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Rural Bound: Determinants of Metro to Non-Metro Migration in the U.S

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Abstract: A general global precept is that agglomeration forces lead to migration from rural to urban areas. Yet, for much of the period since the early 1970s, more people moved from metro to nonmetro U.S. counties. The underlying causes of this pattern have changed over time with economic shocks and changing household preferences. For instance, the post 2000 period has seen a significant decline in domestic migration rates, significant increase in commodity prices that favor rural areas, and potential changes in the valuation of natural amenities that would affect migration. This study investigates the determinants of U.S. gross migration from metro to nonmetro counties and nonmetro to metro counties for the 1995-2000 and 2005-2009 periods in order to compare the differences in rural to urban and urban to rural migration as well as compare the 1990s to the 2005 to 2009 periods. The paper uses (1) extensive county-to-county migration flows and (2) uses the utility maximization theory that extends the framework of discrete choice model. The results show that population density, distance to urban areas, industry mix employment growth, natural amenities, and percent of older people are key factors underlying these migration patterns. We also find a slight fading of effects of natural amenities and population density and slight increase in the effects of wage and employment growth during 2005 to 2009 period.

JEL Classification: J11, J61, R11

Keywords: *metro to nonmetro migration, urban to rural migration, county-to-county migration, natural amenities*

Introduction

Agglomeration economies are attracting people from rural to urban settings with now more than 50% of the world's population residing in urban areas and expectations that the urban share will rise to 70% by 2050 (China Development Research Foundation, 2010). The historic direction of internal U.S. migration was also rural-to-urban or nonmetro-to-metro. However, the prevailing nonmetro-to-metro trend reversed during the 1970s, with this pattern mostly holding thereafter. Based on the USDA metropolitan classification, the 2000 Census data show that between 1995 and 2000, about 220,000 more people moved to nonmetropolitan areas from metropolitan areas than the reverse. Recently released American Community Survey (ACS) data show that between 2005 and 2009, net domestic migration to nonmetropolitan areas in relation to metropolitan areas totaled about 100,000 annually.[1] Yet, these patterns are unevenly distributed. About one-half of nonmetro counties lost population between 2005-2009 and 57% lost population over the 1995-2000 period.

Understanding the causes of relatively favorable U.S. nonmetropolitan net-migration patterns and their changes over time is important for assessing whether the general urbanization trend will slow as incomes increase and for crafting better regional development policies aimed at reducing regional inequities. Namely, if for example, U.S. rural areas have primarily benefited from commodity booms or its mainly high-natural amenity areas that are gaining population, it will be harder to develop effective policies aimed at improving rural economic prospects. Yet, supporting the possibility that U.S. rural areas can remain competitive in terms of migration, Partridge et al. (2010) find that while firms increasingly prefer to locate nearer to agglomeration economies, households prefer to be more distant from urban areas.

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[1] A word of caution when comparing the data for the two time periods: While 1995-1999 Census data are 5 year aggregates, the ACS 5-year estimates are not five years of aggregated data. They are a 5-year period estimate from 2005-2009 using annual data (see Benetsky and Koerber, 2012, for details). The general pattern of recent positive net-migration to nonmetropolitan areas did reverse itself in 2011 and 2012 (Cromartie, 2013).

Several conceptual frameworks have been advanced to explain the reversal that took place in 1970s and 1990s. Main explanations for the reversal in the 1970s were “period effects,” “regional restructuring perspective,” and “suburbanization.” The period-effects follow the unique circumstances during the 1970s such as the 1973-74 oil crisis and subsequent recession (Frey and Johnson, 1996). The regional restructuring perspective is based on the structural changes that led to the transformation of the urban economy from traditional heavy industries to the service economy (Frey and Johnson, 1996) and a boom in extractive and manufacturing activities in nonmetro areas (Fuguitt and Beale, 1996). Kim (1983) contends the 1970s reversal was due to expanding suburban development and increased retirement migration to rural areas.

A primary conceptual framework for the reversal in the 1990s is deconcentration perspective which is attributed mainly to movement of people and firms to low-density and high-amenity locations and regional restructuring perspective which refers to changes in economic opportunities (Frey and Johnson, 1996; Partridge et al., 2010b). Although traditionally agglomeration economies have been found to be positively associated with in-migration, the deconcentration hypothesis occurs in the form of retiree migration to nonmetro locations (Frey and Johnson, 1996; Nelson and Nelson, 2011); migration to metro adjacent and then out-commute to work (Cromartie, 1998; Partridge et al., 2010a); rural gentrification which is tied to economic restructuring due to advances in telecommunications (Nelson et al., 2010); and amenity-based migration (Rudzitis, 1999; Nelson and Nelson, 2011; Kahsai et al., 2011). Yet, other studies stress structural economic changes as partly responsible for the reversal (Frey and Johnson, 1996; Ghatak, et al., 1996).

An unexplored aspect of the reversal literature is the systematic integration and analysis of the deconcentration and regional restructuring perspectives. There is also a need to know how sensitive these key arguments to different time periods and how different are these forces in describing metro-to-nonmetro migration and nonmetro-to-metro migration. By comparing the set of determinants between metro to nonmetro and nonmetro to metro, one could answer the question whether metro-to-nonmetro migrants consider different factors than their nonmetro-to-metro counterparts? Therefore the present study extends the literature by more broadly examining the underlying factors associated with deconcentration and economic restructuring arguments of metro to nonmetro migration. Employing a more unified framework, this paper determines the extent of the effect of these arguments on metro to nonmetro migration. It tests whether the recent attraction of nonmetro counties is derived from more economic factors such as wages, industry mix, and proximity to urban areas, or other reasons such as natural amenities and retirees. Thus, in order to form better policy, this analysis enhances our understanding of metro-to-nonmetro migration, while addressing many lingering questions in the literature.

Moreover, we investigate whether the effects of these factors differ over time and whether these determinants vary between metro-to-nonmetro and nonmetro-to-metro flows. For example the 1990s was characterized by a strong national economy (with weak rural commodity markets) versus the sluggish national economic environment post-2000 (with strong rural commodity markets), in which gross migration flows greatly diminished (Partridge et al., 2012). Considering net migration, Partridge et al. (2012) found that economic migration in general greatly declined after 2000, but they did not consider urban-rural migration patterns. Likewise population growth and net migration studies find that the effect of natural amenities may be diminishing in recent time periods in nonmetropolitan counties (Rickman and Rickman, 2011; Partridge et al., 2012), but these studies do not specifically consider metro-to-nonmetro flows. Moreover, retiree migration may have strengthened in the second time period as more and more baby boomers are attaining retirement age.

Comparing both metro-to-nonmetro and nonmetro-to-metro migration flows using the same set of factors is vital from a policy perspective because such an analysis shed lights on factors associated with in- and out-migration in metro and nonmetro localities and whether these factors are important in light of recent migration patterns. It is also essential to know for policymaking whether the role of the determinants vary depending on whether the nonmetro counties are located near metropolitan areas or whether they are located remotely. For example, Partridge, et al. (2008b) and Wu and Gopinath (2008) study the effects of proximity to urban areas on population growth in rural U.S. counties and find that there are strong negative growth effects of distances to higher tiered urban areas. Yet, while the economic gains in nonmetro counties are visible near metro counties, many nonadjacent, rural counties have seen increases.

This study further strengthens the literature by utilizing econometric modeling that uses gross county-to-county migration flows to estimate a spatial interaction model (Greenwood, 1985; Cushing and Poot, 2004; Etzo, 2010). The current approach allows us to employ the utility maximization theory of migration using the discrete-choice framework based on the random utility maximization (Davies, 2001), while taking advantage of an equivalent relation between the conditional logit model (CLM) and Poisson regression (Cushing and Poot, 2004; Arzaghi and Rupasingha, 2013). We utilize aggregate county-to-county migration flows from the Census Bureau for 1995-2000 and 2005-2009 and consider a metro household's opportunity to move to all possible non-metro counties (and vice versa). This yields a very large number of observations for each time period (more than two million), allowing for high statistical power, while mitigating endogeneity problems. Likewise, the related literature reviews emphasize the importance of distance between origin and destination in migration decisions (Greenwood et al., 1991; Cushing and Poot, 2004). Yet, distance is typically *not* considered when using population growth or net migration. As a result of incorporating origin to destination choices, the present study will be able to assess the effect of distance. In addition, another advantage of our empirical approach is that we can directly consider whether distance effects are waning over time with newer information technologies and how distance interacts with job opportunities and amenities in shaping migration. Hence, our approach has both theoretical and methodological extensions.

Our findings show support for both the deconcentration and regional restructuring hypotheses, but the effects of some deconcentration measures may have diminished over time. While natural amenities are a very strong predictor in both metro-to-nonmetro and nonmetro-to-metro migration flows, the effect in nonmetro counties may have also diminished over time, compared to metro counties. Distance is a deterrent for both metro-to-nonmetro and nonmetro-to-metro flows, with little change over time. Amenities also become relatively more important for long distance moves. The results suggest that migrants moving from metro-to-nonmetro areas are more likely to settle in densely populated nonmetro counties than less dense nonmetro locations, suggesting some minimal threshold size effects for nonmetro areas. Yet, the effect is diminishing over time in nonmetro areas, implying that some agglomeration constraints may be overcome. Results also lend support for suburbanization hypothesis that more migrants are attracted to rural counties that are adjacent to metro areas.

We next present an overview of the conceptual model and econometric approach, followed by a description of the data, and estimation. The results are then presented followed by a conclusion and a discussion of the rural development implications.

The model and econometric approach

Our conceptual approaches follow (Goetz, 1999): individuals maximize utility (U_i) which is defined over characteristics of places, i = 0,1,2,...,p, in which utility can be affected by numerous factors such as real income (y) and amenities (a); prospective migrants evaluate the expected utility of residing in different places over a given planning horizon; more specifically, they compare the utility derived at their current location (U_0) with the utility that can be derived from other locations, net of costs of migrating (c_i), between *0* and *i*; and based on all the information available to migrants, they are able to rank any two locations, using the locations' attributes. This process can be depicted as:

(1) $\Delta_i = U(y_i - c_i, a_i) - U(y_0, a_0)$.

Utility-maximizing individuals will migrate whenever $\Delta_i > 0$. Otherwise they stay at the origin.

Based on location characteristics and costs allows us to utilize the random utility approach developed by McFadden (1974). This approach is widely used in the empirical industrial organization literature on firms location decisions (Guimarães, et al., 2003, Guimarães, et al., 2000, Arauzo-Carod et al., 2010) but it is relatively new to the migration literature (Davies, et al. 2001; O'Keefe 2004; Christiadi and Cushing 2008; Arzaghi and Rupasingha 2013). The random utility model leads to the application of the CLM for various destination choices. Based on equation (1), a potential migrant will choose a particular location if expected (net) utility in that location is greater than utility in the current and other potential locations. Formally, consider a resident at metro county i aiming to relocate to non-metro county j, where $i = 1, \ldots, 1090$ (total number of metro counties in 1995-2000 sample) and $j = 1, \ldots, 2052$(total number of non-metro counties in 1995-2000 sample). As usual, for any alternative county choice, the utility derived for this individual (U_{ij}) can be written as:

(2) $U_{ij} = \beta' X_{ij} + \varepsilon_{ij}$

where X_{ij} is a vector of the choice-specific attributes including those of the current location and migration related costs (Arzhagi and Rupasingha, 2013); ε_{ij} is a random error term. Thus the utility for an individual for locating at j is composed of a deterministic and a stochastic component. Following utility maximization, the individual will choose the location that yields the highest utility (i.e. $U_{ij} > U_{ik}$, for all $k \neq j$). So the probability that an individual in county i relocates to county j is,

(3) $P_{ij} = P\left(U_{ij} > U_{ik}\right)$ for all $k \neq j$

McFadden (1974) shows that if ε_{ij} are *i.i.d* and extreme value type-I distributed,[2] then the probability P_{ij} can be rewritten as,

$$(4) \quad P_{ij} = \frac{\exp(\beta' X_{ij})}{\sum_{j=1}^{2052} \exp(\beta' X_{ij})}$$

Equation (4) expresses the familiar CLM formulation. With independent observations, the corresponding log likelihood function for all the individuals moving from any metro county i to a specific non-metro county j is,

$$(5) \quad \log \mathrm{L} = \sum_i d_{ij} \log P_{ij} = n_{ij} \log P_{ij}$$

where d_{ij}=1 if a resident in metro county i chooses to reside in non-metro county j and zero otherwise; n_{ij} is the number of individuals moving from metro county i to non-metro county j.

Since residents in all 1090 metro counties can possibly migrate to any of the 2052 non-metro counties, the coefficients β' can be estimated by maximizing the following log-likelihood function,

$$(6) \quad \log L_{cl} = \sum_{i=1}^{1090} \sum_{j=1}^{2052} n_{ij} \log P_{ij}$$

It is well recognized in the CLM literature that estimating equation (6) is cumbersome and even infeasible for a large number of alternative choices.[3]

An alternative proposed by Guimarães, et al. (2003) is to estimate the CLM by an "equivalent" standard Poisson regression model (PRM). They prove that under certain conditions, the log-likelihood functions of the conditional logit and the Poisson regression are

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[2] This assumption implies the Independence of Irrelevant Alternatives (IIA) property that requires that for any household, the ratio of choice probabilities of any two alternatives is independent of the utility of any other alternative.

[3] However, the ability to include a large number of spatial alternatives is important because factors usually identified as most relevant for location decisions are at a small geographical level, which cannot be adequately captured by large areas in the spatial choice sets (Gabe and Bell. 2004; Guimarães et al., 2003). Following a suggestion by McFadden, D. (1978), one solution is to estimate the model using a randomly selected sub-sample (Friedman, et al., 1992, Guimarães, et al., 2000, Hansen, 1987, Woodward, 1992). Although the resulting estimators are consistent, the efficiency is reduced due to dropping of some information, and also the small sample properties are unknown (Guimarães, et al., 2003).

identical, which in practice implies that the coefficients of equation (6) can be equivalently estimated by estimating a standard PRM with taking n_{ij} as a dependent variable and X_{ij} as explanatory variables.[4] To see the equivalence more clearly, let n_{ij} be independently Poisson-distributed with conditional mean,

(7) $E(n_{ij}) = \mu_{ij} = \exp(\alpha + \beta' X_{ij})$

Then, the standard log-likelihood function of the PRM can be written as

(8) $\log L_p = \sum_{i=1}^{1090} \sum_{j=1}^{2052} (-\mu_{ij} + n_{ij} \log \mu_{ij} - \log n_{ij}!)$

As shown in Guimarães, et al. (2003), after taking the first order condition of equation (8) with respect to α and inserting back the derived expression of α to equation (8), the concentrated log likelihood function can be simplified to

(9) $\log L_p = \sum_{i=1}^{1090} \sum_{j=1}^{2052} n_{ij} \log P_{ij} - N + N \log N - \sum_{i=1}^{1090} \sum_{j=1}^{2052} \log n_{ij}\,!$

where the first term in (9) is the log likelihood of the CLM, and the other two terms are constants.

Clearly, the most important advantage of the PRM over the CLM is its superior computational ability in handling a large number of spatial alternatives that comprise an individual's choice. Beyond this, the PRM is also effective in controlling for the violation of the Independent of Irrelevant Alternatives assumption, which is especially problematic for the CLM when a large number of narrowly defined spatial alternatives are involved in the decision making (Guimarães, et al., 2004).

Variables, data, and estimation issues

We separately examine the 1995-2000 and 2005-2009 periods to assess how migration patterns changed over the two decades. The advantage of these two periods is that they are about

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[4] See, for example, Arauzo-Carod and Antolín (2004), Arauzo Carod (2005), and Gabe and Bell (2004) for applying the Poisson approach as a substitute to estimate the CLM.

10 years apart and both occur in a general positive net migration period for nonmetro areas and overall gross migration flows were relatively constant during each respective period.[5] One concern is that the latter period includes the housing crisis and subsequent Great Recession. However, as pointed out in footnote 6, the housing crisis and Great Recession had remarkably little effect on overall gross migration flows, which remain at historically low levels post 2000. Yet, as described below, we will take special care to avoid having the housing crisis (and Great Recession) confound our results by accounting for factors such as controlling for nonmetro counties adjacent to a metropolitan area to control for the pattern that the housing crisis was more severe in far-suburban and exurban locations and we also account for lagged median housing prices to control for places with greater than expected market prices.[6] Likewise, we account for underlying industrial demand shocks to address differential demand effects from the Great Recession and housing crisis.

We separately appraise nonmetro-to-metro migration and metro-to-nonmetro migration in order to assess differing causes for their respective patterns. Namely, heterogeneity implies that people who move one direction (say to an urban area from a rural area) would likely have very different preferences and abilities than those who migrate the other way. For one, there is some tendency for higher ability people to sort into metro areas, implying that returns to agglomeration differ across people (Duranton et al., 2008). Likewise we expect that nonmetro-to-metro migrants may relatively value urban amenities associated to population density whereas, metro-

[5] Cromartie (2013) shows net migration rates for nonmetropolitan areas was positive during both sample time periods, though nonmetropolitan net migration rates did turn negative in 2011 and 2012. U.S. Census Bureau (2014) reports that overall gross-migration rates across state and/or county borders respectively equaled 5.6% and 6.4% between 1995-96 and 1999-00. The corresponding figures for 2005-06 and 2008-09 were 4.7% and 3.7%. The Great Recession seemed to have relatively little influence on these gross migration flows, as gross migration flows across state/county borders respectively still only totaled 3.9% and 3.8% in 2011-12 and 2012-13, suggesting that in terms of overall migration patterns, using periods after the Great Recession may not yield very different patterns.

[6] We do not expect that the housing crisis to have tangibly affected aggregate migration flows of given metropolitan areas, which is what we are primarily interested in. Yet, we expect that *intra-metropolitan area* patterns were affected as farther out suburbs were particularly hard hit, but this was offset as central areas fared relatively better. For the metropolitan area as a whole, the net migration rates would not be measurably affected.

to-nonmetro migrants may place a higher weight on other rural features of quality of life. This sorting and preference heterogeneity implies that not only do metropolitan and nonmetropolitan characteristics (**X**) vary, but likely so do the underlying regression coefficients.

As discussed in the Introduction, the reversal in the 1990s is explained mainly in terms of the deconcentration and economic restructuring perspectives. Although not mutually exclusive, the deconcentration argument may be manifested in amenity-based or quality-of-life migration, retiree migration, moving to suburbs (largely commuters), and preference for lower density or low agglomeration locations, and the economic restructuring argument may be expressed in industry structure, jobs, and wage related migration. The studies discussed above strongly support the amenity-based or quality-of-life argument, in which some metro workers choose to forego higher metro earnings in exchange for the quality of life found in some nonmetro localities. This quality of life is mainly attributed to natural and man-made amenities (Knapp and Graves, 1989, Mueser and Graves, 1995). We use the natural amenity index developed by McGranahan (1999) and hypothesize it to be positively associated with in-migration.

Another argument is that metro areas have simply expanded or people just moved to metro-adjacent counties. Partridge et al. (2008b) find that the proximity to larger metropolitan areas has been an important driving force for rural population gains since at least 1950. Following Wu and Gopinath (2008), we include an indicator variable in our full-sample metro-to-nonmetro model for counties that are adjacent to metro areas and expect it to be positively associated with nonmetro in-migration. Likewise, if metropolitan migration to adjacent nonmetro counties is to a large part driven by commuting back to the metro area, we would expect local labor market conditions to matter less to possible migrants than local rural labor market conditions in remote nonmetro counties. Yet, this does not mean that adjacent county in-migrants do not care about local economic conditions, simply because not all of them are going to commute to the metro area. Moreover, even for commuters, their spouse may want to work locally or they may want the option value of being able to work locally in the future.

Gravity models of migration use population density and distance as standard pull factors. We use population density per square mile as both a measure of agglomeration and as an attraction force in gravity model formulations, which also directly relates to deconcentration perspective. Traditionally, population density is found to be positively associated with in-migration, but in case of metro to nonmetro migration, deconcentration hypothesis argues that migrants may prefer low density or low agglomeration locations.

Migration is costly for financial, information, and personal reasons. Migration costs rise with the moving distance. The deconcentration perspective suggests that one motive for metro residents to move suburbs is to live in more open landscape and then commute to work in metro locations. Distance plays a key role in this kind of movement as it becomes a primary deterrent (Wu and Gopinath, 2008; Partridge et al., 2010a). Our distance variable is calculated using the distance between each pair of county centroids via highway (divided by 100). Following Davies et al. (2001), we conjecture that the deterring effects of distance may decline as distance increases, and we include a distance-squared term to capture these nonlinearities, which is expected to have a positive coefficient.

As discussed above, retirement-based migration to nonmetro counties is said to be growing with increasing numbers of baby boomers reaching retirement age. While our migration data do not identify retiree migrants from other migrants, we test the general hypothesis from past studies that one reason that nonmetro counties gain migrants may be due to their retiree attraction. We include the percentage of the population that is 65 and over for each base year and expect a positive relationship (Jensen and Deller, 2007; Rayer and Brown, 2001), postulating that retiree migrants may be self-sorting to nonmetro counties that have a higher percent of their age group (perhaps reflecting better public and private services for retirees).

Though the economic factors are downplayed as a pull factor to rural areas (focusing more on rural quality of life), some studies stress structural economic changes as partly responsible for the reversal. Indeed, the commodity booms of the 1970s (Ghatak, et al., 1996) and post 2000 period have bolstered certain rural economies. To test the validity of these claims, we incorporate the average county wage and industry-mix employment growth rate. Empirical results on the relationship between per capita income or earnings and in-migration have been mixed. Some studies found a positive link (Davies, et al., 2001). Consistent with a spatial equilibrium view, Markusen and Schrock (2006) find that migrants will accept lower wages to live in locales with higher amenities—i.e., relative wage levels are a compensating differential.[7] Due to these offsetting effects, the expected effects of the wage variable is ambiguous.

As a sign of employment availability, we use industry-mix employment growth rate from shift-share analysis, which is routinely used as an exogenous instrument for job growth by previous studies (Bartik, 1991; Blanchard and Katz, 1992; Partridge et al., 2012) as an exogenous measure of local demand conditions.[8] The industry mix variable is the 'share' variable from shift-share analysis. It captures the fact that nationally some industries grow faster or slower than others and these structural differences affect local labor markets through their differential industry composition. This index is constructed by summing the products of the initial industry shares in the county at the beginning of each time period (1990 and 2000) at four-digit level and the corresponding national U.S. industry growth rates, producing an exogenous

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[7] Even though wages are lagged five years before the initial period of the dependent variable, there is a chance they had begun to adjust in anticipation of future migration behavior. However, as discussed below, it is unlikely that this would tangibly occur because the dependent variable is migration for county-to-county pairs and it is doubtful that wages tangibly adjust from one of the county-to-county pairs when each county is paired with over three thousand county pairs. In addition, our regression models include origin-county fixed effects, which removes any omitted bias due to time-invariant omitted variables in the origin county. Yet, we experimented with using a 15-year lag of wages to further mitigate any fear of endogeneity, but the results were essentially unaffected suggesting endogeneity is not a major concern. We also replaced the 15-year lag of wages with 15-year lagged per capita personal income because per capita personal income should be less affected by endogeneity (not shown), but the general pattern of results were also unaffected.

[8] A direct incorporation of unemployment rate in the empirical model, for example, can be problematic due to endogeneity of the unemployment rate, which may be simultaneously determined with migration (Etzo, 2010).

measure of local labor demand shocks.[9]

We also include several other county characteristics that past research has shown to be associated with U.S. domestic migration. These factors include economic variables such as median housing value and volatility of local economies, as well as government policy variables such as per capita taxes and government expenditures. Higher housing prices may discourage in-migrants, though they also may reflect unmeasured amenities (Jeanty et al., 2010; Murphy et al., 2006) and they could reflect housing market conditions. Likewise, following the Roback (1982) spatial equilibrium model, populous metropolitan areas that lack large-scale natural amenities and have weak zoning would have lower housing prices (e.g., Dallas or Atlanta), illustrating how housing prices differ from the population density measure.

Several studies have considered whether migration is also associated with risk and uncertainty (Daveri and Faini, 1999, Rosenzweig and Stark, 1989, Stark and Levhari, 1982; Arzhagi and Rupasingha, 2013). We incorporate the volatility of unemployment in the destination county to control for risk. Specifically, we use the coefficient of variation of the unemployment rate between 1990 and 1999, and 2000 and 2009 for each destination county as a measure of risk and hypothesize it to be inversely associated with in-migration. The Tiebout hypothesis (Tiebout, 1956) suggests that if mobility is costless, individuals will "vote with their feet" by moving to a locality that provides the optimal mix of local public goods. Thus, we include per capita local taxes and per capita local government expenditures, which include intergovernmental transfers. Taxes are hypothesized to be negatively associated with in-migration and government expenditures are positively associated with in-migration.

This paper utilizes county-to-county migration data from the 2000 decennial census for the population 5 years old and over for the period between 1995 and 2000 and the same data

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[9] The result is the predicted growth rate if all of the county's industries grew at the national growth rate. The level of detail used in the calculation is the four-digit level using employment data from the EMSI consulting company.

from the American Community Survey (ACS) for 2005 to 2009. A key difference between the two surveys is in how past migration is defined. The 2000 Census asked where a resident lived 5 years ago while the ACS asks where a resident lived 1 year ago. Therefore the 2000 Census data include movers who moved over the last 5 year time span and the ACS data includes only people who moved during the previous year. Based on this, even though the 2005-2009 ACS is a 5-year dataset, it is a 5-year estimate using 1-year datasets. Documentation is available at the Census Bureau website on the compatibility of the data between the 2000 Census and the 2005-2009 ACS (Benetsky and Koerber, 2012). Benetsky and Koerber (2012) analyze the relationship between ACS and 2000 Census migration data and show that the flows in the 2005-2009 ACS are highly correlated with the 2000 Census flows, with a Pearson's r of about 0.94. They also regress 2005-2009 ACS flows on the 2000 Census flows and find that the ACS flows account for about 89.0% of the flows in the 2000 Census. Based on these findings, they conclude that the ACS flow data is a good estimate of migration relative to the 2000 Census data, declaring, "[d]espite comparing two different surveys utilizing two different migration questions, there is congruence in the relative magnitude of county-to-county movers found between the surveys" (p. 10). The main way our results would be tangibly affected is if *conditional* on our control variables for demographics and economic conditions, in-migration rates are systematically different across counties for one-year and five-year flows *beyond* a simple scaling effect where the sum of the one-year flows may be larger than the five-year flows (which would simply change the scaling of the regression coefficients). The migration data is cross-sectional, providing an *n* by *n* matrix of internal migration flows for all U.S. counties.

A major concern with migration models is possible endogeneity, in which the error term may be correlated with some of the explanatory variables. A key cause of such endogeneity is that labor demand-shift variables are jointly determined with migration. Our use of the industry mix variable as an exogenous proxy for demand shifts greatly mitigates this concern. We also use five-year lagged period values (1990 and 2000) for explanatory variables as in the ‘weakly exogenous’ regressors assumed by (Levine, et al., 2000). This approach implies that future migration does not affect current levels of explanatory variables. To further account for omitted variable bias, we include origin fixed effects. Finally, the research design is less exposed to endogeneity concerns than in standard models of net migration for an individual county. Specifically, in the individual county models used in most of the literature (e.g., population growth or net migration), job growth and net migration are jointly determined. However, when estimating migration between 3,000 plus counties pairs, the relative share of total migration for a county that is explained by *one* county *pair* is typically quite small, meaning that shifts in migration between a single county pair would have a much smaller influence on a county’s overall economic activity—reducing the severity of any endogeneity. We discuss other ways we mitigate endogeneity below.

Estimation and results

We estimate a PRM, taking advantage of the equivalence relation between the log-likelihood functions of the CLM and the PRM (Guimaraes, et al., 2003). To ensure compatibility between the conditional logit and Poisson models, it is necessary that we incorporate location fixed effects in our empirical application (Guimaraes, et al., 2004). Ideally, both origin and destination county fixed effects must be incorporated, but due to limited computational power, we only use origin county fixed effects. To assess whether close proximity to metropolitan areas is leading to different results, in the metro to nonmetro model, we also separate nonmetro counties into two sub-samples: nonmetro-adjacent (rural urban continuum codes 4,6, and 8) and nonmetro-nonadjacent (rural urban continuum codes 5,7, and 9).

The descriptive statistics are summarized in Table 1 for both metro to nonmetro flows and nonmetro to metro flows for both time periods. The estimation procedure for metro to nonmetro flows employs a full sample model (about 2.2 million metro to nonmetro county-to-county flows for each time period) and the two subsamples for (1) metro flows to nonmetro-adjacent (around 1.13 million county-to-county flows, denoted as *subsample 1*) and metro flows to nonmetro-nonadjacent (around 1.04 million county-to-county flows, denoted as *subsample 2*). Then we estimate the model for migration from all nonmetro to all metro counties. In all cases, we report heteroskedasticity-robust standard errors. This is particularly important for Poisson regression, because while we expect that the coefficients of the Poisson model mainly remain consistent in the presence of over-dispersion, the standard errors may be heavily underestimated. We also include log likelihood values of each specification in order to show the appropriateness of each specification and the results of a Wald test to indicate the suitability of the fixed-effects Poisson models.

Table 2 presents fixed effect Poisson estimation results for metro-to-nonmetro county migration for the full sample, two sub samples, and nonmetro-to-metro migration for both time periods.[10] As suggested in previous studies, our results show that natural amenities are a strong predictor in metro-to-nonmetro migration in both time-periods. The coefficients for all samples in both periods are highly significant and positive. All else constant, for one standard deviation increase in the natural amenity index, a nonmetro county's in-migration increases by 23 percent[11] for the full sample in 1995-2000 period. However the effect seems to have weakened in the second period in all samples. The value of the amenity coefficient for the full sample has decreased from 0.091 in the first period to 0.065 in the second. The respective figures for the nonmetro-adjacent are 0.075 and 0.025 and for the nonmetro-nonadjacent are 0.100 and 0.088.

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[10] When comparing the results between two time periods, we caution the reader that, despite assurances given in Benetsky and Koerber (2012), there might be differences between one migration measure and the other associated with the variables in the analysis.

[11] This is calculated using $100 * ((e^{\beta_k * \delta}) - 1)$ where δ indicates standard deviation or a factor change in the covariate (see Long, 1997).

Accordingly, for one standard deviation increase in the natural amenity index, a nonmetro county's in-migration increases by 16 percent for the full sample in the 2005-2009 period. This finding suggests that even though natural amenities are still a key determinant of metro-to-nonmetro migration, its overall effect on this migration direction may have diminished, which supports the findings of Partridge et al. (2012). The positive and significant coefficient for the natural amenity variable in the nonmetro-to-metro model suggests that natural amenity is a strong factor in rural-to-urban migration, and the results for 2005-2009 show no notable temporal change in the overall effect of natural amenities. For a one standard deviation increase in the natural amenity index, a metro county's in-migration from nonmetro counties increases by 59 and 58 percent, respectively for the 1995-2000 and 2005-2009 models.

The non-metro adjacent to a metropolitan area coefficient is highly significant and positive in both time periods, supporting the suburbanization hypothesis. The size of its estimated parameter increased in the second time-period, indicating that the influence of locating in nonmetro adjacent counties may have grown, *ceteris paribus*. A nonmetro-adjacent county has a 38 percent greater number of expected in-migrants, holding all other variables constant in 1995-2000 time-period. The respective number for the latter period is 43 percent.

The estimated coefficients for the distance variable is negative and highly significant in both metro-to-nonmetro and nonmetro-to-metro models for all samples for both periods, implying that longer distance is associated with lower migration flows. For example, a 100 mile increase in the distance between metro-nonmetro county pairs is associated with a nonmetro county's in-migration rate decreasing by 56 percent. In comparing across the two sub-samples in metro-to-nonmetro flows, the nonmetro-nonadjacent sample seems to have smaller distance effect than in the nonmetro-adjacent sample. This implies that distance is more important to migrants moving into adjacent counties as many of them tend to be commuters who have economic *and* noneconomic links to metro counties, but prefer to live in more distant counties.

The coefficient on the distance-squared variable is positive, suggesting that the deterring effects of distance declines as distance increases.[12] A comparison of the two periods shows that the absolute value of the distance coefficient slightly increasing in the second period for all samples. This results may be in conflict with some of the claims in the previous literature (Juarez, 2000) that distance may be less of a migration barrier than in the past, but support the view that cost of moving to remote locations increases as technological advances may increase the value of other types of agglomeration economies found in metro areas (Partridge et al., 2008b). This result may also be at odds with the argument that telecommuting has aided longer rural-urban commutes but rather, it may be primarily facilitating longer commutes *within* large urban areas because the worker can occasionally telecommute.

The population density results in all specifications confirm the traditional gravity model hypothesis that migrants are attracted to more populous locations. Results in the metro-to-nonmetro specifications are consistent with the view that these migrants prefer more populated rural locations. In terms of the magnitude, a 50 person increase in population per square mile is associated with a 48 percent increase in a nonmetro county's in-migration rate in the first time-period. The effect is even more notable for remote nonmetro counties by comparison of the size of the estimated coefficients. Although the significance and the sign of population density coefficient remains the same for the second period in the metro-to-nonmetro specifications (2005-2009, Columns 5-7), the absolute value of the coefficient decreases substantially in the second period. The regression coefficient in the full sample decreased from 7.796 in the first period to 0.345 in the second. A 50 person increase in population per square mile is associated with only a 2 percent increase in a nonmetro county's in-migration. The temporal differences are

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[12] Using the marginal formula for the Poisson function, the marginal distance effect reaches zero at 1,575 miles in the metro-to-nonmetro 1995-2000 sample and 1,544 miles in the 2005-2009 sample. The corresponding zero marginal distance effects are at 1,709 and 1,683 miles in the nonmetro-to-metro sample.

also clearly visible in the metro-to-nonmetro subsamples. The advantages of population appear to have declined for metro-to-adjacent nonmetro migrants, in which improved information technologies may have reduced the need for local agglomeration economies associated with population density. Despite the temporal decline, the “high” returns to population density for metro-to-remote rural migration continued in both periods, suggesting that existing agglomeration economies remain an important consideration when moving to remote areas.

Compared to the metro-to-nonmetro results, the size of the coefficient for population density is markedly smaller in the nonmetro-to-metro-county migration results, though some of this is scaling in that population density is much higher in the metropolitan destination compared to the nonmetro destination in the metro-to-nonmetro results. However, there was virtually no change in in-migration in a typical metro county (0.1 percent) for a 50 people increase in population per square mile. The size of the coefficient remains relatively unchanged between the two time periods. Thus, at the margin, returns to population density for potential metro-to-remote-nonmetro migrants is much larger than for nonmetro-to-metro migrants, consistent with some threshold level of population density being a key draw in more remote settings.

The coefficient of wage and salary per job is significant and positive in all specifications (except in the metro-to-nonmetro-adjacent sample in the first period, which has an unexpected negative sign) for both periods, indicating that, *ceteris paribus*, migrants are more likely to move to counties that have higher wage rates, confirming the labor market theory that in-migration is more likely for regions experiencing relatively high wage levels. On average, a one-thousand dollar increase in nonmetro county salary is associated with a one percent increase in in-migration to that county and the same increase in a metro county is associated with a 10 percent increase in in-migration to that county.

The results between two time periods in metro-to-nonmetro model show considerable nominal variation for the wage variable’s results. For example, while the estimated coefficient for the full metro-to-nonmetro sample increased from 0.006 in the first period to 0.044 in the second period, the estimated coefficient for the metro to nonmetro-nonadjacent sample increased from 0.050 in the first period to 0.067 in the second period. However, the coefficient for nonmetro-adjacent is negative and significant in the first period but is positive and significant in the second period. The smaller migration response to wages for in-migration to metro adjacent counties compared to remote nonmetro counties is expected because local labor market conditions should play a smaller role for those who commute back to metro areas.[13] The notable temporal change in the wage coefficient suggests that this labor market factor may have become an even more important a determinant of migration from metro to nonmetro counties than in the 1990s, downplaying the claim that economic factors may have become less important in metro-to-nonmetro migration. For example, a one thousand dollar increase in nonmetro salary is related to a 4 percent increase in in-migration to that county in the second period. However, a decrease in the size of the coefficient in the second time period in the nonmetro to metro flows indicates that the effect of the wage variable may have weakened over time, suggesting a smaller role for economic effects (as least through wages).

The estimated coefficient for the industry mix variable that measures labor demand shocks is positive and statistically significant in all specifications for both time-periods. All else constant, a one standard deviation increase in the industry mix employment growth in a given nonmetro county was related to a 19 percent increase in population moving to that county from a given metro county between 1995-2000, and the corresponding figure for nonmetro-to-metro model was 44 percent. This result supports the economic restructuring argument of reversal and shows that positive demand shocks are a strong pull factor in metro-to-nonmetro migration, indicating the job availability is a key factor in rural areas, perhaps due to thin labor markets.

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[13] Future research should identify the responsiveness of commuting from adjacent counties to wages in the nearest urban area. In the metro-to-nonmetro case, this effect is controlled for with the origin county fixed effect.

There are also noticeable differences with regards to the magnitude of the coefficient of this variable between samples in the first period in the metro-to-nonmetro model: the coefficient for nonadjacent sample is larger than that for the adjacent sample. This relative difference also indicates the possibility that many migrants to adjacent counties are commuters who have jobs in the nearby metro area, though its statistical significance in adjacent counties suggests that local conditions play a role. The differences are also visible between the time periods. The numerical size of the coefficient in all specifications increased noticeably. These results run counter to Partridge et al.'s (2012) findings that employment related migration responses declined after 2000—though a key difference is that Partridge et al. were concerned with net migration from all sources (especially metro to metro). In summary, the effect of industry mix employment on both metro to nonmetro and nonmetro to metro migration flows is highly significant and the effect seems to be increasing over time.

One main explanation given in the early literature for the rural "reversal" is that retirees moved to nonmetro areas. Our proxy to measure this argument is to include the share of population who are over 64 years old. The estimated coefficients for this variable do not have the hypothesized positive sign, although they are highly significant in all samples in both periods for metro-to-nonmetro model. In other words, nonmetro counties that have a higher concentration of older people are not attractive to migrants coming from metro counties. A comparison between the two time periods shows that there are visible temporal changes in the coefficients. The absolute value of the coefficients in all samples has increased from the first period to the second. To further consider this issue, in results not shown, we re-estimate the models by replacing the share of over 64 year old with the percent of households with retirement and social security income, but the results are similar with the same temporal tendencies between the two time-periods. We also test another specification using a dummy variable for retirement-destination counties developed by Economic Research Service (the number of residents 60 and older grew by 15 percent or more between 1990 and 2000 due to in-migration). Interestingly, the estimated coefficient of this variable is positive and highly significant in the first period for all samples in metro-to-nonmetro flows. However, the results change in the second period: estimated coefficient is not significant for the full sample, negative and significant for the nonmetro-adjacent sample and positive and significant for the nonmetro-nonadjacent sample. Even though this coefficient continues to be positive and significant for the nonmetro-nonadjacent sample from the first to the second period, the size of the coefficient decreases from 0.518 to 0.174 in the second. The coefficient of the retiree attraction variable is negative and significant in the nonmetro-to-metro estimation but the temporal changes seem to have reversed: the absolute value of the coefficient in the second period in the nonmetro to metro model decreased, indicating a weakening effect.

The results show that lower per capita local taxes coefficient is highly significant and negative in all specifications for both periods in the metro-to-nonmetro model, though the absolute value of the coefficient seems to have increased in the second period. The estimated coefficient of local government expenditure per capita in the metro-to-nonmetro model is highly significant but has an unexpected negative sign across the specifications in the first period. The results are similar in the second period for the full and metro-adjacent sample but the coefficient is not statistically significant in the nonadjacent sample. Though we control for economic conditions, government expenditures are affected by economic conditions, which may underlie some of this pattern. As for nonmetro-to-metro results, the coefficient of the government expenditure variables is highly significant and has the expected positive sign for both time periods.

The estimate for the median housing value variable is highly significant but has an unexpected positive sign in all samples for both time-periods in the metro-to-nonmetro model, consistent with unmeasured amenities affecting the results.[14] In this manner, we would not expect households moving from metro locations to have large negative marginal responses to what should be relatively low nonmetro housing prices. Conversely, this estimate is negative and highly significant in the nonmetro-to-metro model for both periods suggesting that higher housing costs deter nonmetro migrants to metro areas. The unemployment risk variable has the expected negative sign and is statistically significant in all specifications, indicating some evidence that a stable job market at the destination is important for in-migrants, *ceteris paribus*.[15] Note the relatively smaller marginal response in the adjacent sample, supporting the notion that local labor market conditions matter less in adjacent counties to metro migrants. The absolute size of this coefficient increases significantly in the second period, indicating the increasing importance of job market stability in the destination location.

Distance and the Role of Job Opportunities and Amenities

In this sub-section, we assess whether the attraction of job opportunities and natural amenities vary from long- to short-distance moves from metropolitan to nonmetropolitan locales. Greater distance can reduce the amount of information that migrants have on potential destinations including whether there are suitable job opportunities (Brown and Scott, 2012). We expect that potential economic migrants would have better labor market information about nearby locations, suggesting that the potential effects of job growth as an attractive force diminish with greater distance. Regarding amenities, we expect that nearby places would have similar packages of natural amenity bundles, even if the amenity scores differ between two relatively nearby locations. Thus, we expect the draw of amenities to be stronger in more distant locations because different regions offer entirely different bundles of amenities. To assess these possibilities, we

[14] Jeanty et al. (2012) contend that a positive migration coefficient on median housing values may suggest that there are omitted amenities capitalized into housing values. They suggest possible solutions for future research.

[15] This is also true in the metro-to-adjacent-nonmetro subsample in which many of the in-migrants are expected to be commuters.

respectively add interactions of industry mix job growth and the amenity score with distance, in which the results are respectively reported in Tables 3 and 4.

Table 3 shows a significant and negative coefficient on the interaction between industry mix job growth and distance, supporting our hypothesis that the pull effects of job growth diminish with distance. The effect is more prominent for metro-to-nonmetro migration in the first period though the effect becomes insignificant in the metro-to-nonadjacent model in the second period. The larger negative magnitude of the adjacent distance×industry mix job growth variable is a little surprising, suggesting that local job market conditions matter less at greater distances (which would be more difficult to commute). This pattern may be because natural amenities matter more for the more distant moves in general, which is discussed more below. The magnitudes of the distance interaction coefficient are larger in the latter period, which suggests that shorter job-related moves were more of the norm during the sluggish post-2000 environment, perhaps due to greater risk aversion (though we caution that the coefficient is imprecisely measured in the metro to nonadjacent model).

Table 4 shows that the coefficient for the interaction between distance and the natural amenity scale has the expected positive coefficient. However, the coefficient is only statistically significant in the earlier period and the magnitude of the coefficient is also smaller in the latter period. So at least for the earlier period, while having strong natural amenities is important regardless of the distance of the metro to nonmetro move, the amenity pull effect is stronger for more distant moves.

Conclusions

The study provides new insights into the changing U.S. migration patterns, where migration has historically been from non-metro areas to metro areas, but has changed to show more migration from metro to non-metro areas during last two decades. We find support for both the deconcentration and economic restructuring perspectives put forth by previous studies, with some exceptions and temporal changes. More specifically, key destination county characteristics such as natural amenities, population density, distance, wage and salaries, industrial mix, adjacent to metro counties, and share of population over 64 years old to be significantly associated with metro to nonmetro migration. All these factors have hypothesized outcomes except the share of population over 64-years old variable which is negative.

While our results suggest that attempts by local policymakers to improve and promote local natural amenities to attract people and businesses may still be good policy, the persistence of such policy over time may be questionable. Nonmetro-to-metro flow results suggest that natural amenities are still important in retaining population in nonmetro locations because these movers still prefer to locate in high amenity metro locations and the effects show no change over time. We also find that migration respond to agglomeration economies even in nonmetro areas, suggesting that some threshold of agglomeration economies are necessary, though it is also contrary to the claims by the deconcentration perspective that these movers prefer less dense areas. This may be due to easy access to rural amenities but at the same time enjoying some level of urban amenities including access to technology. The effects seems to be somewhat muted over time. We also find that distance from metro counties negatively affect in-migration in nonmetro areas but this effect is more pronounced in nonmetro adjacent than in nonmetro nonadjacent counties, indicating the possibility that many of the migrants to adjacent counties consider commuting. There are no notable temporal changes in the distance effects, downplaying the argument that people may move out to rural areas and then telecommute. In summary, results for both population density and distance show that urban amenities in rural areas and proximity to metro areas are important if nonmetro areas are to attract and retain migrants.

While our results show that nonmetro counties with very high retiree growth (15 percent of more) tend to attract more migrants from metro locations, the overall results diminish the claim that retiree attraction may be good policy for nonmetro counties in general. Results show that economic restructuring argument has some validity in metro-to-nonmetro migration and labor market opportunities play a significant role. The effect of industry mix variable seems to be unchanged in the nonmetro-to-metro migration over the two periods, but this effect has clearly increased in metro to nonmetro migration, indicating that government policies that are geared towards creating jobs tend to attract more and more people into nonmetro areas.

Further analysis suggested that the job growth effects for metropolitan to nonmetropolitan migration declined with greater distance from the origin. Indeed, there is evidence that the role of distance in affecting how job growth affects migration increased in the post-2000 period, perhaps suggesting greater risk aversion. In similar analysis, the draw of natural amenities also increased with distance in explaining metropolitan to nonmetropolitan migration, but the effect was only statistically significant in the earlier period. We also confirm that local taxes are still a deterrent for in-migration, whether the migration is from metro to nonmetro or nonmetro to metro areas. One important exception is housing values at the destination, where we find that while higher values attract more migrants from metro to nonmetro areas (perhaps due to unmeasured amenities), the opposite is true for nonmetro-to-metro migration.

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Table 1. Variable description and descriptive statistics: Metro to nonmetro vs. nonmetro to metro migration full samples

Variable	Description	Metro to Nonmetro Migration				Nonmetro to Metro Migration			
		1995-2000		2005-2009		1995-2000		2005-2009	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Inflows (dependent)	Migration from metro to nonmetro (or nonmetro to metro) counties	2.45	32.95	0.90	13.82	2.35	28.45	0.86	13.15
amnscale	Natural amenities index	-0.05	2.25	-0.05	2.25	0.25	2.32	0.25	2.32
metroadj	Nonmetro counties that are adjacent to a metro area (0,1)	0.52	0.50	0.52	0.50				
distance/100	Actual distance between an origin county and destination county on average, in miles	9.10	5.96	9.10	5.96	9.10	5.96	9.10	5.96
distance_sq	Distance squared	118.41	181.64	118.41	181.64	118.41	181.64	118.41	181.64
popden/1000	Population per square mile	0.04	0.11	0.05	0.11	0.56	2.40	0.62	2.79
wage	Wage and salary per job	16.47	3.26	23.20	3.80	19.67	4.01	28.58	6.63
indusmix	Industry mix employment growth, calculated by multiplying each sum across all industries of the product of the industry's national employment growth (1990 to 2000, and 2000–07) with the initial period (1990 2000) industry employ share in the county	13.76	4.89	9.12	2.51	16.43	5.12	10.85	2.72
elder	Percent of population over 64 years old	16.24	4.12	16.07	3.91	12.54	3.64	12.48	3.40
pctax/1000	Per capita local taxes	0.65	0.49	0.96	0.81	0.68	0.41	1.03	0.60
pcgexp/1000	Per capita local government expenditure	1.90	0.86	2.96	1.22	1.81	0.68	2.87	1.23
mhv/1000	Median housing value	43.56	20.36	70.55	36.16	72.70	42.63	109.41	54.90
cvurate	Coefficient of variation of unemployment rate	0.21	0.09	0.24	0.09	0.23	0.08	0.29	0.08
Obs.		2,103,245		2,109,260		2,128,421		2,089,500	

Table 2. Fixed Effect Poisson Estimation Results

	Metro to Nonmetro Migration						Nonmetro to Metro Migration	
	1995-2000			2005-2009			1995-2000	2005-2009
	Full Sample	Metro to adjacent	Metro to nonadjacent	Full Sample	Metro to adjacent	Metro to nonadjacent	Full Sample	Full Sample
amnscale	0.091***	0.075***	0.100***	0.065***	0.025***	0.088***	0.200***	0.198***
	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.009)	(0.008)	(0.011)
distance	-0.819***	-0.895***	-0.656***	-0.896***	-0.966***	-0.729***	-0.752***	-0.808***
	(0.044)	(0.042)	(0.059)	(0.050)	(0.050)	(0.058)	(0.081)	(0.093)
distance_sq	0.026***	0.029***	0.019***	0.029***	0.031***	0.022***	0.022***	0.024***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)
popden	7.796***	7.464***	9.207***	0.345***	0.193***	4.763***	0.020***	0.022***
	(0.306)	(0.352)	(0.330)	(0.022)	(0.025)	(0.193)	(0.005)	(0.005)
wage	0.006*	-0.009**	0.050***	0.044***	0.029***	0.067***	0.099***	0.055***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
indusmix	0.035***	0.029***	0.041***	0.070***	0.058***	0.065***	0.071***	0.145***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)	(0.006)	(0.002)	(0.006)
elder	-0.050***	-0.033***	-0.068***	-0.082***	-0.066***	-0.102***	-0.064***	-0.058***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.003)	(0.005)
pctax	-0.244***	-0.198***	-0.332***	-0.312***	-0.210***	-0.550***	-0.143***	-0.347***
	(0.036)	(0.051)	(0.036)	(0.031)	(0.036)	(0.043)	(0.038)	(0.036)
pcgexp	-0.088***	-0.055**	-0.110***	-0.099***	-0.136***	0.029	0.139***	0.137***
	(0.024)	(0.028)	(0.023)	(0.016)	(0.021)	(0.018)	(0.022)	(0.016)
mhv	0.004***	0.006***	0.004***	0.003***	0.009***	0.001***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
cvurate	-0.361**	-0.013	-0.808***	-1.160***	-1.131***	-1.175***	-0.340**	-1.454***
	(0.169)	(0.185)	(0.178)	(0.175)	(0.197)	(0.209)	(0.162)	(0.212)
metroadj	0.324***			0.356***				
	(0.025)			(0.029)				
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log L	-9356425	-6388894.8	-2717527.7	-5051182.9	-3344577.6	-1562524.7	-10056934	-5224726.2
Wald	9230.28	6720.33	17017.11	7955.29	5394.61	8499.52	13722.21	8354.70
Obs.	2,137,330	1,110,772	1,025,595	2,197,914	1,146,845	1,006,495	2,141,009	2,180,850

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Fixed Effect Poisson Estimation Results with Interaction Term for Distance and Industrial Mix

	Metro to Nonmetro Migration						Nonmetro to Metro Migration	
	1995-2000			2005-2009			1995-2000	2005-2009
	Full Sample	Metro to adjacent	Metro to nonadjacent	Full Sample	Metro to adjacent	Metro to nonadjacent	Full Sample	Full Sample
amnscale	0.091***	0.074***	0.100***	0.065***	0.026***	0.088***	0.200***	0.197***
	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.009)	(0.008)	(0.010)
distance	-0.787***	-0.856***	-0.633***	-0.863***	-0.917***	-0.705***	-0.760***	-0.850***
	(0.053)	(0.052)	(0.068)	(0.055)	(0.056)	(0.068)	(0.074)	(0.078)
distance_sq	0.026***	0.029***	0.019***	0.029***	0.032***	0.022***	0.022***	0.024***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)
popden	7.766***	7.368***	9.223***	0.339***	0.181***	4.775***	0.019***	0.022***
	(0.301)	(0.342)	(0.340)	(0.023)	(0.026)	(0.199)	(0.005)	(0.005)
wage	0.005*	-0.009**	0.050***	0.044***	0.029***	0.067***	0.099***	0.055***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
indusmix	0.044***	0.040***	0.048***	0.084***	0.077***	0.077***	0.069***	0.133***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.003)	(0.008)
indusmix*distance	**-0.002*** **	**-0.003*** **	**-0.002***	**-0.004*** **	**-0.006*** **	**-0.003**	**0.000**	**0.004***
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.002)**	**(0.001)**	**(0.002)**
elder	-0.049***	-0.033***	-0.068***	-0.082***	-0.065***	-0.102***	-0.064***	-0.059***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.003)	(0.005)
pctax	-0.233***	-0.186***	-0.326***	-0.312***	-0.207***	-0.550***	-0.142***	-0.345***
	(0.037)	(0.052)	(0.034)	(0.031)	(0.036)	(0.044)	(0.037)	(0.035)
pcgexp	-0.090***	-0.058**	-0.111***	-0.098***	-0.135***	0.029	0.139***	0.138***
	(0.024)	(0.028)	(0.023)	(0.016)	(0.021)	(0.018)	(0.022)	(0.016)
mhv	0.004***	0.006***	0.004***	0.003***	0.009***	0.001***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
cvurate	-0.362**	-0.019	-0.805***	-1.156***	-1.145***	-1.159***	-0.346**	-1.466***
	(0.168)	(0.185)	(0.179)	(0.176)	(0.199)	(0.214)	(0.163)	(0.211)
metroadj	0.322***			0.355***				
	(0.025)			(0.029)				
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log L	-9345874	-6378391.3	-2716053.8	-5048510	-3340895.4	-1562135.5	-10056635	-5223313
Wald	10140.13	7095.98	17492.35	8254.32	5694.52	8846.96	13700.80	8085.21
Obs.	2,137,330	1,110,772	1,025,595	2,197,914	1,146,845	1,006,495	2,141,009	2,180,850

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4. Fixed Effect Poisson Estimation Results with Interaction Term for Distance and Natural Amenity Scale

	Metro to Nonmetro Migration						Nonmetro to Metro Migration	
	1995-2000			2005-2009			1995-2000	2005-2009
	Full Sample	Metro to adjacent	Metro to nonadjacent	Full Sample	Metro to adjacent	Metro to nonadjacent	Full Sample	Full Sample
amnscale	0.061***	0.040***	0.062***	0.058***	0.017	0.062***	0.034	0.054**
	(0.013)	(0.015)	(0.014)	(0.012)	(0.018)	(0.016)	(0.024)	(0.025)
amnscale*distance	**0.005*** **	**0.006*** **	**0.006*** **	**0.001**	**0.001**	**0.004**	**0.028*** **	**0.025*** **
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.003)**	**(0.003)**	**(0.005)**	**(0.006)**
distance	-0.815***	-0.892***	-0.651***	-0.895***	-0.965***	-0.724***	-0.728***	-0.787***
	(0.046)	(0.043)	(0.059)	(0.051)	(0.050)	(0.060)	(0.055)	(0.071)
distance_sq	0.025***	0.028***	0.018***	0.028***	0.031***	0.022***	0.016***	0.018***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
popden	7.925***	7.666***	9.366***	0.349***	0.198***	4.833***	0.026***	0.029***
	(0.314)	(0.367)	(0.325)	(0.023)	(0.024)	(0.191)	(0.005)	(0.005)
wage	0.004	-0.010***	0.048***	0.044***	0.029***	0.067***	0.102***	0.056***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
indusmix	0.035***	0.029***	0.040***	0.070***	0.058***	0.065***	0.071***	0.143***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)	(0.002)	(0.006)
elder	-0.049***	-0.033***	-0.068***	-0.082***	-0.065***	-0.102***	-0.066***	-0.059***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)
pctax	-0.230***	-0.165***	-0.327***	-0.308***	-0.203***	-0.544***	-0.004	-0.245***
	(0.036)	(0.053)	(0.038)	(0.030)	(0.037)	(0.043)	(0.029)	(0.029)
pcgexp	-0.100***	-0.075***	-0.119***	-0.101***	-0.140***	0.025	0.054***	0.086***
	(0.024)	(0.028)	(0.022)	(0.016)	(0.021)	(0.018)	(0.017)	(0.012)
mhv	0.004***	0.006***	0.004***	0.003***	0.009***	0.001***	-0.008***	-0.008***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
cvurate	-0.333**	0.026	-0.766***	-1.157***	-1.127***	-1.148***	-0.014	-1.216***
	(0.168)	(0.185)	(0.178)	(0.175)	(0.198)	(0.211)	(0.159)	(0.238)
metroadj	0.328***			0.357***				
	(0.026)			(0.030)				
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log L	-9346479	-6379587.7	-2712982	-5050993	-3344416.2	-1561784.5	-9752745	-5138697
Wald	8676.02	5986.72	16210.56	8000.65	5372.07	8100.88	10480.42	6622.02
Obs.	2,137,330	1,110,772	1,025,595	2,197,914	1,146,845	1,006,495	2,141,009	2,180,850

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1