Retirement migration among the baby boomers: cohort dynamics and spatial structure in Australia

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1) Introduction

The oldest members of the Baby boom will soon reach retirement age. The unprecedented rise in people withdrawing from the labour force will not only have striking fiscal implications, but will also result in an increased pool of potential retirement migrants. This means that, even if retirement migration intensities stay constant, the size of cohorts will lead to an increased volume of retirement migration. The implications for the development of planning strategies to ensure adequate health, housing, welfare and provision of aged care services in the right place at the right time will be substantial. Given these anticipated changes in population age structure, service requirements and pressure on the public pension system, it is little surprising that governmental agencies, planners, demographers and population geographers have started to look ahead to when the baby boomers will reach retirement age.

The crucial question regarding future changes in migration is whether the retired baby boomers will migrate at the same rate compared to their predecessors. Building on the work by Easterlin (1980), evidence from the United States has established that the large cohort size of the baby boom had a depressing effect on migration intensities during the 1970s and 1980s, and that cohort size also influenced the spatial patterns and timing of moves (Pandit, 1997a; Pandit, 1997b; Plane and Rogerson, 1991; Rogerson, 1987). A review of the relevant literature shows, however, that only few studies have analysed the effect of cohort size on mobility outside the US. In fact, using Dutch data, Mulder (1997) found no significant relationship between migration intensities and cohort size. Hence, it appears that the evidence for a depressing effect of large cohort size on migration is limited to the US and, therefore, not fully conclusive. The literature does not provide a definitive answer to the question as to whether the boomers' migration behaviour has been distinctive from earlier cohorts as they moved through the life course. Yet understanding the cohort dimension of mobility is essential to accurately predicting future patterns and intensities of migration among the impeding surge of retirees.

Despite ample evidence of the importance of cohort effects, our comprehension of causes of temporal variations in mobility is largely confined to the effects of age and, to a lesser degree, period. The aging of the population and the progression of large cohorts into older, less mobile age groups tend to result in decreased mobility levels. The Australian literature has shown, however, that, despite population ageing, migration intensities have remained remarkably stable since the late 1970s (Bell and Rees, 2006). The question arises whether the stability of these patterns is the result of economic or housing market conditions having a positive effect on mobility, and thus outweighing the negative influence of a changing age structure, or whether cohort effects play a role in encouraging mobility.

The analyses of such trends is made difficult by the lack of adequate data. As emphasised by Bell and Rees (2006), few cross-sectional analyses of migration have thus far employed migration data classified by birth cohort as the third dimension in addition to age and period. The use of conventional cross-sectional period-cohort census data that are classified by age and period impedes the separation, identification and analysis of the influence of age and period, on the one hand, and birth cohort on the other. Changes in the propensity to move by age reflect the occurrence of triggering events, which tend to occur at particular life course stages. Changes by birth cohort reflect differences in cohort behaviour as they progress through the life course and show the impact of common experiences and social change, while those by calendar time can show changing influences of economic conditions.

Using data from the AIM database that are fully classified by age, census period and birth cohort, this research aims to determine the influence of birth cohort on mobility while controlling for the effects of age and calendar time (period). Age-period-cohort (APC) models have been used widely in the social sciences to disentangle these effects (Mason and Wolfinger 2002; O'Brien, 2000; Yang, 2007). With the exception of the work by Mulder (1993), APC models have rarely been applied to migration. The analysis presented in this paper extends the literature by exploring how cohort size shaped the migration dynamics of the Australian baby boom as it has moved through the life course. Facilitated by the increasing availability of migration data and improved analysis tools, this will be done by employing formal APC modelling techniques to estimate age, period and cohort effects on migration for the period 1976 to 2001. This paper addresses the following questions: (1) After controlling for the effects of age and period, do the baby boomers migrate more or less compared to preceding and succeeding cohorts? (2) If yes, is the change in migration intensity related to cohort size? And (3) Do economic circumstances or housing cost play a role in these changes?

The next section introduces the data used in the APC analysis. Following the discussion of the methodology, the effects of age, period and cohort on migration in Australia are examined by applying APC modelling techniques. Next, type of move and gender are added to the equation, distinguishing different types of movements by using a simple rural/urban dichotomy. Section 4 reports the results. The paper concludes with a discussion of findings.

2) Data

The analysis presented in this paper uses data from the Australian Internal Migration (AIM) database, which is derived from the census and holds data on five year migration transitions for the five intercensal periods from 1976-81 to 1996-01, disaggregated by sex and by five year age groups. A detailed description of this dataset can be found in Bell et al. (1999).

Originally collected on a period-cohort observation plan, the AIM database disaggregates transitions into age-period-cohort spaces to facilitate APC analysis (Bell and Rees, 2006). The period-cohort data reported in the census capture migrants that belong to a given birth cohort in a given 5-year period. Age is not measured at the time of the move but at the end of the 5-year period. Thus, a given cohort is aged 5 years younger at the beginning of the period. Birth cohorts are observed for different age groups. For example, the 1921-26 cohort is observed at ages 55-59 to 75+, while the 1961-66 cohort is observed for ages 10-14 to 35-39. Thus, when using this type of datasource for cohort analysis, it is crucial to control for age effects. Figure 1 presents migrant counts (in 1,000) for total mobility by period-cohort, calculated from the AIM database and tabulated in a Lexis diagram.

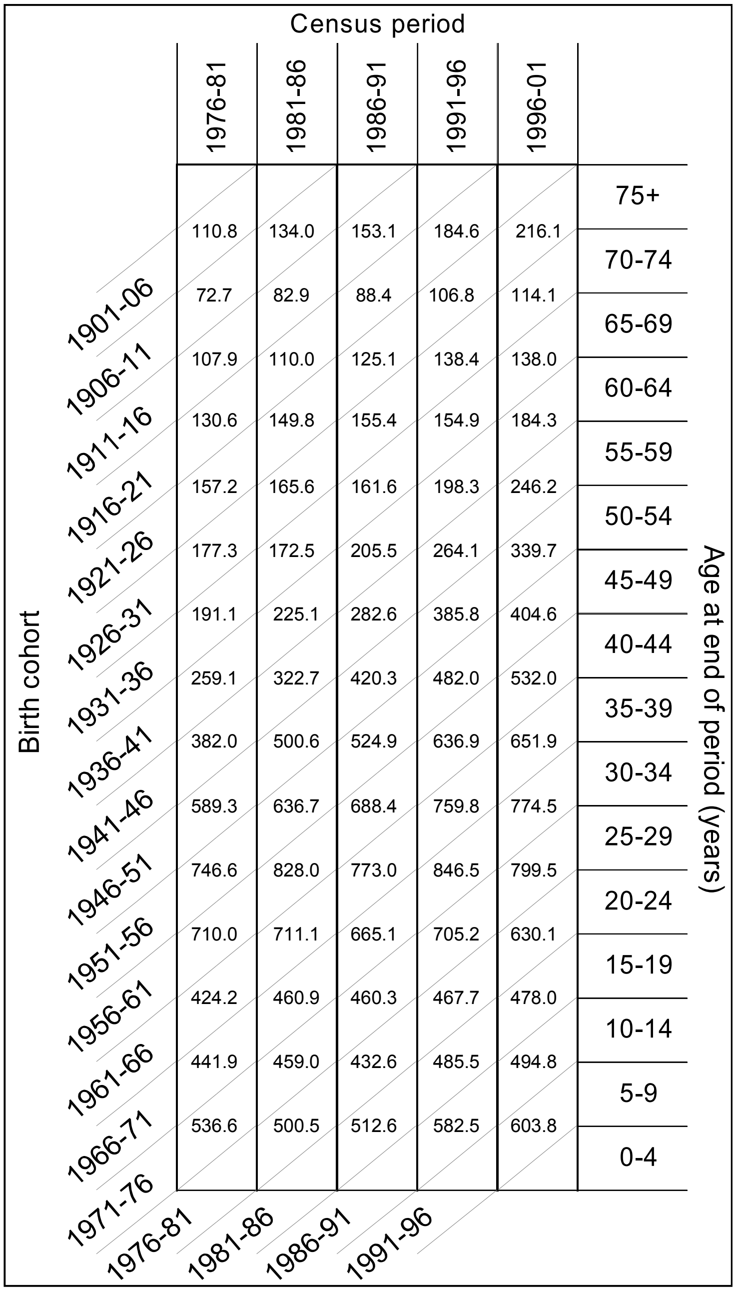

Figure 1. Lexis diagram with migrant counts (in 1,000) for period-cohort spaces

Estimating the effect of cohort size on migration intensity is difficult because of the linear dependency between age groups, periods and birth cohorts (Mason et al., 1973). This feature, which is unique to APC models, means that any two factors allow the third one to be derived (Mason and Wolfinger, 2002). For example, if the age group of a given number of migrants at the end of the census period (e.g. 10-14 years) and the period of observation (e.g. 1981-86) are known, the birth cohort (e.g. 1971-76) of these migrants can be identified (*Age + Period = Cohort*). The linear dependency between age, period and cohort can be broken if migration intensities are estimated for age-period-cohort spaces. In age-period-cohort data, a given birth cohort still corresponds to one period, but since the period-cohort space is split into a younger and an older APC space, the cohort now corresponds to two age groups. Thus, the linear dependency is broken if age-period-cohort spaces are used (*Age* + *Period* ≠ *Cohort*).

Migration counts for APC spaces are calculated using the period-cohort data shown in Figure 1. Period-cohort spaces are then split into a younger and an older APC space. Since mobility varies strongly by age, it is not feasible to simply divide the period-cohort spaces into equal parts (Bell and Rees, 2006). Instead, a set of separation factors derived from single-year national mobility profiles for 1-year age groups are used. The separation factors represent the proportion of mobility in a given APC space of the total mobility in the corresponding period-cohort space. For each period, the period-cohort counts (originally disaggregated into 15 age groups) are split into 29 APC spaces according to the following equation. A detailed description of this procedure can be found in Bell and Rees (2006).

$$APC_{ij(young)} = PC_{ij} * SF_{ij}$$

where $APC_{ij(young)}$ is the younger APC space in period i at age j (APC 2 in Figure 2), PC_{ij} is the observed period-cohort migrant count in period i at age j and SF_{ij} is the separation factor for the period-cohort count in period i and at age j. Note that no older APC space is calculated for the 75+ age group. The final dataset thus comprises 145 observations (29 APC spaces over 5 periods). To relate the migrant counts to the size of the population in the origin region, the counts are divided by the population at risk of migrating at the origin at the beginning of the period.

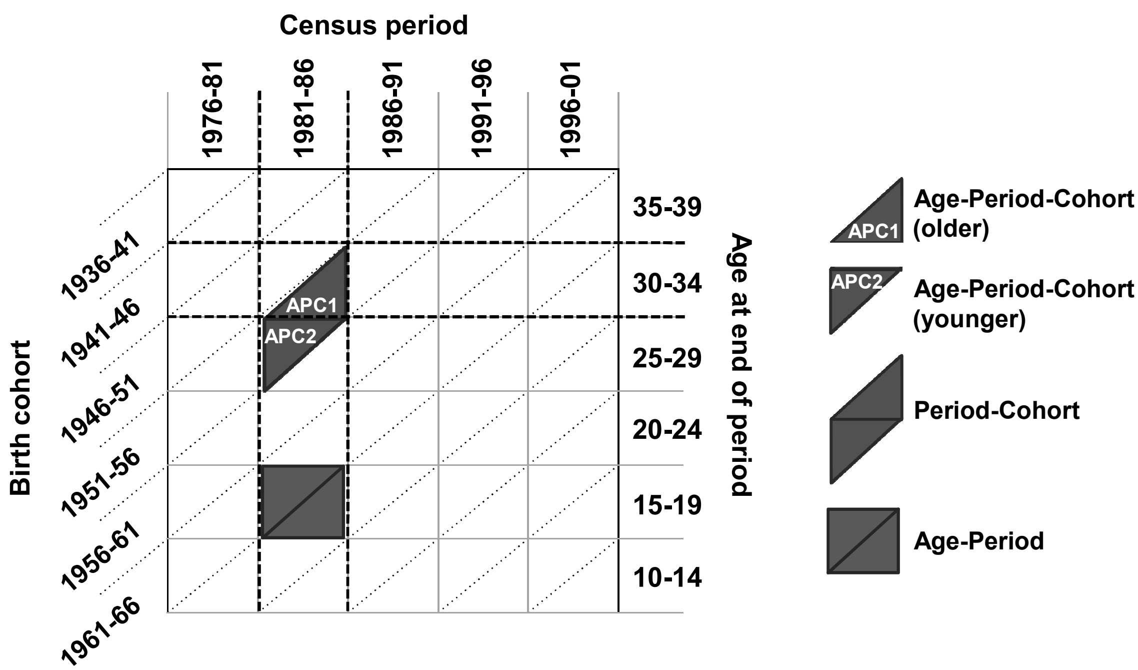

Figure 2. Migration data observation plans

To shed light on the role that cohort size, economic circumstances and housing cost play in changing migration intensities, data were collected from published sources on several indicators. Data on birth cohort size, GDP and unemployment rates of 20-29 year olds, 1976-2001, were obtained from the Australian Bureau of Statistics (ABS). Data on housing interest rates (per cent per annum) were obtained from the Reserve Bank of Australia.

The question whether changes in migration intensity are related to cohort size is analysed using the full APC model and two extended models that also include cohort groups and cohort size categories, respectively (see Section 3 for details). The cohort groups model allows the comparison of the migration behaviour of the baby boom generation to older and younger cohorts. Accordingly, 5-year birth cohorts were grouped into pre-baby boom, baby boom, and post-baby boom cohorts.

The cohort size model addresses potential effects of the timing and size of the Australian baby boom on mobility. Figure 3 shows the change over time in the size of 5-year birth cohorts. In Australia, the baby boom peaked in 1971, resulting in the 1971-76 birth cohort to be the largest of all baby boom cohorts. The cohorts born after 1986, however, represent the baby boom echo and are even larger in size than the baby boom. To evaluate the impact of cohort size on migration, cohort size records were divided into 4 quantiles (four classes with approximately equal membership counts). These quantiles were then used to group cohorts into three groups: those cohorts with a size below the 0.25 quantile (25% of the cohort size values fall below the 0.25 quantile) are classed as "small", cohorts with a size above the 0.25 quantile and below the 0.75 quantile are classed as "medium", and cohorts with a size above the 0.75 quantile are classed as being "large" in size (see Figure 3). This means that there are 621,000 to 796,000 live births in the small 5-year birth cohorts, 796,001 to 1,360,000 live births in the medium size cohorts and 1,360,001 to 1,550,000 live births in the large cohorts.

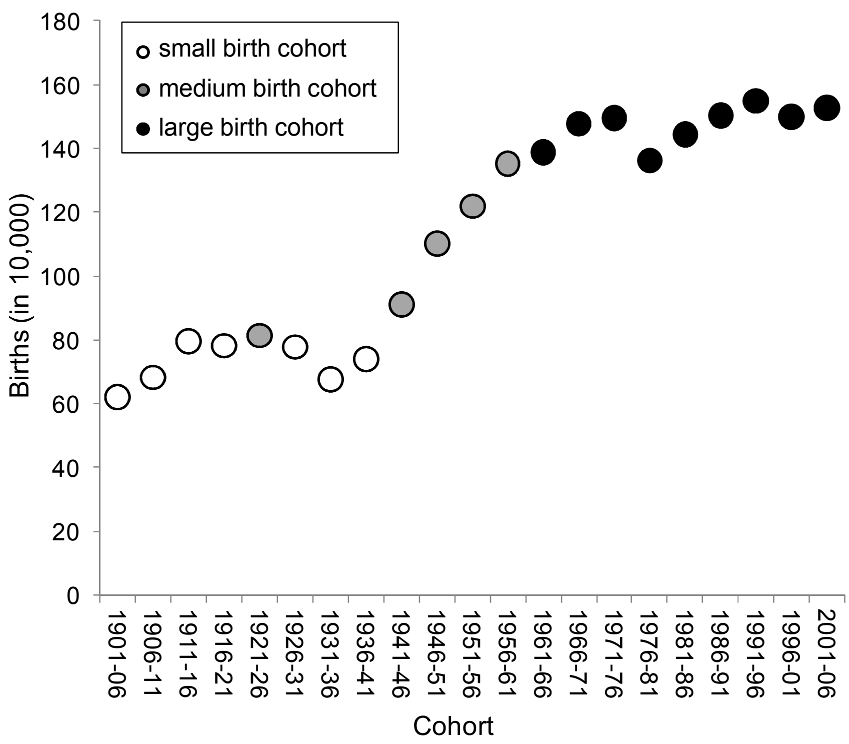

Figure 3. Australian 5-year birth cohorts by size

Dependent variable

In the present study, migrant counts for APC spaces are used as the dependent variable. Besides total mobility, the effect of cohort on migration propensity, while controlling for age and period effects, is also examined by type of move and sex.

Independent variables

The multivariate models include a series of dummy variables representing age groups, census periods and birth cohorts. To evaluate alternative model specifications, dummies for cohort size and cohort groups are added to the model. The period dummies are replaced by three interval variables that have been used as indicators of period characteristics: GDP, housing interest rate and unemployment rate of 20-29 year olds.

Geography

The literature suggests that cohort size effects vary by type of move (Pandit, 1997a). To study these variations in the Australian context, APC models are run for five types of moves. Migrant counts and corresponding populations at risk are calculated for an aggregation of 69 temporally consistent regions (TSDs), which are harmonised to correct for boundary changes over the five census periods (Blake et al., 2000). The TSDs are aggregated using a metropolitan/non-metropolitan dichotomy in which the TSDs that cover the capital cities are classified as "metropolitan" and the remaining TSDs as "non-metropolitan" (see Figure 4). Five types of moves are distinguished: local moves within the same TSD, intrastate moves (a) from the capital city to a non-metropolitan TSD, (b) from a non-metropolitan TSD to the capital city, (c) between non-metropolitan TSDs in the same state, and also interstate moves to a TSD in another State.

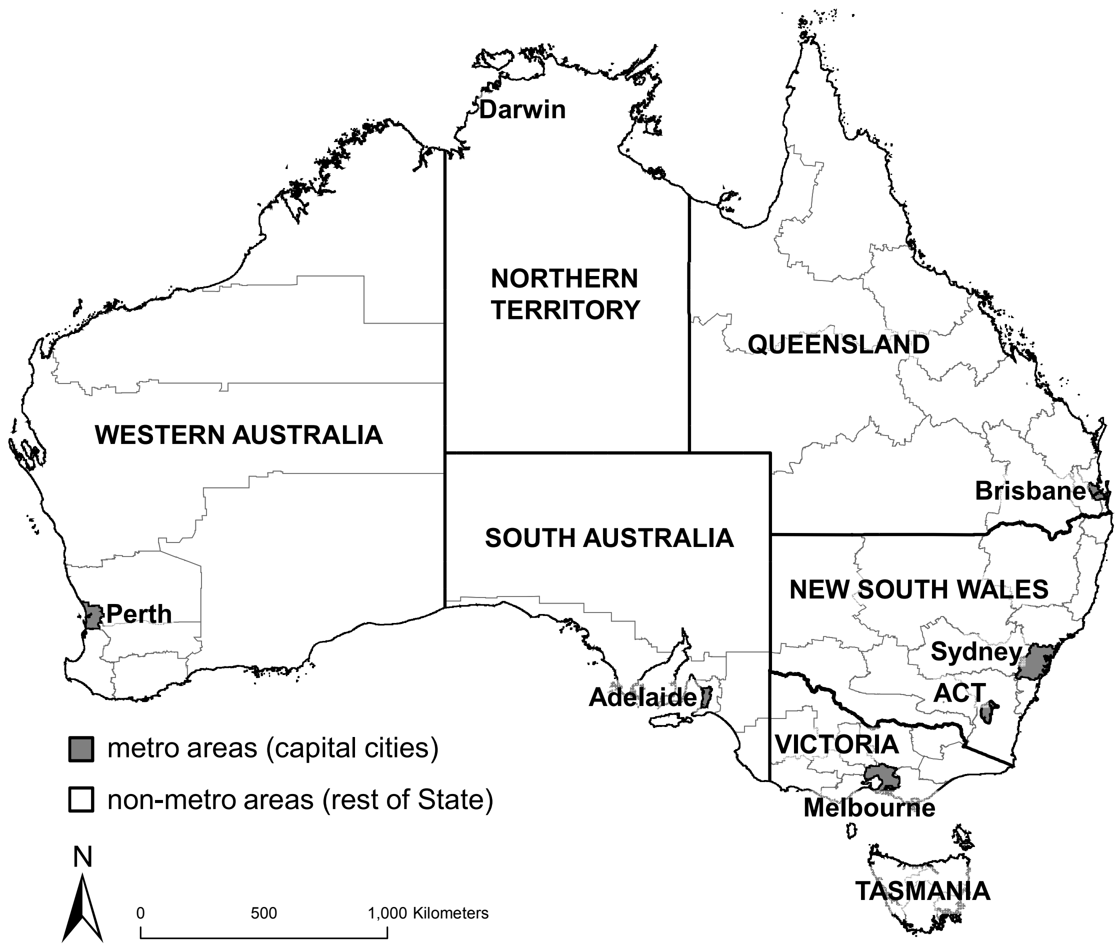

Figure 4. Map of TSDs, Australia, 1976-81 – 1996-01

3) Methodology

Age-period cohort models brake down the time trends in migration into the effects of age, birth cohort and calendar time. This research aims to uncover how cohort effects shape migration behaviour when age and period effects are controlled for. The literature suggest using ordinary least squares (OLS) regression Age-Period-Cohort (APC) models for this purpose. However, in migration studies the dependent variable (i.e. the migrant count) is measured as a nonnegative integer. This means that the data rarely meet the distributional assumptions underlying linear regression models (e.g. OLS), resulting in poor model fit. Therefore, other approaches to modelling age, period and cohort effects on discrete outcomes are required. Poisson regression models have been frequently used to analyse migration (Boyle, 1995; Flowerdew, 1991). The Poisson distribution requires that the mean equals the variance, an assumption that is often violated if count data are used (Long and Freese, 2006). Table 1 presents some preliminary results of this research, showing that in the data used here the variance is much greater than the mean. This means that the data are overdispersed and the use of a Poisson model would result in spuriously small standard errors of estimates (Barron, 1992).

Table 1. Descriptive statistics, migrant counts for APC-spaces, by type of move

	total mobility	same TSD	metro to non-metro	non-metro to metro	non-metro to non-metro	interstate
Number of observations	145	145	145	145	145	145
Mean	196,775	138,461	12,459	10,836	11,570	23,449
Variance	14,500,000,000	7,310,000,000	45,200,000	71,900,000.00	45,400,000	233,000,000

A better fit to overdispersed count data is achieved when negative binomial regression models are employed. Despite the advantages of this GLM type for modelling count data, it has been infrequently used in migration studies. The negative binomial model is similar to the Poisson model, but it includes an additional parameter (alpha) to account for overdispersion. Alpha thus reflects unobserved heterogeneity among observations (Long and Freese, 2006). The parameter determines the degree of dispersion in the predictions. Higher values of alpha indicate stronger overdispersion. If alpha equals zero, the data are not overdispersed and, in this case, the negative binomial specification is the same as the Poisson.

In the present age-period-cohort analysis, migration rates at age *a*, in period *p*, and for birth cohort *c* were estimated. All statistical computations were performed using statistical software (STATA Version 10). The negative binomial model with a log link takes the following form:

$$\log \lambda_{a,p,c} \equiv \beta_0 + \beta_a x_a + \beta_p x_p + \beta_c x_c + \alpha_{a,p,c} \qquad (1)$$

where $\lambda_{a,p,c}$ is the predicted value of migrant count $y_{a,p,c}$ for a particular age group, period and cohort; x_a, x_p and x_c are the independent variables of age group, period and cohort with corresponding regression coefficients β_n, and $\alpha_{a,p,c}$ is the dispersion parameter.

If the independent variables of age group, period and cohort are represented by a series of dummy variables, the model can also be expressed as:

$$\begin{aligned}
&\log \lambda_{a,p,c} \equiv \beta_0 \\
&+ \beta_{a5-9} x_{a5-9} + \beta_{a10-14} x_{a10-14} + \ldots + \beta_{a75+} x_{a75+} \\
&+ \beta_{p1976-81} x_{p1976-81} + \beta_{p1981-86} x_{p1981-86} + \ldots + \beta_{p1996-01} x_{p1996-01} \\
&+ \beta_{c1901-06} x_{c1901-06} + \beta_{c1906-11} x_{c1906-11} + \ldots + \beta_{c1991-96} x_{c1991-96} \\
&+ \alpha_{a,p,c}
\end{aligned} \tag{2}$$

where the independent variable x_a (age) is represented by 15 dummies (5-9 to 75+), x_p is represented by 5 period dummies (1976-81 to 1996-01) and x_c is represented by19 dummies for cohort (1901-06 to 1991-96). The youngest age group (5-9), the first period (1976-81) and the oldest cohort (1901-06) were treated as the reference categories and are thus omitted. Interactions between age and cohort were not included in the model due to problems that would arise from over-identification of the model and an inconveniently high number of parameters.

The size of the population at risk (PAR) of migrating clearly affects the migrant count. The population at risk was entered into the model as an offset term to account for the variation in migrant counts by population size at the origin. In the present model, the offset term $t_{a,p,c}$ is the count of people at risk of migrating for a particular age, period and cohort. If the natural logarithm of the population count is included into the model, the equation can be rewritten as:

$$\begin{aligned}
&\log \lambda_{a,p,c} \equiv \beta_0 \\
&+ \beta_{a5-9} x_{a5-9} + \beta_{a10-14} x_{a10-14} + \ldots + \beta_{a75+} x_{a75+} \\
&+ \beta_{p1976-81} x_{p1976-81} + \beta_{p1981-86} x_{p1981-86} + \ldots + \beta_{p1996-01} x_{p1996-01} \\
&+ \beta_{c1901-06} x_{c1901-06} + \beta_{c1906-11} x_{c1906-11} + \ldots + \beta_{c1991-96} x_{c1991-96} \\
&+ \alpha_{a,p,c} + \log(t_{a,p,c})
\end{aligned} \tag{3}$$

A taxonomy of models was run to shed light on the relative importance of age, period and cohort effects, to address the cohort size effects, to compare the baby boom as a whole to older and younger generations, and to shed light on the role of economic conditions. Figure 5 shows the model specifications for the full and partial APC models. The full APC model (Model 1), the partial age-period (Model 1a: A-P) and age-cohort (Model 1b: A-C) models and the single cohort (Model 1c: C) model were run to determine how the model fit differs between the full and the partial models. Partial A-P or A-C models are usually preferred as less predictors are required to represent the underlying data, but in the case of A-P-C analysis, partial models have one important disadvantage: the estimated cohort trends are not controlled for age and/or period effects. As it will be shown in the next section, the cohort effects estimated by partial models differ significantly from those estimated by the full APC model. The differences are most pronounced if the dummies for age are omitted.

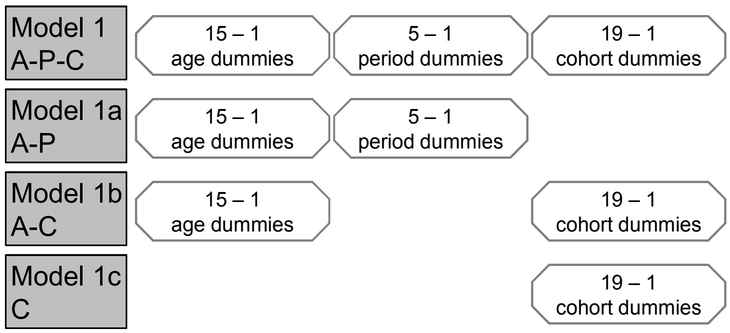

Figure 5. Specification of full and partial APC models

The goodness of fit of these models was compared using the Akaike Information Criterion (AIC). There is no reliable single measure of percent variance explained in count models (i.e. such as the adjusted R-squared in OLS regression). A number of pseudo-R-squared have been developed to help in assessing model fit, such as McFadden's R-squared, but the pseudo-R-squared has a different meaning to that used in OLS regression and thus has to be interpreted with caution. It addition, it can only be used to compare nested models. The fit of negative binomial regression models is better assessed using measures of information. The AIC is a measure of goodness of fit that is based on maximum likelihood estimation and can be used to compare non-nested models (Akaike, 1973). The lower the values of AIC, the better the fit of the model to the data. A single AIC value, however, is not interpretable due to the unknown constant. It is rather the value relative to other AIC values in the taxonomy of models that is important for determining model fit. Two models are commonly classed as indistinguishable if the difference in the AIC values is less than 2 (Burnham and Anderson, 2002).

In a second step, the full A-P-C model (Model 1) was extended to include cohort groups, cohort characteristics and period characteristics as predictors. The specifications of these extended models are shown in Figure 6.

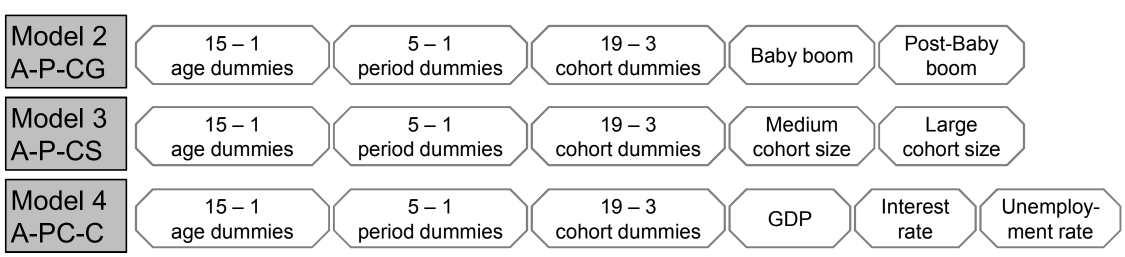

Figure 6. Specification of cohort group, cohort size and period characteristic APC models

An Age-Period-Cohort Group (A-P-CG) model (Model 2) was run to model the effect of being a member of the baby boom generation on mobility. The specification of the A-P-CG model is the similar to the A-P-C model discussed above. The A-P-CG model includes 15-1 age dummies, 5-1 period dummies and 19-3 cohort dummies. Besides the oldest cohort dummy being omitted as the reference category, two other cohort dummies were omitted due to collinearity. This model also includes 3-1 dummies that represent cohort groups: the pre-baby boom cohorts (born before 1946), the baby boomers (born between 1946-51 and 1971-76) and the post-baby boom generation (born after 1976). The cohort dummies remained in the model to ensure the comparability of model results. If the cohort dummies were omitted from the model, the parameter estimates for age and period would be adjusted accordingly to account for the variation not being captured by cohort dummies. One of the important disadvantages of omitting all cohort dummies is that the parameter estimates for cohort group dummies cannot be directly compared to the estimated cohort effects obtained by the APC model, thereby hindering interpretation of results. The A-P-CG model takes the following form:

$$\begin{aligned}
&\log \lambda_{a,p,c} \equiv \beta_0 \\
&+ \beta_{a5-9} x_{a5-9} + \beta_{a10-14} x_{a10-14} + \dots + \beta_{a75+} x_{a75+} \\
&+ \beta_{p1976-81} x_{p1976-81} + \beta_{p1981-86} x_{p1981-86} + \dots + \beta_{p1996-01} x_{p1996-01} \\
&+ \beta_{c1901-06} x_{c1901-06} + \beta_{c1906-11} x_{c1906-11} + \dots + \beta_{c1991-96} x_{c1991-96} \\
&+ \beta_{\text{pre-boom}} x_{\text{pre-boom}} + \beta_{\text{boom}} x_{\text{boom}} + \beta_{\text{post-boom}} x_{\text{post-boom}} \\
&+ \alpha_{a,p,c} + \log(t_{a,p,c})
\end{aligned}$$

An Age-Period-Cohort Size (A-P-CS) model (Model 3) was used to model the effect of cohort size (O'Brien 2000). The model specification of the A-P-CS model is the same as for the A-P-CG model, except that this model includes 3-1 dummy variables that represent cohort size (instead of cohort groups). As in the A-P-CG model, 2 cohort dummies are omitted due to collinearity. Absolute birth cohort size was categorised into small, medium and large size cohorts. The equation takes the following form:

$$\begin{aligned}
&\log \lambda_{a,p,cc} \equiv \beta_0 \\
&+ \beta_{a5-9} x_{a5-9} + \beta_{a10-14} x_{a10-14} + \dots + \beta_{a75+} x_{a75+} \\
&+ \beta_{p1976-81} x_{p1976-81} + \beta_{p1981-86} x_{p1981-86} + \dots + \beta_{p1996-01} x_{p1996-01} \\
&+ \beta_{c1901-06} x_{c1901-06} + \beta_{c1906-11} x_{c1906-11} + \dots + \beta_{c1991-96} x_{c1991-96} \\
&+ \beta_{smallcohort} x_{smallcohort} + \beta_{mediumcohort} x_{mediumcohort} + \beta_{largecohort} x_{largecohort} \\
&+ \alpha_{a,p,cc} + \log(t_{a,p,cc})
\end{aligned}$$

The migration literature has shown that economic conditions affected the migration behaviour of the US baby boom (Milne, 1993; Nelson and Sewall, 2003; Pandit, 1997a; Plane, 1994). In the present study, the effects of GDP, housing interest rates and unemployment levels on migration were examined using an age-period characteristic-cohort model in which age and cohort are represented by dummies, and calendar time is represented by period characteristics (i.e. GDP, housing interest rate and unemployment rate).

$$\begin{aligned}
&\log \lambda_{a,pc,c} \equiv \beta_0 \\
&+ \beta_{a5-9} x_{a5-9} + \beta_{a10-14} x_{a10-14} + \dots + \beta_{a75+} x_{a75+} \\
&+ \beta_{GDP} x_{GDP} + \beta_{interestrate} x_{interestrate} + \beta_{unemployment} x_{unemployment} \\
&+ \beta_{c1901-06} x_{c1901-06} + \beta_{c1906-11} x_{c1906-11} + \dots + \beta_{c1991-96} x_{c1991-96} \\
&+ \alpha_{a,pc,c} + \log(t_{a,pc,c})
\end{aligned}$$

All models outlined above were run for total mobility as the dependent variable. In a second step, the full A-P-C model, the A-P-CG model, the A-P-CS model and the A-PC-C model were also run separately for each type of move.

4) Results

This section begins with the evaluation of model fit using AIC, followed by the presentation of age, period and cohort effects estimated by the full A-P-C model. Next, the results from the period- and cohort characteristics and groups models are summarized. This is followed by the results from the full A-P-C models and the characteristics models run separately by type of move. Potential variations of effects by sex are also addressed.

As shown in Table 2, the examination of AIC values revealed that for total mobility the full negative binomial A-P-C model has the best model fit (i.e. the lowest AIC values). In other words, according to the AIC the full A-P-C model represents the migrant counts most accurately. This finding is remarkably consistent across types of moves. A comparison of AIC for the full model and the partial models shows that the difference in AIC is 213 between the A and the C models, and 180 between the C and the P models. These findings confirm the importance of age in explaining migration trends, but also points to cohort effects being relatively more influential in shaping migration behaviour than period effects.

Table 2. AIC of the taxonomy of negative binomial models by type of move

	total mobility	same TSD	metro to non-metro	non-metro to metro	non-metro to non-metro	interstate
A-P-C Model	3,266	3,169	2,278	2,126	2,074	2,642
A-C Model	3,270	3,174	2,423	2,178	2,122	2,653
P-C Model	3,480	3,378	2,718	2,678	2,544	2,897
A Model	3,272	3,197	2,485	2,312	2,228	2,647
P Model	3,665	3,560	2,785	2,863	2,813	3,086
C Model	3,485	3,381	2,735	2,701	2,593	2,913

The first set of modelling results from the A-P-C models is based on analyses of total mobility for persons. The number of migrants was estimated using a series of age, period and cohort dummies as predictors. Figure 7 shows the parameter estimates of age, period and cohort effects from the full A-P-C model with 95% confidence intervals. The parameter estimates are reported as incidence rate ratios (IRR), which are the exponentiated negative binomial coefficients. The interpretation of IRRs is similar to odds ratios used in event history analysis: the ratio of the incidence of migration in persons of a particular age, period or cohort to that in the comparison group (the first age group, period and cohort). If the ratio is above 1, these persons are more likely to move than the reference group, while values below 1 indicate lower risks of moving. Figure 7 shows that the parameter estimates for age closely resemble the pattern found in national migration age profiles. Mobility was highest among young adults, even if period and cohort effects were controlled for. The pattern in the parameter estimates for age points to cohort effects being adequately controlled for age effects. The parameters estimates for period are remarkably stable across time, showing only a slight downward trend. The estimates suggest that period effects had very limited impact on migration trends.

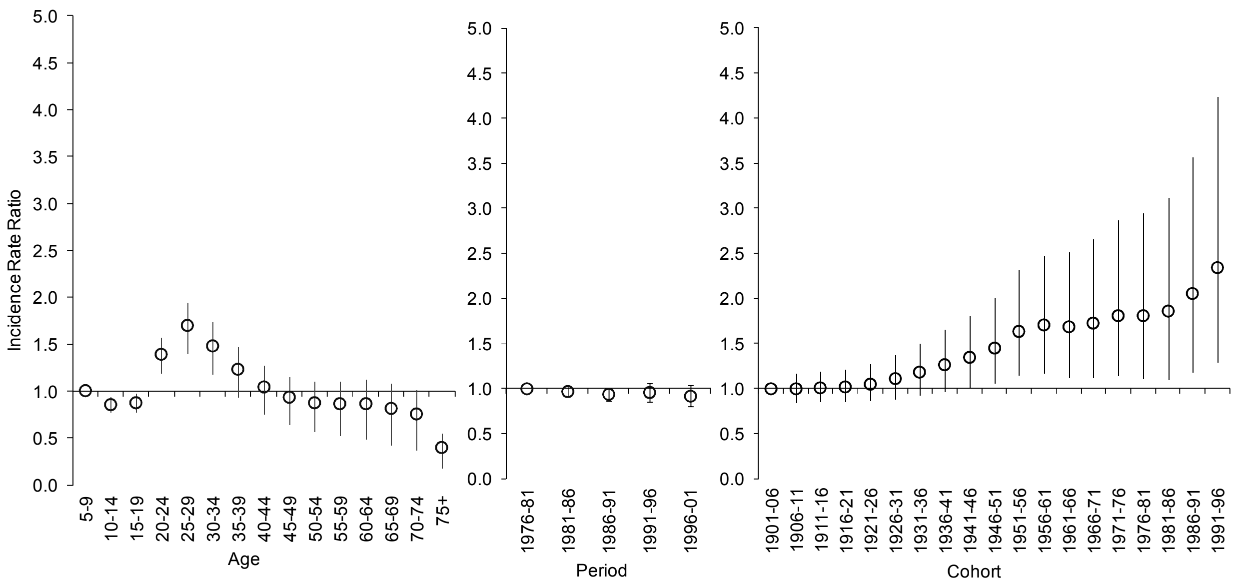

Figure 7. Parameter estimates (incidence rate ratios) of age, period and cohort from the full A-P-C model (with 95% CIs) for total mobility, persons

The parameter estimates for cohort show that, after controlling for age and period effects, migration propensities increased progressively across cohorts. The baby boom cohorts born between 1946 and 1976 had a higher risk of migrating than older cohorts, but the post-baby boom generation is characterised by even higher risks. Cohort effects on migration are thus not restricted to the baby boom but show a consistent trends across cohorts. The relative risk of moving by cohort began to rise in the 1921-26 cohort and showed a stable increase until the 1956-61 cohort. The rise in migration propensity levelled off for the 1961-66 and 1966-71 cohorts, but continued to increase among those born between 1966 and 1976, and, after a short dip in the 1976-81 cohort, finally showed a clear increase for the youngest cohorts. The sharp increase in migration propensity for the youngest cohort may be due to the small number of observations (i.e. the AIM dataset the 1991-96 cohort is observed for only 2 APC spaces). The levelling off among the later baby boom cohorts is somewhat consistent with the findings of Pandit (1997a) and Plane and Rogerson (1987), who found that the US baby boomers moved at depressed rates.

Further insights into the effects of cohort on migration can be obtained by comparing the estimated parameters from the full A-P-C model with those from the partial A-P, A-C and C models. Figure 8 shows how the results for cohort change if partial models are used, which means that age and/or period effects are not controlled for. The differences between IRRs for individual cohorts between the partial and the full model highlight the importance of controlling for age and period in the analysis of cohort effects. If period effects are not controlled for (i.e. the A-C model), estimates for cohort are lower than those from the full model but follow a similar trend. The IRRs obtained from the P-C model show that, if age effects are not controlled for, the estimates are significantly different. The observed variation from the full model is primarily a function of the age at which cohorts-specific migration intensities are observed. For example, the results from the P-C model show that the 1956-61 cohort has the second highest IRR of all cohorts. This is primarily due to the fact that migration intensities for this cohort are observed between the peak mobility ages of 20-24 and 40-44 years. Similarly, parameter estimates for the youngest cohorts born after 1986 are very high since migrant counts for these cohorts are only available for the relatively mobile children aged under 14 years. The IRRs from the C model show a similar pattern, although estimates are slightly lower to account for the negative period effect that is not controlled for in the C model.

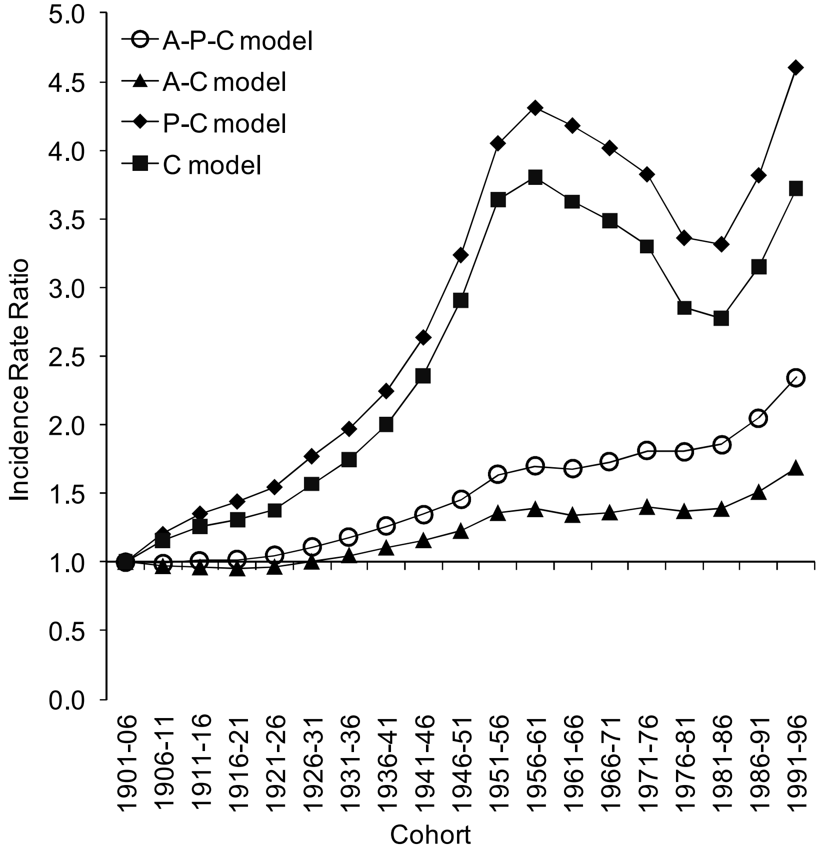

Figure 8. Parameter estimates (incidence rate ratios) of cohort from the partial A-C, P-C and C models for total mobility, persons

Table 3 reports the results from the taxonomy of models that were run for total mobility. Estimated incidence rate ratios, significance levels and goodness-of-fit statistics are presented for 4 models: Model 1 is the A-P-C model with dummies for age, period and cohort. Model 2 is the Age-Period-Cohort Groups model with added cohort group dummies. Model 3 is the Age-Period-Cohort Size model that includes dummies for cohort size. In Model 4 the period dummies are replaced by period characteristics.

The dispersion parameter alpha is significantly different from zero for all models *(α = 0.009 - 0.010, $p < 0.01$)*, underlining the preference for a negative binomial over a Poisson model. The log likelihood is similar across models. The chi-square goodness-of-fit statistics show that all models are statistically significant at the 1 % level. The parameter estimates for the full A-P-C have been discussed above. Now the focus shifts from models with dummy variables for age, period and cohort to the results from the cohort groups and characteristics models reported in Table 3.

The results from Model 2 (A-P-CG) with cohort groups added as predictors show that the baby boom cohorts had a 45% higher incidence of moving than the pre-baby boom cohorts *(IRR = 1.45, p = 0.023)*. In line with the findings presented earlier on the A-P-C model, the movement propensities among post-baby boom cohorts were even higher than those of the baby boom *(IRR = 2.34, p = 0.005)*.

Table 3. Negative binomial regression of migration for total mobility (N: 145)

Variable	Model 1: A-P-C IRR	Model 2: A-P-CG IRR	Model 3: A-P-CS IRR	Model 4: A-PC-C IRR
AGE				
5-9	1	1	1	1.00
10-14	0.86**	0.86**	0.86**	0.86**
15-19	0.88*	0.88*	0.88*	0.88*
20-24	1.39**	1.39**	1.39**	1.39**
25-29	1.70**	1.70**	1.70**	1.69**
30-34	1.48**	1.48**	1.48**	1.48**
35-39	1.23*	1.23*	1.23*	1.23
40-44	1.04	1.04	1.04	1.04
45-49	0.93	0.93	0.93	0.92
50-54	0.88	0.88	0.88	0.87
55-59	0.86	0.86	0.86	0.85
60-64	0.86	0.86	0.86	0.85
65-69	0.82	0.82	0.82	0.81
70-74	0.76	0.76	0.76	0.75
75+	0.40**	0.40**	0.40**	0.40**
PERIOD				
1976-81	1	1	1	
1981-86	0.97	0.97	0.97	
1986-91	0.93	0.93	0.93	
1991-96	0.95	0.95	0.95	
1996-01	0.91	0.91	0.91	
COHORT				
1901-06	1	1	1	1.00
1906-11	0.99	0.99	0.99	0.98
1911-16	1.01	1.01	1.01	1.00
1916-21	1.01	1.01	1.01	1.01
1921-26	1.05	1.05	0.62**	1.04
1926-31	1.11	1.11	1.11	1.10
1931-36	1.18	1.18	1.18	1.17
1936-41	1.26*	1.26	1.26	1.25
1941-46	1.35*	1.35*	0.79**	1.33*
1946-51	1.45**		0.85**	1.44*
1951-56	1.63**	1.13*	0.96	1.61**
1956-61	1.70*	1.17**		1.68**
1961-66	1.68*	1.16*	0.72*	1.66*
1966-71	1.73*	1.19*	0.74*	1.70*
1971-76	1.81*	1.25*	0.77*	1.78*
1976-81	1.81*	0.77*	0.77*	1.78*
1981-86	1.85*	0.79*	0.79*	1.83*
1986-91	2.05**	0.88	0.88	2.01*
1991-96	2.34			2.29**
COHORT GROUPS				
Pre-Baby Boom		1		
Baby Boom		1.45*		
Post-Baby Boom		2.34**		
COHORT CHARACTERISTICS				
Small cohort size			1.00	
Medium cohort size			1.70**	
Large cohort size			2.34**	
PERIOD CHARACTERISTICS				
GDP				1.00
Housing interest rate				0.99
Unemployment rate				1.01
Alpha	0.009**	0.010**	0.009**	0.009**
Log likelihood	-1,597	-1,607	-1,597	-1,597
Likelihood ratio chi-square	460** (36 df)	440** (36 df)	461** (36 df)	460** (35 df)
AIC	3,266	3,257	3,269	3,268

(* p ≤ .05; ** p ≤ .01)

The parameter estimates from Model 3 (A-P-CS) for total mobility show that the direction and magnitude of the effect of cohort size on migration propensity is similar to the effect that cohort groups had on mobility. Medium-sized cohorts (796,001 to 1,360,000 live births over a 5-year period) had a 70 % higher chance of moving compared to small birth cohorts (621,000 to 796,000 live births) *(IRR = 1.70, p = 0.006)*. Similar to the post-baby boom generation, large-sized cohorts (1,360,001 to 1,550,000 live births) had an even greater risk of moving than medium sized cohort *(IRR = 2.34, p = 0.005)*. The results of Model 4 (A-PC-C) with economic predictors replacing period dummies confirm earlier findings from the A-P-C model that period effects have negligible influence on mobility. Neither GDP nor housing interest rates affected migration propensities of the populations observed in the AIM database. This also holds for unemployment rates, which did not influence movement risks.

In the next section, the result of the full A-P-C models run separately for each type of move are reported. Table 4 presents the parameter estimates (IRRs), significance levels and goodness-of-fit statistics for the taxonomy of A-P-C models for local moves within the same TSD, intrastate moves between metropolitan and non-metropolitan regions, and interstate moves. The log-likelihood value is lowest (-999) for the model with non-metro to non-metro moves as dependent variable, pointing to the best fit of this model compared to those of other types of moves. The likelihood ratio chi-square test statistics that all regression coefficients are equal to zero is significant across all models at the 1% level, indicating that there are significant effects of the predictors. Across all models, the signs of most predictors are similar to those of the A-P-C model (Model 1 in Table 3) for total mobility, some dissimilarities between models exists for the cohort parameter estimates.

The parameter estimates for cohort from the full A-P-C models run separately by type of move (see Table 4) are also presented in Figure 9. As mentioned above, the patterns differ from those observed for total mobility. The overall patterns in cohort effects show a higher incidence of moving for younger cohorts relative to the reference cohort born 1901-06, except for intrastate moves from non-metro to metro TSDs. The propensity to undertake the latter type of move decreased across cohorts and yielded a small inflection for those born 1936-41 to 1951-56 and a second, slightly larger peak for those born 1966-71 to 1976-81. While the incidence rate ratios for the models of moves in the same TSD and interstate moves increased more or less steadily across cohorts, the propensity to move intrastate from metro to non-metro TSDs and between non-metro TSD shifted downwards for birth cohorts born after 1951-56 and 1936-41, respectively. The parameter estimates for non-metro to metro, non-metro to non-metro and interstate moves all show a peak for the 1971-76 cohort, which is the largest cohort of all Australian baby boom cohorts.

Table 4. Negative binomial regression of migration by type of move (N: 145)

	same TSD	metro to non-metro	non-metro to metro	non-metro to non-metro	interstate
	IRR	IRR	IRR	IRR	IRR
AGE					
5-9	1	1	1	1	1
10-14	0.87**	0.70**	0.93**	0.83**	0.81**
15-19	0.87*	0.52**	1.73**	0.83**	0.73**
20-24	1.41**	0.82**	2.78**	1.09**	1.22**
25-29	1.81**	1.04	2.00**	1.15**	1.51**
30-34	1.58**	0.87**	1.46**	1.00	1.35**
35-39	1.31*	0.66**	1.15**	0.81**	1.12
40-44	1.13	0.48**	0.97	0.64**	0.90
45-49	1.02	0.42**	0.83**	0.54**	0.73*
50-54	0.95	0.47**	0.69**	0.49**	0.65**
55-59	0.90	0.59**	0.59**	0.48**	0.65*
60-64	0.86	0.69**	0.54**	0.48**	0.69*
65-69	0.83	0.60**	0.52**	0.42**	0.65*
70-74	0.80	0.42**	0.47**	0.33**	0.56**
75+	0.46**	0.36**	0.50**	0.30**	0.22**
PERIOD					
1976-81	1	1	1	1	1
1981-86	0.96	1.05**	0.97*	1.02**	0.99
1986-91	0.91*	1.15**	0.90**	1.05**	1.02
1991-96	0.98	0.99	0.91**	1.01	0.94
1996-01	0.94	0.94*	0.92**	1.00	0.87*
COHORT					
1901-06	1	1	1	1	1
1906-11	0.99	1.01	0.92*	0.97	1.03
1911-16	1.00	1.08	0.84**	0.95	1.10
1916-21	0.99	1.10*	0.79**	0.96	1.14
1921-26	1.01	1.17**	0.76**	1.00	1.19
1926-31	1.06	1.27**	0.74**	1.06	1.25*
1931-36	1.12	1.35**	0.75**	1.11**	1.36*
1936-41	1.19	1.42**	0.77**	1.15**	1.51**
1941-46	1.27	1.44**	0.79**	1.15**	1.64**
1946-51	1.38*	1.46**	0.79**	1.13**	1.74**
1951-56	1.57*	1.48**	0.76**	1.11*	1.87**
1956-61	1.65**	1.39**	0.75**	1.05	1.91**
1961-66	1.63*	1.27*	0.81**	1.04	1.91**
1966-71	1.66*	1.20	0.89	1.06	2.01**
1971-76	1.73*	1.17	0.91	1.08	2.11**
1976-81	1.75*	1.13	0.88	1.06	2.03**
1981-86	1.83*	1.08	0.82*	1.00	2.00*
1986-91	2.07*	1.04	0.80*	0.96	2.12**
1991-96	2.39**	1.02	0.79*	0.94	2.35**
Log likelihood	-1,547	-1,101	-1,025	-999	-1,283
Likelihood ratio chi-square	457** (36 df)	578** (36 df)	801** (36 df)	803** (36 df)	508** (36 df)
AIC	3,169	2,278	2,126	2,074	2,642

(* p ≤ .05; ** p ≤ .01)

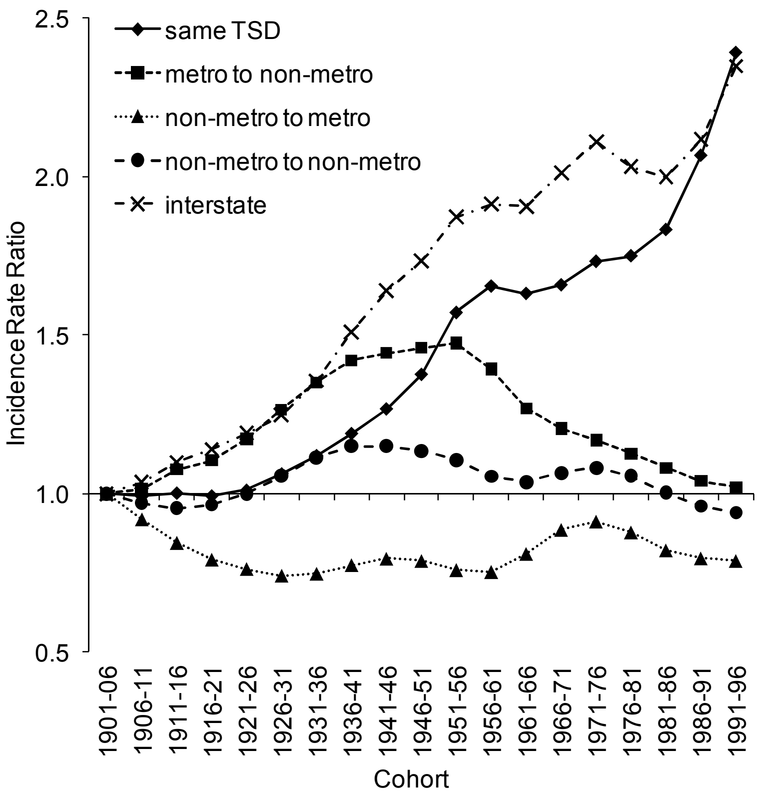

Figure 9. Parameter estimates (incidence rate ratios) of cohort from the full A-P-C model run separately by type of move, for persons

In the next section, the results from Models 2 to 4 by type of move are presented. The parameter estimates for cohort, which are reported here, were calculated separately for each type of move. Figure 10 shows the IRRs and significance levels for cohort effects from Model 3 (A-P-CG). The results for moves within the same TSD and interstate migration are similar to those for total mobility. The magnitude of the cohort effect for intrastate moves from metro to non-metro areas is smaller compared to total mobility, particularly for the post-baby boom cohorts. For intrastate moves between non-metro areas, the cohort effect is negative for the post-baby boom generation. For intrastate moves from metro to non-metro areas, the cohort effect is negative for the baby boom and the post-baby boom generation compared to the pre-baby boomers.

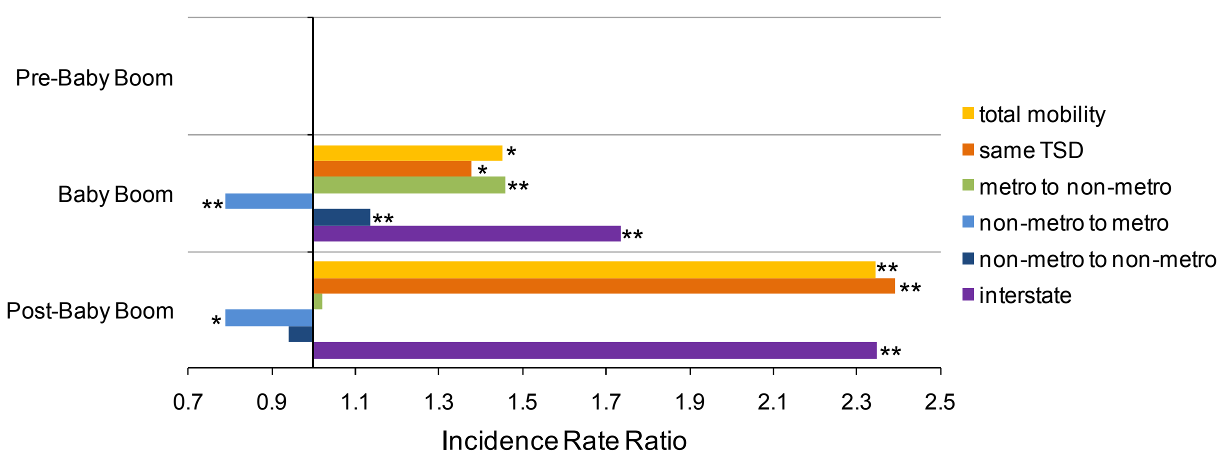

Figure 10. Parameter estimates (incidence rate ratios) of cohort effects from the Age-Period-Cohort Groups (A-P-CG) model by type of move (* p ≤ .05; ** p ≤ .01).

Figure 11 shows the IRRs and significance levels for cohort effects calculated with Model 4 (A-P-CS) by type of move. Overall, cohort effects are similar in magnitude and direction to those reported for Model 3 (A-P-CG). However, some differences are noteworthy. Medium-sized cohorts had a higher risk of moving locally in the same TSD than the baby boom cohorts, but a lower risk of moving intrastate from metro to non-metro areas (when compared to the reference category).

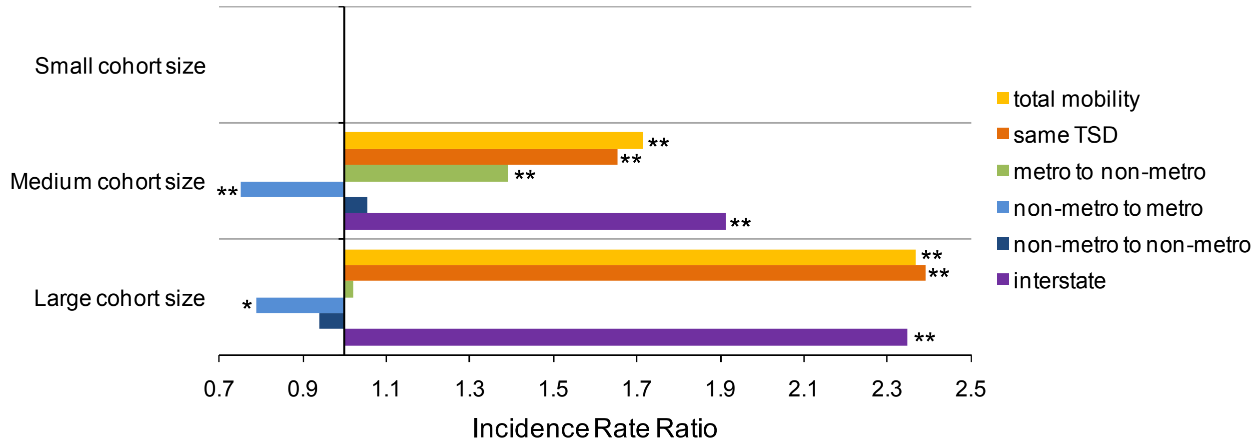

Figure 11. Parameter estimates (incidence rate ratios) of cohort effects from the Age-Period-Cohort Size (A-P-CS) model by type of move (* p ≤ .05; ** p ≤ .01).

Figure 12 illustrates the effects of period characteristics on mobility. While GDP, housing interest rates and unemployment had no effect on total mobility (see Table 3), the latter two economic indicators appear to have had an effect on migration propensity for particular types of moves. While an increase in the housing interest rate encouraged intrastate moves to non-metro TSDs and interstate to a TSD in another State, the risks of moving in the same TSD or intrastate from a non-metro to a metro TSD decreased. This finding suggests that interest rate rises were felt more strongly by the residents in capital cities (i.e. the metro TSDs) and movement to non-metro TSDs is seen as a means of avoiding or escaping high housing costs. Quite the opposite pattern of parameter estimates is observed for unemployment rates: high unemployment encouraged local moves, while at the same time significantly decreasing the propensity to move over longer distances.

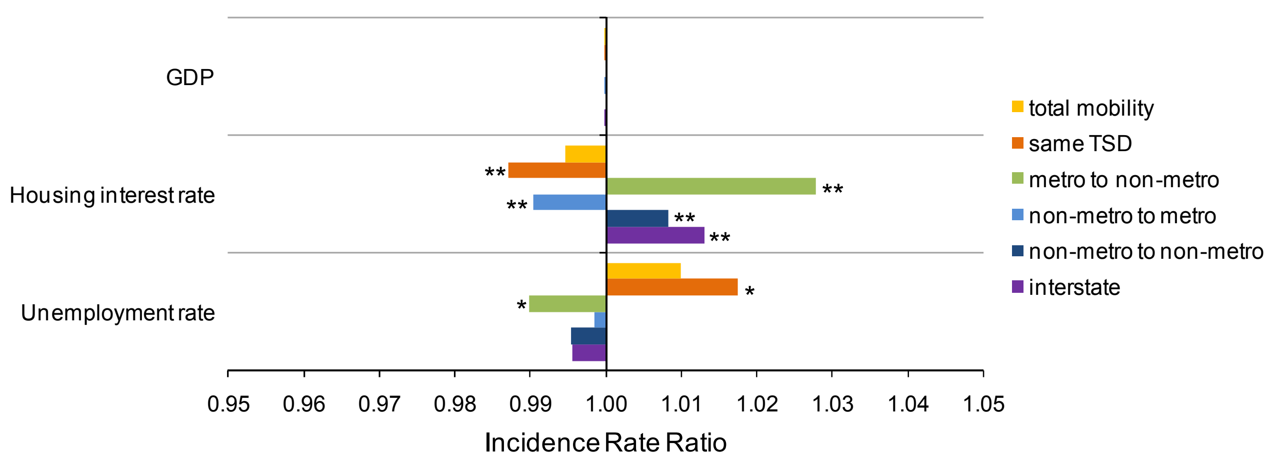

Figure 12. Parameter estimates (incidence rate ratios) of cohort effects from the Age-Period Characteristics-Cohort (A-PC-C) model by type of move (* p ≤ .05; ** p ≤ .01).

Attention is now turned to sex differences in the effects of age, period and cohort on mobility. Figure 13 shows the parameter estimates for age, period and cohort from the full A-P-C model for total mobility, run separately for males and females. The age pattern is similar to the effects reported for persons in Figure 7. Differences in IRRs for age by sex represent the earlier peak of mobility and higher movement propensity at age 20-24 years for females compared to males. Parameter estimates for period and cohort showed markedly similar effects for males and females, underlining the fact that most migration decisions are made at the household level. The pattern of IRRs for cohort shows a slight difference in effects among members of the 1956-61 and 1961-66 birth cohorts. The levelling off among the later baby boom cohorts is somewhat more pronounced for males than for females, suggesting that potential job-shortages caused by large cohorts entering the labour market were felt more strongly by males as the primary earner in the family.

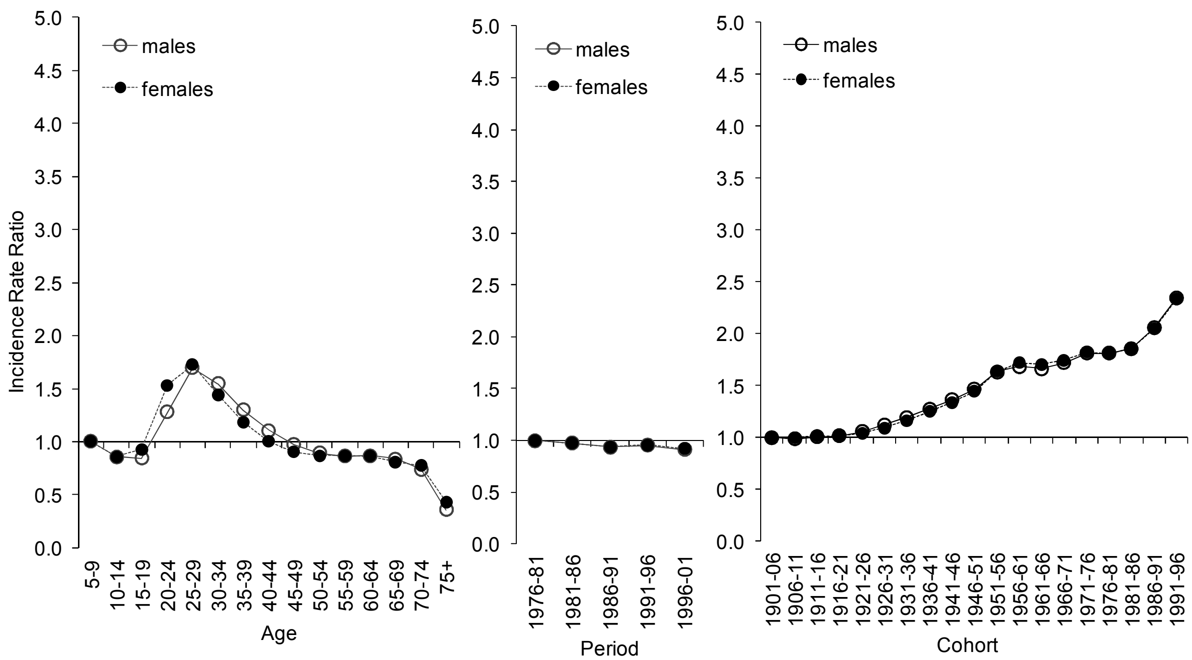

Figure 13. Parameter estimates of age, period and cohort from the full APC model for total mobility by sex

In the following section, the results from Models 2 to 4 by sex are presented. The parameter estimates for cohort, which are reported here, were calculated separately for males and females. Figure 14 shows the IRRs and significance levels for cohort effects from Model 3 (A-P-CG) by sex. Figure 15 shows the results for cohort effects calculated with Model 4 (A-P-CS), and Figure 16 illustrates the effects of period characteristics on mobility for males and females. Overall, cohort effects were similar in magnitude and direction to those for persons, and the differences between males and females are very small.

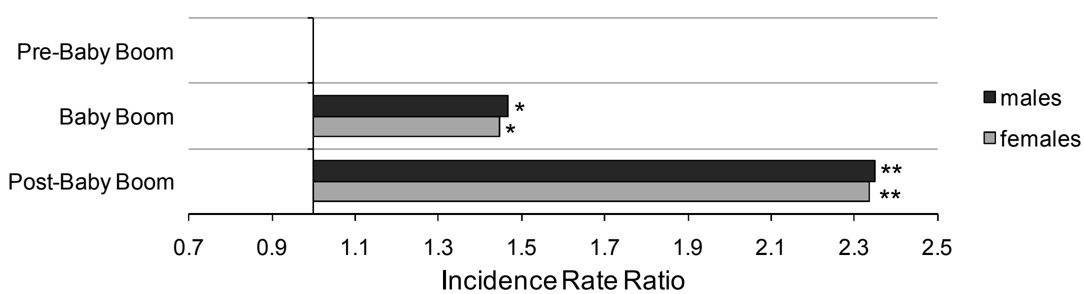

Figure 14. Parameter estimates of cohort effects from the Age-Period-Cohort Groups (A-P-CG) model by sex

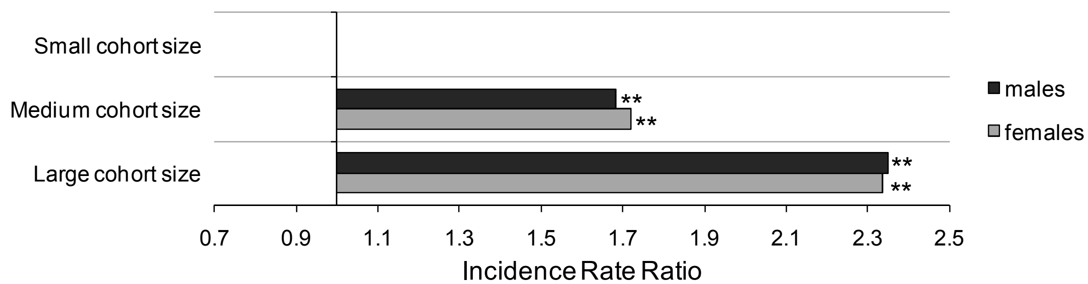

Figure 15. Parameter estimates (incidence rate ratios) of cohort effects from the Age-Period-Cohort Size (A-P-CS) model by sex (* p ≤ .05; ** p ≤ .01).

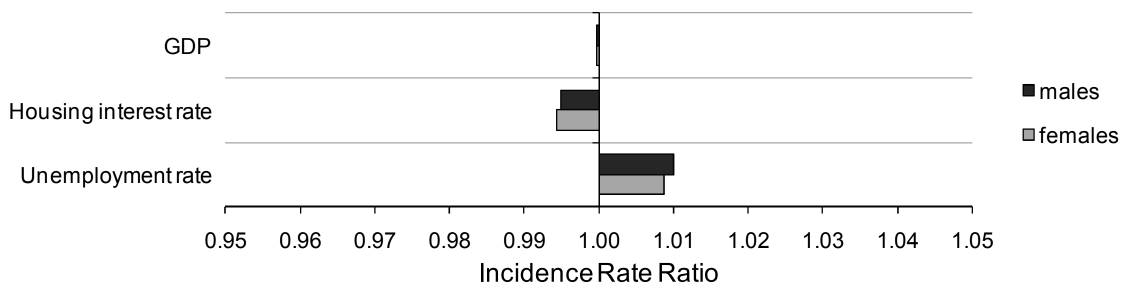

Figure 16. Parameter estimates (incidence rate ratios) of cohort effects from the Age-Period Characteristics-Cohort (A-PC-C) model by sex (* p ≤ .05; ** p ≤ .01).

5) Discussion

This study aimed to empirically disentangle the effects of age, period and cohort on migration intensity. A novel application of APC modelling was used in this analysis of migration trends among the baby boom. While Poisson regression models are typically used in migration studies, it was demonstrated that negative binomial models can provide a better fit to the data. Based on the results from the AIC, the full A-P-C model was found to be the most appropriate for describing the data.

The findings demonstrate that, after controlling for age and period effects, the IRR for cohort increased from the oldest to the youngest cohort. The full A-P-C model results revealed that the baby boom cohorts born between 1941-46 and 1971-76 had a higher incidence of moving (total mobility) than the pre-baby boom cohort, but the post-baby boom generation had even higher movement propensities. If the US experience regarding migration behaviour of baby boom cohorts held in the Australian context, migration intensity should have dropped for the youngest baby boom cohorts (i.e. Australians born 1971-76). The results clearly show, however, that parameter estimates did not decline for the 1971-76 cohort but rather increased. The levelling off for the 1956-61 and1961-66 birth cohorts can partly be explained by soaring housing prices and interest rates peaks that characterised the Australian housing market in the late 1980s, at the time when these cohorts entered the housing market. The A-P-CG model with cohort groups as predictors confirmed the findings from the A-P-C model: the baby boom had an 45% higher risk of moving than the pre-baby boomers *(IRR = 1.45, p = 0.023)*.

The results from the A-P-C and the A-P-CG models by type of move reveal significant variations in cohort effects by type of move. Most Australians who change residence between censuses only move over short distances. This means that the results for total mobility are influenced to a large degree by the effects for short-distance moves. The IRRs representing cohort effects for local moves in the same TSD and interstate moves increased strongly across cohorts. They dipped slightly for the 1961-66 cohort, pointing to a depressing effect of high interest rates on the mobility of this cohort as it entered the housing market at the age of 25-30 years in the 1986-91 period. Parameter estimates for metro to non-metro moves were highest for the 1936-41 to 1951-56 cohorts, which were aged 30-50 years in the late 1980s, at a time when the tightening housing market played a key role in the increased out-movement of families from the metropolitan centres. Moves from metro to non-metro TSDs by the 1936-41 to 1951-56 cohorts coincided with increased migration between non-metro areas, reflecting the increased popularity of non-metro regions to raise a family. Migration from non-metro to metro TSDs are the only migration streams for which parameter estimates decreased across cohorts, a result that partly reflects the choice of the reference category. For moves in the same TSD and interstate moves, the parameter estimates (IRR) were higher for the baby boom than for older cohorts, but lower compared to younger cohorts. For intrastate moves to non-metro TSDs, IRRs were highest for those cohorts born just before the baby boom and the oldest baby boom cohorts, but declined for the youngest boomers and the post-baby boom cohorts.

A key question regarding future retirement migration intensities is whether cohort effects are likely to influence the age-specific migration propensities among the retirement-aged population once the baby boom reaches retirement. A comparison of parameter estimates of cohort (A-P-C model) for the older pre-baby boom cohorts with those for the baby boomers shows (a) that among older boomers born between 1946-51 and 1956-61, migration intensity remained stable for non-metro to metro and non-metro to non-metro flows, and (b) that migration intensity increased compared to previous cohorts for local, metro to non-metro and interstate moves. So, which changes can be anticipated to occur once the baby boomers reach retirement age? The literature points to retirees moving predominantly from metro to non-metro TSDs and also over longer distances to interstate destinations. Therefore, compared to current retirees, intrastate and interstate retirement migration propensities among the older members of the baby boom could potentially increase in the near future. \

It has been well established in the literature that the migration intensity among large cohorts is lower compared to small cohorts (Greenwood, 1988; Long, 1988; Pandit, 1997a; Pandit, 1997b; Plane, 1992, 1993; Plane and Rogerson, 1991; Rogerson, 1987; Wilson, 1983). Most of these findings, however, are based on studies of US data. In the US the baby boom peaked in 1957 with a TFR of 3.7. In Australia, fertility peaked much later in 1961 with a TFR of 3.5, and remained at or above 3.0 until 1965 (ABS, 2006a). Therefore, the timing and size of the Australian baby boom, as well as the market conditions upon labour force entry of the large cohorts differed significantly from the US experience. Pandit (1997a) has shown for the US that the depressing effect of large cohort size on migration tends to be stronger for longer-distance moves than for short-distance moves. The results from the A-P-CS models have demonstrated that in Australia medium-sized cohorts had a 70 per cent higher chance of moving compared to small cohorts. Large cohorts were 2.3 times more likely to move than small cohorts. Large cohort size encouraged local and interstate mobility, while the effect on intrastate moves from non-metro to metro areas was significantly negative. The positive cohort effect on local and interstate mobility coincides with a rightward shift of the migration age profile over the last 20 years, while the negative effect of cohort size on non-metro to metro moves may be a product of the net drift to non-metropolitan areas in the vicinity of the capital cities in Australia's most populous States New South Wales, Victoria and Queensland (Bell and Hugo, 2000).

With the exception of intrastate moves to non-metro TSDs, the findings from this analysis suggest that in Australia birth cohort size is not negatively related to migration propensity as it is the case for the baby boom in the US (Pandit, 1997; Plane and Rogerson, 1987). These contrary results to the US experience may be explained by the different timing and size of the baby boom compared to the US, and the differences in housing market and economic structure.

The results from the full A-P-C model run separately for males and females demonstrate that there are very few sex differences in migration behaviour. The estimated parameters for period show that housing interest rates inhibit the mobility of both sexes in a similar way, and that the mobility of females is are also affected by high unemployment rates. The estimates for cohort reveal that being a member of the large baby boom cohort has similar effects on both males and females. Taken together, these results highlight the importance of analysing cohort effects on migration in a household context.

Plane and Rogerson (1987) and Pandit (1997a) have shown for the US that age-specific migration intensities among members of large cohorts decrease once the cohort reaches the labour force entry stage. This effect seems to be most pronounced for the youngest members of large generations. The APC analysis presented here confirms that changes in movement intensity are at least in part related to economic and housing market conditions. However, the strength and significance of period effects varies by type of move. Overall, housing interest rates seem to have a more pronounced effect than unemployment rates, while in the A-PC-C models GDP had no effect on mobility. This means that the findings from the US that large cohort size coupled with economic recession and high unemployment leads to depressed migration rates cannot be confirmed in the Australian context. An increase in unemployment rate encourages local mobility, but depresses longer distance moves. The opposite pattern was observed for interest rates. An increase in interest rates resulted in less movements in the same TSD and from non-metro to metro TSDs, while intrastate movements to non-metro TSDs as well as interstate mobility were encouraged. This pattern reflects the changing housing market structure of the 1980s and 1990s: soaring house prices in the capital cities, together with interest rates peaking in the late 1980s, resulted in substantial out-migration from the capitals to non-metropolitan areas with lower house price levels.

Of course, this study has limitations. The migration data hold in the AIM database allow the construction of synthetic cohorts and, thus, APC analysis, but the data only cover a limited number of age groups per cohort. In other words, the migration behaviour of 20-30 year old baby boomers cannot be directly compared to the movements of pre-baby boom cohorts at the same age and retirement migration intensities can only be observed for the pre-baby boom cohorts. Given that in APC analyses cohort effects can be identified while controlling for age and period effects, strong conclusions can be drawn from this research despite the data limitations.

6) Conclusion

The results for the taxonomy of models used in this study provide valuable insights into the migration behaviour of the Australian baby boom compared to their predecessor and successor cohorts. The following conclusions can be drawn regarding the migration behaviour of the Australian baby boom as it moved through the life course: (a) the incidence of moving (total mobility) increased across cohorts observed in the AIM database; (b) the risk of moving among baby boomers is higher than those of older cohorts, but lower than those of younger cohorts; (c) cohort effects differ by type of move and, although to a lesser degree, by gender; (d) the baby boom cohorts were found to move over short-distances at higher rates than predecessor cohorts, which is mainly a function of a delay of local moves in the period 1986-91 due to an interest rate peak, and the subsequent increase in the next period when the interest rates had decreased to a lower level. This period-cohort interaction effect was associated with a rightward shift of the migration profile; (e) the depressing effects of large cohort size on mobility could only be found for intrastate moves to non-metro TSDs.

The observed patterns in parameter estimates for cohort differ from those observed for the US (Pandit, 1997a; Plane and Rogerson, 1987). These variations may be due to the different timing and intensity of the baby boom in both countries, the addition of the even larger baby boom echo population to this study, as well as the dissimilar nature of the national economic and housing market patterns.

If the established cohort effects also hold for the retirement-aged population, several changes in retirement migration intensities are likely to occur once the baby boom reaches retirement age: (a) the baby boomers may move within the same TSD, intrastate from metro to non-metro areas and interstate at higher rates upon retirement; (b) intrastate migration can be expected to decrease for the youngest boomers and the baby boom echo generation; (c) due to its size, the baby boom echo generation is likely to exert an even greater impact on regional population age structure, particularly if interstate migration patterns among these cohorts will increase as suggested by the A-P-C model results; and (d) that the future effects of interest rate changes on local mobility and intrastate moves to the capital cities are difficult to foresee.

In conclusion, the results from the APC analysis highlight the generational, regional and sex differential in the incidence of migration and the continuing increase in overall migration propensity for younger cohorts. The timing and relative size of the Australian baby boom, as well as the economic and housing market conditions prevalent at the time of labour- and housing market entry have probably been the most important determinants of the changes in cohort-specific migration intensities in Australia. It is likely that upon retirement the baby boomers will move locally and interstate at higher rates, but intrastate (particularly the younger boomers) at lower rates compared to their predecessors, assuming no major changes to economic and housing market conditions.

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