Research Article

Age, period, and cohort effects contributing to the Great American Migration Slowdown

Robert Bozick

Contents

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Robert Bozick[1]

Abstract

BACKGROUND
Between 1964 and 2019, the percentage of people in the United States who had moved in the previous year decreased from 20.3% to 9.8%. It is unclear whether this trend was driven by period-specific factors that gradually diminished the prospects of moving for the population as a whole or whether distinct features of birth cohorts differentially contributed to the migration slowdown.

OBJECTIVE
The present study assesses whether the migration slowdown in the United States was primarily driven by period effects or by cohort effects.

METHODS
Using 46 waves of data across the 1964–2019 Annual Social and Economic Supplements to the Current Population Survey, I estimate a series of mixed-effects models predicting the probability of moving and a linear model with age x period interaction terms predicting the probability of moving.

RESULTS
Cohort effects are more salient in slowing the rates of migration than are period effects. The migration slowdown occurred in part because members of the Silent and Baby Boom generations, who had a higher probability of moving at all ages, matured out of their prime years of geographic mobility in young adulthood and were replaced successively by members of Generation X, the Millennial generation, and Generation Z, who comparatively have a lower probability of moving.

CONCLUSION
The findings suggest that migration measures and subnational population projections that rely on period-level inputs might potentially mischaracterize current and future demographic trends in the United States.

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CONTRIBUTION
This study is the first age-period-cohort analysis of the contemporary migration slowdown in the United States.

1. Introduction

One of the more consistent demographic trends in the United States over the past 60 years has been the steady decline in rates of internal migration, which last peaked in 1964–1965, when one-fifth of the American population had changed residence in the prior year (U.S. Census Bureau 2019). Despite a few year-to-year fluctuations, this rate has been consistently dropping ever since. By 2018–2019, only 9.8% of the American population had changed residence in the prior year, the lowest internal migration rate on record (U.S. Census Bureau 2019). This decline has been observed across all major sociodemographic groups (Fischer 2002; Frey 2009). Brookings Institution demographer William Frey (2009) aptly named this steady long-term trend the Great American Migration Slowdown. I call it the migration slowdown for ease of expression.

The migration slowdown has attracted a great deal of attention from demographers, sociologists, and social historians, and for good reason: The United States was founded by immigrants and grew via an ethos of expansionism. Guided by Manifest Destiny, the belief that a higher power had commanded the spread of democracy and capitalism throughout North America, colonists and early settlers took advantage of cheap land on the western side of the continent; the landscape was dramatically reshaped by rapid population growth. As the Industrial Revolution took hold, transportation routes created an unprecedented grid of connectivity that changed the geographic trajectories of migrants, with movement from rural to urban areas eventually surpassing movement from east to west. More recently, with 20th-century globalization and all the attendant features of modernity – including global expansion in trade, new modes and hubs of transportation, growing urban centers with modern amenities, and increasing opportunities for higher education – Americans appeared poised for a period of hyper-mobility. However, the opposite happened, begging the question: Why did domestic migration rates decline in the midst of this extraordinary period of social change?

A number of researchers have attempted to answer this question, with results pointing to a range of explanations for the migration slowdown, including elevated levels of unemployment and economic strain, which diminish resources required to move (Milne 1993; Pandit 1997); larger birth cohorts, which amplify economic strain via greater competition in the labor market (Pandit 1997; Plane and Rogerson 1991); a decline in job/employer transitions, which in turn suppresses the pull factor of labor

market opportunities in potential destinations (Hyatt et al. 2018; Molloy et al. 2017); a rising rate of home ownership, which anchors individuals and their families to their neighborhoods and local communities (Cooke 2011); a rise in the proportion of dual-earner families, which complicates job transfers to and job searches within potential destinations (Cooke 2013; Foster 2017); widespread technology and information communication networks, which alleviate the need for professional workers to live close to where they work (Cooke 2013); and a growing psychological sense of community rootedness, which may be a natural culmination of the expansionism that propelled the growth of the country in its infancy (Fischer 2002). All of these explanations find empirical support in some form or another, and all serve to enhance our understanding of American population dynamics in the late 20th and early 21st centuries.

In this paper, I contribute to this body of research by applying an age-period-cohort approach to examine the etiology and maintenance of the migration slowdown. Unlike the research to date, however, my study does not aim to pinpoint specific drivers of the migration slowdown. Instead it serves to reset the empirical focus of the migration slowdown by "zooming out" to identify where to look for such drivers, either within the particulars of specific historical periods or as distinct features of birth cohorts that comprise the population at any given time. With data capturing the entire span of the migration slowdown (1964–2019) and with multiple methods to identify and quantify age-period-cohort effects, my study provides the most comprehensive assessment of the historical contours of the migration slowdown from a distinctly demographic perspective on long-term social change.

I lay the foundation for my analysis by outlining the role that aging, the characteristics of different time periods, and the distinct life course trajectories of birth cohorts might play in explaining the onset and continuation of the migration slowdown. Next I describe the data sources and methods I apply to identify age, period, and cohort effects, and then I present the findings. I conclude with a discussion of how the findings advance our understanding of trends in internal migration in the United States, their implications for the use of period and cohort measures in characterizing migration trends and forecasting population change, and what they might portend for the next generation.

2. The role of age, periods, and cohorts in explaining internal migration

Age-period-cohort analysis gained traction among population scientists in the 1970s and 1980s, in large part because it empirically fused together the concepts of population structure and social change that motivate demographic inquiry (Hobcraft et al. 1985). However, initial empirical work that attempted to identify the unique contributions of

age, period, and cohort effects across an array of social and demographic phenomena hit roadblocks due to the intractable problem of the exact linear dependency of these three variables. Specifically, period = age + cohort, so the inclusion of all three measures in standard regression models will provide only estimates for two of the three variables. This is typically referred to as the age-period-cohort identification problem. (For discussion of these issues, see seminal work by Fienberg and Mason 1985 and Hobcraft et al. 1985.) However, methodological advancements in recent years have provided some workarounds that, although they cannot solve the age-period-cohort identification problem, do provide new ways to conceptualize and to *estimate* cohort effects net of one's age and period (Harding 2009; Luo and Hodges 2020a; Reither et al. 2015; Yang and Land 2006). The italicization of *estimate* is to emphasize that there is no one consensus method that can unequivocally quantify the additive, independent effects of ages (net of period and cohort membership), periods (net of age and cohort membership), and cohorts (net of age and period). In the absence of such a method, age-period-cohort analyses of demographic events must use available, albeit imperfect, methods to provide an estimate of the true effects of age, periods, and cohorts, as no one method can effectively solve the identification problem.

Despite methodological advancements, formal age-period-cohort approaches have not been applied to the study of the migration slowdown in the United States.[2] A lone exception is Rogers and Rajbhandary's (1997) analysis of intercounty moves among American men from 1948 to 1993, in which they compare migration rates of Baby Boom cohorts with those of previous birth cohorts. As nearly all birth cohorts in the analysis were still in various stages of adulthood, Rogers and Rajbhandary relied on model migration schedules to fill in the "right-censored" distribution of completed lifetime moves. This process essentially imputed total lifetime moves based on the experience of older cohorts, which could compromise conclusions should there be distinct cohort differences in the probability of moving.

Rogers and Rajbhandary's (1997) analysis found evidence of both period and cohort effects. With respect to period effects, they identified a decline in period migration rates across the 1970s and 1980s. With respect to cohort effects, they identified a decline in cohort migration rates from the 1948 through 1964 birth cohorts. As it was conducted prior to recent advancements in age-period-cohort estimation strategies, Rogers and Rajbhandary's (1997) analysis lacks the ability to determine whether net of age, period effects are more salient than cohort effects or vice versa. With data that track the Baby Boom cohorts into retirement, along with the application of newer methods, my analysis updates and extends their work and better clarifies the distinct role of periods and cohorts in explaining the migration slowdown.

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[2] Sander and Bell (2016) applied age-period-cohort methods to understand a similar long-term decline in migration in Australia.

2.1 Age effects

Model migration schedules in demography are developed on the principle that the probability of moving follows an age-graded pattern that is relatively consistent across populations, with variations in the peaks, troughs, and slopes of the distribution depending on the population being studied (Gillespie 2017). In Figure 1 I plot the migration age schedule for the United States using the 1964–2019 Annual Social and Economic Supplements of the Current Population Survey, which is the same data and time frame I use for my multivariate analysis.

Figure 1:   Age schedule on internal migration in the United States, 1964–2019
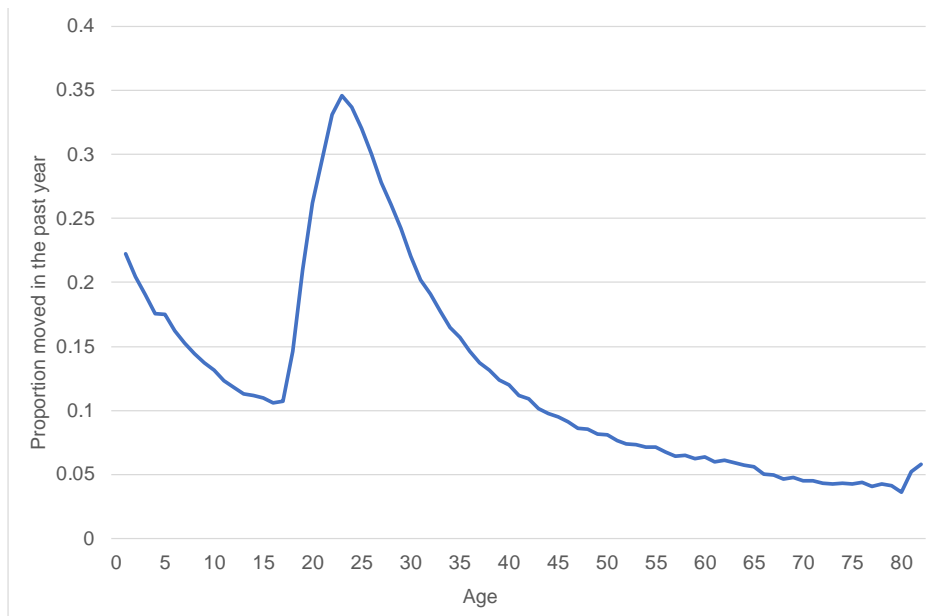
As is typical of most migration schedules, there are two distinct peaks, with the highest occurring during the transition to adulthood, when youths begin going off to college, entering the labor force, joining the military, establishing financial and residential independence from their parents, and forming families of their own (Bernard, Bell, and Charles-Edwards 2014; Gillespie 2017). The other peak is during the infant years and is the result of the aforementioned high migration rates of young adults, who are at their peak childbearing years as well (Bernard, Bell, and Charles-Edwards 2014).

Given the durability of the shape of migration schedules across populations, identifying the presence of age effects in and of themselves is not particularly illuminating. However, accounting for these non-linearities in the age distribution is essential for producing valid estimates of period and cohort effects. More importantly, schedule's shape calls attention to young adulthood as the prime years for geographic mobility. Any attempt to understand the drivers of the migration slowdown need to consider the unique experiences of cohorts passing through this stage in the life course, as they proportionally account for the lion's share of annual migrants.

2.2 Period effects

Period effects are produced by external factors that equally affect all potential movers in all age groups at a particular point in time. Economic conditions are frequently used as a central characteristic of time periods to explain the acceleration or deceleration of migration – in part because moving typically requires economic resources to accomplish and in part because emerging employment opportunities in new destinations incentivize relocation (Gillespie 2017; Molloy, Smith, and Wozniak 2011; Thomas, Gillespie, and Lomax 2019). The salience of time-varying economic conditions is evidenced in a number of studies that find that migration rates fall when unemployment rates rise and vice versa (Milne 1993; Pandit 1997). Beyond overall unemployment, other studies point to differences in the demand for specific skills and the occupation/industry mix of different labor markets as factors that modulate the probability of moving (Dennis and Iscan 2007; Partridge et al. 2012; Sasser 2010).

Noneconomic factors can also serve as external "shocks to the system" that can influence one's decision to move. After the onset of the migration decline, the United States experienced a number of pivotal historical events that may have shaped individuals' sense of connection to (or disaffection with) their communities, which in turn may have affected their probability of relocating. Examples include the Vietnam War; the political and social upheavals of the late 1960s and early 1970s; the oil crisis of 1973; the proliferation of personal computing, the internet, and widespread digital communication; the September 11 terrorist attacks of 2001; and the subprime mortgage crisis and Great Recession of 2008. Further, the time period spanning the migration slowdown was punctuated by hurricanes, tornadoes, wildfires, and earthquakes near major population centers in the United States, which produced distinct regional shifts in migration flows (Cross 2014; Elliott 2015; Fussell et al. 2017).

As mentioned earlier, the goal of this paper is not to identify specific period factors that may have contributed to the migration slowdown but rather to consider whether net of population aging, period or cohort effects are more relevant. If period effects are

dominant, this would suggest that time-varying factors that deter the decision to move for the entire population – such as those discussed in the preceding paragraphs – should warrant additional empirical focus as potential causes for the migration slowdown. Additionally, should period effects drive recent migration trends in the United States, this would instill confidence in the application of migration measures and subnational population projections that rely on period-level inputs.

2.3 Cohort effects

The sum of all unique exposures experienced by a birth cohort as it ages can substantively differentiate it from other birth cohorts with respect to key social and demographic outcomes, creating what are called cohort effects (Ryder 1965). Because cohorts are by definition "implanted in the age-time specification" (Ryder 1965), cohort effects can only emerge when the aging experience is distinctly modified by the historical time period through which cohorts pass at different ages. In empirical terms, cohort effects are the products of period effects that uniquely affect specific birth cohorts, depending on age at the time of exposure.

Cohort effects attracted a lot of attention from social scientists when the Baby Boomers came of age and began embarking on the traditional young adult milestones of school completion, labor force entry, marriage, home ownership, and childbearing (Macunovich 2002). It was thought that because of the group's size relative to the rest of the population, Baby Boomers would face competition for resources at all stages of the life course. This would in turn depress their acquisition of human capital and subsequent economic output and would consequently increase their rates of criminal behavior, unemployment, and political alienation. Presented by economist Richard Easterlin in his 1978 address to the Population Association of America and detailed in his subsequent book, this prediction came to be known as the Easterlin relative cohort size hypothesis (Easterlin 1978, 1980). Working from the assumption that geographic mobility of the large Baby Boom cohorts would be limited by constrained job prospects, the Easterlin hypothesis finds some empirical support in studies of migration (Pandit 1997; Plane and Rogerson 1991). Indeed, the migration slowdown began just as the Baby Boomers entered their prime years of geographic mobility.

Cohort effects are in no way limited to cohort size. All the economic and noneconomic factors described in the previous section on period effects could produce cohort effects should they distinctly affect specific cohorts. For example, when the subprime mortgage crisis and Great Recession occurred in 2008, the Millennial cohorts, who were born in the 1980s and early 1990s, were reaching their prime years of geographic mobility. The depressed economic conditions, limited job opportunities, and

general uncertainty that pervaded that time period may have deterred Millennials from moving, which in turn could lower their overall lifetime rates of mobility (similar to how delayed childbearing lowers overall lifetime fertility). For the older Generation X and Baby Boom cohorts, who were further along in their careers and with more economic resources accumulated, this volatile economic period in the late aughts may have had less of an effect on their migration prospects. This is but one example of how cohort effects in migration may emerge; many other period-specific factors could distinctly contribute to a cohort's propensity to move across the life course.

With data on the generations that both preceded and followed the Baby Boomers, my analysis will estimate cohort differences in rates of migration for every cohort born in the 20th century across the entire span of the slowdown. If cohort effects are more prevalent than period effects, researchers looking to identify drivers of the slowdown should focus on dynamic factors that distinctly diminish or amplify the migration prospects of cohorts as they enter their prime moving years. Additionally, should cohort effects dominate, demographers may need to consider potential biases built into migration measures and subnational population projections that rely on period-level inputs.

To further explore the role of cohorts in explaining the migration slowdown, I go beyond attempting to identify independent effects of age, period, and cohorts by exploring the intersection of the age and time periods from which such cohort effects emerge. To do so, I focus on differences in rates of migration during young adulthood, as model migration schedules consistently show this as the stage in the life course when most moving occurs. If real cohort effects are operating, there should be evidence of an interaction effect between age and time period that in turn produces distinct migration schedules that vary across cohorts. More specifically, if cohort effects are responsible for the downward shift in migration rates observed across the past few decades, recent cohorts should exhibit more "subdued" migration schedules (e.g., lower overall rates and flatter slopes) in young adulthood than earlier cohorts.

3. Data

To identify age, period, and cohort effects, I analyze data from the Annual Social and Economic Supplement (ASEC) to the Current Population Survey (CPS). I use the CPS-ASEC because it is the only source of annual data on internal migration in the United States that permits cohort comparisons throughout the duration of the migration slowdown. Collected by the U.S. Census Bureau, the CPS is a nationally representative monthly survey of households across the United States that provides a wide range of information on population characteristics and the state of the American labor force. The

ASEC is administered annually as part of the March CPS. It asks sample members to report whether they were living in their current housing unit one year prior to the date of the survey. If sample members were not living in the same housing unit one year prior, they are then asked to identify where exactly they were living. The U.S. Census Bureau uses this information to classify sample members as non-movers, movers within the United States, and movers from abroad.

The primary outcome in my analysis is a binary variable distinguishing movers within the United States in the previous year (coded 1) from non-movers (coded 0). I exclude movers from abroad, as the goal of this analysis is to identify the presence of period and cohort effects specific to migration decisions in the domestic context. Foreign laws and policies, foreign labor markets, living conditions of host countries, and international wars/conflicts are key determinants of international migration, so the inclusion of migrants from abroad could bias period and cohort effects that are intended to reflect population dynamics within the United States.

The data for this analysis come from the integrated public use micro sample (IPUMS) version of the CPS-ASEC (Flood et al. 2020). IPUMS contains harmonized migration measures from 1964 onward, allowing for efficient and valid cross-wave comparisons. I analyze the individual-level CPS-ASEC files from 1964 to 2019, spanning the entire time frame of the migration slowdown. The migration question with the one-year reference period was not asked in 1972–1975, 1977–1980, 1985, or 1995, so those ten years are not included in the analysis. Additionally, I restrict the analysis to those between the ages of 18 and 65. Those under the age of 18 are largely dependent on their parents for housing; their inclusion would conflate migration decisions of parents and children from different cohorts and would consequently obfuscate cohort effects. Similar cross-generational dynamics are at play among those over age 65, particularly as senescence progresses and the elderly become dependent on their children and/or younger family members for care. With these restrictions in place, I identify 100 one-year birth cohorts across the duration of the 20th century, from 1900 through 1999. The resulting analytic sample includes 4,604,488 individuals between the ages of 18 and 65, across 46 waves of surveys and belonging to one of 100 birth cohorts.

To guide in the interpretation of the analysis, I use colloquial generational nicknames as shorthand labels for clusters of birth cohorts using the following conventions: The GI generation includes the 1900 through 1929 birth cohorts, the Silent generation includes the 1930 through 1944 birth cohorts, the Baby Boom generation includes the 1945 through 1964 birth cohorts, Generation X includes the 1965 through 1979 birth cohorts, and the Millennial generation includes the 1980 through 1994 birth cohorts. Lastly I include the earliest members of Generation Z, who are represented by the 1995 through 1999 birth cohorts. Because those in the GI generation and the Silent generation are beyond their peak years of migration in young adulthood when the time

series commences in 1964 and because those in Generation Z are just starting to enter young adulthood at the close of the time series in 2019, I focus mostly on the experiences of the Baby Boom generation, Generation X, and Millennials.

4. Methods

As discussed earlier, no single consensus method can unequivocally quantify the independent, additive effects of aging apart from time period and apart from cohort membership. Researchers instead must rely upon available, albeit imperfect, methods to estimate the true effects of age, periods, and cohorts, as no one method can effectively solve the identification problem. Consequently, in this study I use two sets of estimation strategies for undertaking age-period-cohort analyses: mixed-effects models and models with age x period interaction terms. In employing two strategies that have distinct assumptions and trade-offs, I am able to evaluate the robustness of my findings. Given the impossibility of simultaneously estimating independent, additive age, period, and cohort effects, I encourage readers to interpret this analysis as descriptive evidence rather than a definitive explanation.

4.1 Mixed-effects models

I first estimate a series of linear mixed-effects models, a modified form of a traditional hierarchical linear model offered by Yang and Land (2006, 2008), to deal with the age-period-cohort identification problem. The model is considered mixed because it contains both fixed effects and random effects. With this approach, age is included in the model in the first level as a fixed characteristic of sample members, for which a single additive slope parameter is estimated. Variation in migration rates across periods and cohorts is identified via empirical Bayes estimation, in which periods and cohorts are specified as random effects in the second level. This mixed-effects model is referred to as cross-classified because sample members (level 1) are nested within periods as well as within cohorts (level 2). The cross-classified linear mixed-effects model that I estimate has two levels, with the first level specified as follows:

$$MIGRATE_{ijk} = \alpha_{jk} + \beta_1 AGE_i + \beta_2 AGE^2{}_i + \beta_3 AGE^3{}_i + \varepsilon_{ijk} \qquad \text{(Model 1)}$$

In this first level, *MIGRATE*$_{ijk}$ is a binary outcome indicating whether the *i*th sample member belonging to the *j*th birth cohort moved in the year preceding the *k*th survey year. AGE is an additive fixed effect, included also as a third-order polynomial to

accommodate the nonsymmetrical rise and subsequent decline in mobility rates expected between the ages of 18 and 65 per the model migration schedule depicted in Figure 1. I expect β_1 to be positive to capture the sharp increase in migratory behavior that accompanies the transition to adulthood. I expect β_2 to be negative to reflect the decline in migration that follows the peak in young adulthood. Lastly, I expect β_3 to be positive as the decline in migration rates after about age 35 is less pronounced than the initial decline in young adulthood. So that the intercept has a meaningful interpretation in the context of this analysis, I centered AGE (and by extension AGE^2 and AGE^3) at age 18. α_{jk} is the intercept and indicates the mean migration rate for 18-year-olds surveyed in year j and belonging to birth cohort k. ε_{ijk} is the unexplained variance.

The second level of the model is specified as follows:

$$\alpha_{jk} = \gamma_0 + \nu_{0k} + \mu_{0j}, \qquad \nu_{0k} \sim N\left(0, \tau_\nu\right), \mu_{0j} \sim N\left(0, \tau_\mu\right)$$

At this level, γ_0 is the model intercept indicating the mean migration rate for 18-year-olds. ν_{0k} is the random effect of period k averaged over all cohorts j, controlling for age on α_{jk} and assumed to be normally distributed with mean 0 and variance τ_ν. μ_{0j} is the random effect of cohort j averaged over all periods k, controlling for age on α_{jk} and assumed to be normally distributed with mean 0 and variance τ_μ.

One criticism of the cross-classified mixed-effects approach is that the estimated random effects are highly sensitive to non-linearities that can constrain them to be near zero (Bell and Jones 2018; Luo and Hodges 2020b; O'Brien 2017). This could result in artificially understating the true effects of periods or cohorts. Therefore, to evaluate the robustness of the findings when using the cross-classified specification shown in Model 1, I estimate two additional mixed-effects models. First I estimate a two-level model in which both age and period are treated as fixed at level 1 and cohort is treated as random at level 2:

$$MIGRATE_{ij} = \alpha_j + \beta_1 AGE_i + \beta_2 AGE^2{}_i + \beta_3 AGE^3{}_i + \beta_4 \mathbf{PERIOD}_i + \varepsilon_{ij} \quad \text{(Model 2)}$$
$$\alpha_j = \gamma_0 + \mu_{0j}, \ \mu_{0j} \sim N\left(0, \tau_\mu\right)$$

Second I estimate a two-level model in which both age and cohort are treated as fixed at level 1 and period is treated as random at level 2:

$$MIGRATE_{ik} = \alpha_k + \beta_1 AGE_i + \beta_2 AGE^2{}_i + \beta_3 AGE^3{}_i + \beta_4 \mathbf{COHORT}_i + \varepsilon_{ik}$$
$$\text{(Model 3)}$$
$$\alpha_k = \gamma_0 + \nu_{0k}, \qquad \nu_{0k} \sim N\left(0, \tau_\nu\right)$$

It is important to note that these two additional mixed-effects models are subject to the same limitations as Model 1 (e.g., the estimated random effects may be constrained to zero). However, comparing the estimates across these three models permits an assessment of the general form of period and cohort trends, as well as the sensitivity of their forms to model specification. All three mixed-effects models are estimated using restricted maximum-likelihood empirical Bayesian methods. Because they are linear models, the parameter estimates have a linear probability interpretation.

4.2 Age x period interaction terms

The random-effects approach works from the assumption that there are independent, additive age, period, and cohort effects in migration rates. However, critics of the random-effects approach (and similar approaches that seek to estimate independent, additive age-period-cohort effects) note that the "cohorts are not differentiable unless period effects differ between age groups" (Luo and Hodges 2020a). As discussed earlier, if cohort effects are driving the migration slowdown, there should be evidence of an interaction effect between age and time period that in turn produces distinct migration schedules that vary across cohorts. To assess this possibility, I estimate a linear model that includes interaction terms for age and period. This model, which has been prescribed by Luo and Hodges (2020a) to identify cohort effects that align more closely with the theoretical conceptualization of cohorts (Ryder 1965), takes the general form:

$$MIGRATE_i = \alpha_i + \beta_1 \mathbf{AGE}_i + \beta_2 \mathbf{PERIOD}_i + \beta_3 \mathbf{AGE}_i \ x \ \mathbf{PERIOD}_i + \varepsilon_i \quad \text{(Model 4)}$$

In this linear model, *MIGRATE* is a binary outcome indicating if sample member i moved in the past year. **AGE** is a vector of variables indicating age groups, and **PERIOD** is a vector of variables indicating groups of years corresponding to when sample member i was observed in the CPS-ASEC. Unlike the mixed-effects models, which use individual years to measure periods and cohorts, for this model I group ages and periods using five-year intervals. Specifically, I group ages into 11 five-year categories (ages 15–19, ages 20–24,…ages 65–69), and I group periods into 12 five-year categories (years 1960–1964, years 1965–1969,…years 2014–2019). I use five-year intervals instead of single years for clarity of presentation and for ease of interpretation. The results are unaffected by the choice of interval width. The vector of multiplicative interaction terms between age and period represented by β_3 indicates whether the effect of age on migration varies across time periods – i.e., cohort effects. Using the estimated parameters (α, β_1, β_2, and β_3) I calculate predicted probabilities to construct the age schedule of migration for different birth cohorts.

5. Findings

As context for the multivariate analysis, in Figure 2 I plot trends in the proportion of those who had moved in the previous year between 1964 and 2019. For years when the migration question with the one-year reference period was not asked (1972–1975, 1977–1980, 1985, and 1995), I use linear interpolation. The trend line is perforated where values are interpolated. This figure captures the entire span of the Great American Migration Slowdown, from its peak in 1964, when 20.3% had moved in the previous year, through its lowest point, 2019, when only 9.3% had moved in the previous year.[3] The proportion of those who had moved dipped slightly but more or less held steady between 1964 and 1987, at which point there was a pronounced decline through the end of the time series. Between 1987 and 2019, in the span of a little more than two decades, the proportion of the population that had moved in the previous year was nearly cut in half. The trend in this figure can be thought of as "unadjusted" period effects, without controlling for the potentially confounding effects of age and cohort membership.

Figure 2:   Trends in internal migration in the United States, 1964–2019

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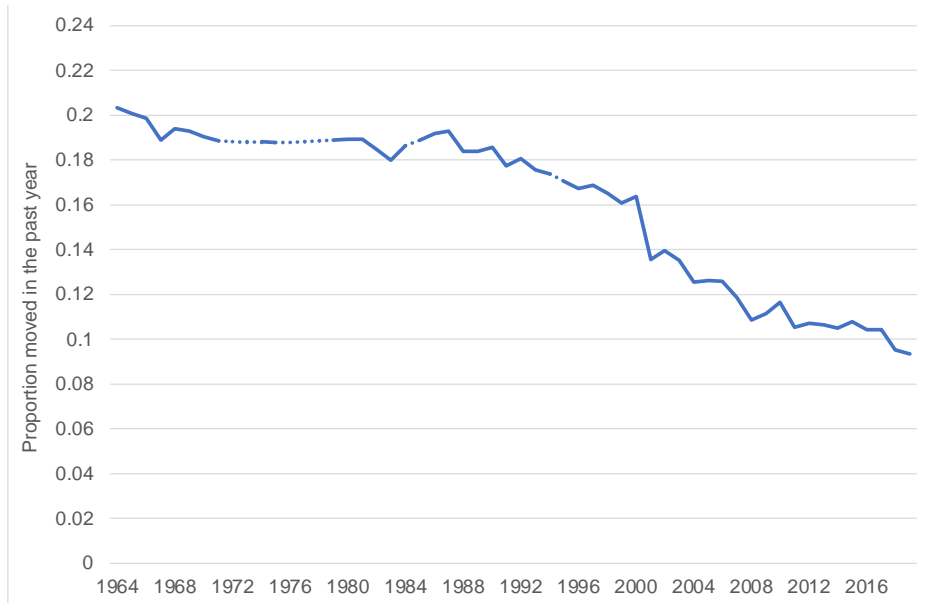
[3] These estimates closely match published figures from the U.S Census Bureau (2019), which plots similar rates with the same data but includes movers from abroad, those under age 18, and those older than age 65.

5.1 Mixed-effects models

In Table 1, I show the parameter estimates from the three mixed-effects models predicting internal migration. In all three models, the coefficients for *AGE, AGE²,* and *AGE³* are in the expected direction, with p-values less than 0.001 – indicating the strong association that age has with the probability of moving. As expected, β_1 is positive, corresponding with an increase in migration during the transition to adulthood; β_2 is negative, corresponding with a decline in migration following a peak in young adulthood; and β_3 is positive, indicating a decline in migration rates in midlife that is less pronounced than the initial decline in young adulthood.

Table 1: **Parameter estimates from mixed-effects models predicting the probability of internal migration**

	Model 1: Age = fixed Period and cohort = random	Model 2: Age and period = fixed Cohort = random	Model 3: Age and cohort = fixed Period = random
Fixed effects			
Intercept α	0.117	0.173	0.238
	0.012	0.011	0.026
	0.000	0.000	0.000
Age β_1	0.023	0.023	0.021
	0.001	0.001	0.001
	0.000	0.000	0.000
Age² β_2	−0.001	−0.001	−0.001
	0.001	0.001	0.000
	0.000	0.000	0.000
Age³ β_3	0.000	0.000	0.000
	0.000	0.000	0.000
	0.000	0.000	0.000
Random effects variance components			
Period τ_u	0.000	--	0.000
Cohort τ_μ	0.001	0.001	--
Likelihood ratio χ²	11,194.88	3,364.48	591.50
N = 4,604,488			

Note: For fixed-effects estimates, standard errors are in the second row and p-values are in the third row. Fixed effects for periods in Model 2 and fixed effects for cohorts in Model 3 are suppressed for clarity of presentation.

To illustrate potential period effects, I first plot the random period effects from Model 1 in Figure 3a ($\alpha_k = \gamma_0 + \nu_{0k}$). Next I plot the fixed period effects from Model 2 in Figure 3b ($\alpha_j + \beta_4\mathbf{PERIOD}_i$). Finally I plot the random period effects from Model 3 in Figure 3c ($\alpha_k = \gamma_0 + \nu_{0k}$). When period is treated as random (Figure 3a and 3c), the probability of internal migration net of age and cohort membership marginally declines across the duration of the slowdown. When period is treated as fixed (Figure 3b), the decline is more evident. Regardless of model specification, the declines observed here are considerably less pronounced than the "unadjusted" period effects presented in Figure 2. Most importantly, across all three model specifications, the estimated period effects were by and large stable across the last two decades of the slowdown, when the proportion of those who had moved in the previous year dropped by nearly half. Put differently, the pronounced decline in the probability of moving shown in Figure 2 is considerably attenuated – but not erased – when we account for age and cohort membership.

Figure 3: **Period effects from mixed-effects models predicting the probability of internal migration**
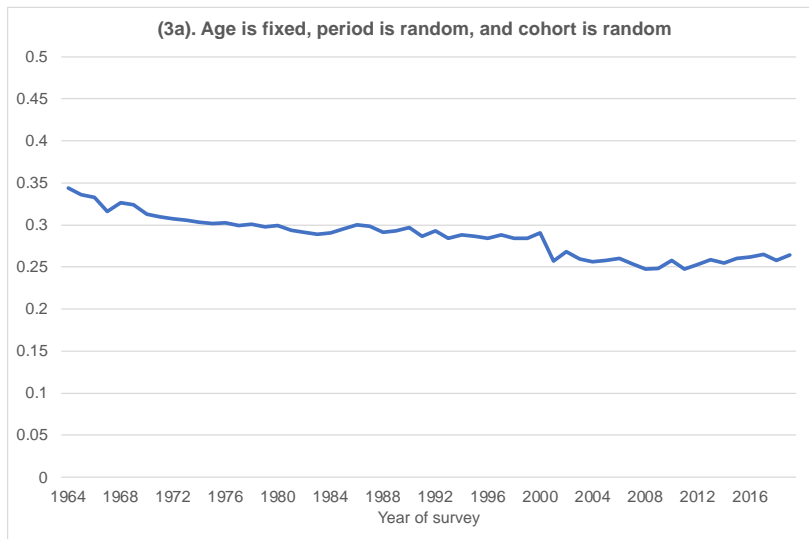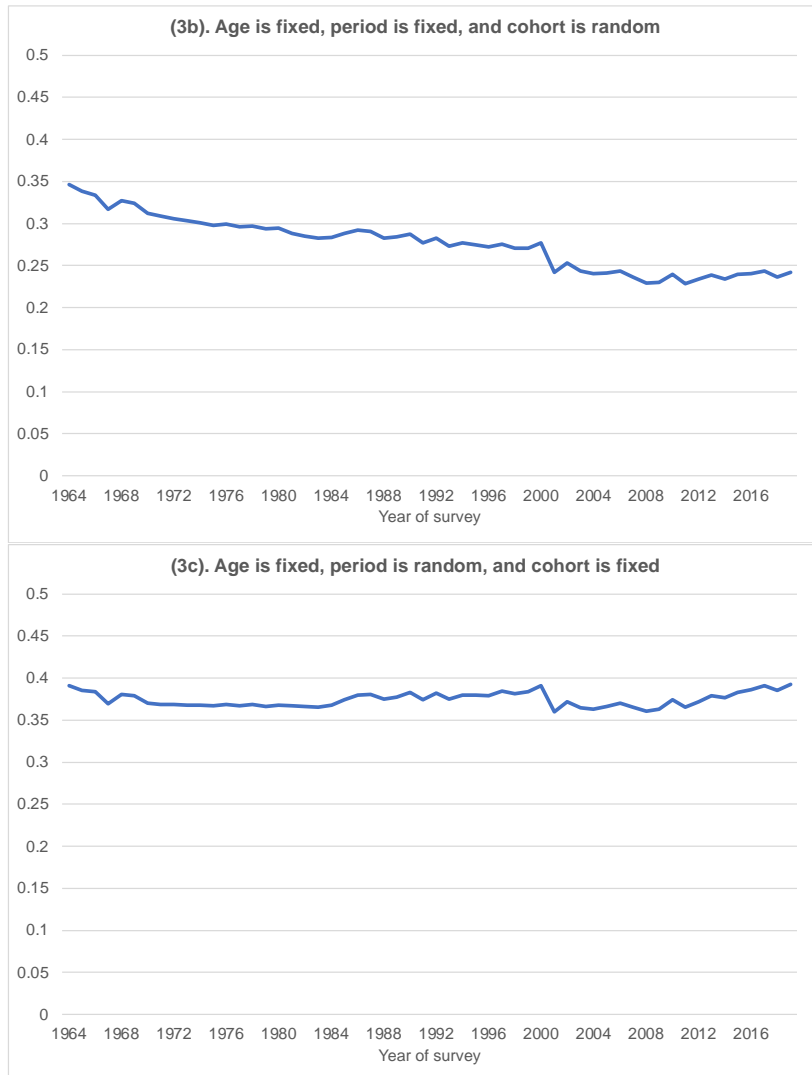
Figure 3:   (Continued)

To illustrate potential cohort effects, I first plot the random cohort effects from Model 1 in Figure 4a ($\alpha_j = \gamma_0 + \mu_{0j}$). Next I plot the random cohort effects from Model 2 in Figure 4b ($\alpha_j = \gamma_0 + \mu_{0j}$). Finally I plot the fixed cohort effects from Model 3 in Figure 4c ($\alpha_j + \beta_4\textbf{COHORT}_i$). While period effects across the migration slowdown are somewhat subdued, Figure 4 reveals striking patterns with respect to the migration profiles of the different cohorts. Members of the GI generation, the Silent generation, and the Baby Boom generation had similar or in some cases elevated probabilities of moving. However, starting with Generation X, the probability of migrating began to decline. This decline was substantially more precipitous for members of the Millennial generation and for Generation Z. To illustrate using the probabilities from the cross-classified model estimates in Figure 4a, 18-year-old Baby Boomers born in 1955 had a 0.316 probability of moving in the previous year, whereas 18-year-old Millennials born 40 years later, in 1995, had only a 0.182 probability of moving in the previous year.

Figure 4:   Cohort effects from mixed-effects models predicting the probability of internal migration
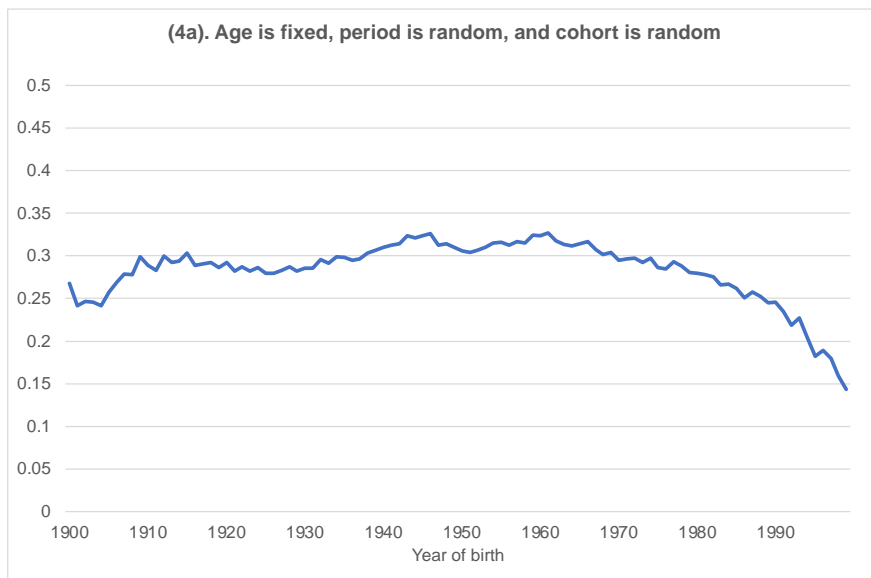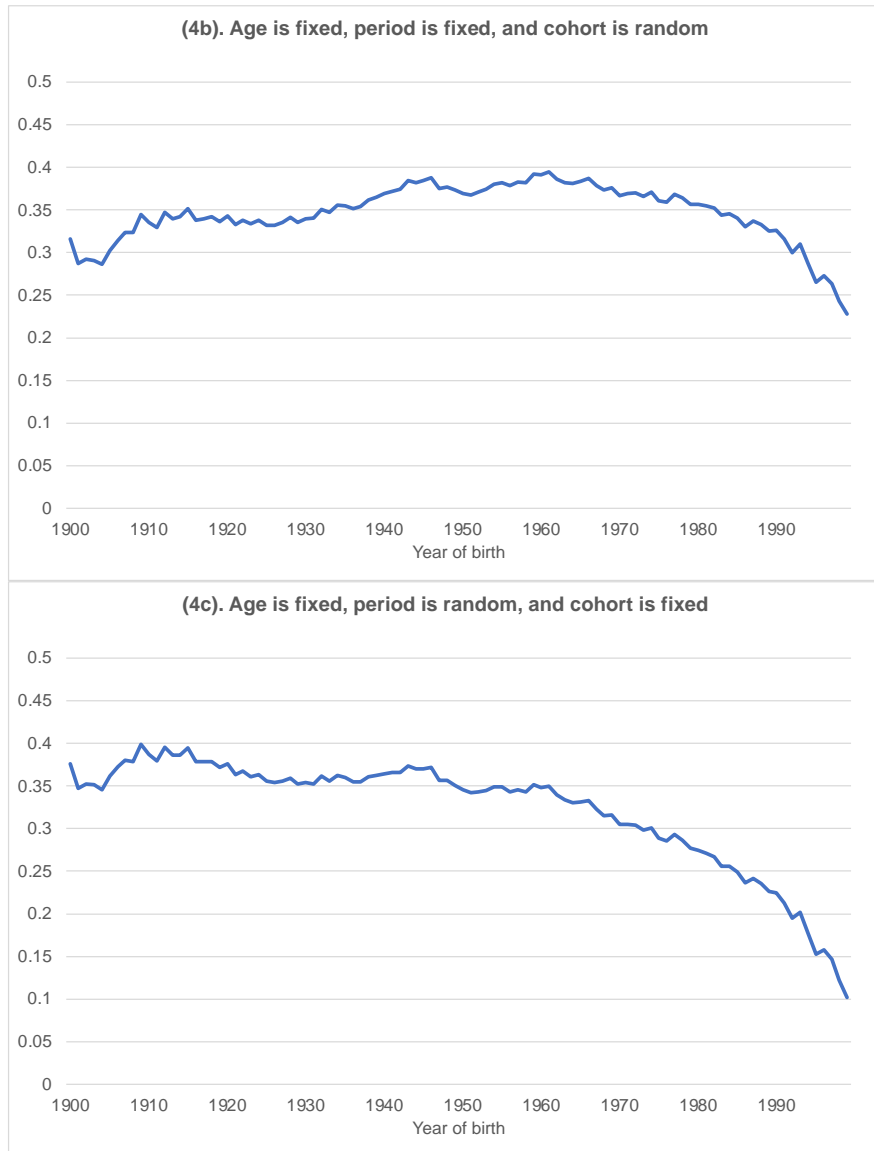
Figure 4: **(Continued)**

(4b). Age is fixed, period is fixed, and cohort is random

(4c). Age is fixed, period is random, and cohort is fixed

The distinct generational patterns evidenced in Figure 4 cast the migration slowdown as a trend driven in large part by the changing migration profiles of cohorts as they pass through their prime years of geographic mobility. Rates of internal migration were at their peak when the youngest members of the Silent generation and the Baby Boom generation were aging into their prime years of geographic mobility. As these cohorts had a greater than average likelihood of moving, rates of internal migration declined only slightly. However, starting around 1987, as Generation X was entering young adulthood and the Baby Boom generation was entering midlife, the decline in migration began in earnest. The decline became even more precipitous in the early 2000s, when the Millennials began to come of age. With Millennials' lower than average likelihood of moving, the rate of internal migration plunged – reaching its lowest levels as the youngest members of Generation Z entered young adulthood.

5.2 Age x period interaction terms

To further illustrate the role that cohorts play in the migration slowdown, I estimate models with interaction terms between age and period, as recommended by Luo and Hodges (2020a). I then use the parameter estimates from that model to calculate predicted probabilities, which I plot in Figure 5. In this figure, migration age schedules are displayed by birth cohort. To assist in interpretation, trend lines for the Baby Boom cohorts are colored in blue, trend lines for the Generation X cohorts are colored in red, and trend lines for the Millennial cohorts are colored in green.

Figure 5:   Probability of internal migration at different ages by birth cohort
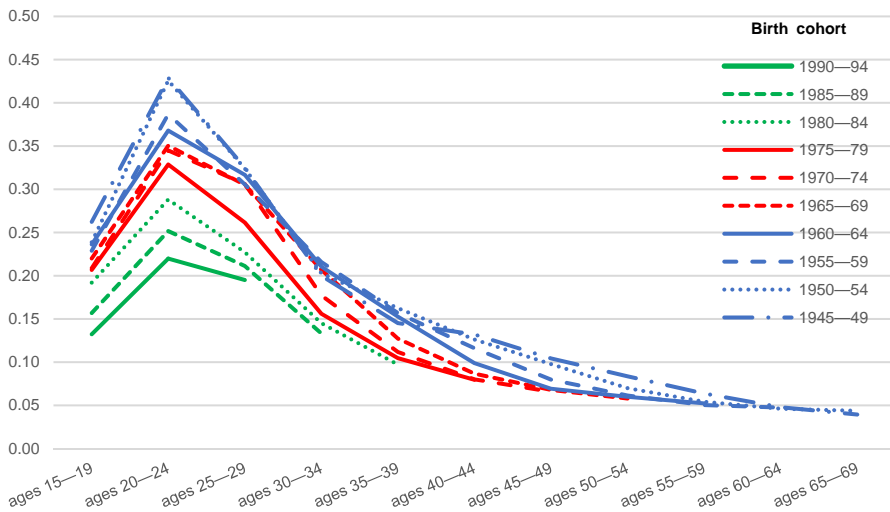
Note. Blue lines indicate Baby Boomer birth cohorts, red lines indicate Generation X birth cohorts, and green lines indicate Millennial birth cohorts.

The first thing to notice in Figure 5 is that the overall shape of the different age schedules across cohorts is the same, attesting to the strong role that age plays in structuring the contours of migration across the life course. All cohorts evidence an increase in migration as they leave adolescence and embark on the transition to adulthood. A few years into this transition, however, the probability of moving begins to decline as the cohorts enter their 30s and beyond.

While the overall shape is largely constant across cohorts, there are two differences of note. First, compared with Baby Boomer and Generation X cohorts, the Millennial cohorts have considerably lower rates of migration when they are first observed in their late teen years and when they reach their apex of geographic mobility in their early 20s. For example, during the peak ages of migration (ages 20–24), Baby Boomers born in 1945–1949 had a 0.429 probability of migrating in the past year, compared with a substantially lower 0.222 probability of migrating observed among Millennials born in 1990–1994. Given the stability in the shape of migration age schedules, the trends shown in Figure 5 provide strong evidence that Millennials will experience considerably lower levels of geographic mobility across their life spans when compared with Generation X, whose members will in turn experience considerably lower levels of geographic mobility across their life spans when compared with Baby Boomers.

Second, for Baby Boomers, the upward slopes between age 18 and age 24 and the downward slopes starting at about age 25 are steep – indicating a compressed, acute period of migration in the late teens/early 20s. In contrast these slopes are less pronounced for Millennials, meaning that not only are Millennials less likely than Baby Boomers to move in young adulthood, but when they do move, there is greater variability in the timing. These divergent age schedules across cohorts align with research in sociology that finds that across the 20th century and early 21st century, there was a gradual decoupling of key events in young adulthood (e.g., finishing school, leaving the parental home, entering the labor force, and forming a family), which in turn contributed to a lengthening transition from adolescence to adulthood (Shanahan 2000). Taken together, the findings from the age x period interaction term analysis shown in Figure 5 complement and reaffirm the findings about cohort effects observed in the mixed-effects models. More recent birth cohorts are moving far less than earlier birth cohorts, which in turn accounts for a substantial portion of the observed migration slowdown in the United States.

6. Discussion

Across the latter part of the 20th century and into the first two decades of the 21st century, the internal migration rate of Americans fell by half, an unexpected trend coined the Great American Migration Slowdown by demographer William Frey (2009). Despite broad social changes that at face value would seem to anticipate heightened geographic mobility during this period, Americans instead became, per sociologist Claude Fischer's (2019) observation, "ever-more rooted." Researchers have identified a myriad of possible explanations for this surprising trend (Cooke 2011, 2013; Fischer 2002; Foster 2017; Hyatt et al. 2018; Milne 1993; Molloy, Smith, and Wozniak 2017; Pandit 1997; Plane and Rogerson 1991). However, it is unclear from the existing research base whether the migration slowdown was driven by period-specific factors that gradually diminished the prospects of moving for the population as a whole or whether distinct characteristics of birth cohorts differentially contributed to declines in migration. The present study, which includes the first age-period-cohort analyses of the migration slowdown, explicitly fills in this gap in the literature.

The key finding from my analysis is that both period and cohort effects are affecting the contours of the migration slowdown, but cohort effects appear to be more salient. In substantive terms, this means that the declining rate of internal migration observed across the past few decades in the United States is best understood via the lens of cohorts with different probabilities of moving gradually progressing through their prime years of geographic mobility. The Baby Boom generation had the highest probabilities of moving.

When these cohorts were in their young adult years, rates of internal migration declined slightly but largely remained steady. However, once these cohorts moved into midlife and were succeeded by Generation X, and later by the Millennial generation and Generation Z, rates of internal migration plummeted. This is because Generation X, the Millennials, and Generation Z have lower probabilities of moving at all observed ages and across all observed time periods.

My analysis updates and clarifies the findings of Rogers and Rajbhandary (1997), which is to my knowledge the only attempt to disentangle period and cohort effects in the secular decline in migration rates in the United States. They identified a decline in cohort migration rates from the 1948 through 1964 birth cohorts, whereas my analysis identifies a sustained, *elevated* probability of geographic mobility across these birth cohorts. This difference is likely due to the fact that Rogers and Rajbhandary's analysis, which was based on data only through 1993, used period rates to extrapolate future moves for younger cohorts with incomplete, "right-censored" migration histories. Further, they focused only on men and did not include women in their analysis. In contrast, my analysis uses completed adult migration histories of both women and men from the Baby Boom generation.

While my study does not aim to adjudicate the different proposed explanations for the slowdown, it is worth highlighting that my findings indirectly refute the Easterlin relative cohort size hypothesis. If the size of one's cohort is responsible for depressing the economic prospects of its members, which in turn diminishes their rates of geographic mobility, then we would expect the lowest rates of migration among the Baby Boom and Millennial generations (which have the largest birth cohorts) and the highest rates of migration among Generation X (which has the smallest birth cohorts). However, my analysis shows that the highest migration rates are registered for the Baby Boom cohorts and the lowest migration rates are registered for the Millennial cohorts, with Generation X in between. Cohort effects play a considerable role in the shape and pace of the migration slowdown, but the size of a cohort does not appear to be a relevant factor.

The findings from my analysis have practical implications for the utility and value of standard demographic measures used to describe migration and to conduct population projections. Given that cohort effects are stronger than period effects, migration measures and population projections that rely on period-level inputs may mischaracterize internal population dynamics in the United States. With respect to summary migration measures, the period total migration rate, which is akin to the total fertility rate (Kolk 2019), and migration expectancy, which is akin to life expectancy (Long 1973), both use age-specific period rates to summarize the total migration experience of a synthetic cohort exposed to current-period age-specific risks of migration. Such measures, particularly when used to forecast migration trajectories of Millennials and Generation Z, may somewhat overstate migration given that these measures incorporate the Baby Boom cohorts as well as

Generation X, who comparatively have a higher likelihood of moving. Similarly, subnational population projections that use cohort component methods rely on age-specific migration rates, which could potentially distort the projection in later years – especially should Millennials and Generation Z remain "ever-more rooted" in the years to come. At least in the short term, applying conservative assumptions regarding internal migration may improve the accuracy of both summary migration measures and subnational population projections.

Despite the many strengths of my study, including national time series data that span the entire time frame of the slowdown and the application of different methods to identify cohort effects, my analysis is limited in that it is able to gauge only overall rates of internal migration – effectively treating a short move within the same town the same as a long-distance move across the country. Although the CPS-ASEC does distinguish intracounty, intercounty, and interstate moves, these are weak measures of distance, as some moves across state borders are short (such as moving from Kansas City, Missouri, to Kansas City, Kansas), and some intrastate moves are substantially farther (such as moving from El Paso, Texas, to Houston, Texas). Future research with different data sources will be needed to explore the potential role of period and cohort effects in shaping the relative dispersion of migration.

Another limitation of this analysis is that it uses mixed-effects models, which are criticized because their estimated random effects are highly sensitive to non-linearities that can constrain them to be near zero (Bell and Jones 2018; Luo and Hodges 2020b; O'Brien 2017). This could result in artificially understating the true effects of periods or cohorts. To circumvent this limitation, I test the robustness of my results using different age-period-cohort combinations as random or fixed. Additionally I explore the salience of cohort effects by estimating models with interaction terms between age and period. As no one method can effectively solve the age-period-cohort identification problem, I treat all these findings as corroborating descriptive evidence rather than as definitive causal explanations. Regardless of the method, however, there are notable cohort differences in the probability of moving, which in turn are playing an important role in the slowing of the overall migration rate.

In closing, my age-period-cohort analysis of the Great American Migration Slowdown reveals stark generational differences in migratory behavior that have substantial effects on internal population dynamics. Given that this analysis was conducted using data collected prior to the onset of the COVID-19 pandemic, it is unclear if a turnaround in migration is on the horizon. As the pandemic set in, journalistic accounts reported that large swaths of college students were forced to move home or off campus, densely populated urban areas were evacuated by affluent residents, and low-income families faced a potential eviction crisis. This array of factors suggests the likelihood of at least a short-term, period-specific spike in rates of internal migration.

However, lockdown measures intended to slow the spread of COVID-19 created an economic recession that may permanently alter the migration trajectories of the youngest members of the Millennial generation and Generation Z, who are experiencing simultaneous health and economic crises as they reach their prime years of geographic mobility. As the aftermath of the pandemic and the recession progresses, demographic analyses that distinguish period and cohort effects will be needed to assess whether geographic mobility patterns are affected for the entire population in the short-term and whether this situation will further hinder the long-term migration prospects of the youngest generations.

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