, σ^2. Predictions from this model can be obtained as

$$y_{T+1|T} = \mu + \alpha y_T, \tag{6.5}$$

where T is the last observation of $y(t)$. The 95 % prediction intervals for this value are calculated in the normal way. Once fitted, AR models can be used to forecast future values of the time series process.

When observations are taken simultaneously on two or more time series, a multivariate model to describe the interrelationships among several series of data can be developed. In other words, VAR models are the multivariate equivalent of the AR model outlined above. A VAR model describes the evolution of m variables as a linear function of their past observed values. The variables can be arranged into a set of $m \times 1$ vectors. A VAR model of order 1, denoted VAR(1), when $m = 3$ is defined as:

$$\begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \cdot \begin{bmatrix} y_1(t-1) \\ y_2(t-1) \\ y_3(t-1) \end{bmatrix} + \begin{bmatrix} u_1(t) \\ u_2(t) \\ u_3(t) \end{bmatrix}$$

This can be expressed in matrix notation as:

$$\{\mathbf{y}(t)\} = \{\mathbf{C}\} + \mathbf{A}\{\mathbf{y}(t-1)\} + \{\mathbf{u}(t)\} \tag{6.6}$$

where $\mathbf{C}$ is a $m \times 1$ vector of constants, $\mathbf{A}$ is a $m \times m$ matrix and $\mathbf{u}(t)$ is an $m \times 1$ vector of error terms. The matrix $\mathbf{A}$ captures the correlations over time and among regions. As the regional data are highly correlated, the VAR models are used to predict all of the crude rates used in the projection model. These include the crude rates of birth, death, destination-specific outmigration, and immigration and emigration.

For simplicity, only VAR(1) models were considered in the study. Most of the patterns are explained by the first lag, although alternative specifications with longer lags may be used. However, given the relatively short time series, it is difficult to test what the best model may be. The structure of the VAR model is not restricted and some parameters which might not be significant are included in the projection model. One major advantage of this approach is that the forecasts of the demographic inputs are predicted, not only based on past trends, but also by trends exhibited simultaneously in other regions.

6.3.4 Results: Forecasted Regional Closed and Open Populations

The conventional procedure for producing regional population forecasts generally is one of first obtaining probabilistic forecasts of the component rates and, then, second, of drawing on those rates to produce probabilistic forecasts of the associated projected population. Generally, it is convenient to first forecast the regional populations, ignoring international migration and then adding emigration and immigration to follow that up with the corresponding “open” projections.

Figure 6.3 presents vector autoregressive (VAR) probabilistic forecasts of the six crude destination-specific internal outmigration rates from the North, Midlands, and South regions, for the years 2009–2021. The predicted rates and corresponding predicted intervals are revealing. For example, the outmigration rates from the North and Midlands are, in general, significantly higher than those for the South, as are the predicted intervals for the North to South and Midlands to South flows. The narrowest prediction interval is that of the North to Midlands flow.

The forecasted rates of the demographic components were used as inputs into the multiregional population projection model, and simulations produced the desired median forecasts and associated prediction intervals up to the year 2021.

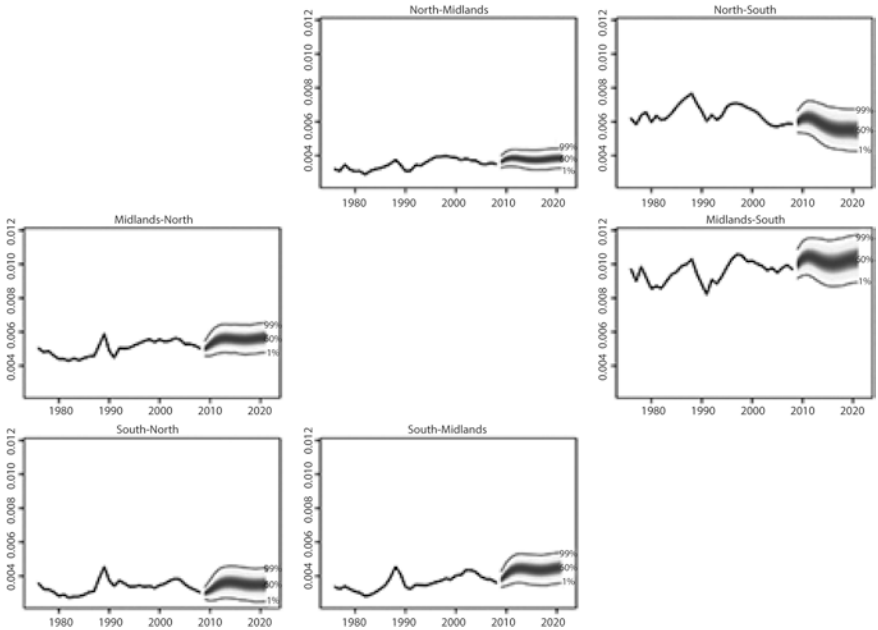

Fig. 6.3 Vector autoregressive forecasts of crude destination-specific outmigration rates from the North, Midlands, and South regions: 2009–2021. *Source*: Raymer et al. (2012)

Details of the methodology and results are described in Raymer et al. (2012). Figure 6.4 contrasts the results of the "closed" multiregional model forecasts with those obtained for the simplest probabilistic uniregional growth rate model for each of the three regions. In each instance, the median forecasted totals produced by the uniregional model are higher and the prediction intervals are generally wider. Model specification clearly makes a difference, and the overall results challenge the argument that simple models outperform complex models. Specification matters, even with a small and relatively stable example.

It is quite likely that the differences exhibited in Fig. 6.4 would be significantly larger if more regions were considered, especially if a disaggregation by age were introduced as well. As Raymer et al. (2012) observe, if the numbers of regions were increased, say, to the 9 Government Office Regions in England, the multiregional model would contain 72 interregional migration flows to be modelled instead of the 6 flows modelled by the three-region model. If a disaggregation by age or age groups were introduced, the variation would be considerably greater and the VAR models used in this example would become inappropriate. The VAR models used above are not designed to handle large matrices of time series flows. To overcome this obstacle, one could change the focus from component rates to a focus on the time-varying parameters of *model schedules* describing the changing levels and age patterns fitted to those component rates. The next section of this chapter illustrates such a strategy by describing parameterized population models and forecasts (Table 6.2).

Finally, in comparison with recent subnational projections produced by the Office for National Statistics (ONS), the Raymer et al. (2012) median (and even 25th percentile) results are somewhat higher. They projected that in 2021 there would be 15.70 million persons in the North, 10.69 million persons in the Midlands and 30.03 million persons in the South. The ONS utilizes a cohort-component projection model with a combination of recent trends (5–10 years) and expert judgements, whereas the above multiregional model forecasts were based solely on historical data ***aggregated over age and sex***.

Both age and sex are very important for producing more accurate population projections. However, to include age and sex in a subnational probabilistic framework, the correlations across age groups, between sexes, as well as over time/space and between demographic components would have to be considered. Since this would multiply the number of parameters considerably, alternative specifications to reduce the dimensionality of the age-specific data would have to be considered.

Extending the approach used in Raymer et al. (2012) to include more regions, such as the nine Government Office Regions in England, let alone the nearly fifty counties, would require a different approach. The VAR models, used in this chapter, are not designed to handle so many different series. One idea would be to include some structure in the VAR models. Another would be to focus on modelling just the time-dependent structures in the migration flow tables, as Sweeney and Konty (2002) did for regions in California. Finally, yet another approach would be to introduce parameterized model schedules (Rogers 1986). By reducing

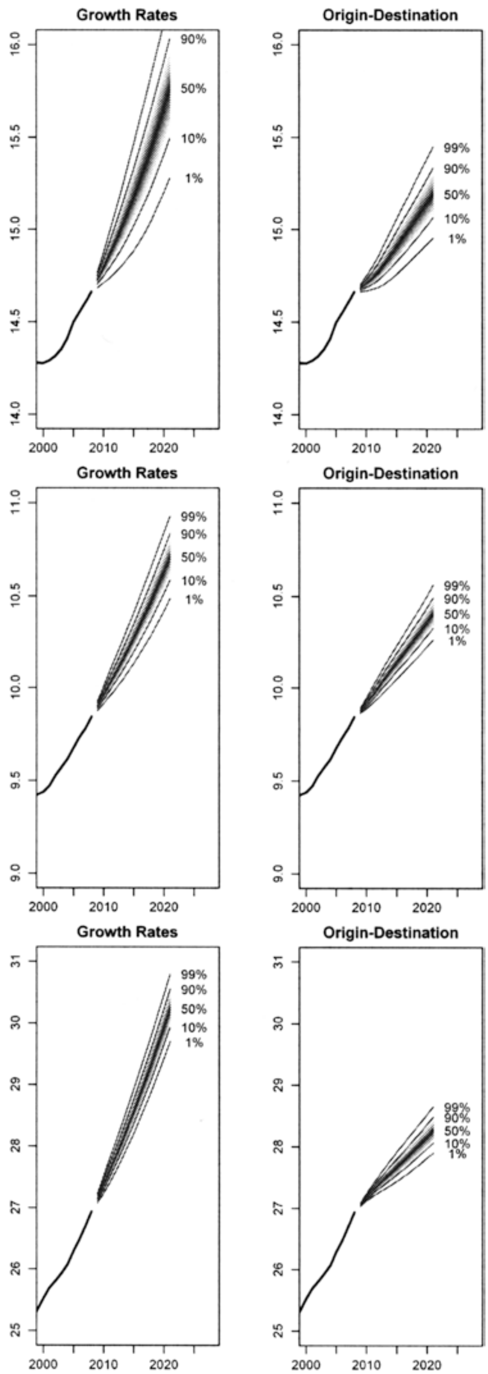

Fig. 6.4 Two closed regional population forecasts (in thousands) for the North, Midlands, and South regions: 2009–2021. *Source* Raymer et al. (2012)

Table 6.2 Closed and open multiregional population forecasts (in thousands) for the North (*top*), Midlands (*middle*) and South (*bottom*) regions, 2009–2021

Region	Percentile	Closed model	Open model: IM counts and EM rates
North	25	15.08	16.6
	50	15.15	16.7
	75	15.21	16.79
Midlands	25	10.32	11.36
	50	10.36	11.41
	75	10.40	11.47
South	25	28.07	32.97
	50	28.17	33.12
	75	28.27	33.28
Total	25	53.47	60.93
	50	53.67	61.23
	75	53.88	61.54

Note: *IM* immigration, *EM* emigration
Source Raymer et al. (2012)

the dimensionality of the migration flow tables, the modelling of the migration flow tables would be greatly simplified. For example, a multiregional region with nine subpopulations requires 72 origin-destination-specific flows. If one were to just focus on the time-dependent model schedule parameters, one would model just 27 time series instead of 72 time series.

6.4 Parameterized Multiregional Forecasting Models: A Time Series Approach

6.4.1 Introduction

Disaggregated multiregional population projections generally need to keep track of enormous amounts of data. The disaggregations incorporated in such projections are introduced either because forecasts of the specified population subgroups are important in their own right, or because it is believed that simple and regular trends are more likely to be discovered at relatively higher levels of disaggregation.

High levels of disaggregation permit a greater flexibility in the use of the projections by a wide variety of users; they also often lead to a detection of greater consistency in patterns of behavior among more homogeneous population subgroups. But greater disaggregation requires the estimation of ever greater numbers of data points, both those describing initial population stocks and those defining the future rates of events and flows that are expected to occur. The practical difficulties of obtaining and interpreting such data soon outstrip the benefits of disaggregation.

Mathematical descriptions of schedules of demographic rates, here called *parameterized model schedules,* offer a means for condensing the amount of information to be specified as assumptions. They also express this condensed information in a language and in variables that are more readily understood by the users of the projections, and they provide a convenient way of associating the variables to one another, extrapolating them over time, and relating them to variables describing the economic environment that underlies the projections.

The use of parameterized model schedules in the population projection process allows one to develop an effective description of how the components of demographic change (for example, mortality, fertility, and migration) are assumed to vary over time, in terms of a relatively few parameters. To the extent that the assumptions correctly anticipate the future, the projection foretells what indeed comes to pass. And insofar as the parameters are readily interpretable by nondemographer users of the projection, they make possible the assessment of the reasonableness of a set of assumptions instead of a set of projected population totals.

Finally, a trend extrapolation of each and every age-specific rate in a population projection is an excessive concession to flexibility that can readily produce erratic results. On the other hand, to assume that change in a set of rates occurs uniformly at all ages is to go against experience. Parameterized model schedules offer a way of introducing flexibility while retaining the interdependence between the rates of a particular schedule.

6.4.2 Parameterized Model Schedules

Parameterized model schedules describe the remarkably persistent regularities in age pattern that are exhibited by many empirical schedules of age-specific rates. Mortality schedules, for example, normally show a moderately high death rate following birth, after which the rates drop to a minimum between ages 10 and 15, then increase slowly until about age 50, and thereafter rise at an increasing pace until the last years of life. Fertility rates generally start to take on nonzero values at about age 15 and attain a maximum somewhere between ages 20 and 30; the curve is unimodal and declines to zero once again at some age close to 50. Similar unimodal profiles may be found in schedules of first marriage, divorce, and remarriage.

The most prominent regularity in age-specific schedules of migration is the high concentration of migration among young adults; rates of migration also are high among children, starting with a peak during the first year of life, dropping to a low point at about age 16, turning sharply upward to a peak near ages 20–22, and declining regularly thereafter, except for a possible slight hump or upward slope at the onset of the principal ages of retirement.

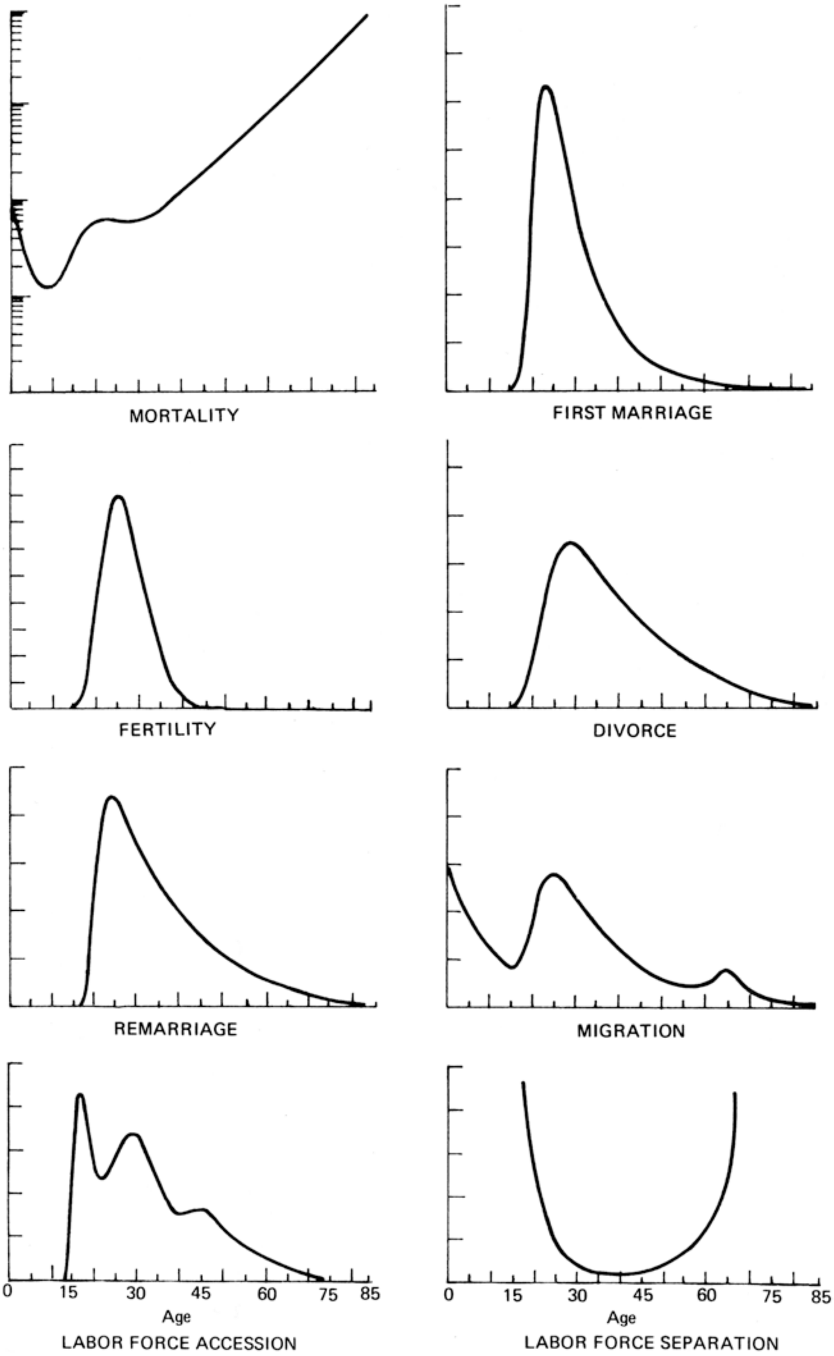

Fig. 6.5 An assortment of model schedules. *Source* Rogers (1986)

Figure 6.5 illustrates a number of typical age profiles exhibited by schedules of rates in multistate demography. All were fitted with various reduced forms of the model migration defined in Eq. (6.7) below.

The shape, or *profile,* of a schedule of age-specific rates is a feature that may be usefully examined independently of its intensity, or *level.* This is because there are considerable empirical data showing that although the latter tends to vary significantly from place to place, the former remains remarkably similar.

A large number of model schedules have been developed by actuaries, demographers, and statisticians over the past decades. In general, such schedules take one of two distinct approaches to summarizing a demographic schedule of rates in terms of a relatively few parameters: *functional* (analytical) representations and *relational* representations. Functional representations describe the age pattern of the entire schedule by a mathematical curve whose shape depends on the particular function that is adopted and on the values assumed by the several parameters that appear in this function. The Heligman and Pollard (1980) model mortality schedule and the Rogers and Castro (1981) model migration schedule are examples of this class of model schedules. Because the age patterns of most demographic schedules involve, at the very least, indices that position the mathematical curve along the age axis (location), establish its level (height), and determine its upward and downward slopes (shape), functional representations of such schedules necessarily require several parameters to describe most age patterns. This need for multiple parameters has led many demographers to adopt the more economical relational representations instead. Relational representations describe an observed age pattern by associating it with a “standard” pattern and specifying the observed schedule’s particular deviations from this standard pattern in terms of, typically, one or two parameters. The Brass (1974) and Lee and Carter (1992) model mortality schedules, the Coale and Trussell (1974) model fertility schedule are members of this class of model schedules.

6.4.3 A Parameterized Forecasting Model

McNown et al. (1995) set out parameterized forecasting models of the U.S. population that emphasize model selection over demographic accounting and that do so by focusing on the temporal evolution of model schedule parameters for the schedules used in the projection process.

The application of such a methodology to fertility and mortality provides a unified forecasting system for two key sources of demographic change. Because of the absence of adequate data over time on migration, the contribution of this demographic component of change often are dealt with by assuming a fixed annual level or rate of net migration. This forecasting system yields unconditional or conditional forecasts of age-specific vital rates, and the populations implied by these rates. Reliance on time series methods, rather than on expert opinion, yields forecasts that are replicable and based on transparent assumptions. The use of time series methods also yields interval forecasts of the model schedule parameters, and, indirectly, interval forecasts of the demographic rates, populations, and other summary measures of demographic change.

When the vector autoregressive models (VAR), used in the preceding section of this chapter, are unsuitable for models of larger scale, autoregressive integrated moving average (ARIMA) models may be more appropriate alternatives. If plots of the times series suggest nonstationary behavior, first or higher order differencing may be required.

The use of parameterized schedules provides a compact representation of the vast quantity of data involved in projections of age-specific rates. Summarizing complete age profiles with a small number of parameters yields a transparent description of historical and projected changes in these profiles. Age profiles of mortality, fertility, and migration may be represented by variants of the multiexponential model,

$$\begin{aligned} f(x) = {} & a_1 \exp(-\alpha_1 x) \\ & + a_2 \exp\left\{\alpha_2(x-\mu_2) - \exp\left[-\lambda_2(x-\mu_2)\right]\right\} \\ & + a_3 \exp\left\{\alpha_3(x-\mu_3) - \exp\left[-\lambda_3(x-\mu_2)\right]\right\} \\ & + a_4 \exp(\lambda_4 x) \\ & + c \end{aligned} \tag{6.7}$$

where x indicates years of age, and y_x, is a rate or probability at age x. The other elements in this function are parameters that collectively define the age profiles. In previous research, for example, in Rogers and Little (1994) and it was demonstrated that variants of the multiexponential model can satisfactorily represent age profiles of mortality, fertility, and migration across a number of populations. In modeling mortality, the individual terms of the function are included to represent, respectively, a constant term, infant and childhood mortality declining exponentially through the early years of age, the "accident hump" of young adult mortality, and senescent mortality following an upward sloping curve (McNown and Rogers 1992). For fertility, only the third term of the function is retained, with the four parameters estimated over the childbearing ages (Knudsen et al. 1993). Migration schedules, on the other hand, typically involve the entire multiexponential model. Projections made at five year intervals normally follow the standard equation

$$\{\mathbf{P}(t+1)\} = \mathbf{G}(t)\{\mathbf{P}(t)\} + \{\mathbf{I}(t)\} \tag{6.8}$$

where, as before, $\{\mathbf{P}(t)\}$ is a vector of populations by age at year t, $\mathbf{G}(t)$ is the growth matrix of fertility and survivorship rates, and $\{\mathbf{I}(t)\}$ is a vector of net immigrants by age.

The question regarding the relative performance of simple versus complex models is often addressed by presenting the issue in *ex ante* terms. Recognizing that every population projection starts out without a "track record," with which to evaluate performance, a conventional approach focuses on two indices of such performance: the plausibility of the point forecast produced and the range of uncertainty surrounding that point forecast. The latter calls for the development of a stochastic forecasting methodology. Model schedule representations of past age-specific fertility and mortality rates, ARIMA models of their parameterized representations over time, and Monte-Carlo simulations of their associated future stochastic population projections form the core of this methodology.

6.5 Discussion and Conclusion

In considering the question of whether simple models outperform complex models it is essential to recognize that there is not merely one simple model against which the complex cohort component model can be compared. Rather there are many different simple methods—growth rate extrapolations, trend extrapolations, ARIMA models, etc.—from which to choose. Furthermore, within each of these categories there are subsequent modeling decisions that can substantially affect the results produced by the simple projections. For example, after choosing trend extrapolation as a simple projection framework, one must then decide on the base period over which to establish the trend. In the case of fertility projections, for example, it is clear that a choice from among the most recent five years, the past ten years, or the past thirty years will lead to three vastly different values for the trend in fertility. Yet another example is offered within the ARIMA modeling framework, in which the projections of total population may demonstrate the sensitivity of the point and interval forecasts to judgmental issues of model specification. A true measure of forecasting uncertainty needs to incorporate both the uncertainty over the choice of technique and that of model specification.

Experiments carried out with simple models, have revealed an apparent trade-off between plausible point forecasts and narrower interval forecasts. Methods that base trend estimates on long historical periods tend to produce narrower confidence intervals. The smaller confidence intervals of the methods that rely on longer time series result from the inverse relation between dispersion and the number of observations, as implied by standard statistical formulas. The implausibility of the point forecasts result from the use of historical trends that are no longer relevant to current and future demographic changes.

The particular integration of time series methods, parameterized model schedules, and the cohort component projection framework presented, for example, in McNown et al. (1995) provides a compromise within the trade-off between narrow interval forecasts and plausible central forecasts. For forecast horizons of thirty years or less, this projection methodology produces point and interval forecasts that appear reasonable in relation to those developed by others. Although consumers of demographic projections would prefer even narrower forecast intervals, the uncertainty described by these projections is a reflection of the historical variation in the components of demographic change.

In conclusion, a number of observations are suggested by this review of the simple versus complex models debate. They are listed here, in no particular order, to stimulate further informed debate on the issue.

First, whether simple models outperform complex models is an empirical issue that depends on the particular historical period observed and the degree of demographic variability exhibited during this period. In consequence, it is imperative to somehow control for the relative degree of difficulty associated with each historical period. Rigorously developed forecasting tournaments could be a useful vehicle for introducing such control.

Second, paralleling the degree of difficulty of the phenomenon is the degree of robustness of the model adopted to forecast that phenomenon. Although many argue that "there is no single best model for all occasions," that proposition is unconvincing because forecasters usually cannot anticipate the likely occasions that are in prospect. They are in the position of couples at a ballroom dancing competition, drawing dancing assignments out of a hat. To be best at waltzing does them no good, if the selection is to dance a tango. Thus of what *ex ante* use are findings such as: "…exponential extrapolation was found to be most accurate for rapidly growing or declining areas, whereas linear extrapolation was most accurate for moderately growing areas." (Isserman 1977, p. 247)

Third, accuracy is a multidimensional notion for which aggregate indices, such as root-mean-square errors, are an inadequate measure. Such indices are subject to the ruses of heterogeneity. For example, they weight equally the errors contributed by populations of vastly different sizes. And they are highly susceptible to compensating errors generated by fertility, mortality, and migration forecasts that err in opposing directions, thereby according to a spurious sense of accuracy for the forecasting exercise.

Fourth, the simple versus complex classification has been viewed as a dichotomy when in fact it is a continuum. If, simple exponential growth models with no age or locational disaggregation represent one end of the continuum, among the extrapolative linear forecasting models, and detailed multiregional growth models the other, then what can be said of the relative accuracy of models that lie in between these extremes? Should their performance indices lie in between those of the two defining the continuum? And if they do not (which is likely), then what conclusions can one legitimately draw about the simple versus complex model issue?

Fifth, model performance is a multifaceted concept that involves much more than forecasting accuracy alone. Additional attributes such as transparency, utility, and face validity all play an important role in the presentation of official population forecasts. Even though simple models may have predicted last year's population more accurately, would one bet one's earnings that they will do so again for next year's population?

Much of demographic analysis has focused on the appropriate specification and accurate measurement of the dependent variables at the center of population forecasting activities. This body of work has helped to identify regularities that may have been obscured by earlier inappropriate representations and measurements. The modeling strategy that this suggests for population forecasting efforts may be summarized in the motto: *forecast only changing behavior, taking appropriate advantage of well-established regularities and accounting relationships, and do not forecast "*de novo*" relationships that are stable enough to not need forecasting.* Exploiting observed regularities in the relative age patterns of demographic rates and adopting the standard age-specific demographic accounting equations are prominent examples of such an approach, and it is a strategy that still offers the best hope for marginally reducing the error made in past forecasts.

Finally, demographic forecasts should fit the needs of users, particularly with regard to level of detail and age disaggregation. Forecasts of the total population are of little use to school boards or health care providers, who are more concerned with future populations of specific age groups. Users of demographic forecasts should also understand that projections come with some degree of uncertainty. Conditional confidence intervals offer estimates of the extent of uncertainty, and these are particularly useful if they are statistically based intervals.

The particular integration of time series methods, parameterized model schedules, and the cohort-component projection model presented in this chapter provides a framework for demographic forecasting that is consistent with these objectives. The simple models that may be employed as benchmarks in evaluating the plausibility of forecasts do not fare well according to these *ex ante* criteria, however. But the demonstrated success of simple extrapolations in *ex post* forecast accuracy studies establishes a role for these methods, in tracking the performance of complex methods that do meet the criteria of face validity, internal consistency, and level of detail.

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Chapter 7
When Regions Are Status Categories: Does Longer Life Lead to Longer Ill Health?

Abstract An average individual's remaining life expectancy free of disability—referred to as healthy or active life expectancy—is a popular measure of population's state of health. Such expectancies are often calculated to address the question whether the currently observed increases in total life expectancy are accompanied by increases in active life expectancy. Past studies used to conclude that the positive trends in the prolongation of life had not been matched by similar trends in the extension of healthy life. Typical of their assessments was the pessimistic conclusion that Americans were not living longer healthy lives. Additions to life expectancy, it was argued, were concentrated in the disabled years—primarily years of long-term disability. This chapter challenges such conclusions and demonstrates that a reliance on prevalence rather than incidence rates in the analysis leads to the pessimistic assessment.

Keywords Active life expectancies · Dependent elderly populations · Activities of daily living · Multistate demography

7.1 Introduction

A number of past studies of longevity and health among the elderly that have compared changes in total life expectancy with corresponding changes in disability-free life expectancy have concluded that the positive trends in the prolongation of life have not been matched by similar trends in the extension of *healthy* life. Many reached the relatively pessimistic conclusion that Americans were not living longer healthy lives. Additions to life expectancy, it used to be argued, were mostly concentrated in the disabled state.

A representative sample of answers to the question appeared in the May 1991 special issue of the *Journal of Aging and Health*, entitled "Living Longer and Doing Worse? Present and Future Trends in the Health of the Elderly" (Haan et al. 1991). The answers to this question were mostly on the pessimistic side. Common

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DOI 10.1007/978-3-319-22318-6_7

to almost all such studies was a reliance on *prevalence* rather than *incidence* rates for the analysis (e.g., Crimmins et al. 1989).

7.2 The Problematic Prevalence Rate Once Again

Can prevalence rates be increasing even while incidence rates for dependency and for recovery remain unchanged or are improving? Consider, for example, the transitions between independent (healthy) and dependent (disabled) statuses set out in Fig. 7.1. These numbers came from a longitudinal data set: the 1986 Longitudinal Study of Aging (LSOA) collected by the U.S. Department of Health and Human Services (Rogers et al. 1990). This data set is the result of a reinterview of 5151 individuals, aged 70 and over, in an earlier survey, the 1984 Supplement on Aging (SOA).

Classifying the respondents as dependent or independent on the basis of their responses, and appropriately weighting the sample flows to approximate national totals, gave rise to the aggregate flows set out in Fig. 7.1. Respondents were considered dependent if they were institutionalized (in 1986) or needed assistance with any one of the following seven tasks (called Activities of Daily Living, or ADLs for short) eating, bathing, dressing, transferring (getting in or out of a bed or chair), walking, toileting (getting to or using the toilet), and getting outside.

7.2.1 A Simple Illustration

According to Fig. 7.1, about 11,629,247/13,081,356 = 88.9 % of the U.S. elderly population aged 70 and over was independent in 1984 and 1,452,109/13,081,356 = 11.1 %

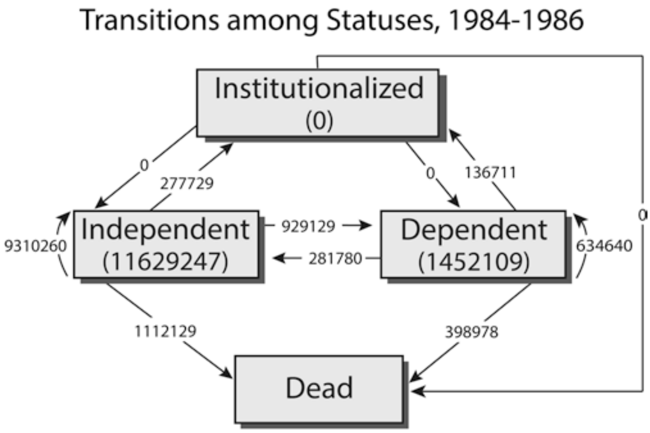

Fig. 7.1 Transitions among active life statuses: United States, 1984–1986. *Source* Adapted from Rogers et al. (1989)

was dependent. Two years later, only 84.65 % of the populations was independent and 15.35 % was dependent. Those institutionalized between 1984 and 1986 were added to the dependent category, thereby inflating it somewhat. Because no data on the institutionalized population in 1984 were collected by the survey, one could not adopt a three-way status disaggregation and had to either add the institutionalized population to the dependent total or to delete it altogether. After experimenting with both alternatives, and concluding that the general "story" told by both versions was the same, the first alternative was adopted.

Applying the proportions describing the interstatus transitions, set out in Fig. 7.1, to the 1984 two-status population, and adding the "new" entrants (i.e., the population aged 70–72) into the elderly population during the 1984–1986 interval, one obtains the 1986 population distribution:

Dependent population
(0.53119)1,452,109 + (0.10378)11, 629,247 + 302,179 = 2,280,388

Independent population
(0.19405)1,452,109 + (0.80059)11,629,247 + 2,982,821 = 12,574,861

where

0.53119 = 634,640/(136,711 + 634,640)
0.10378 = (277,729 + 929,129)/11,629,247
0.19405 = 281,780/1,452,109
0.80059 = 9,310,260/11,629,247.

A comparison of the 1986 % dependent with its 1984 counterpart reveals that the prevalence of dependence increased over the two years. (This occurs even if the institutionalized population is left out of the 1986 dependent total.) The perspective of the prevalence-rate life table model would lead one to conclude that the population was experiencing a deterioration in its health status. But this pessimistic view is unwarranted; data over a single unit time interval are insufficient to produce such a finding. What one needs are comparable data for the second unit time interval (1986–1988) and a comparison of the interstatus transition proportions.

Alternatively, consider the hypothetical scenario of no change. Keeping the proportions fixed at their 1984–1986 values, gives the projection:

Dependent population
(0.53119)2,280,388 + (0.10378)12,574,861 + 306,540 = 2,822,859

Independent population
(0.19405)2,280,388 + (0.80059)12,574,861 + 3,099,460 = 13,609,276

The prevalence of dependency increases once again (from 15.35 to 17.18 %), yet the projection assumed that health status transition proportions did not change over time. How can health conditions become worse if the probabilities of becoming dependent, recovering to independent status, and dying are all held constant? The answer lies in the measure of health conditions: *the prevalence index*. By combining both subpopulations in its denominator, it biases the findings in the direction of increased dependency, whenever the independent population is very much larger than the corresponding dependent population. The much heavier weighting that it accords to the transition to dependency virtually guarantees that the subsequent percentage dependent figure will increase. For example, in the above numerical illustration, the independent population is approximately eight times the size of the dependent population. Consequently, the probability of the transition to dependency (0.10378) receives eight times the "weight" received by the corresponding probability of transition to independence (0.19405). The result is an increase in the percentage of the population that is dependent.

The above discussion has ignored the effects of age composition. But the same result occurs in a unistate age-specific analysis, as the results of a full-blown age-specific analysis that produces a prevalence-based life table demonstrates.

7.2.2 The Prevalence Rate Life Table Model

Imagine a normal life table that starts with a cohort of, say, 100,000 70-year olds and survives them age-by-age until the last member dies. Because the LSOA data span a 2-year interval (1984–1986), consider a life table that deals with 2-year age groups: 70–72, 72–74, and so on, until the last open-ended age group of 96 years and older. The mortality regime is that which existed during 1984–1986, and the two sexes are combined. Standard calculations, using 1986 prevalence rates, give rise to a remaining life expectancy of 12.88 years at age 70 and of 7.74 years at age 80 (Rogers et al. 1990).

The LSOA data reveal that 9.1 % of 70- to 72-year olds in 1986 were in the dependent status, as indicated by their need for assistance in carrying out at least one of the seven ADLs recorded by the survey. The life table lists 192,942 persons as being members of the stationary life table population aged 70–72 years at last birthday, the first entry in the usual $L(x)$ column. Applying the prevalence rate of 9.1 % to that figure yields 17,562 dependent persons, with the remaining 175,380 individuals classified as independent. Continuing on in this manner gives rise to a total life table dependent population of 276,716 and a corresponding total independent population of 1,011,476. Dividing each of these two figures by the size of the initial cohort of 100,000 results in a life expectancy free of dependency, of 10.11 years and a corresponding expectation of life with dependency of 2.77 years. Thus, according to this 1986 life table, a 70-year old individual can expect to live 78.49 % of his or her expected remaining lifetime in the independent state. This index is the *active life percentage*. Because this form of life table does not distinguish between independent and dependent individuals in the starting cohort, no separate active life expectancy percentages can be calculated for the two subpopulations: those independent and those dependent at age 70. Moreover, note that a projection from 1986 to 1990 shows a decline in the Active Life Expectancy to 74.69 % (Table 7.1).

Table 7.1 A comparison of the unistate prevalence life table model results

Model	Active life expectancy for the independent population at age 70
1. *Prevalence-rate life table model (1986)*	
Life expectancy at 70	12.88
Active life expectancy at 70	10.11
Active life %	78.49
2. *Prevalence-rate life table model (1990)*	
Life expectancy at 70	12.88
Active life expectancy at 70	9.62
Active life %	74.69

Source Rogers et al. (1990)

The idea of combining mortality and morbidity or disability data to analyze expected disability-free years of life within the life table perspective is not new, having been already proposed, for example, by statisticians almost over a century ago (DuPasquier 1912). Yet a number of studies continue to use Sullivan's (1971) particular formulation of the Expectation of Life Without Disability Index, obtained from what for convenience may be called "the prevalence rate life table model." The use of *incidence* rates in a computational sequence that produces an empirically based multistate life table is relatively more recent, however, with the first such empirical model appearing in Rogers et al. (1989). Both forms of life table develop estimates of the number of remaining disability-free years of life.

According to Sullivan (1971), for example, this expectation of disability is an estimate of the number of years of disability a member of a life table cohort would experience if current age-specific rates of mortality and disability prevailed throughout the cohort's lifetime. Two features characterize the Sullivan method of calculating a life table. First, the age-specific disability rates referred to are prevalence rates and not incidence rates. That is, they do not define the rate at which healthy individuals become disabled individuals. *Second*, only cross-sectional data for one point in time—on the age-specific fractions disabled at time t—are needed to fit the model. Both features are dropped in the multistate life table, which needs panel-type data that describe movements between two distinct points in time, t to $t + 1$, say.

7.2.3 When Regions Are Status Categories: A Multistate Model of Active Life

A multistate life table analysis of active life expectancy begins with a derivation of age-specific transition probabilities that describe the interstate movements of the two state-specific subpopulations—independent and dependent persons—and their respective probabilities of dying within the age interval. Starting with a radix of arbitrary size for each of the two subpopulations, the computational procedure both survives persons in their current status and also moves persons from one status to the other. Adding up the number of person-years that are lived in each status by those originally in each of the two radices gives rise to expectations of remaining life lived in each of the two statuses (independent and dependent).

By way of illustration, consider the health data collected by the first and second waves of the Massachusetts Health Care Panel Study and used by Katz et al. (1983). Calculating a standard multistate life table model using that data set that allowed returns to independence, Rogers et al. (1989), found that active life expectancy for those initially independent decreased with age, from 14.7 years for those aged 65 years to 5.6 years for those aged 80 years and to 3.8 for those aged 85 and older. The single-year-of-age multistate analysis outlined in that article also provides a set of active life expectancies for those initially *dependent*—the corresponding numbers for this group being 11.1, 2.5, and 0.9 years, respectively.

Returning next to the LSOA data illustrated in Fig. 7.1, consider the results of a standard multistate life table of that data, set out in Table 7.2, which records the active life expectancies for the total United States population, according to initial independent and dependent functional statuses. The results are reported for the total population only, and age is in even-numbered years, beginning at age 70, because the LSOA began at age 70 and reinterviewed respondents two years later. Therefore, the risk of an occurrence of an event was calculated over a two-year interval. Overall, life expectancies decrease with increasing age, and the proportion of time spent in an independent status decreases correspondingly. Further, life expectancies are higher for the independent than the dependent population.

Panel A in Table 7.2 records that individuals who were *independent* at age 70 could expect to live another 13.4 years, on average, of which 75 % could

Table 7.2 Expectations of remaining life for individuals aged 70 and over: two functional statuses, United States, 1984[a]

A. Independent at age x				B. Dependent at age x		
Age x	Total remaining years	Remaining independent years	Remaining dependent years	Total remaining years	Remaining independent years	Remaining dependent years
70	13.4	10.1 (75 %)	3.4 (25 %)	12.5	6.4 (51 %)	6.1 (49 %)
72	12.2	8.9 (73)	3.3 (27)	11.3	5.5 (48)	5.8 (52)
74	11.1	7.8 (71)	3.3 (29)	10.1	4.1 (41)	6.0 (59)
76	10.0	6.8 (68)	3.2 (32)	8.9	2.8 (32)	6.1 (68)
78	9.0	5.9 (66)	3.1 (34)	8.0	2.4 (29)	5.7 (71)
80	8.1	5.2 (63)	3.0 (37)	7.2	2.0 (28)	5.2 (72)
82	7.3	4.5 (61)	2.8 (39)	6.5	1.6 (25)	4.9 (75)
84	6.6	3.9 (59)	2.7 (41)	5.9	1.4 (24)	4.5 (76)
86	6.0	3.4 (57)	2.6 (43)	5.3	1.1 (21)	4.2 (79)
88	5.5	3.1 (56)	2.4 (44)	4.8	0.9 (18)	4.0 (82)
90	5.2	2.9 (56)	2.3 (44)	4.5	0.8 (19)	3.7 (81)
92	4.9	2.6 (53)	2.3 (47)	4.3	0.8 (19)	3.5 (81)

Source: Calculations based on LSOA data (U.S. Department of Health and Human Services 1988)
[a]Based on 7ADLs. (dependent is defined as limited in 1 or more ADLs)
Percentages may vary due to rounding

be expected to be spent in the active status and 25 % in the dependent status. Individuals who were independent at age 90 could expect to live another 5.2 years, of which 56 % could be expected to be spent in the active status and 44 % in the dependent status.

Panel B in Table 7.2 records that individuals who were *dependent* at age 70 could expect to live another 12.5 years, on average. Such individuals could expect to live about one-half of their remaining years in active life (i.e., by a “recovery”). Individuals in the United States who were dependent at age 90 could expect to live another 4.5 years, of which 80 % would be spent in the dependent status. With increasing age, the chances of experiencing life in a dependent status increases and the chances of experiencing a recovery decreases.

In conclusion, an individual who was independent at age 70 could expect to live an additional 10.1 years in an active status. An individual who was independent at age 70 could expect to spend 3.3 years in the dependent status (13.4 year minus 10.1 years). Overall, individuals who were dependent at age *x* relative to those who were dependent at age *x* could expect longer, more active lives, with a smaller proportion of time spent in a dependent status (compare panels A and B).

7.3 Changes in Active Life Among the Elderly in the United States: 1984–1988

In a later study, Rogers et al. (1991) turned to the data produced by the Longitudinal Study of Aging (LSOA) in its second wave. At the time of the study, the LSOA data included interviews in 1984, 1986, and 1988. Because it originally began as a survey of the noninstitutionalized population, the 1984 survey included only the civilian population. The LSOA in 1986, however, also included those elderly who became institutionalized between 1984 and 1986. Moreover, the LSOA in 1988 included those who remained institutionalized between 1986 and 1988, and those who were institutionalized but who “recovered” and reentered the civilian population in 1988. Therefore, this latter data set permitted the calculation of transitions into and out of institutions between 1986 and 1988.

In this study, respondents were classified as independent, dependent, or institutionalized based on their ADL responses and on whether they reported spending time in an institution. For consistency with the earlier research, life-table results were once again based on the seven ADLs used earlier. Individuals who were institutionalized were included in the multistate analysis. Those who were neither institutionalized nor dependent were coded as being independent.

Figure 7.2 displays the static and dynamic aspects of individuals and their statuses for and transition patterns between 1986 and 1988. The estimates are weighted to represent the U.S. population aged 72 and above. The numbers in parentheses show the 1986 population. The numbers along the curved arrows represent the number of individuals who remained in their status between 1986 and

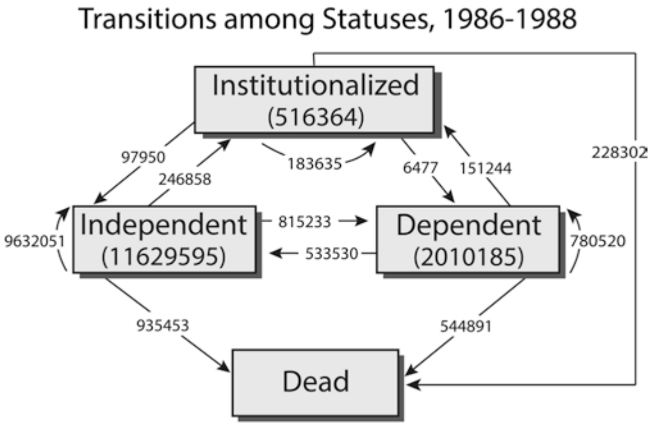

Fig. 7.2 Transitions among active life statuses: United States, 1986–1988. *Source* Adapted from Rogers et al. (1991)

1988. Finally, the numbers along the straight arrows show transitions between statuses occupied in 1986 and 1988.

Several important points emerge from this illustration. First, the independent population is much larger than either the dependent or the institutionalized population—for example, the 1986 independent population is almost six times larger than the corresponding dependent population. Second, the independent and dependent populations display a greater propensity to retain their status than to transfer to any other status—for instance, between 1986 and 1988, some 83 % of the independent respondents remained independent and 39 % of the dependent respondents remained dependent. Third, most of the institutionalized population either remained institutionalized or died—of those who were institutionalized in 1986, 44 % died in 1988, and 36 % remained in an institution. Fourth, among those who were dependent or institutionalized in 1986, a relatively large percentage were able to regain a more active status—for example, over one-quarter of those who were dependent in 1986 became independent in 1988, and almost 20 % of those who were institutionalized in 1986 became independent in 1988. This latter finding, that a larger proportion of the elderly institutionalized population became independent rather than dependent, is surprising. These results may be due to elderly who have short "spells" of institutionalization because of physical ailments; once these ailments are remedied, the elderly can become independent again. Or, it may be that these transitions do not represent a "true" picture because they do not control for the age structure of the population. A more useful and precise set of results, is possible with an age-specific multistate analysis (Rogers et al. 1991). Such an analysis revealed a number of interesting findings. First, as might be expected, persons who were initially independent were projected to have longer lives than those in the other two statuses. For example, those who were independent at age 72 could expect to live almost 12 more years, to age 84; those in the dependent status could expect to live an additional 10 years, to 82; and those in institutions could expect to live 7 more years, to 79 (Table 7.3).

Perhaps of greater importance than total life expectancy, however, are the expected years to be spent in active life. Those who were independent at age 72

Table 7.3 Expectations of remaining life for individuals aged 72 and over: United States, 1986[a]

Age x	Total remaining years	Remaining independent	Remaining dependent years	Remaining institutionalized years
A. Independent at age x				
72	11.7	9.6 (83 %)	1.4 (12 %)	–6 (6 %)
74	10.6	8.6 (81)	1.4 (13)	–6 (5)
76	9.6	7.6 (80)	1.4 (14)	–6 (6)
78	8.7	6.7 (78)	1.3 (16)	–6 (7)
80	7.8	5.9 (76)	1.3 (17)	–6 (8)
82	7.0	5.1 (74)	1.3 (18)	–6 (8)
84	6.4	4.6 (71)	1.3 (20)	–5 (8)
86	5.8	4.0 (69)	1.3 (22)	–5 (9)
88	5.2	3.5 (67)	1.2 (23)	–5 (10)
90	4.9	3.3 (67)	1.2 (25)	–4 (8)
B. Dependent at age x				
72	10.3	6.0 (58 %)	3.7 (37 %)	0.7 (6 %)
74	9.3	5.0 (54)	3.6 (38)	0.7 (7)
76	8.4	4.2 (50)	3.5 (42)	0.7 (8)
78	7.5	3.5 (47)	3.3 (44)	0.7 (10)
80	6.8	3.0 (45)	3.0 (44)	0.7 (11)
82	6.1	2.5 (41)	2.9 (47)	0.7 (12)
84	5.6	2.0 (35)	2.8 (51)	0.8 (14)
86	5.1	1.6 (31)	2.7 (54)	0.8 (15)
88	4.8	1.5 (31)	2.6 (55)	0.7 (14)
90	4.5	1.4 (31)	2.5 (56)	0.7 (13)
C. Institutionalized at age x				
72	7.2	4.6 (64 %)	0.7 (10 %)	1.9 (27 %)
74	5.0	2.3 (47)	0.4 (8)	2.3 (46)
76	4.2	1.6 (38)	0.3 (7)	2.4 (55)
78	4.1	1.7 (41)	0.3 (8)	2.1 (51)
80	3.9	1.6 (40)	0.3 (9)	2.0 (51)
82	3.3	1.0 (31)	0.3 (8)	2.0 (61)
84	3.0	0.9 (31)	0.3 (9)	1.9 (63)
86	3.0	0.8 (26)	0.4 (12)	1.8 (62)
88	2.7	0.6 (21)	0.4 (13)	1.8 (66)
90	2.3	0.4 (16)	0.2 (9)	1.8 (75)

Source Calculations based on I.SOA data (U.S. Department of Health and Human Services 1990)
[a]Based on 7 ADLs (dependent is defined as limited in 1 or more ADLs)
Percentages may vary due to rounding

could expect to live ten of their 12 remaining years, or over 80 % of their lives, in an active state; another 1.4 years (12 %) in the dependent, and 0.6 years (6 %) in an institution.

Even for those who were initially dependent, especially at the younger ages, it was projected that a large percentage of their lives would be spent in an active state. For example, those who were dependent at age 7 could expect to spend almost 60 % of their lives active; 36 % of their lives as dependent, and only 6 % of their lives as institutionalized. However, with increasing age, the chance of transiting to an independent state decreased, and the chance of remaining dependent increased, as did the chance of becoming institutionalized.

Among those who were institutionalized, the general trend was to remain institutionalized. However, a chance to become active or to return to a dependent state was evident. For example, at age 74, those who were institutionalized could expect to live an additional five years, half of which would likely be spent in an institution, but with almost half projected to be spent in an active state.

Multistate life table models assume homogeneity of the population at each age with respect to the probabilities of making a transition from one status to another. A disaggregation by sex, for example, reduces heterogeneity. So does a disaggregation of those in the dependent status. The sample size of the LSOA permits only a few such disaggregations. In Table 7.4, are set out the life expectancies of elderly persons (aged 72 and over) disaggregated into three functional statuses: independent, less (minor) dependent, and more (major) dependent. The calculations were based on data collected by the Longitudinal Study of Aging (LSOA) for 1984–1986 and 1986–1988.

In Rogers et al. (1991) the less-dependent status is viewed as a transitional rather than a permanent state of being; it is likely that individuals pass from independence first to less and then to more dependence, or from independence to less

Table 7.4 Comparisons of expectations of remaining life for individuals at age 72: United States, 1984 and 1986[a]

Initial survey Year	Total remaining years	Remaining independent years		Remaining less dependent years		Remaining more dependent years	
A. Independent at age 72							
1984	12.0	8.7	(72 %)	1.3	(11 %)	2.0	(17 %)
1986	12.4	10.0	(81 %)	1.0	(8 %)	1.4	(12 %)
B. Less dependent at age 72							
1984	10.9	5.4	(49 %)	2.8	(26 %)	2.7	(25 %)
1986	11.2	6.6	(59 %)	2.4	(22 %)	2.1	(19 %)
C. More Dependent at age 72							
1984	10.0	3.6	(36 %)	1.3	(13 %)	5.1	(51 %)
1986	10.7	5.7	(53 %)	1.2	(11 %)	3.9	(36 %)

Source Rogers et al. (1991)

[a]Based on 7 ADLs (less dependent persons are those limited in 1 or 2 ADLs; the more dependent have more limitations)

Percentages may vary due to rounding

dependence and then back to independence. The more dependent status is apt to be more permanent, with relatively few individuals recovering from this status. After some experimentation, a definition of minor dependence as dependence in at most two out of seven activities of daily living was adopted.

Table 7.4 shows that according to the 1984–1986 data, individuals who were independent at age 72 could look forward to a relatively long, active life: 72 % of their 12.0 expected remaining years of life were likely to be lived in the independent status, 11 % in the less-dependent status, and 17 % in the more-dependent status. Those with minor dependencies at age 72 were projected to end up balancing active lives with years of dependency: 49 % of their 10.9 expected remaining years of life being spent in the independent status, 26 % in the less dependent status, and 25 % in the more dependent status. Finally, persons with major dependencies at age 72 generally were expected to remain more dependent, but with a chance of returning to independent status: only 36 % of their expected average remaining lifetime of 10.0 years were projected to be spent in the independent status, 13 % in the less-dependent status, and 51 % in the more-dependent status.

Table 7.4 also allows contrasts to be made of these expectations of remaining life at age 72 with the corresponding life expectancies calculated using data for the 1986–1988 period. Because those interviewed in the earlier 1986 survey aged over the ensuing two-year time interval, the results are necessarily based on persons aged 72 years and over. To provide controlled comparisons, the mortality rates of the earlier periods were retained. Thus changes in status-specific life expectancies resulted entirely from changes in health status transition propensities.

Although mortality rates were held constant, the total life expectancies at age 72 increased over the two-year interval, purely as a consequence of changes in health status transition probabilities. Even with fixed mortality rates, longevity increased. Had mortality rates been allowed to follow observed trends, longevity probably would have increased even more.

The life expectancies presented in Table 7.3 indicate that elderly individuals in the United States are leading longer lives and longer lives free of dependencies. For example, persons aged 72 and independent in 1984 could expect, on the then current rates, to live 72 % of their remaining lives in the independent state, whereas comparable individuals two years later could expect to experience the even larger fraction of 81 %. *Active life was apparently increasing along with longevity*.

It appears, then, that longer life is not necessarily being accompanied by more years of disability and functional dependence. In fact it is much more likely that the reverse is the case, and that the pessimistic literature on the subject is simply wrong. A reason for the pessimistic conclusions that have appeared in past published studies of active life was their use of prevalence rather than incidence rates in their life table calculations.

7.4 Another Application of Multistate Demography

The preceding application of multiregional demography to health statuses has demonstrated that the mathematical apparatus for tracing the demographic consequences of movements of people between regions is the same as that for assessing the impacts of their movements between other states of existence: for example married to non-married, employed to unemployed, and in school to out of school.

This recognition has had a profound impact on formal demography as it has produced a powerful generalization of what were conventional techniques for analyzing the transitions that people experience over their lifetime, as they progress from birth to death. For a second application of multistate demography, consider the illustration in which the "migration" of people between regions that are transitions between the four marital statuses of single, married, widowed, and divorced.

Consider the female population of Sweden in 1974 (Rogers 1985 p. 86). It increased by 14,446 people during 1974. Starting the year with a total of 4,098,535 women, the population experienced 53,200 births of baby girls and 38,754 female deaths during the ensuing year (international migration is ignored in this illustration). Thus the total at the end of the year stood at 4,112,981 persons. Expressed in crude birth and death rates, then,

$$\begin{aligned} P(1975) &= (1 + b - d)\ P(1974) \\ &= (1 + r)\ P(1974) \\ &= (1 + 0.003525)\ 4{,}098{,}535 \\ &= 4{,}112{,}981 \end{aligned}$$

During the year, 97,436 women, 2.38 % of the female population, changed their marital status with marriages accounting for 45.68 % of the changes, widowhoods for 25.62 %, and divorces for 28.70 %. First marriages amounted to 84.85 % of the total number of marriages. The Swedish data on marital status changes may be expressed in the form of the matrix projection model defined in Chap. 2. Instead of migrations between regions, one has movements between states. The accounting equations now assert that the population in each marital state at the end of the year is equal to the population at the start of the year, minus deaths and movements out of the state, plus movements into the state. In the case of the single (never-married) population, $P_S(t)$ say, there is also the increment due to births. For example,

$$\begin{aligned} P_S(1975) &= (1{,}659{,}430 - 7{,}562 - 37{,}768 + 15{,}257) \\ &\quad + 36{,}519 + 119 + 1{,}305 \\ &= 1{,}667{,}300 \end{aligned}$$

which expressed in rates is

$$\begin{aligned} P_S(1975) &= (1 - 0.004557 - 0.022760 + 0.009194)\ 1{,}659{,}430 \\ &\quad + 0.019318(1{,}890{,}436) + 0.000309(385{,}070) \\ &\quad + 0.007977(163{,}599) \\ &= 1{,}667{,}300 \end{aligned}$$

Collecting the four subpopulations into a vector $\{\mathbf{P}(t)\}$, one may define the familiar matrix projection model (Rogers 1985, p. 87):

$$\{\mathbf{P}(t+1)\} = \mathbf{G}\{\mathbf{P}(t)\}$$

or

$$\begin{bmatrix} 1,667,300 \\ 1,870,171 \\ 391,835 \\ 183,675 \end{bmatrix} = \begin{bmatrix} 0.981878 & 0.019318 & 0.000309 & 0.007977 \\ 0.022760 & 0.965736 & 0.001036 & 0.038766 \\ 0 & 0.013204 & 0.952746 & 0 \\ 0 & 0.014793 & 0 & 0.951772 \end{bmatrix} \begin{bmatrix} 1,659,430 \\ 1,890,436 \\ 385,070 \\ 163,599 \end{bmatrix}$$

Classifying the Swedish female population by marital status is a useful form of disaggregation because it illuminates patterns of marital status change. Classifying the same population by residential status identifies patterns of spatial redistribution. In 1974, for example, 766,565 of the 4,098,535 Swedish women lived in Stockholm, the capital city (Rogers 1985 p. 88). Among these 14,726 migrated to the rest of Sweden during the year and 12,858 migrated in the reverse direction. The Stockholm population experienced 6640 deaths and 9991 births; the corresponding totals for the rest of Sweden were 32,114 and 43,209, respectively. The following bioregional projection model describes population redistribution during that period:

$$\begin{bmatrix} 768{,}048 \\ 3{,}344{,}933 \end{bmatrix} = \begin{bmatrix} 0.985161 & 0.003859 \\ 0.019210 & 0.999471 \end{bmatrix} \begin{bmatrix} 766{,}565 \\ 3{,}331{,}971 \end{bmatrix}$$

Combining the classification by marital status with that of location gives rise to eight states and an 8 by 8 projection matrix. All of the preceding has ignored age. Incorporation of that added dimension into the analysis is straightforward and is described in Rogers (1985, pp. 88–90).

7.5 Discussion and Conclusion

Common to most topics in mathematical demography is an underlying concern with the transitions that people experience over time in the course of passing from one state of existence to another: for example, transitions from being healthy to being sick, from being single to being married, from being employed to being unemployed, and from being alive to being dead. The study of transition patterns generally begins with the collection of data and the estimation of missing observations, continues with the calculation of the appropriate rates and corresponding probabilities, and often ends with the generation of simple projections of the future conditions that would arise were these probabilities to remain unchanged. In short, much of mathematical demography deals with the problems of *measurement* and *dynamics* in *multistate* population systems.

Multistate demographic analysis has produced a generalization of classical demographic techniques that unifies most of the methods for dealing with transitions between multiple states of existence. For example, in the 1970s it became clear that multiple decrement mortality tables, tables of working life, nuptiality tables, tables of educational life, and multiregional life tables were all members of a general class of increment-decrement life tables called *multistate life tables* (Hoem and Fong 1976; Rogers 1973a, b, 1975, 1995; Rogers and Ledent 1976; Schoen and Nelson 1974). It also became evident that projections of populations classified by multiple states of existence could be carried out using a common methodology of *multistate projection*, in which the core model of population dynamics is a multistate generalization either of the continuous age-time model of Lotka (LeBras 1971; Rogers 1975) or of the discrete age-time model of Leslie (Rogers 1966, 1968).

Finally, multistate demography adopts matrix algebra to express, in compact form, a number of relationships that would be very difficult to identify and study using scalar (nonmatrix) arguments. Conceptualizing a multidimensional demographic process in matrix form confers advantages that are both notational and analytical in character. Matrix notation often leads to insights that otherwise may have been obscured by the more complicated nonmatrix formulations. And formulating a demographic problem in matrix terms places at our disposal a large mathematical apparatus on matrices and their properties. As a result, what at first is introduced as a purely pragmatic and notationally elegant conceptualization can ultimately become the vehicle for insights that are not readily obtainable otherwise.

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Chapter 8
Conclusion

Abstract Our understanding of patterns and behavior of mortality, fertility, migration, nuptiality, education, and labor force participation is enhanced by a focus on occurrences of events and transfers, and on their association with the populations that are exposed to the risk of experiencing them. A multiregional perspective permits such an association; a uniregional perspective does not. For example, there is no such individual as a net migrant, and attempts to explain the behavior of net migrants are likely to lead to misspecified models and biased findings. The propensity to experience various events and transfers differs across sub-populations; analyses and projections that can take this inhomogeneity into account can identify the contribution made by each sub-population to the total. A multiregional perspective permits such an association; a uniregional perspective does not. Furthermore, our understanding of migration propensities is enriched by information regarding the degree to which current migration occurs among those who have migrated previously. Such information reveals, for example, how much of the current increase in levels of migration can be attributed to "repeaters" as opposed to "first-timers".

Keywords Double entry bookkeeping · Incidence rates · Prevalence rates

8.1 Double Entry Bookkeeping

In the late stages of preparing this monograph, I came upon a book, written by Gleeson-White (2013), entitled *Double Entry*, a story about how a new kind of financial record-keeping system of accounts was developed in 1494 by Luca Pacioli, the "father" of double-entry bookkeeping. As I read her book, I realized that the very same bookkeeping principles were relevant for the accounting of migration flows. Instead of credits and debits, we have inmigrants and outmigrants. Just as a credit in one account must be offset by a debit in another, so too must inmigrants to one region be offset by outmigrants from another region. And

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most importantly, just as the sum of all credits to all accounts must be exactly equal to the sum of all debits from all accounts, so too must the sum of all inmigrants equal to the sum of all outmigrants. Net migration for the total population system must exactly equal zero. This condition is not met by uniregional population projections (recall Chap. 2, for example). Adding the 50 net migrant totals produced by uniregional population projections for each state of the USA, one does not get a sum of zero. Carrying out the corresponding multiregional 50-state population projection, however, does.

As I have argued in Chap. 2, the culprit is the inmigration rate embedded in the net migration rate, a measure of prevalence and not incidence. Prevalence rates confound migrant flow totals with population totals; the "wrong" population is in the denominator. To correct this misspecification one needs to use only outmigration rates in the population projection: one needs a multiregional (multistate) model.

8.2 Incidence not Prevalence

When faced with the task of modeling the dynamics of two or more interdependent population subgroups, demographers, economists, geographers, and sociologists, in the past, adopted one of two distinct approaches. They either (1) examined each subpopulation apart from the others by appending to it a "net migration" rate to express its exchanges with the rest of the total population, or (2) disaggregated the total population into subgroups by means of a "prevalence" rate that ignored those exchanges and focused only on their redistributional consequences, (i.e., changes in relative shares of the total stock of individuals). The migration and spatial population dynamics literature adopted the first strategy; the labor force participation and dynamics literature adopted the second (Bureau of Labor Statistics 1982). Both approaches introduced population composition biases into the analysis of behavior. With the development and diffusion of multiregional/multistate demographic methods, neither modeling strategy is warranted unless dictated by the unavailability of transition data.

Although the fundamental idea of a multistate perspective had an earlier history outside of demography, appearing in the statistical literature earlier in the twentieth century (e.g., DuPasquier 1912), that literature did not attract the attention of mathematical demographers until the 1960s, probably because the languages used by the two disciplines were quite different. Mathematical demographers were brought up on life tables and cohort-survival population projection models, not stochastic process models. They began to develop their own kind of multiregional (and, shortly later multistate) models. A conference convened in Washington, DC and supported by IIASA and the National Science Foundation, sought to "marry" the two perspectives by bringing together the two groups (Land and Rogers 1982), and the ultimate result was the flourishing remarkable growth of contributions to the theory and applications of multistate demography. A search on Google for

"Applications of Multistate Demography" brings up a list of over 34 thousand items. Clearly it is impossible to summarize here a prospective view of the likely future evolution of the field. Nonetheless, it may be useful to identify a few of the applications that are of particular relevance for demographers.

In addition to the early applications to, for example, migration (Rogers 1968), marital status change (Schoen and Nelson 1974), labor force participation (Hoem and Fong 1976), annuity and insurance calculations (Keyfitz and Rogers 1982), and active life expectancy studies (Rogers et al. 1989), we now have applications in the public health literature, in education and human capital formation, in agent-based modeling in historical demography and, indeed, even in ecological studies of non-human populations, for example, of birds and animals (Westerberg and Wennergren 2005).

8.3 A Final Word

The six principal questions considered in this monograph have been drawn from empirical applications of multiregional/multistate demography that I have contributed to during the past half century. A unifying thread throughout these applications is the use of that perspective to clarify issues that sometimes tend to be obscured or inappropriately addressed in studies that have used a traditional uniregional/unistate perspective. The fundamentals have become widespread and are now receiving attention from scholars in a large number of countries. The active period of methodological development of the past has continued to prove the power of a fruitful new idea. This monograph has been assembled in the hope that a simple presentation of that idea will reach an even wider audience.

The development of multiregional/multistate life table and population projection models has brought the demographic tradition much closer to the statistical/causal one, and a marriage between the two perspectives has been developed successfully (e.g., Willekens 2014). An important consequence of such a merger is the further development of the micro and macro branches of formal demography, with microdemography increasingly devoted to the formal causal analysis of the behavior of decision-making agents, such as the individual or the family, and macrodemography continuing to examine the behavior of aggregates, for example, the relationships between various population subgroups and different measures of economic performance and well-being.

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