Landscape and Urban Planning 148 (2016) 68–79

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

The influence of age-specific migration on housing growth in the rural Midwest (USA)

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HIGHLIGHTS

- We model age-specific population changes that characterize rural housing development.
- Age-structure plays a critical role in housing location decisions.
- The influence of rural amenities on housing density changes varies by age group.

ARTICLE INFO

Article history:
Received 29 August 2014
Received in revised form
30 September 2015
Accepted 10 December 2015
Available online 6 January 2016

Keywords:
Age-specific migration
Housing density change
Natural amenities
Projection

ABSTRACT

Natural resource policymakers and planners increasingly rely on regional and national-level spatial data describing projections of future housing growth, to anticipate development impacts on natural resources and identify policy and planning needs. Such projections have not always been well-grounded in demographic and other factors that influence population and thus housing growth. We develop an empirical model describing population change and housing growth in the rural Midwestern U.S., as a function of demographic transition, socioeconomic factors, and natural amenities. The empirical model is estimated as a set of three equations characterizing: (1) population growth within three age groups, (2) the influence of farmland cover and other county level variables, and (3) household size, housing services, and second home ownership. The estimated population and housing growth models provide a consistent estimate of past change and can be used to project future change. We found age-structure to be an important factor in housing location decisions. Specifically, the influence of natural amenities on both population growth within counties and subsequent housing density changes varies by age group.

1. Introduction

Natural resource policymakers and planners increasingly rely on regional and national-level spatial data describing projections of future housing growth to anticipate development impacts on natural resources and identify policy and planning needs. Two examples include wildland–urban interface mapping applications (e.g. Radeloff et al., 2005, 2010) and the "Forests on the Edge" assessments (e.g., Stein et al., 2005, 2013). Housing growth is of interest to natural resource managers and land use planners, because residential development can have a variety of ecological and environmental effects (e.g. Radomski & Goeman, 2001; Schindler, Geib, & Williams, 2000), and can influence subsequent land use decisions involving how remaining resource lands are managed (e.g. Kline, Azuma, & Alig, 2004; Munn, Barlow, Evans, & Cleaves, 2002; Wear, Lui, Foreman, & Sheffield, 1999). Moreover, housing growth both influences and is influenced by natural resource protection policies. For example, natural area protection can increase housing values (e.g. Geoghegan, 2002; Irwin, 2002) which in turn can stimulate additional development. Alternatively, higher housing values and rapid development can encourage residents to support greater protection of remaining natural areas (e.g. Kline, 2006; Kotchen & Powers, 2006). Better understanding of the factors that influence development can help resource managers and land use planners to anticipate new development and develop ways to protect desired ecosystem characteristics.

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http://dx.doi.org/10.1016/j.landurbplan.2015.12.005
0169-2046/

Ideally, projections of future housing growth would be based on demographic, socioeconomic, topographic, and amenity factors shown to influence housing development. A variety of studies have suggested ways to econometrically model population growth and migration based on demographic and socioeconomic factors (e.g., Graves, 1979; Mulligan & Vias, 2006; Shumway & Davis, 1996), as well as climate and other natural amenities (Carruthers & Vias, 2005; Deller, Tsai, Marcouiller, & English, 2001; Mueser & Graves, 1995; McGranahan, 2008; McGranahan, Timothy, & Lambert, 2010; Rappaport, 2007). Many of these efforts have demonstrated the influence of age structure on population growth and migration patterns, finding that individuals tend to seek out different socio-economic and amenity characteristics depending on their stage in life (e.g., Clark & Hunter, 1992; Chen & Rosenthal, 2008; Graves & Linneman, 1979; Winter, 2011). However, to our knowledge, methods to account for age structure have not been extended to the analysis and prediction of housing growth except at the national scale (Montgomery, 1996, 2001). Rather, existing housing density prediction and mapping methods mostly have relied on the use of population forecasts published by the U.S. Census to predict future housing growth (e.g., Theobald, 2005). Although population forecasts can provide a reasonable approximation of future housing growth, this approach does not permit examining the role of age structure and other factors that conceivably might influence regional patterns of housing growth.

In this paper, we build on the housing forecast work of Theobald (2005) by drawing on methods used in regional population growth and migration models. These methods enabled us to take advantage of the additional information contained in demographic data pertaining to age structure, along with other socioeconomic and natural amenity information, to empirically model and project housing densities at the county-level. We focused our analysis on the seven Midwestern states of the United States, including Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, and Wisconsin. We developed an empirical model describing the location and magnitude of population density change since 1950 using a panel model (i.e., cross-section/time series model). We used the model to describe population density change as a function of economic and demographic factors within three age groups: young mobile age (18–25), middle working age (25–65), and retirement (over 65). The three equations identify factors that are correlated with migration by age group. We also examined the impact of natural amenity variables on differences in population growth rates among counties. Because some natural amenity variables, such as average seasonal temperatures, humidity, and proximity, are time-invariant, we used the Hausman–Taylor estimator to examine the impact of both time-varying variables and time-invariant variables. Lastly, we estimated a panel model describing housing density change as a function of population change, including factors that might influence how the two to differ.

1.1. Conceptual model

Housing densities largely depend on populations (e.g. Blanco, 1963; Lowry, 1966; Muth, 1971) which themselves are determined by in-migration, out-migration, and birth and death rates. Population growth differs from net migration by net mortality (i.e., deaths less births). However, because birth and death rates are strongly influenced by age structures (Bennett & Olshansky, 1996), in-migration and out-migration often exist as more apparent determinants of population change. Blanco (1963) and Lowry (1966) also both suggest that changes in the employment opportunities of a region can have a significant impact on population changes taking place. For these reasons, a local labor market can be specified as two simultaneous equations: (1) a population growth equation to represent labor supply; and (2) an employment growth equation to represent labor demand.

An example of this structural form is the pair of equations specified by Lewis, Hunt, and Plantinga (2002) as,

$$PG_{it} = f_1(EG_{it}, P_{it}, X_{it}, Y_{it})$$

$$EG_{it} = f_2(PG_{it}, E_{it}, X_{it}, Z_{it}) \tag{1}$$

where the endogenous variables, PG_{it} and EG_{it}, are net population growth rate and employment growth rate in county i over time period t. The terms P_{it} and E_{it} are population and employment at the beginning of period t, respectively, X_{it} is the set of exogenous variables that affect both migration and employment, and Y_{it} and Z_{it} are the sets of exogenous variables specific to each of the dependent variables. The structural model permits empirical testing of the relative effect of migration on employment and vice versa. Further, it is possible to investigate key drivers of population change by combining the equations (1) into the reduced form:

$$PG_{it} = f(P_{it}, E_{it}, X_{it}, Y_{it}, Z_{it}) \tag{2}$$

which provides an equation to be estimated.

In this study, we are primarily interested in accounting for the age-structure effects on population change as manifested by housing development. We assume that individuals hold housing stock primarily as an input into the production of housing services and as an investment (Montgomery, 2001). Individual demand for housing stock depends on the attributes of houses, including those related to location, such as proximity to services (e.g. medical facilities) and recreational opportunities. Housing demand will also depend on household wealth and on variables affecting the value of housing as an asset, such as interest rates and expected price appreciation. These factors, combined with variables that influence preferences for housing services, such as age, income, and technology, contribute to the degree to which the housing stock aligns with the preferences of would-be occupants. Among these, we suspect that age is particularly important because it can conceivably influence demands for the location attributes of housing. Depending on the age group—young mobile age (18–25), working age (25–65), or retirement age (65 and older)—residential places must satisfy different needs in terms of employment, education, public and health facilities, and natural amenities (Clark & Hunter, 1992; Rappaport, 2007). Past studies have shown, for example, that counties characterized by abundant environmental services experience greater in-migration of the retirement age group (65 and older), because retirees tend to be attracted to amenity-rich areas and may not be concerned with employment opportunities (Blomquist, Berger, & Hoehn, 1988).

Changing preferences for household size, housing location, and second home ownership may also cause divergence between population change and housing density change. Shifts in income or demographic factors, such as the age structure of the population, can influence preferences and demand for housing. If we denote the total housing stock, H_{it}, at time t in county i as the product of population, P_{it}, and per capita housing stock, h_{it}:

$$H_{it} = P_{it} * h_{it} \tag{3}$$

the rate of change in housing stock, HG_{it}, has two components:

$$HG_{it} = \frac{\partial H_{it}/\partial t}{H_{it}} = \frac{\partial P_{it}/\partial t \quad h_{it}}{P_{it} h_{it}} + \frac{P_{it}\,\partial h_{it}/\partial t}{P_{it} h_{it}} = PG_{it} + hG_{it} \tag{4}$$

$$= PG_{it}\left(1 + \frac{P_{it}\,\partial h_{it}/\partial t}{\partial P_{it}/\partial t\, h_{it}}\right) = PG_{it}(1 + els_{it}) \tag{4-1}$$

On the right hand side of Eq. (4), PG_{it} is the rate of population change; hG_{it} is the rate of change in per capita holdings of

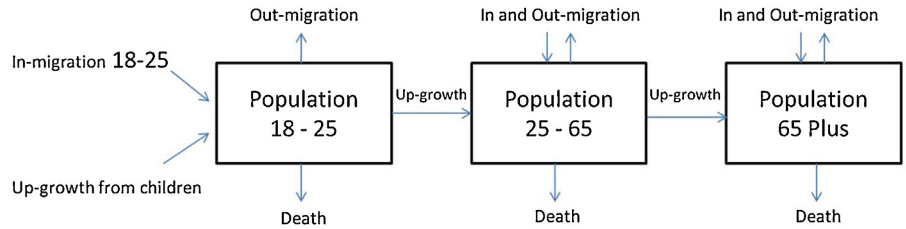

Fig. 1. Sources of county-level population change for three age groups.

housing. Assuming that H_{it} is measured as the number of housing units, we can define per capita housing stock, h_{it}, as the average number of housing units per person. If housing preferences are static and the economy is in equilibrium, the change in housing stock would equal the change in population. That is, $hG_{it} = 0$ and Eq. (2) would be sufficient to predict changes in housing density on the landscape. Divergence between population growth and change in housing stock will result when $hG_{it} \neq 0$ and will be a function of those variables affecting individual housing demand.

The second Eq. (4-1) represents the relationship between housing stock growth and population growth expressed as an elasticity, els_{it}, that shows the percent change in *per capita* housing stock given a one percent change in population. If per capita housing stock is constant in a county while the population changes over time, the rate of change in housing stock is equivalent to the rate of population change (i.e., $els_{it} = 0$). This would be the case if each household occupies exactly one housing unit and average household size remains constant. With population growth, however, per capita housing stock can change for several reasons. In the long run, the elasticity of per capita housing stock has a positive sign if average household size (i.e., number of people per household) declines. This could happen if people are wealthier, such that fewer people share each housing unit, or if age class structure changes (Montgomery, 1996). Increases in the number of people who own second or vacation homes could also lead to the same result (i.e., $els_{it} > 0$). In the short run, deviation may occur as a disequilibrium phenomenon. Migration may respond relatively quickly to changing economic conditions, while the housing stock adjusts relatively slowly so that $els_{it} < 0$. In periods of local economic contraction, people migrate out and leave housing units empty (i.e., $h_{it2} > h_{it1}$ and $P_{it2} < P_{it1}$) and in periods of economic expansion, new housing construction lags behind in-migration and fewer housing units are empty (i.e., $h_{it2} < h_{it1}$ and $P_{it2} > P_{it1}$).

1.2. Specification of empirical model

Preferences and income evolve and change over individual life cycles, giving rise to differences among age cohorts between population change and housing density change. Moreover, because of the role that age plays in influencing preferences for both housing and natural amenities, as well as for the divergence of population from housing stock, it is possible for differences between population change and housing density change to vary by age class. To account for these possibilities, we use a three-age-class specification for modeling population change and an aggregate model for comparison as follows:

$$PG_{it}^{age} = f^{age}(X_{it}, W_i) + \varepsilon_{it}^{age} \quad (5)$$

where PG_{it}^{age} denotes net population growth rate by age group in county i over time period t; X_{it} is the set of time-varying variables that affect both migration and employment; W_i is the set of time-invariant variables. We assume that all regressors are uncorrelated with the error term, ε_{it}.

We chose three age groups for analysis to account for differences among people in their young mobile years (18-to-25 years old), people in their working and family years (25-to-65 years old), and people in their retirement years (over 65 years old). Age-specific population growth includes in-growth from the next younger age group, children for the youngest age group, and out-growth into the next older age group, or mortality in the oldest age group (Fig. 1). Equation (5) includes a set of exogenous variables hypothesized to influence migration for which time series data are available (all variables are described in Table 1). Each equation by age group includes average population growth rate for each age group for the 7-state study area, so that the coefficients for the other exogenous variables reflect how county-level population growth rate deviates from the regional population growth rate.

The remaining variables in the model are values at the beginning of the population change period (i.e., values at 1980 are used to explain population change from 1980 to 1990). They include attributes of the place that influence people's decisions to migrate into, stay at, or migrate out from it (e.g. unemployment, presence of amenities, and distance from urban centers). They also include attributes of the people that reside at the place at the beginning of the population change period (e.g. household income, population density, age class distribution, and education). These demographic variables affect migration in two ways. First, people outside the location may be more or less likely to migrate to a place with a highly educated population, for example. Second, people who currently reside at the place may be more or less likely to migrate away from the place if they are highly educated.

Economic explanatory variables include the unemployment rate and median family income in 1989 dollars. The unemployment rate represents economic opportunity within counties. The median family income can be a proxy for a number of economic factors, including the range of consumer and cultural amenities offered by counties, as well as the prevalence of social problems stemming from poverty (Lewis et al., 2002). Demographic variables include the age-class structure of the population (the proportion of the population in the county that are young adults and that are elderly), population density, and the proportion of the population over 25 years of age that has completed high school. The age-class distribution of the current population matters because it contributes to the attractiveness of a place as a destination (e.g. if there is a large elderly population, young people may not be attracted to migrate to the place or vice versa). It also reflects the availability of people to move into the next age group or upgrowth (e.g. if there is a large young population at the beginning of the population change period, one may expect a large increase in the middle age group as a result of the aging of the existing population). The level of education reflects the quality of educational services for children in a county.

Unlike socioeconomic and demographic variables, natural amenity variables such as landscape and climate attributes contain both time-varying and time-invariant variables. Landscape attributes include water area, topography, farmland, distance from a big city, and urban influence codes. Water area and topography are time-invariant variables that reflect the availability of recreational facilities that may provide job opportunities, whereas the proportion of farmland by county is a time-varying variable in our

Table 1
Variables, description, and source.

Variables		Description	Data source
ΔHousing		Annual housing stock change rate, by county	Census 1950–2010
Δ Adult pop in county		Annual population growth rate for total adult population, by county and decade	Census 1950–2010
Δ Adult pop in region		Annual population growth rate for total adult population in the study area, by decade	Census 1950–2010
Δ 18 to 25 pop in county		Annual population growth rate in age group 18–25, by county and decade	Census 1950–2010
Δ 18 to 25 pop in region		Annual population growth rate in age group 18–25 in the study area, by decade	Census 1950–2010
Δ 25 to 65 pop in county		Annual population growth rate in age group 25–65, by county and decade	Census 1950–2010
Δ 25 to 65 pop in region		Annual population growth rate in age group 25–65 in the study area, by decade	Census 1950–2010
Δ Over 65 pop in county		Annual population growth rate in age group over 65, by county and decade	Census 1950–2010
Δ Over 65 pop in region		Annual population growth rate in age group over 65 in the study area, by decade	Census 1950–2010
Population density		Population density (per acre) for total adult population, by county and decade	Census 1950–2000
% Pop under 18		Percent of population that is in the under 18 category, by county and decade	Census 1950–2000
% Pop over 65		Percent of population that is in the over 65 category, by county and decade	Census 1950–2000
Income		Median family income in 1989 dollars, by county and decade	Census 1950–2000
Unemployment		Unemployment rate by county and decade	Census 1950–2000
Education		Percent of population over 25 that has completed high school, by county and decade	Census 1950–2000
Occupancy rate		Occupancy rate of housing stock, by county	Census 1950–2000
Farmland		Percent of farmland area, by county from 1950 to 2000	County and City Data Books
Water area		Percent of water areas, by county (=log(100 × percent of water area))	USDA
Climate (standardized)	Winter temp.	Mean Temperature for January by county	Economic Research Service http://www.ers.usda.gov/Data/NaturalAmenities/
	Sunlight	Mean hours of Sunlight by county	
	Summer temp.	Mean temperature for July by county	
	Humidity	Mean relative humidity by county	
Topography	Flat	If categories belongs to 1 = flat plains and 2 = smooth plains, 1; else 0	http://www.ers.usda.gov/Data/NaturalAmenities/
	Mild relief	If categories 4 = irregular plains, 5-8 = tablelands, or 9&10 = plains with hills, 1; else 0	
	Open hills	If categories 13 = open low hills, 14 = open low hills, and 15 and 16 open high hills or low mountains, 1; else 0	
	High hills	If category high hills = category 19, 1; else 0	
Urban influence	Metro	If metro counties (urban influence codes 1 and 2), 1; else 0	http://www.ers.usda.gov/Data/NaturalAmenities/
	Micropolitan	If micropolitan counties (urban influence codes 3, 5, 8), 1; else 0	
	Non-metro	If noncore counties (urban influence 4, 6, 7, 9–12), 1; else 0	
Distance		Distance between the county center and the nearest big city (population > 500,000)	USDA Forest Service

model that represents decreasing jobs in agriculture from technological advance and farm consolidation (McGranahan, 2008). In addition, climate attributes include four time-invariant measures: mean temperature in January, mean hours of sunlight, mean temperature in July, and mean relative humidity by county. Although these climate variables can also change over a very long time period, we use them to represent general climate conditions and assumed them to be time-invariant in this study.

The relationship between the rates of population change and housing density change (Eq. (4)) provides a theoretical foundation for our empirical analysis. The empirical model of housing density change is specified as:

$$HG_{it} = f^h(PG^{18}, PG^{25}, PG^{65}, X^h, W^h) + \varepsilon_{it} \quad (6)$$

where PG^{18}, PG^{25}, and PG^{65} are net population growth rate by age group; and X^h and W^h represent vectors of time-varying and time-invariant variables, respectively, affecting the difference between the rates of population change and housing change. As noted above, if the elasticity of per capita housing stock with respect to population is zero (i.e., $els_{it} = 0$), the coefficients on the age-specific population growth rates will sum to one and the coefficients on the X^h and W^h variables will be zero.

We expect the rates of population change and housing change to diverge in the short run as a disequilibrium phenomenon due to fluctuation in the local economy because there is generally a lag in the housing stock response to a population-change driven fluctuation in housing demand. We represent short run disequilibrium in our model with the occupancy rate of the housing stock, which serves as a proxy for housing price. Specifically, when occupancy rate is high, housing prices rise, thereby stimulating new construction. Conversely, when occupancy rate is low, housing prices fall, and housing stock declines or is converted to other uses.

We also expect the rates of population change and housing change to diverge in the long run for a variety of reasons. Per capita housing demand varies with age. For example, young people may be more willing to share housing with roommates and elders may opt to live alone as spouses pass on so that, as the age class distribution of the population changes, per capita housing stock changes. Per capita housing stock is strongly linked to household income (Montgomery, 1996, 2001). Construction of vacation or

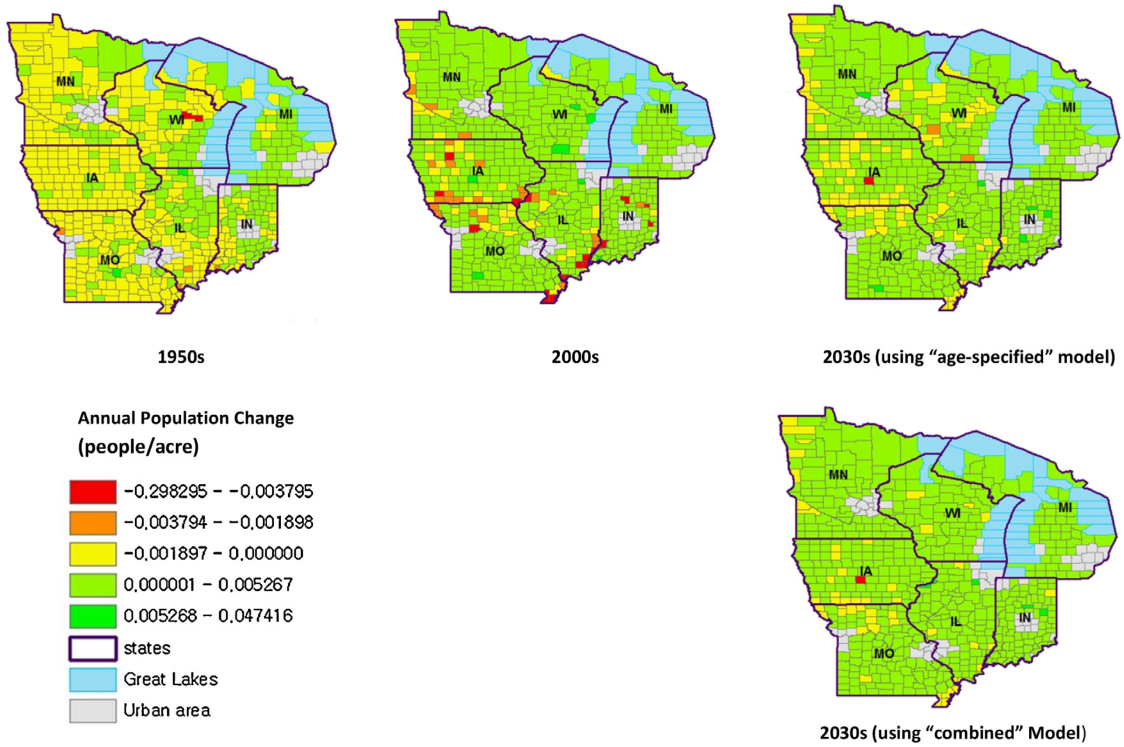

Fig. 2. Annual population density change (sum of age groups) by county in 1950s, 2000s, and 2030s (projection) from "age-specified" population growth model and projections from "combined" population growth model in the study area.

second homes can also cause the rates of change in population and housing stock to diverge. We use the distance from a big city to represent proximity to populations likely to own second homes in this county and amenity variables, including topography, the proportion of farmland area, and climatic characteristics, to represent recreational opportunities and other natural services. To test the interaction between rural and urban areas, we use urban-influence codes that reflect the effect of increasing urban influence.

1.3. Data and estimation methods

We tested our theoretical model of population and housing growth in the northern Midwest of the United States, including the states of Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, and Wisconsin (Fig. 2). Population growth from 1950 to 2010 in these seven states combined was 58%, compared to 101% for the US, with Indiana leading at 114% and Iowa trailing at 16% (US Department of Commerce, Census Bureau, 2015). More recently, population growth for the region has averaged 4% from 2000 to 2010, compared to 10% for the US. This coincides with a 10% increase in housing units for the region, compared to 14% for the US, with Minnesota leading at 14% and Michigan trailing at 7%. Significantly for this study, the region currently has a significant population of older residents, with the percent of population over age 65 in each state at or above the 13% average for the US (US Department of Commerce, Census Bureau, 2015).

Our theoretical model assumes that economic opportunity and location-specific natural amenities influence migration, and thus to a large degree, population change. Our independent variables consist of proxy variables intended to represent these factors (Table 1). Our model assumes that individual housing demand also depends on the age-class structure of the population. This means that the growth rate of the housing stock may diverge from the growth rate of the population. To account for these issues, we used a two-step model estimation approach that first estimated county-level models of population change (Equation 5) and then estimated county-level models of housing density change (Eq. (6)), using panel data with observations both across counties and over time: six decadal observations (1960–2010) for each of 591 non-urban counties in our rural Midwest study area. Counties identified as part of a major city based on US Census Bureau designation as a primary metropolitan statistical area were dropped from the sample to focus our analysis on rural land development. We eliminated only those counties that were highly urbanized, as many counties with some urbanization also face significant changes in land use.

In our approach, we specify the population growth-housing density change model as a recursive system. That is, population growth is an important driver of housing density change but not vice versa. Hence, in our model, the housing stock adjusts relatively slowly to shifts in housing demand that are induced by population change and other economic factors. It is conceivable that some endogeneity exists between population growth and housing; housing density change may influence population growth by virtue of its influence on the local economy. This phenomenon, however, can be more consistent with a recursive modeling approach than a simultaneous modeling approach. Population growth within counties stimulates local housing markets by increasing demand for residential housing. The housing market, in turn, influences core economic factors, such as income and employment rate, which attract in-migration into the county.

1.4. Population change

Our theoretical model specifies population change rate in each age group as a function of regional demographic characteristics, including lagged population density, economic opportunity, and location-specific natural amenities. We estimated four versions of the population change model as follows:

- Model 1—Demographic and economic variables only—one equation to represent all age groups combined.
- Model 2—Demographic and economic variables only—three equations to represent each age group separately.
- Model 3—Demographic, economic, natural amenity, and climatic variables—one equation to represent all age groups combined.
- Model 4—Demographic, economic, natural amenity, and climatic variables—three equations to represent each age group separately.

Panel data models require a fully populated data set such that every variable has an observation for each cross-sectional unit and in every time period. County-level data are available in time series for key demographic and socioeconomic variables. However, data limitations preclude including explanatory variables representing all potential influencing factors. As a result, there likely are relevant, unobserved factors specific to counties that are not included explicitly in our model. We expect that these unobserved factors are correlated with our observed independent variables and, hence, lead to endogeneity.

$$y_{it}^{\text{age}} = x_{it}{}'\beta + z_i{}'\alpha + u_i + \varepsilon_{it} \quad (7)$$

where ε_{it} is the error term and u_i denotes the county-specific random term. x_{it} are time-varying variables, some of which may be correlated with u_i, and z_{it} are time-invariant variables, some of which may also be correlated with u_i. To account for the possible endogeneity, we estimated the population change models 1 and 2 with fixed-effects, intercept coefficients for each county, that remove unobserved endogeneity, thereby producing a consistent estimator for coefficients of time-varying variables. One drawback of the fixed-effects model is that time-invariant variables that are observed must be eliminated from the model so their effects so that their effects are absorbed into the fixed-effects coefficients and cannot be individually identified.

In order to include natural amenity and climatic variables, many of which are effectively time-invariant, we used the Hausman–Taylor estimator. The Hausman–Taylor estimator is an instrumental variable estimator that allows the coefficients of time-invariant variables. It recognizes that some of the independent variables may be correlated with u_i and some may not:

$$y_{it}^{\text{age}} = x_{1it}{}'\beta_1 + x_{2it}{}'\beta_2 + z_{1i}{}'\alpha_1 + z_{2i}{}'\alpha_2 + \varepsilon_{it} + \mu_i \quad (8)$$

where again ε_{it} is the error term and u_i denotes the individual specific random term. x_{1it} are time-varying variables that are uncorrelated with u_i; z_{1i} are time-invariant variables that are uncorrelated with u_i; $x_{2\text{it}}$ are time-varying variables that are correlated with u_i; z_{2i} are time-invariant variables that are correlated with u_i. The exogenous variables, x_{1it} and z_{1i} serve as instruments (Baltagi, Bresson, & Pirotte, 2003).

Our data and sources are described in Table 1 and summary statistics are shown in Appendix A. They include county-level decadal observations of population change by age group ranging from 1960 to 2010. Our lagged exogenous variables require county-level decadal data from 1950 to 2000 for median family income, unemployment rate, occupancy rate of housing stock, education, percent of population in under 18 category, percent of population in the over 65 category, population density, and percent of farmland area. The exogenous variables also contain the regional level decadal rate of change in population in the 7-state study area. The county-specific variables that are treated as time-invariant include distance between the county seat and the nearest big city (population > 500,000) and natural amenity characteristics previously found to influence migration (e.g., McGranahan, 2008; McGranahan et al., 2010). Distance from a big city represents proximity to urban amenities. In 2000, only 7 cities were "big" by our measure. Natural amenity variables include mean hours of sunlight, mean relative humidity, mean temperature for January and July, representing winter and summer respectively. These variables were available from the last natural resource inventory administered by the USDA Natural Resources Conservation Service (Nusser & Goebel, 1997). To represent urban influence, we used dummy variables for metropolitan and micropolitan counties based on urban influence codes developed by USDA Economic Research Service; the reference type includes noncore counties. Topography variables consist of dummy variables for mild relief (irregular plains, tablelands, and plains with hills), open hills, and high hills based on categories of land-surface forms mapped in the National Atlas of the United States of America. The reference topography is flat and smooth plains. We recognize that, strictly speaking, some of these variables are not time-invariant. For example, winter and summer temperatures may follow long-term cycles. Again, because we used them to represent general climatic conditions, we assumed them to be functionally time-invariant. Urban influence and distance from county center to the nearest big city, as defined by population, are also likely to have shifted over the time. Nonetheless, we use them as rough proxies for relative proximity to urban amenities and coefficient estimates should be interpreted accordingly.

For the Hausman–Taylor estimator to be consistent, all variables in the model must be uncorrelated with the idiosyncratic errors, e_{it}, and also a specified subset of the variables must be uncorrelated with the individual specific random term, u_i. We used the Sargan–Hansen test of over-identifying restriction to test these conditions. The test statistic is not significantly different from zero, indicating that the conditions are met.

1.5. Housing density change

We estimated three versions of the housing density change model (Eq. (6)) as follows:

- Model 1—Demographic and economic variables only—one variable to represent total population rate of change.
- Model 2—Demographic and economic variables only—three variables to represent population rate of change for each age group separately.
- Model 3—Demographic, economic, natural amenity, and climatic variables—three variables to represent population rate of change for each age group separately.

We estimated Models 1 and 2 using fixed effects and Model 3 using the Hausman–Taylor estimator. Demographic and economic variables include population growth rate by age group and occupancy rate of housing stock as a proxy for housing price.

2. Results

2.1. Population change

Estimation results for the population change models are shown in Tables 2 and 3. We estimated the combined age group equation in order to construct population growth rate projections to compare to the age-specific model (described below). The results suggest that the age class structure of the population has a significant influence on migration and housing growth. Coefficient estimates for the age-specific population growth rate equations differ across ages in magnitude, significance, and, in some cases, sign. Results also suggest that people are influenced by economic conditions, as well as attributes of current residents when choosing whether to move into or remain in a county. This is confirmed by the statistical significance (at the 5% level or higher) of the coefficient estimates for almost all of the economic and demographic variables

Table 2
Estimation results for the population growth rate for all ages (Model 1) and by age group (Model 2) using fixed effect estimator with panel data, including demographic and economic variables.

Variables	Model 1				Model 2			
	All ages[a]		18–25[a]		25–65[a]		Over 65[a]	
Δ Adult pop-region	0.5712	(7.04)						
Δ 18–25 Pop–region			1.0204	(46.2)				
Δ 25-65 Pop-region					1.1820	(18.6)		
Δ Over 65 Pop-region							0.3984	(9.6)
Unemployment	−1.64e−04	(−1.5)	−4.09e−04	(−2.2)	−1.99e−04	(−2.6)	−2.22e−04	(−2.5)
Occupancy rate	−0.0670	(−9.2)	−0.0355	(−2.8)	−0.0530	(−10.8)	−0.0446	(−7.3)
% Pop under 18	0.0338	(5.6)	0.1242	(12.4)	0.1211	(30.5)	0.0023	(0.5)
% Pop over 65	0.0626	(5.2)	0.3185	(15.3)	0.1059	(12.7)	−0.2134	(−19.3)
Population density	−0.0839	(−9.0)	−0.1328	(−8.3)	−0.0754	(−11.9)	−0.0020	(−0.2)
Income	4.14e−07	(5.6)	8.82e−07	(8.8)	7.77e−07	(18.9)	4.22e−07	(9.1)
Education	−1.05e−05	(−1.1)	−3.4e−05	(−2.2)	1.73e−05	(2.7)	−1.89e−06	(−0.2)
Constant	0.0363	(4.5)	−.0640	(−4.8)	−.0235	(−4.4)	0.0639	(9.8)
Within R^2	0.10		0.60		0.53		0.29	
F test (*p*-value)	41.14	(0.0)	554.51	(0.0)	416.43	(0.0)	151.91	(0.0)
Housman test	503.94	(0.0)	643.61	(0.0)	597.76	(0.0)	56.41	(0.0)
# of obs./groups	3545/591							

[a]The *t*-statistics for each estimated coefficient are in parentheses.

included in the models. We also note that the coefficient estimates for the demographic and economic variables are remarkably stable between the two sets of models; the changes are negligible when natural amenity and climatic variables are added and the Hausman–Taylor estimator is used.

Variation in economic conditions across counties appears to influence migration decisions in a manner consistent with economic theory. Relatively high median family income appears to attract in-migration and discourage out-migration; the coefficient estimates are all positive and significant. Relatively high unemployment rates appear to discourage in-migration and encourage out-migration; coefficient estimates are significant and negative. For the retirement age group, this may be a reflection of amenities associated with stable communities. High occupancy rates should lead to high housing prices and thus discourage in-migration and encourage out-migration. The negative and significant coefficient estimates in all of the models indicate that affordability matters and people are attracted to communities with low housing prices.

Table 3
Estimation results for the population growth rate for all ages (Model 3) and by age group (Model 4) using Hausman–Taylor estimator with panel data, including demographic, economic, and natural amenity variables.

Variables[b]	Model 3				Model 4			
	All ages[a]		18–25[a]		25–65[a]		Over 65[a]	
TV endogenous								
Δ Adult pop-region	0.5674	(6.9)						
Δ 18–25 pop–region			1.0185	(45.4)				
Δ 25–65 pop–region					1.1889	(18.6)		
Δ Over 65 pop-region							0.3995	(9.6)
Unemployment	−1.73e−04	(−1.6)	−4.3e−04	(−2.3)	−2.07e−04	(−2.7)	−2.22e−04	(−2.5)
Occupancy rate	−0.0665	(−9.0)	−0.0352	(−2.8)	−0.0525	(−10.7)	−0.0446	(−7.3)
% Pop under 18	0.0340	(5.6)	0.1246	(12.3)	0.1213	(30.3)	0.0024	(0.5)
% Pop over 65	0.0621	(5.1)	0.3179	(15.2)	0.1055	(12.6)	−0.2132	(−19.2)
Population density	−0.0836	(−8.9)	−0.1300	(−8.1)	−0.0759	(−11.9)	−0.0027	(−0.4)
Farmland	−0.0017	(−1.1)	−0.0014	(−0.5)	−0.0019	(−1.8)	−6.2e−04	(−0.5)
TV exogenous								
Income	3.98e−07	(5.4)	8.59e−07	(8.45)	7.63e−07	(18.3)	4.21e−07	(9.1)
Education	−8.73e−06	(−1.0)	−2.94e−05	(−1.9)	1.8e−05	(2.9)	−2.58e−06	(−0.4)
TI endogenous								
Distance	−0.1363	(−8.1)	−0.1643	(−6.7)	−0.1040	(−7.9)	0.0115	(1.5)
TI exogenous								
Water area	0.0022	(2.0)	0.0047	(2.9)	0.00249	(2.7)	8.12e−05	(0.2)
Winter temp.	−2.34e−03	(−5.8)	−0.0023	(−3.8)	−0.0015	(−4.7)	0.0003	(1.5)
Sunlight	2.37e−04	(2.6)	2.37e−04	(1.9)	1.8e−04	(2.4)	2.48e−06	(0.1)
Summer temp.	0.0023	(3.2)	0.0015	(1.4)	0.0014	(2.4)	−2.4e−04	(−0.8)
Humidity	−0.0028	(−5.6)	−0.0035	(−5.1)	−0.0022	(−5.6)	−1.27e−04	(−0.8)
Mild relief	0.0029	(1.2)	0.0036	(1.1)	0.0029	(1.44)	0.0010	(1.7)
Open hills	0.0033	(1.1)	0.0037	(0.9)	0.0041	(1.6)	0.0014	(1.8)
High hills	0.0300	(4.8)	0.0382	(4.4)	0.0268	(5.3)	0.0073	(4.1)
Metropolitan	0.0130	(5.5)	0.0212	(6.4)	0.0127	(6.6)	3.69e−05	(1.0)
Micropolitan	0.0057	(2.8)	0.0117	(4.1)	0.006	(3.6)	−0.0007	(−1.3)
Constant	0.0893	(1.7)	0.1019	(1.42)	0.0435	(1.0)	0.0774	(5.2)
Wald chi^2 (*p*-value)	367.71	(0.0)	4398.07	(0.0)	3369.53	(0.0)	1905.19	(0.0)
Sargan–Hansen (*p*-value)	2.78	(0.096)	4.112	(0.04)	1.938	(0.16)	0.040	(0.84)
# of obs.	3545							

[a]The *t*-statistics for each estimated coefficient are in parentheses.
[b]TV refers to time varying; TI refers to time invariant.

The estimated coefficients for the demographic variables are more difficult to interpret because, conceivably, these variables can have a positive or negative influence on population change. For example, education appears to influence different age groups differently. The coefficient estimate for the young age group is negative and significant at the 5% level. One explanation might be that young people from highly educated nonmetropolitan counties tend to have more career opportunities elsewhere and therefore tend to leave those counties. The coefficient estimate for the middle age group is positive and statistically significant, perhaps suggesting that families are attracted to communities in which education is valued.

The age class distribution of the population, as reflected in the percentage of the population under 18 and percentage of the population over 65 (Table 2), appears to affect age-specific population growth as well. The coefficient estimates for the proportion of the population that is in the child age group (under 18) are positive and statistically significant for total population growth and for the young and middle age groups, but not significantly different from zero for the retirement age group. For the young age group, it may simply reflect the presence of a child group (under 18) that “ages” into the young age group (18–24) over the subsequent decade (upgrowth). For the middle age group, which is more likely to have children, this result may reflect the presence of child-based amenities like good school districts that tend to attract in-migration. The coefficient estimates for the proportion of the population that is in the retirement age group are positive and significant for total population growth and for the young and middle age groups, but are negative and significant for the retirement age group. This may simply reflect a natural progression of aging in communities. Where a high proportion of the population is in the retirement age group at the beginning of the decade, homes vacated by elderly who have passed on or moved to care facilities during the decade may be re-occupied by young people purchasing first homes. Results concerning population density are as expected—coefficient estimates are negative and statistically significant for all but the retirement age group, suggesting that congestion is a dis-amenity that discourages in-migration.

As noted above, adding natural amenity and climatic variables to the models had almost no effect on economic and demographic variable coefficient estimates (Table 3), even as many of these variables do appear to influence migration. Coefficient estimates are similar for the young and the middle age groups. Only the coefficient for high hills is statistically significant for the over 65 age group. In the discussion that follows, we focus on the coefficient estimates that are significantly (5% level) different from zero for the two younger age groups.

Farmland—cropland and pasture—is a typical land use type in rural counties and was included to represent different visual and recreational characteristics on the landscape. Its influence on migration does not appear to be strong in this model. The coefficient estimate is marginally significant (10% level) only for the middle age group for which it is negative. Whether farmland can be considered as a positive or negative amenity can be ambiguous. Previous studies have suggested that farmland sometimes is considered a dis-amenity if intensification of agricultural production leads to a decline in desired landscapes associated with more traditional or extensive farming activities (e.g., Kline & Wichelns, 1996a:421–422). Similarly, technological advances in agriculture coupled with farm consolidation sometimes can be associated with decreasing employment opportunities in agriculture (e.g., McGranahan, 2008). However, other studies have shown that people often value farmland because they associate it with pastoral scenic views, wildlife habitat, and other amenities (Irwin, Isserman, Kilkenny, & Partridge, 2010; Kline & Wichelns, 1996b; Rosenberger, 1998). Our results concerning the potential influence of farmland on migration is consistent with this ambiguity.

The coefficient estimate for water area is positive and statistically significant (at the 5% level), possibly because it has scenic value and may support recreational facilities that provide employment. The climate coefficients are positive for summer temperature and days of sunlight and negative for winter temperature and humidity. One possible interpretation of these results is that people are drawn to places with strong seasons as long as they are not too humid. The topography results are consistent with results found by McGranahan (2008) that indicated that varied topography favors migration. Here, the positive estimated coefficients suggest a preference for hills over plains.

The coefficient estimates for the urban influence dummy variables and the distance to the nearest big city indicate that population growth is greater in counties with access to urban areas that might provide economic benefits (e.g. shopping and employment opportunities), cultural amenities (e.g. museums, etc.), and health care (e.g. major research hospitals). While not statistically significant, the signs are opposite for the same coefficients in the over-65 age group which would be expected if, upon retirement, people prefer to migrate from congested cities to rural counties that provide inexpensive residential living and medical care specifically for the retirement age group.

2.2. Housing stock growth rate

In the population growth rate equations, we attempted to identify factors that lead people to want (or not want) to live in a particular place. With the housing stock growth rate equation, we attempted to identify factors that would influence the amount of housing stock held by individuals in each place. As noted earlier, this equation reflects variation in the number of houses per person across counties, variation that could arise from second-homeownership or propensity to share housing units with others. Estimation results are presented in Table 4.

Adding age-specific population growth rate improved the fit of the fixed effects model substantially—within-R^2 increased from 30% to 59%. Within-R^2 indicates how much of the deviation from the county mean housing stock growth rate is explained by the regression. Variation across counties is captured in the fixed effects coefficients. We hypothesized that the housing stock growth rate is also influenced by environmental factors that are relatively time-invariant. In the fixed effects model, those effects cannot be estimated because they are collinear with the fixed effects. When we estimated the full model using the Hausman–Taylor estimator, the change in the coefficient estimates for the time-varying variables was negligible. Many of the coefficient estimates for the time-invariant variables are statistically significant. In what follows, we describe the Hausman–Taylor results.

Demographic variables—The coefficients for the population growth rate variables are all highly statistically significant, indicating that the primary driver for housing stock growth is population growth. The coefficient estimates are 0.14, 0.44, and 0.14 for the young, middle, and retirement age groups respectively. The magnitude of these coefficients reflects the relative population size in each age group; over the 6-decade time horizon, the proportion of the adult population in each age group averaged 15%, 69%, and 16% for the young, middle, and retirement age groups respectively. The coefficients for the size (proportion) of the population in the county that is below 18 years of age and that is above 65 years of age are both negative and highly significant.

Economic variables—The effect of housing price, for which occupancy rate serves as a proxy, is positive, as predicted, and is statistically significant. Home builders respond to high prices by building more housing. The estimated coefficient for the farmland

Table 4
Estimation results for housing stock change rate in the six decades (1950–2010) using fixed-effect estimator and Hausman–Taylor estimator with panel data.

Variables[b]	Model 1		Model 2		Model 3	
	Total population[a]		Age-specific[a]		Age-specific	
TV exogenous						
% Pop under 18	0.0383	(11.9)	−0.0317	(−11.1)	−0.0337	(−11.7)
% Pop over 65	0.0225	(3.2)	−0.0829	(−12.1)	−0.0828	(−12.1)
TV endogenous						
Δ Adult pop-county	0.3530	(30.7)				
Δ 18–25 Pop-county			0.1371	(35.1)	0.1375	(35.4)
Δ 25–65 Pop-county			0.4351	(39.1)	0.4391	(39.5)
Δ over 65 pop-county			0.1447	(13.5)	0.1444	(13.5)
Occupancy rate	0.0518	(11.4)	0.0800	(22.7)	0.0799	(22.8)
Farmland					0.0028	(3.8)
TI exogenous						
Water area					2.96e−04	(0.2)
Winter temp.					0.0041	(3.9)
Sunlight					−0.0003	(−2.1)
Summer temp.					−0.0055	(−3.8)
Humidity					0.0029	(2.2)
Mild relief					−0.0040	(−1.1)
Open hills					−0.0054	(−1.1)
High hills					−0.0305	(−2.2)
Metro					0.0068	(1.4)
Micropolitan					0.0022	(0.7)
TI endogenous						
Distance					0.1793	(3.3)
Constant	−0.0513	(−10.5)	−0.0420	(−11.1)	.0797	(0.7)
Wald chi^2					4308.34	
Within R^2	0.30					
Hausman (*p*-value)	629.68	(0.0)	760.13	(0.0)		
Sargan–Hansen (*p*-value)[c]					0.004	(0.95)
# obs./# groups	3541/591		3541/591		3541	

[a] *t*-statistics parentheses.
[b] TV refers to time-varying; TI refers to time-invariant.
[c] Test of over-identifying restriction for cross-section time-series model: Sargan–Hansen statistic. For the Hausman–Taylor estimator to be consistent, it is necessary to argue that all regressors are uncorrelated with the idiosyncratic errors, and also that a specified subset of the regressors is uncorrelated with the fixed effect term. Rejection implies that some variables of the subset are not exogenous or correlated with the fixed effect term.

variable is positive and statistically significant in the full model. We speculate two reasons for that result. First, agricultural land is a likely location for new residential development; it is relatively flat and accessible. Second, it may have amenity appeal for second-home owners (Stedman, 2006).

The coefficient estimate for distance to a big city is positive and significant. This is the expected result if the proportion of the housing stock that is occupied seasonally (second homes) increases with distance from major population centers.

Natural amenity variables—The estimated coefficients for climatic variables are varied and somewhat puzzling. While the coefficient for winter temperature is positive and statistically significant (at the 5% level), the coefficient of summer temperature is negative and statistically significant (at the 5% level). This could indicate an attraction for second-home owners to locations that have moderate climates compared to their primary home location. The positive coefficient for humidity and the negative coefficient for sunlight are not what we expected. The coefficient of high hills is negative and statistically significant, which may reflect that the availability of space for constructing new houses has been decreased. Other time-invariant natural amenity variables do not have a statistical significance in estimates.

2.3. Projecting housing density change

In order to illustrate the prediction for the future population and housing density in the study area, we used the equations to project county-level population growth and housing density changes based on state-level population projections for the years 2000–2030 available for the US Bureau of Census. We constructed the projections using the age-specific population growth rate equations and compared them to projections constructed using the combined-age population growth rate equations. Projections are shown in Figs. 2 and 3.

State-level Census population projections are produced using the components of population change such as births, deaths, and net migration (domestic and international) (US Department of Commerce, Census Bureau, 2013). We assumed that real income growth was consistent with a real annual growth rate of 2% (real annual per capita GNP growth has been a little over 2% since the 1950s USDC 2012 Statistical Abstract). Demographic variables, including the proportion of the child age group (under 18) and the retirement age group (over 65) and population density by county, were modified with new projections of the county population 2010–2030. Other economic variables such as unemployment rate, occupancy rate, and the proportion of educated people were assumed to be constant across the years 2010–2030. The area of farmland was assumed to change at an average annual growth rate of the previous decade (1990–2000).

The population in the study area is projected to grow older over the next two decades (Vincent & Velkoff, 2010). The aging baby boomers and trends in in-migration drive much of this population change. In 2030, the number of population aged 65 and older is projected to be about 10 million, which is an approximately 55% increase compared to about 6.5 million in 2010. At the same time, the population in young age groups is projected to decrease in many counties in our study area. Compared to the national growth rate, the regional population growth rate for young age groups in our study area is even lower, especially in Illinois, Indiana, and Iowa, which contain a large area of rural land. In-migration is also expected to play a substantial role in population growth by age group over the next two decades because in-migration into the

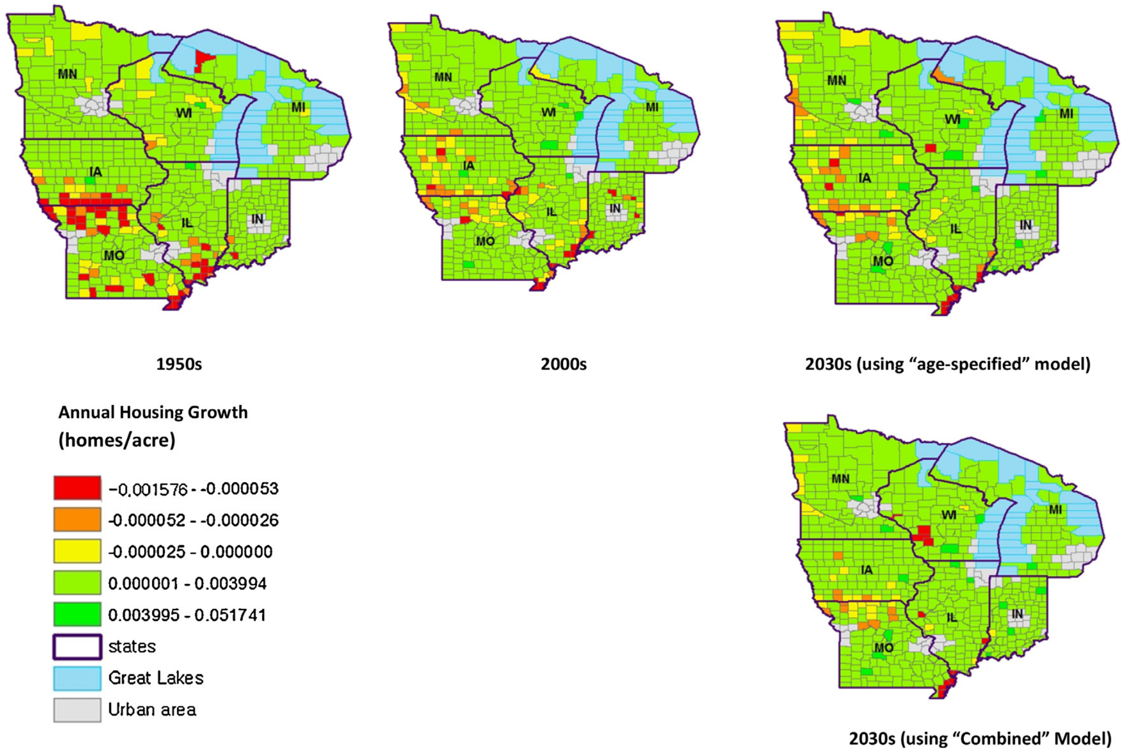

Fig. 3. Annual housing density change rate by county in 1950s, 2000s, and 2030s from the housing stock change model in the study area (projection data source: U.S. Census Bureau, Population Division, Interim State Population Projections, 2005).

Table 5
Results from tests for measuring the forecast accuracy.

	All ages	Young	Middle	Retirement	Housing (age-specific)
RMSE[a]	5093.40	787.59	2656.67	353.22	1344.18
MAE[b]	1915.05	323.08	1036.92	225.89	591.91
MAPE[c]	0.04	0.09	0.04	0.04	0.03

[a]RMSE: root mean square error.
[b]MAE: mean absolute error.
[c]MAPE: mean absolute percentage error.

studying and working age groups (18–65) mitigates the impact while the aging of the baby boom enlarge the proportion in the retirement age group (65+) (Vincent & Velkoff, 2010). As the population in our study area grows older, the preference for housing, in terms of location, size, and second home, is expected to change. This changing age structure of the population may have an impact on the housing development in our study area. The forecast accuracy of our model is estimated in Table 5. We used the 2010 data of population by age and housing number in the study area for validation, and measured the prediction accuracy of forecasting models by calculating RMSE, MAE, and MAPE to estimate the difference between actual values and forecast values. Values for MAPE indicate less than 5% except that of young age group.

The historical maps in Fig. 2 illustrate the depopulation of rural America in the 1950s. Looking into the future, our projections show lower growth in the north-western and southern counties than in other sections of the Midwest. Compared to growth rates in the 2000s, projected population growth rates in the Midwest are more stable with a moderate increase in most rural counties in 2030s. This trend is more pronounced in the age-specific model projections than in the combined age model projections, indicating that the changing age class structure of the population is a factor. The trend shown in Fig. 3 is for housing development to become more diverse across counties over time. The age-specific projections show housing growth rates that are relatively high in the middle counties in Wisconsin and Illinois and relatively low in the counties near the urban areas of Chicago. This may be due to second home ownership. In the combined age projections, that tendency is moderate. This outcome highlights the importance of the age class structure of the population in predicting housing development because the preference of housing changes over life stages.

3. Discussion and conclusion

We have developed a modeling framework and methods for examining and projecting population growth and housing density change as they are influenced by the location decisions of individuals within three age groups. The modeling framework and methods potentially provide an improved way to forecast future housing density growth based on population forecasts provided by the US Census, by incorporating the additional information contained in age structure and other demographic, socioeconomic, and natural amenity data. We found that the age cohort of in-migrants is an important factor in residential location choices and that, in particular, the effect of natural amenity factors on population and housing growth varies by age. Although economic factors, such as income and unemployment, have important influences on net population growth rate for all age groups, natural amenity factors also appear to play a role. Proximity to big cities also seems to positively influence location choices of young and middle age groups but has little effect on location choices in the retirement age group. Because age plays a role in influencing individuals' interests and preferences, population growth by age group seemingly can have a significant influence on both population and housing growth within regions.

Previous studies have demonstrated that the selection of a particular retirement destination is most often influenced by factors such as scenic terrain, warm climate, recreational opportunities, local economy, lower cost of living, and other community characteristics (Bennett, 1996; Fournier, Rasmussen, & Serow, 1988). Our analysis verifies that retirement age people seemingly prefer certain amenity types near their residential locations. In addition, while proximity to big cities tends to be a positive and significant factor among people in the young and middle age group, it may be a negative factor for the retirement age group. Second home ownership or smaller households (hence more housing per capita) appears to be higher at greater distances from cities. Since communication and transportation technologies can facilitate the maintenance of family ties at considerable geographic distances, retirees may avoid counties that are congested, overpriced, and vulnerable to crime. As baby boomers began retiring, the trend of amenity-seeking migration among retirees may have increased and may have an important impact on housing density change in rural counties with scenic natural resources.

Our study results indicate that the Hausman–Taylor model can be a consistent estimator that can be used to approximate the parameters of the key variables that affect housing density change, including population change, occupancy rate, and natural amenity variables. In this study, we focused on developing an empirical model that explains the location and magnitude of county-level housing density change since 1950 in the north-central US. The strength of estimated population and housing growth models is that they provide a consistent summary of past behavior. However, these models do not describe the future. The projection of the future trends depends on the implicit assumption that people will behave in the future as they have in the past.

Simulating future trends in housing development under a range of possible assumptions regarding future population growth presents many challenges. In particular, as the number of retired baby boomers increases, the regional age structure in the U.S. will dramatically change in the next two decades (Vincent & Velkoff, 2010), with associated changes in housing density growth faced by land use planners. Because model prediction depends on uncertain parameter estimates and uncertain predictions of exogenous variables, it is difficult to produce precise projections. In this study, we used simplified assumptions about exogenous variables to illustrate methods for predicting future housing density in the study area. Methods for examining the influence of uncertainty and evaluating robustness of the model predictions include bootstrapping and building response surfaces for the exogenous variables. Such additional analysis could enable planners and policymakers to evaluate the nature and magnitude of the uncertainty in model predictions.

Acknowledgments

This research was supported by the USDA Forest Service North Central Research Station (joint venture agreement 03-JV-11231300-065). This work does not necessarily reflect the views of the funding agency and no official endorsement should be inferred. We are grateful to Edward A. Stone for contributions to an early version of this manuscript and construction of data sets and preliminary models. We are grateful to Robert Haight for advice.

Appendix A.

Table A1
Variables, mean, standard error, and median for measures.

Variables		Mean	Standard error	Median
ΔHousing		0.00875	0.000198	0.007197
Δ Adult pop in county		0.00256	0.000209	0.00144
Δ Adult pop in region		0.007169	0.00007937	0.0084
Δ 18 to 25 pop in county		0.000913	0.000543	0.0015
Δ 18 to 25 pop in region		0.0067289	0.00036071	0.0047
Δ 25 to 65 pop in county		0.004081	0.00022	0.003108
Δ 25 to 65 pop in region		0.007882	0.00005148	0.006
Δ Over 65 pop in county		0.01000476	0.0002103	0.0094
Δ Over 65 pop in region		0.0139872	0.0001113	0.0138
Population density		0.0908	0.0020	0.0548
% Pop under 18		0.305120	0.0009093	0.3
% Pop over 65		0.1420	0.000678	0.138
Income		25142.1533	131.85839	25384
Unemploment		5.3086	0.055358	4.6
Education		56.3948	0.58619	56.7
Occupancy rate		0.8702	0.0020879	0.9115
Farmland		0.7391	0.0052	0.83565
Water area		0.037265	0.015902	0.06535
Climate	Winter temp.	22.91421	0.14278	23.6
	Sunlight	139.0720	0.3502249	141
	Summer temp.	73.85468	0.06348	74.3
	Humidity	58.0365	0.054870	58
Topography	Flat	0.18163	0.00699	0
(Dummy)	Mild relief	0.5508	0.009024	1
	Open hills	0.2369	0.00771	0
	High hills	0.0306	0.003124	0
Urban influence	Metro	0.252714	0.00788	0
(Dummy)	Micropolitan	0.26061	0.007964	0
	Noncore	0.48667	0.0090	0
Distance	0.392	0.00355	0.363	

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.landurbplan.2015.12.005.

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