NO COUNTRY FOR OLD MEN (OR WOMEN) --
DO STATE TAX POLICIES DRIVE AWAY THE ELDERLY?

Karen Smith Conway and Jonathan C. Rork

Over the last forty years, state income tax breaks targeting the elderly have grown, often justified by arguments that the elderly move across state lines in response. Using two complementary sources of elderly migration data and several measures of elderly income tax breaks, we investigate the relationship between these tax breaks and migration. We employ different empirical methodologies that emphasize *changes over time*, including panel regression models spanning four censuses (1970-2000) and several different socioeconomic groups of elderly. Our results are overwhelming in their failure to reveal any consistent effect of state income tax breaks on elderly interstate migration.

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”Unfortunately, one of our most cherished treasures – our retirees – are leaving in favor of more tax-friendly states,”

--Dave Nabity, 2004 Nebraska gubernatorial candidate

“There is active recruitment by some states to lure retirees to locate in other states. A state’s tax burden is one of the top three reasons to move to a state,”

-- Testimony by proponents of Missouri bill HB 444 that eliminated income taxes on Social Security benefits. The bill was enacted in 2008.

“*This tax cut… will help attract retirees to our state and make our economy even stronger,”*

--Georgia Governor Sonny Perdue promoting legislation that would eliminate all income taxes on retirement income.[1]

I. INTRODUCTION

Since 2006, Missouri enacted a new income tax deduction for elderly taxpayers who receive Social Security benefits or other retirement income (2008), Iowa voted to phase out its tax on Social Security benefits, beginning in 2007, and Georgia steadily increased its retirement income exemption such that by 2016 all retirement income is exempt for those aged 65+. These states are not isolated cases. The number and type of state income tax breaks offered to elderly taxpayers has grown steadily over the last forty years (Zahn and Gold 1985, Mackey and Carter 1994, Conway and Rork 2008a,b,c). During this time, a large majority of states have also reduced or eliminated their so-called EIG or ‘death’ taxes -- taxes on estates, inheritances and gifts (hence, EIG) – taxes which are borne disproportionately by the elderly (Conway and Rork 2004). While ‘fairness’ concerns are often given as a rationale for such policies, an attempt to recruit the elderly or a fear that high taxes drive them away are also offered, as revealed above.

Are state tax policies a major consideration in elderly location decisions? Certainly, the information about tax policies appears readily available and widely dispersed. The AARP

[1] Sources for these quotes are http://www.davenabity.com/nebraskasissues_liberate.htm, accessed 9/25/08), (http://www.house.mo.gov/billtracking/bills071/sumpdf/HB0444c.pdf, accessed 9/5/08), and (http://www.ajc.com/blogs/content/shared-blogs/ajc/georgia/entries/2007/01/29/bill_eliminates.html, accessed 9/25/08), respectively.

publishes regularly a handbook that summarizes each state's major tax policies and their implications for retirees (*State Handbook of Economic, Demographic and Fiscal Indicators).*[2] Federal employees are briefed on the differences in state tax treatment in their retirement planning seminars.[3] Numerous web sites, such as retirementliving.com, and investment reports, such as "Retiree Tax Heaven (and Hell)" (published August 2008 in *Kiplingers*), offer advice on the tax consequences of location. Despite widespread changes in state tax policies towards the elderly and improved information about such policies, however, the five-year rate of interstate elderly migration is remarkably constant at around four percent and the patterns of movement are very persistent (Flynn et al 1985, Longino and Bradley 2003, Conway and Rork 2010).

This research investigates the role that state taxes and tax breaks play in elderly migration – and by extension claims such as those listed above. Most previous research on elderly migration estimates the effects of state tax policies in general (e.g., the top marginal tax rate) and uses cross-sectional data. Our research improves upon this work along two dimensions. First, we focus on income tax breaks targeting the elderly, which should be unambiguously desirable to the elderly, as well as the state's EIG taxes. Second, our analyses emphasize *changes over time* in state policies and elderly migration. By using panel data methods, we can control for state-specific unobservable characteristics, such as cultural and natural amenities, that may lead to considerable persistence in migration patterns.

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[2] The 2008 edition (reporting data for 2006) is the most current edition at this writing. At least five earlier editions of this handbook exist as well, one for 1996, 1998, 2000, 2003 and 2006.

[3] For example, federal employees in retirement planning seminars are given a workbook that suggests moving to a lower cost location (both in terms of housing costs and taxes) as a strategy for stretching retirement income and includes a worksheet to calculate costs at multiple locations. See Part 3 and worksheet 8 in *Guidebook to Help Late Savers Prepare for Retirement, Workbook 1*, National Endowment for Financial Education, 2003.

The rarity of an elderly interstate move makes a large sample necessary for credible analyses; the persistence in elderly migration patterns makes a large sample important for detecting genuine changes in these patterns over time.[4] We therefore begin with migration measures created from the largest sample possible – U.S. census tabulations of the number of elderly moving between each pair of states from the last four censuses (1970-2000). However, these data do not contain individual characteristics and thus prohibit a more refined analysis targeting those elderly most likely influenced by tax breaks (e.g., relatively young, healthy, wealthy). We therefore augment our analyses of the census tabulations with the smaller, census-based, Integrated Public Use Micro-data Series (IPUMS), also available for 1970-2000. The IPUMS contains individual characteristics, allowing us to create migration measures for different socioeconomic groups of elderly.[5] Our analyses control for other state tax and expenditure policies and other state characteristics and are subjected to an extensive set of robustness checks of both data choices and empirical approach. Our results are overwhelming in their failure to reveal any consistent effect of state tax policies on elderly migration across state lines.

II. STATE INCOME TAX BREAKS FOR THE ELDERLY

Income tax breaks for the elderly present a unique opportunity to examine whether elderly migration responds to tax incentives. While these tax breaks certainly have revenue consequences for the state (e.g., Bernstein 2004), they seem less likely to be associated with other unobserved aspects of the public sector and their consequences are much smaller than

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[4] Conway and Rork (2010) demonstrate that even when using migration measures based on very large samples (approximately1/6th vs. 5 percent of the U.S. population), the measures from the smaller sample substantially exaggerate the amount of change over time.

[5] The elimination of the census long form in 2010, on which the IPUMS and census tabulations are based, make 2000 a necessary endpoint. Its replacement, the annual American Community Survey, is so different in both its smaller sample size and its migration questions that comparisons with earlier census data are difficult.

broader tax provisions (such as the top marginal tax rate). Such tax breaks are also often sizable. Conway and Rork (2008a) find that non-elderly, high income households pay approximately twice the state income taxes of equivalent elderly households and that the associated 'tax benefit' of being elderly ranges from $100 (North Dakota) to $2647 (South Carolina) in 2002; see Penner (2000) for similar 1998 calculations. These tax breaks are also visible – e.g., they are reported prominently in the AARP Handbook. As such, they may send a strong signal of a state's desirable treatment of the elderly in general.

These income tax breaks consist of three basic types, each of which has varied a great deal across states and over time, as shown in Figure 1 and Table 1 for the critical years (1964-94) and 48 contiguous states used in our analyses.[6] The first tax break is an extra deduction, exemption or tax credit (henceforth called *deduction*) given solely on the basis of age (typically over age 65). The federal government and nearly all states with some type of income tax grant such deductions.[7] The Tax Reform Act of 1986 (TRA86) substantially reduced the relative size of the federal deduction, and most states followed. The reduced maximum value of state deductions after TRA86 – calculated as the top marginal tax rate, *mtr,* multiplied by the deduction amount -- is evident in Table 1 even as the proportion of states offering deductions has increased (Figure 1). The bottom panel of Table 1 further reveals the direction and degree of *changes over time*, by reporting both the mean change and the range of increases and decreases. Between every census, some states increased while others decreased this tax break and the

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[6]The census flows and IPUMS measure migration that took place during the previous 5 years, and we use tax policies the year before the migration period – e.g., 1964 tax policies are used for 1965-1970 migration.

[7] We focus our discussion here on contiguous states that had some kind of income tax at any time during the period of study. This list includes states that enacted income tax systems during the period (e.g., Illinois, Pennsylvania, Rhode Island, etc.) and those with a very narrow base (i.e., New Hampshire and Tennessee), thereby excluding Florida, Nevada, South Dakota, Texas, Washington, and Wyoming.

magnitude of change differs over time.[8] Still, the maximum value of these tax breaks is typically quite modest, averaging less than $100 in most years of our analyses.

The second is the favorable tax treatment of Social Security benefits. Until the 1983 federal legislation that began taxing a portion of Social Security benefits for high income households, such benefits had not been subject to federal or state taxation. Beginning in 1983, up to half of Social Security benefits were subject to federal income taxation for high income households, and 13 states followed suit.[9,10] In 1993, an additional set of (higher) income thresholds were imposed past which up to 85 percent of Social Security benefits could be taxed. Unlike the extra deduction, this policy appears to be in flux at the state level. The number of states that tax Social Security benefits grew to a high of 18 states in the early 1990's (reflected by the minimum of this tax break in our last sample point, 1994, in Figure 1), but has subsequently declined.[11] This policy began as a nearly universal, modest tax break; the maximum annual benefits for a two-worker couple were only $2952 ($6600) in 1964 (1974). In 1984 – when up to half of benefits could be taxed in some states -- the maximum annual benefits

[8] As noted in Table 1, West Virginia is an outlier in that it switched its tax break a few times between an age-based exemption and a pension exemption. This underscores the importance of considering all three types together, as well as the overall summary measure. We verify that our results are robust to dropping WV.

[9] The income thresholds are $25,000/32,000 for single/married households; income refers to combined income, which equals taxable income plus one-half of Social Security benefits received. Page and Conway (2010) discuss federal and state income tax policies regarding taxation of Social Security benefits and the prevalence and size of the tax. One state, Mississippi, did tax Social Security benefits prior to the 1983 law, but has fully exempted benefits since 1980 (Conway and Rork 2008c, Table 2). In our subsequent empirical analyses, we investigate the robustness of our results to the treatment of Mississippi during this early period and find it makes no qualitative difference.

[10] Three states, Nebraska, Rhode Island and Vermont, have income tax systems based on the federal income tax and so automatically began taxing benefits as well. Ten other states -- Colorado, Iowa, Kansas, Minnesota, Missouri, Montana, North Dakota, Oklahoma, Utah and Wisconsin – began taxing Social Security benefits in the same or similar manner soon afterwards.

[11] According to the AARP 2008 Handbook, 15 states continue to tax Social Security benefits in 2006; however, two of those (Colorado and Connecticut) offer more favorable treatment than the federal government and another three (Iowa, Missouri and Wisconsin) have since eliminated or are phasing out the taxation of these benefits.

had grown to $16,884; in 1994, when up to 85 percent could be taxed, they equaled $27,540. Thus, the average size and, more importantly, the range of maximum values for high income households have grown tremendously – from $0-$165 in 1964 to $327-$2575 in 1994.[12]

The third and perhaps most far-reaching tax breaks are exemptions for pension income. These tax breaks frequently differ by pension type, especially public versus private pensions. Historically, public pensions have received widespread favorable treatment, as the vast majority of states have granted at least a partial exemption (Zahn and Gold 1985, Mackey and Carter 1995 and Manzi et al 2005). State and local government pensions tended to receive equal or better treatment than federal or military ones until 1989 when a U.S. Supreme Court ruling required that state and local government pension exemptions extend to retired federal employees. Subsequent rulings required the exemptions to extend to military retirees as well and further established parity across public pension types (Mackey and Carter 1995, pp. 25-6). These rulings therefore forced some states to revise their policies towards the end of our sample period. As described in section 6, we explore their possible effects in our sensitivity analyses and find no qualitative effect. Unfortunately, a more detailed accounting of public pensions is beyond the scope of our study, as information on such pensions is quite limited.

We focus, instead, on the exemptions for *private pensions*, which have displayed ample variation over our sample period and seem likely to affect more households than public pension exemptions. The federal government has always taxed private pension income, but beginning in the late 1940's states began enacting exemptions for private retirement income, especially

[12] As discussed further in Section 5, our definition of 'maximum value' must be refined for this tax break, because the potential maximum value equals *mtr**100 percent of maximum benefits in every state since only higher income households are subject to the tax. To capture the policy's variation, we therefore define it as *mtr*(1-pt)**maximum benefits, where *pt* is the maximum proportion of Social Security benefits subject to tax. It can be interpreted as the value of the tax break for a very high income household – who faces the top marginal tax rate and whose income is high enough that the maximum proportion of benefits are subject to tax.

pension income (Conway and Rork 2008b, c). These exemptions vary across several dimensions. State definitions of qualifying pension/retirement income differ, with some states extending the exemptions to broader types of retirement income (e.g., dividends and income). To our knowledge, Alabama (which only exempts defined benefit plans) is the only state in our analyses that distinguishes between defined benefit and defined contribution pension plans (Zahn and Gold 1985, Manzi et al 2005).[13] Different age and income limits sometimes apply. The measures used in our analyses and summarized here, from Bakija (2008), refer to the maximum exemption available for a defined benefit, private pension plan.

As shown by Figure 1 and Table 1, the prevalence of these exemptions has grown dramatically in recent years. In 1964, the first year in our empirical analyses, only one contiguous state exempted pension income – Delaware. By 1994, the list had grown to 24 states and the number of states exempting all pension income had grown to five (Alabama, Illinois, Mississippi and Pennsylvania joined Hawaii).[14] The mean value of the exemptions, however, has increased less dramatically, tempered by the fall in top marginal tax rates. Nonetheless, this tax break has displayed both increases and decreases over time of sizable magnitudes. In 1994 for instance, the mean value of $1717 and range of changes since 1984 of +$5000 and -$2600 are sizable fractions of top quartile elderly household income in 2000 ($54,000).

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[13] In addition, Hawaii exempts all pension income from employer contributions; pension income that includes employee contributions is partially taxable. However, we follow the typical approach in interstate migration studies of analyzing only the 48 contiguous states. We further verify that dropping Alabama has no impact on the results.

[14]Two more states, Vermont (1971-92) and West Virginia (1973-80), enacted and then subsequently repealed pension exemptions during this period. By 2007, the list of states granting exemptions had grown to 28 with Iowa, Kentucky, Maine, Missouri, New Mexico and Oklahoma joining the list (AARP 2008 Handbook, Bakija 2008). See Conway and Rork (2008c) for a more detailed listing of policy changes.

Table 1 also summarizes the total tax breaks available to the elderly. It is evident that the different types of tax breaks aren't simply offsetting each other; the total range across states is large, from $20 to $11282 in 1994, the latter accounting for more than 20 percent of the annual income of high income (top quartile) elderly households. While overall tax breaks have steadily increased in average value, in recent years some states have reduced them as well. The changes over time – both positive and negative – also take on a wide range of values.

The variation displayed by these tax breaks – across states and over time – is critical to identifying their effects in our panel migration model. We further investigate the richness of this variation by calculating the percentage of variation explained by year and state fixed effects of 1) each tax break (whether it exists; its maximum value), as well as all tax breaks combined, and 2) the 10-year changes in these measures.[15] Approximately 35 to 54 percent of the variation in the individual tax breaks is left unexplained; the ten-year changes yield an even higher 80 to 90 percent. The corresponding numbers for all tax breaks combined is 28 and 70 percent. The magnitude and cross-sectional/temporal variation of these tax breaks therefore appears ample to identify an effect on elderly migration.

III. PAST ELDERLY MIGRATION RESEARCH

Patterns, motives and determinants of elderly migration have been studied extensively in other disciplines, especially gerontology (e.g., see Walters 2002 for a survey). The effect of state fiscal policy on elderly location decisions has received a small but growing amount of attention from economists. Such studies have taken one of two empirical approaches. The first approach uses individual level data and discrete choice models to estimate the effects of location

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[15] Specifically, we estimate regressions in which the tax breaks are regressed on a full set of year and state fixed effects and obtain the R-squared. We also add the corresponding value of the other tax break as an additional regressor and find that it barely affects the R-squared.

characteristics on the decision to move. Examples include Dresher (1994) and Duncombe et al (2001, 2003), which use a conditional logit framework and compare the characteristics of a random sample of locations with the one actually chosen.[16] This approach has the advantage of being able to control for individual characteristics, include locations beyond the one chosen and explicitly incorporate the behavior of non-movers. However, it also has significant limitations. The number of movers in longitudinal analyses tend to be small (e.g., Dresher's analysis using the PSID contained 91 elderly interstate movers) and the time frame considered is short (e.g., Dresher 1994 considered moves during 1983-88; Duncombe et al 2001, 2003 considered 1995-2000). Moreover, estimation is computationally very demanding as every individual generates *J* observations (*J* is the number of possible locations), which often requires further concessions. These concessions include considering a smaller, random sample of possible locations, stratifying the sample by individual characteristics rather than allowing them to explicitly affect location coefficients, and limiting the size of the sample used. It is also very difficult, if not impossible, to control for unobservable state characteristics.

The second approach uses aggregate data to measure patterns of migration. Some use inter-state migration rates – i.e., the proportion of elderly individuals who are moving into (*in-migration*) or out of (*out-migration*) each state or the difference in the two (*net in-migration*) whereas others use state-to-state migration flow data.[17] Nearly all studies are cross-sectional and focus on a narrow time period, typically the five year period spanned by questions on mobility from a single U.S. census. A recurring result is the so-called 'same sign' problem, in which a

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[16] Yet another approach is taken by Farnham and Sevak (2006). They use longitudinal data to estimate the effects of moving on the local fiscal bundle facing the household. Their emphasis is primarily on local policy.

[17] Recent studies using rates include Cebula (1990), Conway and Houtenville (1998), Gale and Heath (2000) and Conway and Rork (2006) and using flows, Conway and Houtenville (2001, 2003) and Onder and Schlunk (2009).

characteristic affects migration decisions in a logically inconsistent manner. With migration rate analyses, this problem manifests itself when coefficients are the same sign in both in-migration and out-migration equations; with migration flow data, it shows up as origin and destination coefficients having the same sign. For example, EIG taxes are frequently found to have a negative effect on both in-migration and out-migration **(**Conway and Rork 2006) and, in analyses using flow data, have negative coefficients for both the origin and destination (Voss et al 1988, Conway and Houtenville 2001). Like the conditional logit approach, studies using net migration rates or flows generate only one set of coefficients and thus cannot reveal a same-sign problem.

Almost all studies of both types – individual level and aggregate –focus on policies at one point in time. As such, most find that state taxes exert a negative effect on elderly migration. However, Conway and Rork (2006) show that these findings do not stand up when one allows for state unobservables via panel data. The authors employ migration rate data from four different censuses and find that the negative effect of EIG taxes frequently found in cross-sectional studies completely disappears when panel data and techniques are used. The effects of other state policies are similarly affected. Moreover, their approach, which combines panel analysis with a difference-in-difference approach that uses the non-elderly as a pseudo control group, largely eliminates the 'same sign' problem.

The only other policy-oriented, panel study of which we are aware is Bakija and Slemrod (2004), who use federal estate tax return data, tallied by wealth class, state and year, as a proxy for the location decisions of the rich (and likely elderly). In contrast to Conway and Rork (2006), they find that state EIG and income taxes discourage the rich from locating in the state.[18]

[18] Their framework is similar to that of net in-migration studies, precluding the 'same sign' problem. In essence, the federal estates observed in a given state in a given year reflect the net migration of rich individuals in the past.

The differing conclusions between the two studies make sense. Conway and Rork (2006) study the aggregate movement of all elderly, the vast majority of whom will pay no EIG taxes upon death and may enjoy significant advantages from income taxation rather than other types of taxes and fees. Bakija and Slemrod (2004) focus on the very top (typically far less than 10 percent) of the income distribution, a group for whom EIG and income tax considerations are likely to be far more important. Such a group is also more likely to own more than one home and thus have greater flexibility in choosing a legal residence. Even so, the effects they find are modest.

Our reading of current policy debates is that states are not just attempting to recruit the very rich elderly; rather, they view the middle class elderly as a possible growth industry, a group that stimulates local demand for goods and services while placing little strain on local public services (e.g., see *Wisconsin Policy Research Institute Report* 2006). Since this group is unlikely to face state EIG taxes they are probably more influenced by income taxes than EIG taxes. However, low overall income tax burdens may not be attractive to the elderly if states fund their programs with alternative funding mechanisms, such as fees and other taxes, that are more burdensome to the elderly. Income tax breaks targeting the elderly, however, should be unambiguously attractive, especially to the middle and higher income elderly the states seem likely to want to recruit. Only three studies explicitly consider elderly income tax breaks (Conway and Houtenville 2001, 2003 and Onder and Schlunk 2009), and all use data from a single U.S. Census; their results are mixed and often suffer from the 'same sign' problem.

IV. EMPIRICAL STRATEGY AND ECONOMETRIC ISSUES

Our strategy is to study elderly migration behavior over a long span of time, so that we can use the rich time- and cross-sectional variation in state income tax breaks documented in Section 2 to isolate possible causal effects. In this way, we can deal with spurious correlation and state unobservables that are likely confounding the results from existing cross-sectional/longitudinal analyses of both approaches. However, such a strategy essentially precludes using individual-level data, because longitudinal datasets are too small and/or span too short a time period; moreover, the computational challenges of allowing state unobservables appear overwhelming. In this section, we discuss our main model and its possible limitations and econometric issues, as well as our attempts to address them.

We use the richest possible aggregate measure of elderly interstate migration, state-to-state elderly migration flows.[19] Such flows are richer than in- or out-migration *rates*, which are aggregated from migration flows and only convey where individuals are moving to (or from) rather than the origin-destination path actually traveled. Our panel migration flow data comes from two sources of census-based data -- the Census tabulations and the IPUMS -- in which a person is counted as a migrant if s/he lives in a different state at the time of the Census than s/he reports living in five years prior. This method is a common measure of migration, but may underestimate migration of people who move away and then return during the five year period. Our analyses use data from the last four censuses (1970-2000) and refer to interstate migration during 1965-70, 1975-80, 1985-90, and 1995-2000. We follow the standard approach of limiting our analyses to the 48 contiguous states.

[19] Still richer data would be county-to-county migration flows, although using such data in our analyses is likely not worth the cost for several reasons. Such flows are not available in the early census tabulations, so we would be forced to shorten our time horizon or rely on the IPUMS, which with its smaller size is likely more imprecise and riddled with zero flows. Moreover, the benefits of using such flows hinge on being able to control for county-level characteristics, which are mostly unavailable during the early periods of our sample. State-level tax policies, our key variables of interest, are unlikely to affect within-state migration, and adding more observations per state may exaggerate the precision of our estimates. As widely acknowledged in past research and discussed in our conclusion, using state-level aggregates of local characteristics such as crime, cost-of-living, education or property taxes may mask important within-state variation; such variation may affect the desirability of locating in the state and thus excluding it may lead to model misspecification.

The Census tabulations report only the number of people moving between each pair of states, but have the advantage that they are based on approximately 1/6th of the U.S. population (from the Census long form).[20] Given the relative rarity of an interstate move (approximately 4 percent of elderly move in a 5 year period), a large sample is essential. We refer to these as *Census flows.* Reported at the individual-level and containing a wide range of characteristics, the IPUMS allows us to create more refined flows (e.g., high income elderly only), but is based on smaller samples than the Census flows.[21] As a result, the *IPUMS flows* display more random variation over time (Conway and Rork 2010) and a greater prevalence of zero flows than if one uses the *Census flows*. We estimate and summarize a wide range of econometric migration models using both sources of migration flows. By comparing results across the two, we can examine the robustness of our results to the limitations presented by each one.

A. Main Econometric Model

Our primary econometric model is written generally as

(1) $$\ln M^{g}{}_{ijt} = \alpha + \beta D_{ij} + \lambda d_{t} + \partial^{o} \ln Pop_{it} + \partial^{d} \ln Pop_{jt} + \delta^{o} X_{it} + \delta^{d} X_{jt} + \varepsilon_{ijt},$$

where $M^{g}{}_{ijt}$ denotes the number of individuals in group *g* (= elderly, non-elderly, high income elderly, etc.), that moved from state *i* to state *j* during census time period *t* (= 1965-70, 1975-80,

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[20] These state-to-state migration flows are reported in Census Summary Tape File 3 (STF3) for 1980, 1990, 2000 and the Fifth Count file for 1970 and are publicly available in all four census years for ages 5+, but only since 1980 for ages 65+. We therefore requisitioned a comparable tabulation from Census for ages 65+ in 1970.

[21] The IPUMS was created by the Minnesota Population Center in an effort to bring each Census's Public Use Micro-Samples (PUMS) into one place and improve the uniformity of coding across years (Ruggles et al 2010). We use the 1% Form 1 State sample for 1970, the largest available that includes migration information, and the 5 percent samples for 1980-2000; sampling weights are used as appropriate. Alexander et al (2010) uncover possible errors in gender and continuous age in the 2000 IPUMS for respondents over age 65. We follow the authors' recommendations of analyzing only the entire age 65+ group for both genders, with the exception of the IPUMS analysis for the 'younger' elderly (aged 55-70), which is dominated by the larger 55-64 cohort.

1985-90, and 1995-2000). This specification follows the typical gravity model in which the log of the migration flow is a function of the log of the populations at the origin ($\ln Pop_{it}$) and destination ($\ln Pop_{jt}$), plus the log of the distance between the two (captured in equation 1 by D_{ij}).[22] The superscripts *o* and *d* denote the parameters for the characteristics of the origin (state *i*) and destination (state *j*).

To our knowledge, we are the first to estimate a panel elderly migration flow model (the time subscript, *t*) or to compare it to that estimated for the non-elderly or different groups of elderly (thus the group index, *g*).[23] To allow for general shifts over time, we include a full set of census year dummy variables, d_t, in all models. *X* is a vector of state characteristics presumed to influence migration and includes our key variables of interest, income tax breaks. The 'same sign' problem discussed above manifests itself when the coefficients on (un)desirable state characteristics are estimated with the same sign – e.g., $\hat{\delta}^{o}$ *and* $\hat{\delta}^{d} > 0$. Such a result suggests that a variable such as cost of living encourages both out-migration ($\hat{\delta}^{o} > 0$), as expected, as well as in-migration ($\hat{\delta}^{d} > 0$), which is counter-intuitive. One byproduct of our research is to see if panel data analysis can help eliminate this counter-intuitive result in flow models as Conway and Rork (2006) showed for in-migration and out-migration rate models.

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[22] The gravity model has been widely used in empirical flow studies, including past elderly migration flow studies (Voss et al 1988, Conway and Houtenville 2001, 2003, Onder and Schlunk 2009). Fields (1979) provides a rigorous justification for using logs in a migration flow context, and Anderson (1979) provides a theoretical foundation for its use in estimating commodity trade flows. Distance is often expressed in log form to allow for a diminishing effect.

[23] Lin (1999) and Conway and Rork (2010) are exceptions, but neither includes any state policy variables. Lin (1999) uses 3 waves of the PUMS to study whether migration responses to time-invariant variables such as climate and distance have changed. Conway and Rork (2010) explore how much elderly migration flows have changed over four censuses by calculating the variation (via R-squared) explained by a gravity migration model that includes year and flow fixed effects. Frees (1992) provides a general discussion of panel, gravity migration flow models.

Adding a time dimension allows us to treat unobservable state characteristics in three different ways. First, we could simply ignore them by estimating the *standard gravity model* -- D_{ij} in equation (1) is the natural log of the distance 'as the crow flies' between the geographic centers of states *i* and *j*. This specification is similar to what has been estimated in past economic migration flow research that has relied on data from only one census. Second, we add origin and destination state fixed effects to the model; i.e., D_{ij} now includes distance plus J-1 dummy variables for each destination state and I-1 dummy variables for each origin state. We refer to this as our *panel gravity model*. The origin and destination state fixed effects capture any time-invariant, unobserved state characteristic that may affect migration decisions, such as climate, natural amenities, culture and time-invariant policy differences, and the effects of any policy are identified only by those states that experienced a *change*. Our third specification replaces the distance variable and origin/destination fixed effects with a full set of flow-specific dummy variables. State-to-state migration flows are very stable over time, and this specification models that persistence explicitly. More generally, the flow-specific fixed effects capture the effects of any time-invariant state characteristic as well as any variable associated with the flow, such as distance, information networks, vacation patterns, etc. We refer to this as our *flow-fixed effect model*. We emphasize its results because it is the least restrictive specification and yet is similar in coefficient sign and statistical significance to the panel gravity model.

Even after controlling for flow fixed effects, the estimated standard errors could still be biased downward due to serial correlation (e.g., Moulton 1986, Bertrand et al 2004, Cameron et al 2008). In our data, we have three possible clusters – origin, destination and year. We investigate this possible bias in our main model by also calculating standard errors adjusted for three-way clustering and find the usual downward bias.[24] Given the large number of models we estimate, the time-consuming nature of the procedure and the known direction of bias – which should work against our basic finding of no effect -- we report t-statistics based on heteroskedastic-robust standard errors for the rest of the analyses unless noted.

Similarly, our flow-specific model still requires that we control for state population, as the population distribution has shifted over time. We include the total population, rather than the age/group-specific one, so that our models are comparable across groups. It also better captures the strong linkages in migration across age groups, where elderly parents move to be closer to their adult children, for example. The percent of the state population that is elderly is included as part of *X* to capture demographic differences across states.

Certain flow combinations (e.g., Wyoming to Vermont) are rare occurrences in the census and thus are frequently zero. The typical approach is to drop zero flows from the analysis. In our case, however, this approach leads to an unbalanced panel and to differences in the sample size and composition across our different samples, especially as we move to the IPUMS flows. We therefore explore the robustness of our results to an alternative approach, which is to set those zero flows to 1.0 (zero when logged) and include them in the estimation.

B. Additional Econometric Issues and Exercises

While our aggregate, panel data approach helps address the confounding effects of state unobservables, several issues remain. One concern is that elderly migrants may affect state fiscal policy as they become part of the electorate – i.e., policy may be endogenous. More generally, unobservable time-varying influences could still lead to spurious correlation. We

[24] We utilize Doug Miller's Stata ado file *cgmreg*, with flow dummies entered manually, to calculate standard errors clustered by origin, destination and year. See Cameron et al 2008 for further discussion of the procedure and demonstrations of the downward bias caused by ignoring clustering.

address this concern in a few ways. First, we follow the typical approach of including the state characteristics, policies, etc. in place the year prior to the migration period. Migrants should not have directly affected policies in place before they moved. However, the possibility for spurious correlation remains, as policies, migration decisions and other factors may all evolve slowly over time. We therefore explore using higher lags (5-year and 10-year) instead. Another method uses a pseudo-control group, such as the non-elderly or low income elderly who do not benefit from the tax breaks, to sweep away spurious correlation common to both groups via difference-in-differences. This approach is similar to that of Conway and Rork (2006) except that the IPUMS allows us to construct additional pseudo-control groups.

Our final set of exercises address possible shortcomings of our aggregate approach relative to the individual-level, conditional logit approach to migration discussed in Section 3. The conditional logit approach is grounded in McFadden's random utility model (RUM) in which the individual chooses the location with the highest utility, *Uj*, which is a function of location and possibly individual characteristics. The latent dependent variable is P_{ij},

$$P_{ij} = \frac{\exp(Z_{ij}\beta)}{\sum_{k=1}^{J}\exp(Z_{ik}\beta)} \qquad (2)$$

which is the probability that an individual in location *i* will choose location *j* out of 1…*J* possible locations, and the time and group subscripts have been suppressed for simplicity. As such, it explicitly considers the attributes (*Z*) of all possible locations, and treats the decision to move and the choice of destination simultaneously. However, as a conditional logit model, it also suffers from the well-known problem of Independence of Irrelevant Alternatives (IIA). While more complicated and still more computationally expensive estimators exist that avoid it, the gains appear questionable (Davies et al 2001, Christiadi and Cushing 2007). Thus, both the conditional logit and aggregate approaches, as typically estimated, impose restrictions on how alternative locations are considered. It is also not clear to us that a simultaneous approach to migration is superior. A sequential process seems equally plausible, in which individuals would first make the decision to leave their current location (due to high taxes, poor climate, etc.) and then choose the best destination. We nonetheless estimate alternative models that are closer in spirit to the RUM/conditional logit approach.

First, we include nonmovers in our analyses, just as they are often included in location choice models. In terms of equation (1), we now add M_{ii}, the number of elderly individuals who choose to stay in state *i*, a similar approach to that taken by Davies et al (2001) who include nonmovers and the ratio of destination-to-origin characteristics within a conditional logit framework. The flow fixed effect captures the special effect (e.g., no moving costs) of choosing to stay in one's origin state.

We also specify two alternative functional forms that may have advantages over the gravity model (equation 1). The first derives directly from the RUM framework and is exemplified by Sasser (2009). Equation (2) is rewritten in terms of the log of the ratio of the probability of moving from *i* to *j* to the probability of remaining in *i*,

$$(3) \qquad Ln\left(\frac{P_{ij}}{P_{ii}}\right) = Z_{ij}\beta - Z_{ii}\beta.$$

Using the number of movers and non-movers relative to the population in *i* to approximate the probabilities and limiting Z to include only location characteristics, equation (3) simplifies to

$$(4) \qquad Ln\left(\frac{M_{ij}/Pop_i}{M_{ii}/Pop_i}\right) = Ln\left(\frac{M_{ij}}{M_{ii}}\right) = (Z_j - Z_i)\beta.$$

This alternative, '*ratio*' model therefore simply requires us to redefine our dependent variable in equation (1) to be log(M_{ij}/M_{ii}) and our independent variables to be the difference between the destination and origin characteristics. It therefore yields one set of coefficients and cannot result in a 'same-sign' problem. We include population, and year/flow fixed effects for consistency.

The second alternative is an even more parsimonious specification argued by Douglas (1997) to be one that "…has a firmer theoretical basis and uses migration information more efficiently than previous methods," (p. 411). This specification captures the expected *net* migration flow, adjusted for origin and destination populations and can be written as:

$$(5) \qquad \left(\frac{M_{ij} - M_{ji}}{Pop_i * Pop_j}\right) = (Z_j - Z_i)\beta'.$$

where population variables, year dummies and *net* flow-specific dummy variables are included for consistency. This specification is more restrictive in that it estimates the effects of the difference in the destination and origin states' characteristics on the *net flow* of migrants above what would be predicted on the basis of population. Only one observation exists for each state pair (accomplished by dropping the negative net flow $M_{ji} - M_{ij}$) and the populations are rescaled to prevent the denominator from becoming too large. Like equation (4), this specification precludes the 'same-sign' problem.

Finally, perhaps the biggest potential advantage of the individual approach is the ability to let the attributes, *Z*, vary over individuals. In principle, one could include the tax burdens or breaks each person would face in each location, but in practice few if any studies do. Rather, the most common practice is to stratify the sample based on one or more individual characteristics (typically income), which is equivalent to letting all of the location coefficients vary by that characteristic (e.g., Dresher 1994, Duncombe et al 2001, 2003). Using the IPUMS data, we perform similar exercises. We create migration flows for specific groups of the elderly that seem mostly likely affected (e.g., the non-disabled, the relatively young, the high income) and estimate separate models for each. In this way, we allow for individual heterogeneity in a manner similar to past studies. Also, as noted above, creating more refined migration flows allows us to construct pseudo-control groups of elderly migrants who seem less likely to be affected by income tax breaks (e.g., those suffering a disability or low income individuals).

V. DATA DESCRIPTION

In this section, we report and discuss the interstate migration patterns observed in the Census tabulations and compare them to the more refined flows created from the IPUMS. We then discuss the location attributes included in the multivariate models.

A. Census and IPUMS Migration Measures -- Over Time and Across Income Groups

Table 2 compares the key variable in our econometric analyses – state-to-state migration flows -- across different groups of elderly over time. Due to the large number of possible flows (48 x 47 =2256 per census), we report only the top 10 flows, the number of zero flows, the overall rate of migration and the geographic concentration of migration (percentage of migrants accounted for by the top 10 flows) in 1970 and 2000 for 1) the full census, 2) the top income quartile from the IPUMS, and 3) the bottom income quartile from the IPUMS. The top flows are remarkably similar across the three, although as expected the lowest income elderly have a lower overall migration rate and are less concentrated geographically. These flows show the well-established tendency of the elderly to move from the northern industrial states to Florida. One apparent change over time has been a de-concentration of elderly migration across all three groups. Finally, as expected, the prevalence of zero flows increases dramatically in the IPUMS data, especially in the smaller 1970 sample when more than 75 percent of the 2256 possible flows are zero.

A drawback of using flows in descriptive analyses is the dominant role played by population, at both the origin and the destination. We therefore also summarize the migration flows by creating the net in-migration rate (all inflows into state *i* minus all outflows from state *i* divided by the elderly population in state *i*) and report in Table 3 the top five 'importers' and 'exporters' for the same three income groups in 1970 and 2000. Net migration rates provide a nice complement to flows in a descriptive analysis because they net out the empirical tendency for states with large inflows to also have large outflows and they adjust for state population. We would therefore expect to see less persistence over time in net migration rates than flows. The net migration rates again show Florida's importance as a destination, as well as that of Arizona and Nevada. The lack of an income tax or EIG tax in two of these states may lead to spurious correlation between tax policy and elderly migration in cross-sectional analyses. Moreover, the persistence in elderly migration patterns over time and across income groups is immediately apparent here too.

Table 4 formalizes these comparisons by reporting the correlations in both migration flows and net-migration rates over time and across groups. The top panel reveals the strong stability over time. The correlations across census flows in different years all exceed 0.91; even net-migration rates, which we expect to be less persistent because they adjust for population, are very highly correlated over time, especially since 1980 when they too all exceed 0.91. The next two panels show a similarly strong correlation across income groups for each year. The correlations of both migration measures (flows and net rates) between different income groups exceed 0.9 in every year, with only one exception – the top vs. bottom IPUMS income net migration rates in 1970. Recall that only the one percent IPUMS sample is available for 1970, which explains why this correlation is smaller.

These exercises establish the stability of elderly migration patterns over time and different income groups, even after controlling for population, and, when combined with the variation in state tax breaks during the same period, is the first piece of evidence casting doubt on an empirically important relationship between the two. However, the lack of an obvious relationship could be due to countervailing changes in other factors included in *Z*, which we discuss next.

B. State/local Characteristics included in the Empirical Models

The state/local characteristics that we include in our baseline model follow that of Conway and Rork (2006) and are discussed in detail there. In this way, we can see if the results they find for panel elderly migration rate models and EIG taxes carry over when using richer migration flow data. We then augment their specification by including detailed information on elderly state income tax preferences. The variables included, whose definitions and sources are reported in Appendix 1, control for cost of living, amenities, and state and local government expenditures and tax policies other than elderly income tax breaks.

One type of state tax deserves special mention here – EIG taxes – since they disproportionately affect the elderly. Again, we borrow from Conway and Rork (2006) and use the two alternative measures they emphasize: 1) a dichotomous dummy variable for whether the state has an incremental EIG tax or not (i.e., a state that imposes only a 'pick-up' or 'soak-up' tax is coded with a zero), and 2) the effective average state EIG tax rate on a $1 million (in constant 1996 dollars) bequest divided equally between two adult children, reported by Bakija and Slemrod (2004, Table 2). These rates are reported every 5 years from 1965 to 2000; we therefore use 1965, 1975, 1985 and 1995. Our results are very robust to the EIG measure included. For consistency, then, when our income tax break variables are measured in a dichotomous form, we report the results from models in which EIG taxes are measured similarly (the first measure). When our income tax break measures are continuous and thus reflect their magnitude, we report results that include the effective EIG tax rate (the second measure).

Because income tax breaks are our primary variables of interest, we explore several alternative measures, also listed in Appendix 1. These measures vary along two dimensions – discrete versus continuous, and individual components/features versus aggregate. In all cases, our measures capture the *tax advantage* afforded the elderly and thus are predicted to retain elderly residents ($\gamma^o < 0$) and attract new elderly migrants ($\gamma^d > 0$). The four types of measures and associated model specifications we consider are:

1) Dummy variables for each of the three components. The model includes three dummy variables for whether the state had each type of preference (deduction, Social Security exemption, and private pension exemption) in the year prior to the migration period. We choose this as our main model specification due to its simplicity and transparency. However, it fails to capture the magnitude of the tax breaks.

2) The maximum tax benefit associated with each component. This measure is the same as that summarized in Table 1 and is calculated by multiplying the amount of the deduction or exemption by the maximum marginal income tax rate in the state.[25] For the Social Security exemption, we use the maximum Social Security benefits that a two-worker household could

[25] For states that exempt all private pension income, we set the exemption amount at $100,000. The results are robust to choosing other values. We recognize that the deductibility of state income taxes from federal taxes reduces the true value for households who itemize. However, the measures we construct are still accurate measures of the *maximum* possible benefit. Moreover, the effect of federal deductibility should only vary over time.

receive, from which we subtract the maximum amount that could be subject to tax (i.e., zero, 50 percent or 85 percent of benefits). In this way, all three measures are calculated in the same manner and each captures the maximum possible value of the tax preference.[26]

3) Total maximum tax benefit. Although there are a large number of state-to-state flows (and thus observations), only forty or so different state income tax systems exist. It therefore may be asking too much of the data to estimate separately the effect of each tax preference and so we create an alternative measure, the simple sum of the three components described in 2). This measure captures the maximum income tax benefit granted the elderly and does not distinguish between the different policy instruments.

4) TAXSIM-estimated tax benefit. The above three measures, while straightforward, likely miss many complexities of the state income tax systems as well as overstate the actual tax benefits. As a complementary measure, we use the estimated tax benefit of being a representative high income elderly household calculated in Conway and Rork (2008a). Summarizing briefly, the authors use data from the Current Population Survey (CPS) to create a representative 'high income' elderly household (top quartile) and a comparable non-elderly household (same level of income but from different sources). The state income tax burden facing each type of household is calculated via TAXSIM (Feenberg and Coutts 1993). The elderly tax benefit is the difference between the estimated state tax liability of a non-elderly vs. elderly household. This approach

[26] As noted in footnote 11, the Social Security exemption presents a challenge in this regard. Because 50 percent (85 percent) is the *maximum* benefits that can be taxed, our measure is not actually the maximum possible value. Rather, the maximum possible tax benefit is mtr*100 percent of maximum benefits even for those states who tax Social Security benefits for high income households. However, using that as a maximum value obviously defeats the purpose of identifying states that treat Social Security benefits more generously than others. An alternative is to instead use the maximum tax one could pay on Social Security benefits. Such a measure has two serious drawbacks. First, as a maximum 'tax,' its coefficient would have an opposite interpretation from the others. Second and more seriously, such a measure would be difficult to aggregate with the other preferences as we do in our third model specification.

also provides an alternative measure of the average income tax burden, and so in these specifications we replace the state average income tax rate (total state personal income tax revenues divided by total state personal income) with the actual average income tax rate facing a non-elderly, high income household (i.e., the estimated tax liability divided by household income).

While the TAXSIM measure better captures the subtleties of the state and federal income tax code and may better reflect the tax benefits experienced by a typical high income elderly household, it has a critical drawback. TAXSIM (and the CPS) is only available since 1977. We therefore must omit the 1970 data from any analysis using this measure. Moreover, if we adhere to our practice of using the year prior to the migration period, we lose the 1980 data as well. We take two approaches to this problem. First, we estimate models for the 1980-2000 data using the midpoint average (e.g., 1977-78 average for 1975-80 migration) for the TAXSIM variables. Second, as a robustness check we estimate models for 1990 and 2000 following our standard practice of using the year prior to the migration period (1984 and 1994, respectively). Our results may therefore differ between 3) and 4) above either because of the difference in time periods or because of the different way that the policy variables line up with the time period. To explore these differences, we also estimate 3) using only 1980-2000 and 1990-2000 data. Fortunately, our findings are robust to these exercises.[27]

VI. EMPIRICAL RESULTS FROM THE ELDERLY MIGRATION FLOW MODELS

We begin by reporting the results from the Census flows, first for our main specification (using the dummy variables for each component) and then using other measures as described above. We also explore the different econometric specifications described in Section 4, as well

[27] All exercises discussed but not reported are available upon request.

as perform some additional robustness checks. In all cases, we find no credible evidence that income tax breaks – or EIG taxes – affect elderly migration. Next, the models are estimated with the more refined IPUMS flows to investigate if the lack of results is caused by aggregation bias. Again, we find no consistent evidence.

A. Results from the Census flows

Our first goal is to see whether the findings of Conway and Rork (2006) – that panel data and methods are critical to estimating migration effects -- stand up when one uses migration flow data. Table 5 reports the full set of results from our main model for the standard gravity model (no fixed effects) and then introducing first origin- and destination-state and then flow-specific fixed effects.[28] For this last model, Table 5 also denotes the coefficients that remain statistically significant when 3-way clustered standard errors are used. In the standard gravity model (the first two columns), the estimated EIG tax coefficients are again negative and strongly statistically significant – at both the destination (as expected) and the origin. These effects, however, are completely eliminated by the inclusion of either origin/destination or flow-specific fixed effects. Many of the other variables are affected similarly. Also as in Conway and Rork (2006), we find that panel methods remove the persistent 'same-sign' problem of crime that has been found repeatedly in the literature. Once panel methods are used, crime has the intuitive effect of driving out the elderly ($\hat{\delta}^{o} > 0$) and discouraging them from entering ($\hat{\delta}^{d} < 0$). In general, when panel methods are used, far fewer coefficients are statistically significant and most (but not

[28] Results from the individual cross-sections – i.e., estimating each census year separately -- are reasonably similar to those obtained from the pooled analysis and so we emphasize the pooled model results for brevity. The results for the EIG coefficients are very similar if the income tax break variables are omitted, further confirming that the results from Conway and Rork (2006) carry over to a migration flow model.

all) cases of statistically significant, counter-intuitive 'same sign' coefficients are eliminated.[29] Surprisingly, moving from origin- and destination-state fixed effects to the much more numerous flow-specific effects produces similar results in terms of coefficient sign and statistical significance. As this finding carries over to the multitude of models estimated, we emphasize the less restrictive flow-specific fixed effects results in the rest of the paper. As expected, using the 3-way clustered standard errors substantially reduces the statistical significance of the coefficients and confirms our assertion that using heteroskedasticity-robust-only standard errors works against our main finding of no effect. Moreover, only two counter-intuitive results remain and both are only marginally significant – the positive effects of a pension exemption and health and hospital spending on migrating out of a state.[30] Total population and the size of the elderly population are the dominant determinants.

Our key variables – income tax breaks -- are similar to EIG taxes in that they are statistically significant and suffer from the same sign problem in models that ignore state unobservables (the first two columns). Unlike EIG taxes, however, their counter-intuitive effects are more likely to persist even after origin/destination or flow-specific effects are included, although 3-way clustering mostly eliminates their statistical significance. Income tax breaks are expected to retain current elderly residents ($\gamma^o < 0$) and attract new elderly migrants ($\gamma^d > 0$). Yet we find exactly the opposite – Social Security and private pension exemptions are estimated

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[29] Population and, to a lesser extent, percent elderly are expected to exert the same forces at the origin and destination. Population at both destination and origin are expected to positively affect migration flows. Percent elderly population is likely capturing the higher elderly population in these states as well and is partly adjusting for our use of total population. However, to the extent that it is also capturing an amenity of the state – which could be either good or bad to the elderly – one would expect its sign to differ. Many of the other coefficients also have the same sign, but both are rarely statistically significant.

[30] We do not consider the positive, origin wage coefficient to be counterintuitive because a high wage rate (and low unemployment rate) is likely a proxy for a high cost of living for the elderly, who are mostly out of the labor force.

to drive away elderly residents and may repel new migrants. The deduction appears to have no statistically significant effect once fixed effects are included.

To explore whether these findings are due to our choice of tax measures, Table 6 summarizes the key coefficients from flow-specific fixed effect models that use the alternative tax break measures described above as well as our main model for comparison. Capturing the magnitude of the tax measures (3rd and 4th columns) does not lead to intuitive findings. While the *value* of the deductions is estimated to retain elderly residents as expected ($\hat{\gamma}^{o} < 0$), the value of a Social Security exemption repels new migrants ($\hat{\gamma}^{d} < 0$). The rest of the table reveals that aggregating the three components into one summary measure does not help either; our aggregate sum is never statistically significant and the marginally significant TAXSIM measure is the wrong sign at both the origin and destination.

In unreported analyses, we also explore including only the amount of the pension exemption – the most valuable tax break and one that shows strong time variation – and find that it does not improve the results. The estimated coefficients are negative and statistically insignificant at both the origin and the destination. Similarly, we estimate a more parsimonious model that only includes the key tax variables. The results do not improve; two of the three statistically significant tax break coefficients are of the wrong sign. We also try several alternative lag structures: 1) lagging the tax variables five years (instead of one), 2) lagging the tax variables 10 years, and 3) lagging all variables 10 years.[31] While the results are sensitive to the lag specification, all continue to yield counter-intuitive estimates. As noted in Section 2, alternately omitting Alabama, Mississippi and West Virginia, outlier states with regards to tax

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[31] Due to data limitations, the latter two are estimated only for 1980-2000.

breaks, has no effect on the results. Finally, adding a dummy variable equal to one in 1994 for those states whose public pension exemptions were affected by the 1989 Supreme Court ruling also had no qualitative effect.

Table 7 summarizes the alternative specifications discussed in Section 4b for our main model and the model that includes the total value of the tax breaks. The first uses the non-elderly as a pseudo-control group to address possible spurious correlation – e.g., the growing tendency to move south by all age groups – as in Conway and Rork (2006). We calculate and report the difference in the migration coefficients for the two age-specific samples as elderly migration should be more positively affected by elderly tax breaks than non-elderly migration. This exercise improves modestly the results for EIG taxes (both statistically significant coefficients are of the right sign), but it does nothing for the tax break variables; all three statistically significant coefficients are of the wrong sign.

The second incorporates nonmovers – M_{ii} – into the gravity model and yields nearly identical results to the main model. The third specifies a functional form that is more consistent with the conditional logit framework (the log-*ratio* of movers to non-movers) and produces only one set of coefficients – for the destination-origin difference. While the EIG tax again becomes the correct sign, it is only marginally significant. All of the tax break coefficients are of the wrong sign. The last follows Douglas (1997) and is even more restrictive as only net flows (M_{ij} – M_{ji}) are included. None of the key coefficients is even close to statistical significance.

B. Adding evidence from the IPUMS

By looking at the migration patterns of *all* elderly individuals, as we are forced to do when using the full census tabulations, perhaps effects on the mobile, high income elderly are being obscured. We can address this possible aggregation bias by using the IPUMS to construct state-to-state migration flows for elderly expected to respond to tax incentives, such as the relatively young (aged 55-70), the healthy (those who do not report a disability) or affluent (those in the upper quartile of the national income distribution). This approach is similar to stratifying the sample by individual characteristics, as is frequently done in models using individual data. For comparison, flows are also constructed for those less likely to be influenced -- those reporting a disability, returning ‘home’ (to their state of birth) or in the lowest quartile of income. Reporting a disability indicates a possible need for care assistance; likewise, migrants seeking assistance are assumed to be more likely to ‘return home’ (e.g. Longino and Serow 1992). Assistance movers may be less influenced by state tax policy and low income migrants will receive little if any benefit from the income tax breaks. As discussed earlier, the IPUMS flows are based on smaller samples, which leads to increased volatility and a greater number of zero flows, especially in 1970 and as we move to more narrowly defined groups. In addition to comparing across different tax measures, samples and time periods, we therefore also compare our findings for the IPUMS flows created for all elderly against the census tabulations and explore the prevalence and importance of zero flows.

Such an exploration leads to a very large number of estimates, many of which are sensitive to the choices made. We tackle this challenge by focusing on a representative set that reflect best/accepted practices while also briefly summarizing the entire set of results. In unreported analyses, we find that dropping 1970 has little impact on the census results and leads to similar results between the IPUMS and census flows. However, the results are sensitive to the treatment of zero flows, but neither method produces results supporting an intuitive role for income tax breaks. We therefore focus on the results from the 1980-2000 IPUMS subsamples that drop zero flows, which is the standard approach.

Table 8 reports the key results for our main model, using various elderly subsamples. The top panel emphasizes youth and affluence, as both are believed to be associated with amenity elderly migration. For comparison, we also estimate the model for the lowest income quartile. The bottom panel focuses on excluding elderly who may be moving for assistance or family ties as measured by reporting a disability or returning to one's state of birth (also called 'return migration'). Again, we report the results for those reporting a disability for comparison.

Four out of five of the statistically significant coefficients for EIG taxes are the wrong sign – and the one case that is the correct sign is for those elderly who report a disability and thus are believed to be *less* likely to be moving for amenity reasons. Moreover, these results are quite similar to those for all elderly flows, using either the IPUMS or the census. Limiting the analyses to those elderly most (least) expected to be affected has no substantial impact on the results; EIG taxes apparently help retain the elderly if they have an effect at all. This counterintuitive result is stronger, if anything, for the elderly groups most believed to be affected by EIG taxes (high income, non-return, non-disabled). This means that using a difference-in-difference approach to eliminate spurious correlation, by comparing affected and unaffected groups of elderly, does not lead to more intuitive results.

The income tax break coefficients display a similar pattern. Of the thirty-six possible coefficients (3 measures x origin/destination x 6 samples), eleven are statistically significant; of those eleven, ten are of the wrong sign. Only the low income, destination coefficient for the Social Security tax exemption is the correct sign – and low income individuals are not likely to benefit from this tax break. In general, the coefficients are fairly similar between the different groups of elderly, further casting doubt on a meaningful relationship.

The results reported so far are a small subset of the full complement of models we estimated. The full complement entails

4 different sets of tax measures for a total of 8 coefficients (two sets yield 3 coefficients),

2 different time periods (1970-2000 and 1980-2000) for 7 of these 8 coefficients (the TAXSIM measure can only be estimated for 1980-2000),

9 different samples (full census and 8 samples from the IPUMS -- total, aged 55-70, high income, low income, return, non-return, disabled, non-disabled), and

2 different treatments of zero flows,

for a total of (8 + 7) x 9 x 2 = 270 estimated coefficients *each* for the origin and the destination. Table 9 summarizes the results from all of these specifications as well as from some logical subdivisions. Given the coefficients come from different types of tax measures and therefore differ in their interpretation, we use their t-statistics as a comparable measure across models. The t-statistics also convey the statistical significance of the coefficients, although the downward bias in the non-clustered standard errors suggests that this significance is likely overstated.

Table 9 reports the median t-statistic and the percentage that are statistically significant at the 10 percent level for the income tax break coefficients at the origin (which should be negative) and at the destination (which should be positive). The top panel reports these from the full complement of models. The destination t-statistics consistently suggest no significant effect, with a median quite close to zero and the vast majority in the statistically insignificant range. The origin t-statistics tend more towards a positive effect -- which is counterintuitive – with most being statistically insignificant. The middle panel repeats this exercise, stratifying by the tax measure used. Only the credit/exemption behaves at all consistently with theory – the t-statistics tend to be negative at the origin and slightly positive at the destination. For the other two components, however, the results suggest either a zero or counter-intuitive effect. These mixed findings are further confirmed by the t-statistics on the total amount (summed across components); they are squarely centered on zero with small proportions being statistically significant. Conversely, the TAXSIM measures yield strongly counter-intuitive results at the origin and results consistent with a zero effect at the destination.

The bottom of Table 9 reports the results for the IPUMS samples most likely to be amenity movers – those aged 55-70, high income, not disabled or not returning to their state of birth. Here again, the median t-statistics are very close to zero and the vast majority fall in the statistically insignificant range. Moving to elderly samples that are most likely to be affected by the policy therefore also fails to yields evidence of statistically significant effects.

A limitation with the t-statistics is they do not reveal magnitude. The estimated effects could be large but imprecisely estimated in a systematic way that is obscured by the t-statistics. Reviewing the estimated coefficients reveals no such tendency; they are fairly evenly distributed around zero as well.

Finally, we examine in greater detail the results obtained when the most credible sub-sample is used. We believe the 55-70 subsample is superior; its flows are based on the largest subsample and it seems to us the least ambiguous measure of 'amenity' or retirement migration.[32] For this subsample, we again compute the 3-way clustered standard errors to obtain the most accurate evidence of what factors affect amenity migration. Across all tax measures and treatment of zero flows, only one out of 32 income tax break coefficients are statistically

[32]Recall that migration could have occurred up to five years earlier, when these individuals are as young as 50-65, such that the need for assistance seems unlikely.

significant and 17 out of 32 are the incorrect sign. These results also provide evidence as to what factors *do* affect migration. High population and per capita income states experience more in- and out-migration, and high housing prices discourage both. Other measures of cost-of-living (wage and unemployment rate) are also sometimes important in an intuitive way. As for policy, only welfare or health expenditures (pushing out at the origin) and property taxes (repelling from the destination) yield suggestive results.

VII. CONCLUDING REMARKS

Our research investigates whether little examined yet much debated elderly income tax breaks, such as exemptions for retirement income, have an effect on elderly interstate migration behavior. To our knowledge, we are the first to explore different measures of these incentives as possible factors influencing elderly interstate migration. We are also the first to employ elderly migration flow data from four different censuses so that persistent flow patterns can be explicitly modeled via panel methods; we further refine our analyses to include only those elderly most likely to be affected by tax breaks and compare the results to those less likely affected. Our econometric results are subjected to a wide range of robustness checks. The results from all analyses overwhelmingly find no credible effect of state income tax breaks on elderly migration.

Our conclusion is consistent with historical trends in elderly migration and tax policy. Past research has shown (and we confirm) that elderly state income tax breaks and EIG taxes have both varied a great deal across states and over time, while elderly migration patterns have remained largely the same. Our analyses here further demonstrate very strong correlations of elderly migration patterns over time and across different income groups. Put simply, state tax policies towards the elderly have changed substantially while elderly migration patterns have not. Our econometric and descriptive analyses, by controlling for or differencing away other factors in multiple ways, suggest that countervailing influences are not obscuring a relationship. Our conclusion is also consistent with Young and Varner (2011), who find few migration effects among the rich in response to the 'natural experiment' presented by New Jersey's 'millionaire tax' enacted in 2004.

However, our analyses raise questions and suffer from limitations that lead to important caveats. Foremost, our data ends with migration that took place during 1995-2000. Information regarding these tax breaks appears more readily available today than ever before so current elderly may behave differently than their predecessors. The replacement of the 2010 Census long form with the smaller, annual American Community Survey greatly complicates and likely postpones for some time extending these analyses into the 21st century. Also troubling is the counterintuitive results we obtain for several state characteristics, suggesting possible model misspecification, although most are eliminated when appropriate (3-way clustered) standard errors are used. While we have attempted to deal in multiple ways with critical econometric issues such as endogeneity/spurious correlation and individual heterogeneity, they could still persist in our analyses. Perhaps the greatest shortcoming of our analyses and one that has been widely acknowledged in past research is our inability to capture *within* state variation. Many of the key state characteristics, such as health care and education systems, property taxes, cost of living and crime, vary a great deal within the state. Thus, including only the state average obscures that individuals have a menu of options within the state. If this variation is reasonably uniform across the states or time-invariant (e.g., some states have greater local variation than others, but consistently over time), the effects on our estimates should be limited. Exploring the role of within state variation on interstate migration is a promising direction for future research.

Our results notwithstanding, policy debates across the country, as well as the recent actions by states to increase tax breaks for their elderly citizens and eliminate EIG taxes, suggest that many believe these tax breaks are important. While other motives are certainly possible, such as attracting political support from current elderly constituents, the public justification for these policies typically centers on their migration effects. The stakes are nontrivial. These policies have significant revenue consequences; for instance, Bernstein (2004, p. 9) estimates that the total exemption of Social Security benefits cost the state of California $850 million in 1999, the equivalent of 1.2 percent of tax revenue raised that year. These revenue consequences will only grow as the population ages. Our results, as well as the consistently low rate of elderly interstate migration, should give pause to those who justify offering state tax breaks to the elderly as an effective way to attract and retain the elderly.

Table 1

Values of Various State Income Tax Breaks Granted Married Elderly, 1964-1994

I. Dollar Value of Tax Breaks Granted to and Household Income of the Elderly

	Credits and Deductions			Pension Exemptions			All Tax Breaks Combined		
Year	Mean	Range	# States	Mean	Range	# States	Mean	Range	# States
1964	37	5 to 66	21	440	440	1	148	46 to 671	22
1974	50	5 to 119	28	1491	140 to 10000	13	800	168 to 10403	31
1984	104	18 to 1144	33	1607	79 to 10000	21	1445	20 to 10929	36
1994	83	20 to 520	31	1717	310 to 9000	23	2234	20 to 11282	35

II. Changes in Dollar Value of Tax Breaks Granted to the Elderly

	Credits and Deductions			Pension Exemptions			All Tax Breaks Combined		
Year	Mean	Range of Increases	Range of Decreases	Mean	Range of Increases	Range of Decreases	Mean	Range of Increases	Range of Decreases
1964-74	26	6 to 70	33 to 45	1435	140 to 10000	0	679	37 to 10248	n/a
1974-84	63	0.5 to 1144	55	720	79 to 5600	364	625	38 to 6293	6 to 321
1984-94	-15	0.3 to 90	4 to 624	311	34 to 5000	150 to 2600	778	45 to 5748	44 to 2138

NOTES: 1.) Maximum value is calculated by multiplying the top marginal income tax rate (mtr) by the exemption/deduction amount. For states excluding all pension income we assume a maximum amount of $100,000 in calculation. 'All tax breaks' includes the value of exempt SS benefits, see footnote 11 for details.

2.) WV converted an $8000 pension exemption into an $8000 age exemption in 1980, resulting in the large range of credits/deductions seen above.

3.) Calculations are for the 48 contiguous states only.

Table 2

Summary of Migration Flows by Source and Year

Rank	Census		IPUMS Top 25% Income		IPUMS Bottom 25% Income	
			1970			
	Origin	Destination	Origin	Destination	Origin	Destination
1	NY	FL	NY	FL	NY	FL
2	MI	FL	IL	FL	MI	FL
3	IL	FL	MI	FL	IL	FL
4	NY	NJ	NJ	FL	PA	FL
5	OH	FL	OH	FL	OH	FL
6	NJ	FL	NY	NJ	NJ	FL
7	PA	FL	PA	FL	NY	NJ
8	IL	CA	IL	CA	IL	CA
9	NY	CA	MA	FL	IN	FL
10	PA	NJ	IN	FL	MA	FL
# zero flows		299		1712		1696
migration rate		0.0368		0.0434		0.0320
top 10 as % of all flows		30.3		30.1		21.1
			2000			
1	NY	FL	NY	FL	NY	FL
2	NJ	FL	NJ	FL	NY	NJ
3	NY	NJ	MI	FL	NJ	FL
4	OH	FL	PA	FL	MI	FL
5	MI	FL	CA	AZ	PA	FL
6	CA	AZ	OH	FL	CA	AZ
7	PA	FL	IL	FL	CA	NV
8	CA	NV	MA	FL	FL	GA
9	MA	FL	NY	NJ	OH	FL
10	IL	FL	CA	NV	FL	NY
# zero flows		88		694		710
migration rate		0.0431		0.0465		0.0380
top 10 as % of all flows		21.7		17.3		14.2

Table 3

Summary of Net-Migration Rates by Source and Year

TOP IMPORTERS, BY NET-MIGRATION RATE

1970						2000					
Census		IPUMS Top 25 % Income		IPUMS Bottom 25 % Income		Census		IPUMS Top 25 % Income		IPUMS Bottom 25 % Income	
FL	21.41	AZ	10.25	FL	4.77	NV	13.08	NV	4.80	NV	2.30
AZ	16.51	FL	9.24	AZ	3.81	AZ	9.64	AZ	3.93	AZ	1.72
NV	6.19	NV	1.30	NV	2.61	FL	5.78	FL	2.42	FL	1.02
OR	2.53	NH	1.23	DE	1.79	SC	3.58	SC	1.12	GA	0.79
NM	2.09	NM	0.66	WY	1.38	DE	2.99	NC	0.84	NC	0.56

TOP EXPORTERS, BY NET-MIGRATION RATE

1970						2000					
Census		IPUMS Top 25 % Income		IPUMS Bottom 25 % Income		Census		IPUMS Top 25 % Income		IPUMS Bottom 25 % Income	
NY	-4.61	WY	-3.79	WV	-1.15	NY	-4.76	NY	-1.48	NY	-1.01
IL	-3.91	NY	-1.81	NY	-0.96	IL	-2.90	CT	-1.13	IL	-0.49
MI	-3.24	IL	-1.67	IL	-0.77	NJ	-2.18	NJ	-1.12	ND	-0.49
ND	-2.91	DE	-1.54	MT	-0.76	CT	-2.04	IL	-1.01	CT	-0.34
WY	-1.97	ND	-1.29	MI	-0.74	MI	-1.85	MI	-0.75	IA	-0.33

NOTE: All net-migration rates are calculated as (inflows to state *i* – outflows from state *i*) divided by the total elderly population in state *i*. The rates for the top and bottom quartiles are therefore smaller than those for the overall (census) elderly.

Table 4

Correlations of Elderly Migration Measures, by Source and Year

CORRELATION MATRIX OF CENSUS ELDERLY MIGRATION MEASURES *OVER TIME*

State-to-State Migration Flows					Net In-Migration Rates				
	1970	1980	1990	2000		1970	1980	1990	2000
1970	X				1970	x			
1980	0.983	x			1980	0.903	x		
1990	0.925	0.956	x		1990	0.690	0.911	x	
2000	0.917	0.942	0.985	x	2000	0.731	0.926	0.953	x

CORRELATIONS OF ELDERLY MIGRATION FLOWS *ACROSS INCOME GROUPS*, BY YEAR

	1970	1980	1990	2000
Top 25% v. Bottom 25% of Income	0.947	0.952	0.961	0.956
Top 25% Income v. Overall	0.984	0.990	0.989	0.985
Bottom 25% Income v. Overall	0.974	0.981	0.985	0.986

CORRELATIONS OF ELDERLY NET-MIGRATION RATES *ACROSS INCOME GROUPS*, BY YEAR

	1970	1980	1990	2000
Top 25% v. Bottom 25% of Income	0.758	0.932	0.937	0.911
Top 25% Income v. Overall	0.939	0.986	0.974	0.974
Bottom 25% Income v. Overall	0.904	0.937	0.921	0.947

Table 5

Regression Results Using Dummy Indicators of Income Tax Breaks and 1970-2000 Census Flow Data

	origin		*destination*		*origin*		*destination*		*origin*		*destination*	
<u>INCOME TAX BREAKS</u>												
additional credits or deductions	0.060	**	0.041		0.004		-0.011		-0.011		-0.020	
for elderly (1 = YES)	[2.13]		[1.53]		[0.13]		[-0.37]		[-0.52]		[-0.96]	
social security income exemption	0.197	***	0.205	***	0.050		-0.048		0.041	*	-0.061	***
(1 = YES)	[6.49]		[6.89]		[1.49]		[-1.50]		[1.70]		[-2.66]	
private pension income exemption	-0.075	***	-0.266	***	0.079	**	-0.007		0.079	***	0.003	
(1 = YES)	[-2.95]		[-10.53]		[2.49]		[-0.21]		[3.45]	!	[0.14]	
<u>EIG TAXATION</u>												
incremental EIG tax (1 = YES)	-0.307	***	-0.460	***	0.004		-0.007		-0.00004		0.0001	
	[-12.06]		[-17.39]		[0.13]		[-0.20]		[0.00]		[0.00]	
<u>OTHER TAXES</u>												
average income tax rate	-13.336	***	-9.609	***	1.915		1.613		1.276		1.369	
	[-8.21]		[-6.14]		[0.64]		[0.55]		[0.60]		[0.63]	
property tax share	0.085		-0.635	***	-0.036		0.378		-0.032		0.527	**
	[0.38]		[-3.23]		[-0.11]		[1.17]		[-0.16]		[2.35]	
sales tax rate	-0.026	***	-0.051	***	-0.013		-0.012		-0.005		-0.014	
	[-3.08]		[-6.10]		[-0.96]		[-0.95]		[-0.56]		[-1.50]	
other tax share	-0.984	***	-0.782	***	-0.414		0.174		-0.443	*	0.187	
	[-4.17]		[-3.23]		[-1.06]		[0.43]		[-1.65]		[0.65]	
<u>AMENITIES/COST OF LIVING</u>												
per capita income	-0.032	***	-0.083	***	0.035	**	0.034	**	0.029	***	0.038	***
	[-3.33]		[-8.84]		[2.33]		[2.37]		[2.68]		[3.71]	
state median house value ($1000)	0.004	***	0.003	***	-0.001		-0.003	***	-0.001	**	-0.002	***
	[3.99]		[3.87]		[-1.63]		[-2.79]		[-2.31]		[-4.07]	
average state mfg wage	0.014		0.029	***	0.034	*	0.022		0.039	***	0.023	*
	[1.37]		[2.96]		[1.89]		[1.22]		[3.04]	!!	[1.78]	
state unemployment rate	-0.050	***	-0.077	***	-0.010		0.003		-0.012	*	0.003	
	[-5.53]		[-8.68]		[-1.03]		[0.31]		[-1.69]		[0.50]	
% population aged 65 or more	8.833	***	5.948	***	4.954	***	6.872	***	5.507	***	6.687	***
	[12.90]		[7.82]		[3.18]		[4.18]		[4.90]	!!!	[6.03]	!!!
state crime rate	3.1E-04		4.3E-04	***	3.6E-05	*	-2.1E-05		3.9E-05	***	-3.0E-05	**
	[26.60]		[34.60]		[1.88]		[-1.11]		[2.92]	!	[-2.35]	
<u>PER CAPITA EXPENDITURES</u>												
expenditures on health & hospitals	-0.938	***	-1.369	***	0.398	**	0.203		0.386	***	0.206	*
	[-7.80]		[-14.44]		[2.39]		[1.25]		[3.19]	!	[1.69]	
education expenditures	0.515	***	0.530	***	-0.021		0.059		-0.018		0.045	
	[6.57]		[6.85]		[-0.20]		[0.58]		[-0.25]		[0.60]	
welfare expenditures	-0.170	**	-0.392	***	0.046		0.053		0.042		0.035	
	[-2.34]		[-5.53]		[0.64]		[0.78]		[0.70]		[0.69]	
other expenditures	0.348	***	0.264	***	-0.024		-0.078		-0.023		-0.097	***
	[8.08]		[6.52]		[-0.47]		[-1.60]		[-0.65]		[-2.80]	
<u>GRAVITY MODEL VARIABLES</u>												
logged state population	0.815	***	0.672	***	1.349	***	0.937	***	1.308	***	0.902	***
	[49.26]		[41.28]		[12.70]		[8.64]		[18.08]	!!!	[12.68]	!!!
logged distance between states	-1.297	***			-1.517	***						
	[-83.75]				[-109.48]							
year fixed effects	YES				YES				YES			
origin and destination fixed effects	NO				YES				NO			
flow-specific fixed effects	NO				NO				YES			

NOTE: t-statistics from robust standard errors in brackets. *, **, *** denote statistical significance at 10, 5 and 1% levels.
!, !!, !!! denote statistical significance at 10, 5, and 1% levels when 3-way (year, origin, destination) clustering is employed.
Heating days included in first model but not reported.

Table 6
Key Regression Results using Different Income Tax Break Measures and 1970-2000 Census Flows

	dummies (table 5)		*max. value of components*		*total amount*		*total amt (1980-2000)*		*TAXSIM (1980-2000)*	
	origin	dest	origin	dest	origin	dest	origin	dest	origin	dest
Additional Credits/Deductions for Elderly										
are any offered?	-0.011	-0.020								
	[-0.52]	[-0.96]								
value of credit/deduction			-0.237**	0.113						
			[-2.09]	[0.99]						
Social Security Exemption	0.041*	-0.061***								
is it exempt? (1=YES)	[1.70]	[-2.66]								
value of exemption			0.024	-0.060***						
			[1.24]	[-3.21]						
Private Pension Exemption										
is it exempt? (1=YES)	0.079**	0.003								
	[3.45]	[0.14]								
value of exemption			0.004	0.002						
			[0.44]	[0.23]						
Total Value of Elderly Income Tax Breaks										
sum of deductions/credits, social					0.00005	-0.00087	-0.00248	-0.00096		
security and pension exemptions					[0.05]	[-1.05]	[-1.47]	[-0.49]		
Elderly Tax Savings										
high income elderly tax									0.061**	-0.047
									[2.00]	[-1.56]
EIG Taxation										
incremental EIG tax	-0.00004	0.0001								
	[0.00]	[0.00]								
Bakija and Slemrod (2004) tax rate			0.001	0.001	0.037	-0.001	-0.012	-0.001	-0.011	-0.002
			[0.14]	[0.21]	[0.54]	[-0.18]	[-1.47]	[-0.11]	[-1.39]	[-0.20]
Average Income Tax Rate	1.276	1.369	1.339	3.045	2.189	1.475	2.631	0.944		
taxes/income	[0.60]	[0.63]	[0.65]	[1.43]	[1.09]	[0.72]	[0.98]	[0.35]		
non-elderly TAXSIM									-2.380	1.947
									[-1.46]	[1.18]

NOTES: t-statistics from robust standard errors in brackets. *, **, *** denote statistical significance at 10, 5 and 1% levels.
Flow-specific fixed effects, year fixed effects and all other variables reported in the last two columns of Table 5 are included but not reported.
All dollar amounts in thousands.

Table 7
Key Regression Results Using Alternative Specifications and 1970-2000 Census Flows

DUMMY VARIABLE, COMPONENT MODEL

	MAIN SPECIFICATION (Table 5)		DIFFERENCE between OLD and YOUNG		NONMOVER MODEL		RATIO MODEL	NET FLOW MODEL (Douglas 1997)
	origin	dest	origin	dest	origin	dest	dest minus orig	dest minus orig
INCOME TAX BREAKS								
additional credits or deductions	-0.011	-0.020	-0.030	-0.003	-0.010	-0.019	-0.002	0.0001
for elderly (1 = YES)	[-0.52]	[-0.96]	[-1.25]	[-0.12]	[-0.50]	[-0.95]	[-0.11]	[0.46]
social security income exemption	0.041 *	-0.061 ***	0.108 ***	-0.054 **	0.041 *	-0.061 ***	-0.025	-0.0002
(1 = YES)	[1.70]	[-2.66]	[4.07]	[-2.12]	[-1.76]	[2.70]	[-1.44]	[-1.10]
private pension income exemption	0.079 ***	0.003	0.015	-0.014	0.077 ***	0.002	-0.032 *	0.0001
(1 = YES)	[3.45]	[0.14]	[0.59]	[-0.56]	[3.46]	[0.07]	[-1.92]	[1.05]
EIG TAXATION								
incremental EIG tax (1 = YES)	-0.00004	0.0001	-0.021	-0.071 **	0.000	0.000	-0.032 *	-0.0002 **
	[0.00]	[0.00]	[-0.76]	[-2.64]	[-0.02]	[-0.02]	[-1.76]	[-2.09]

TOTAL VALUE MODEL

	MAIN SPECIFICATION (Table 5)		DIFFERENCE between OLD and YOUNG		NONMOVER MODEL		RATIO MODEL	NET FLOW MODEL (Douglas 1997)
	origin	destination	origin	destination	origin	destination	dest minus orig	dest minus orig
INCOME TAX BREAKS								
total amount of elderly tax	0.00005	-0.00087	0.0002	-0.002 **	3.9E-06	-1.5E-08	-1.1E-06 *	-2.6E-07
preferences (credits, ss, and	[0.05]	[-1.05]	[0.20]	[-2.15]	[0.36]	[-0.00]	[-1.87]	[-0.08]
(in $1000)								
EIG TAXATION								
Bakija and Slemrod (2004) tax rate	0.037	-0.001	0.014 *	0.002	0.006	0.001	-0.006	-4.2E-06
	[0.54]	[-0.18]	[1.82]	[0.29]	[0.64]	[0.14]	[-1.22]	[-0.10]

NOTES: t-statistics from robust standard errors in brackets. *, **, *** denote statistical significance at 10, 5 and 1% levels.
Flow-specific fixed effects and year fixed effects are included.
Except as noted, all other variables listed in the last two columns of Table 5 are included but not reported.

Table 8

Key Regression Results Using Dummy Indicators of Income Tax Breaks for Alternative IPUMS Subgroups

		AGES 55 - 70				RICH (Top 25% Income)				POOR (Bottom 25% Income)			
		origin		destination		origin		destination		origin		destination	
INCOME TAX BREAKS													
additional credits or deductions		0.070	**	-0.057	*	-0.001		0.043		-0.028		0.001	
for elderly (1 = YES)		[2.33]		[-1.81]		[-0.03]		[0.92]		[-0.63]		[0.02]	
social security income exemption		0.047		0.002		0.210	***	0.018		0.170	***	0.117	**
(1 = YES)		[1.41]		[0.06]		[4.28]		[0.35]		[3.33]		[2.26]	
private pension income		0.063	*	0.046		0.026		-0.025		0.056		0.021	
(1 = YES)		[1.81]		[1.35]		[0.53]		[-0.50]		[1.09]		[0.40]	
EIG TAXATION													
incremental EIG tax (1 = YES)		-0.050		-0.007		-0.136	***	-0.065		-0.082		-0.035	
		[-1.49]		[-0.21]		[-2.78]		[-1.30]		[-1.59]		[-0.69]	
# of zero flows	1980			587				1223				1175	
# of zero flows	1990			288				803				834	
# of zero flows	2000			191				694				710	

		NON-RETURN				NOT REPORTING DISABILITY				REPORTING DISABILITY			
		origin		destination		origin		destination		origin		destination	
INCOME TAX BREAKS													
additional credits or deductions		-0.041		-0.020		-0.047		0.004		-0.059		-0.047	
for eldelry (1 = YES)		[-1.21]		[-0.59]		[-1.35]		[0.11]		[-1.48]		[-1.17]	
social security income exemption		0.108	***	-0.041		0.144	***	0.026		0.103		-0.036	
(1 = YES)		[2.83]		[-1.05]		[3.60]		[0.63]		[2.35]		[-0.83]	
private pension income		0.069	*	-0.022		0.042		-0.016		0.097	**	0.008	
(1 = YES)		[1.87]		[-0.56]		[1.09]		[-0.38]		[2.12]		[0.16]	
EIG TAXATION													
incremental EIG tax (1 = YES)		-0.087	**	-0.019		-0.073	*	-0.029		-0.028		-0.077	*
		[-2.19]		[-0.48]		[-1.74]		[-0.69]		[-0.61]		[-1.75]	
# of zero flows	1980			751				902				970	
# of zero flows	1990			443				520				645	
# of zero flows	2000			338				372				677	

NOTES: t-statistics from robust standard errrors in brackets. *, **, *** denote statistical significance at 10, 5 and 1% levels.
Flow-Specific fixed effects and year fixed effects are included.
All other variables listed in the last two columns of Table 5 are included but not reported.
1980-2000 flows are utilized, with zero flows dropped.

Table 9

Summary of t-Statistics From Full Set of Analyses

t-STATISTICS FOR ALL SPECIFICATIONS AND SAMPLES

	Origin (theory: negative)	Destination (theory: positive)
% of results with t-stat < -1.65	12.5	9.38
% of results with t-stat > 1.65	26.7	9.7
median t-stat	0.43	0.01

t-STATISTICS FOR ALL SPECIFICATIONS AND SAMPLES, BY INCOME TAX BREAK

Origin (theory: negative)	Credit Exemption	Social Security Exemption	Pension Exemption	Total Value of all Exemptions	TAXSIM Value
% of results with t-stat < -1.65	32.81	0	0	6.25	0
% of results with t-stat > 1.65	3.12	48.20	29.69	3.13	72.80
median t-stat	-1.19	1.61	1.08	-0.09	1.85

Destination (theory: positive)	Credit Exemption	Social Security Exemption	Pension Exemption	Total Value of all Exemptions	TAXSIM Value
% of results with t-stat < -1.65	4.69	28.13	3.13	6.25	6.25
% of results with t-stat > 1.65	14.06	9.39	10.94	12.5	0
median t-stat	0.38	-0.80	0.33	-0.09	-0.10

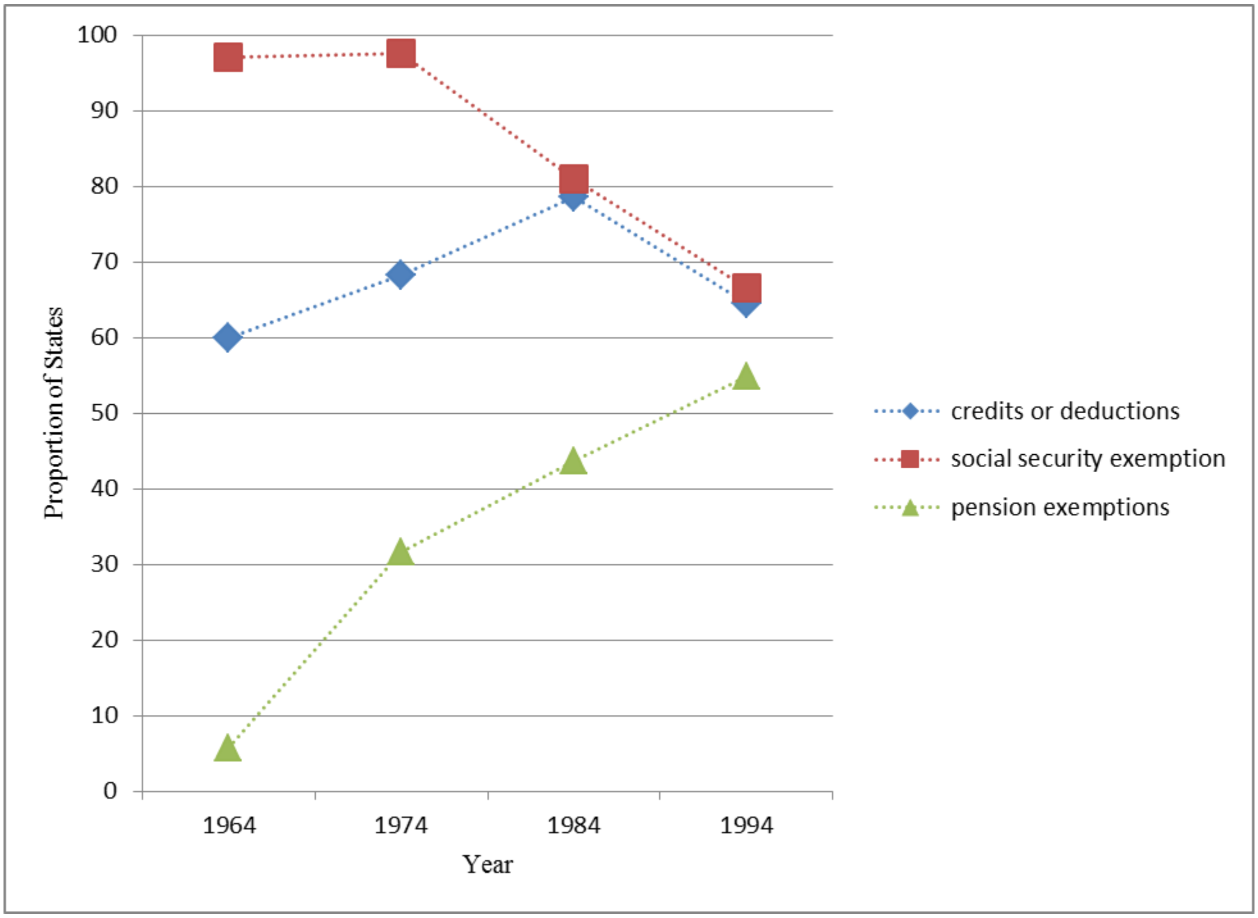
t-STATISTICS for 'AMENITY' IPUMS SUBSAMPLES

(aged 55-70, top 25% income, non-disabled, or non-return)

	Origin (theory: negative)	Destination (theory: positive)
% of results with t-stat < -1.65	10.19	11.11
% of results with t-stat > 1.65	18.52	13.89
median t-stat	0.11	0.00

Figure 1

Proportion of State with Income Taxes Offering a Particular Break



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Appendix 1

Description and Sources of Individual Variables Used In the Panel Regression Analyses (1970-2000)

VARIABLE NAME	EXPANDED DEFINITION WHEN NECESSARY
1. Income Tax Break Measures	
1.1 Dummy Indicator for each Component	
existence of income tax deductions/credits based on age [a]	does state offer any deductions/credits/exemptions based on age? YES = 1
exemption of social security from taxation (YES=1) [a]	does state exempt all social security income from state taxation? YES = 1
exemption of private pension income from taxation [a]	does state exempt any private pension income? YES = 1
1.2 Maximum Values of Income Tax Breaks	
value of income tax deductions or credits for elderly [a,c]	amount of income tax deductions/exemptions for being age 65+ multiplied by top state marginal tax rate and/or dollar amount of tax credit
value of social security exemption [a,c, i]	amount of social security income exempted from taxation multiplied by state top marginal tax rate
value of pension income exempted from taxation [a,c]	maximum amount of private pension income exempted from taxation multiplied by state top marginal rate
1.3 Total Maximum Values of Income Tax Breaks	
total value of elderly tax breaks [a]	sum of all categories in section 1.2 of this table
1.4 Value of Income Tax Breaks as Calculated by TAXSIM	
high income elderly tax bonus [b] [also referred in text as non-elderly TAXSIM burden]	dollar difference in tax bill between highest quartile of a married elderly couple and a non-elderly married couple with same income
2. EIG Tax Measures	
incremental EIG tax [f]	does state tax estates/inheritances beyond pick-up amount? YES = 1, used with 1.1
Bakija & Slemrod tax rate [g]	effective average tax rate on $1 million estate, calculated by Bakija and Slemrod (2004), used with 1.2-1.4
3. Other Tax Variables	
average income tax rate [d,e]	total state personal income tax revenues/state personal income, used with 1.1 thru 1.3
non-elderly TAXSIM burden [b]	average income tax rate calculated for non-elderly household in TAXSIM, used with 1.4
sales tax rate [c]	general sales only; specific excise taxes not included; local sales tax options not included
property tax share [d]	total state & local property tax revenues/total state & local tax revenues
other per capita tax share [d]	total state & local tax revenues excluding personal income, property and general sales/total state tax revenues

Appendix 1 (continued)

Description and Sources of Individual Variables Used In the Panel Regression Analyses (1970-2000)

VARIABLE NAME	EXPANDED DEFINITION WHEN NECESSARY
4. Amenities and Cost of Living	
heating degree days [e]	this is a measure of cold temperatures/climates
median house values [h]	median of individual's reported home value in IPUMS, by state
average manufacturing wage [e]	
state unemployment rate [e]	
% population age 65 and over [e]	
crime rate [e]	calculated as total crimes per 10,000 people
per capita income [e]	
5. Per Capita Government Expenditures (State & Local Combined)	
health and hospitals [d]	
education expenditures [d]	this includes higher education
welfare expenditures [d]	
all other expenditures [d]	any expenditure not contained in the 3 categories above
6. Gravity Model Variables	
state population [e]	aged 5 and over
distance between states [f]	distance between geographic centers of both states (in miles)

SOURCES:

a: Calculated by authors from Bakija (2009)
b: TAXSIM
c: World Tax Data Base, University of Michigan
d: State Government Finances
e: Statistical Abstract of the United States
f: Calculated by authors
g: From Bakija and Slemrod (2004), Table 2
h: Calculated from IPUMS
i: Table 2.A28 from the Social Security Administration's Annual Statistical Supplement, 2006