Rural Bound: Determinants of Metro to Non-Metro Migration in the United States

Anil Rupasingha, Yongzheng Liu, and Mark Partridge

A general global precept is that agglomeration forces lead to migration from rural to urban areas. Yet for much of the time since the early 1970s, more people have 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, a significant increase in commodity prices that favor rural areas, and potential changes in the valuation of natural amenities that would affect migration. This article 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 2005–2009 periods. More specifically, 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. The article uses (1) extensive county-to-county migration flows and (2) the utility maximization theory that extends the framework of a discrete choice model. The results show that population density, distance to urban areas, industry mix employment growth, natural amenities, and percentage 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 a slight increase in the effects of wage and employment growth from 2005–2009.

Key words: Metro to nonmetro migration, urban to rural migration, domestic migration, county-to-county migration, USA counties, natural amenities, industry-mix employment growth, retiree migration, Poisson regression.

JEL Codes: J11, J61, R11.

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, and mostly held 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

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

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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. For example, if U.S. rural areas have primarily benefited from commodity booms or it is mainly high-natural amenity areas that are gaining population, it will be harder to develop effective policies aimed at improving rural economic prospects. Supporting the possibility that U.S. rural areas can remain competitive in terms of migration, Partridge et al. (2010b) find that while firms increasingly prefer to locate near agglomeration economies, households prefer to be more distant from urban areas.

Several conceptual frameworks have been advanced to explain the reversal that took place in 1970s and 1990s. The main explanations for the reversal in the 1970s were "period effects," the "regional restructuring perspective," and "suburbanization." The period effects follow the unique circumstances of 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, which is attributed mainly to movement of people and firms to low-density and high-amenity locations. A further perspective is regional restructuring, which refers to changes in economic opportunities (Frey and Johnson 1996; Partridge et al. 2010b). Although traditionally agglomeration economies have been positively associated with in-migration, the deconcentration hypothesis is associated with the following: retiree migration to nonmetro locations (Frey and Johnson 1996; Nelson and Nelson 2011); migration to metro-adjacent locations, which then requires an out-commute to work (Cromartie 1998; Partridge, Ali, and Olfert 2010a); rural gentrification, which is tied to economic restructuring due to advances in telecommunications (Nelson, Oberg, and Nelson 2010); and amenity-based migration (Rudzitis 1999; Nelson and Nelson 2011; Kahsai, Gebremedhin, and Schaeffer 2011). Yet, other studies stress structural economic changes as being partly responsible for the reversal (Frey and Johnson 1996; Ghatak, Levine, and Price 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 are to different time periods, and how differently these forces describe metro-to-nonmetro migration and nonmetro-to-metro migration. By comparing the set of determinants for these types of migration, one could answer the question of 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 article determines the extent of the effect of these arguments on metro-to-nonmetro migration. It also 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 relocating. 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 were 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 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 sheds light on factors associated with in- and out-migration in metro and nonmetro localities, as well as 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. (2008) 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 random utility maximization (Davies, Greenwood, and Li 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 U.S. 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), which allows 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. Another advantage of our empirical approach is that we can directly consider whether distance effects wane 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 support 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 to the 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 our estimations. 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 by place characteristics, $i = 0, 1, 2, \ldots, p$, where 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. 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:

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

Utility-maximizing individuals will migrate whenever $\Delta_i > 0$; otherwise they stay in place.

Basing our model 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, Figueirdo, and Woodward 2003; Guimarães, Figueirdo, and Woodward 2000; Arauzo-Carod, Liviano-Solis, and Monjón-Antolín 2010), but it is relatively new to the migration literature (Davies, Greenwood, and Li 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 the 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:

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

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 relocates to county j is

$$(3) \qquad P_{ij} = P(U_{ij} > U_{ik}) \quad \text{for all } k \neq j.$$

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

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

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

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

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 1,090 metro counties can possibly migrate to any of the 2,052 non-metro counties, the coefficients β' can be estimated by maximizing the following log-likelihood function:

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

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, Figueiredo, and Woodward (2003) is to estimate the CLM using an "equivalent" standard Poisson regression model (PRM). These authors prove that under certain conditions, the log-likelihood functions of the conditional logit and the

[2] This assumption implies the Independence of Irrelevant Alternatives (IIA) property, which 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 being the 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, Figueirdo, and Woodward 2003). Following a suggestion by McFadden (1978), one solution is to estimate the model using a randomly selected sub-sample (Friedman, et al. 1992; Guimarães, Figueirdo, and Woodward 2000; Hansen 1987; Woodward 1992). Although the resulting estimators are consistent, the efficiency is reduced due to dropping some information, and also the small sample properties are unknown (Guimarães, Figueirdo, and Woodward 2003).

Poisson regression are 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

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

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

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

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

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

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

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, Figueiredo, and Woodward 2004).

[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.

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 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 5, the housing crisis and Great Recession had remarkably little effect on overall gross migration flows, which remain at historically low levels post 2000. Likewise, the Great Recession was the culmination of slow job growth in the post 2000 period. Indeed, U.S. Bureau of Labor Statistics data suggests that the pre-Great Recession period 2000–2007 were the seven slowest years of nonfarm job growth of any seven-year period dating back to the late 1930s (or at least until the Great Recession began). 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.

[5] Cromartie (2013) shows that 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 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 more distant 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.

We separately appraise nonmetro-to-metro migration and metro-to-nonmetro migration 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 (Combes et al. 2012). Likewise, we expect that nonmetro-to-metro migrants may relatively value urban amenities associated with population density, whereas metro-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 migration reversal of the 1990s is explained mainly by 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, and preference for lower density or low agglomeration locations, while 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-based workers choose to forego higher earnings in exchange for the quality of life found in nonmetro localities. This quality of life is mainly attributed to natural and man-made amenities (Knapp and Graves 1989; Mueser and Graves 1995; Deller et al. 2001). We use the natural amenity index (*amnscale*) 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 moved to metro-adjacent counties. Partridge et al. (2008) 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 (*metroadj*) 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 in 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 spouses may want to work locally or they may want the option of being able to work locally in the future.

Gravity models of migration use population density (*popden*) 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 the deconcentration perspective. Traditionally, population density is found to be positively associated with in-migration, but in case of metro to nonmetro migration, the deconcentration hypothesis argues that migrants may prefer low density or low agglomeration locations.

Migration is costly for financial, information, and personal reasons. Migration costs also rise as the moving distance increases. The deconcentration perspective suggests that one motive for metro residents to move to 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, Ali, and Olfert 2010a). Our distance variable is calculated using the distance between each pair of county centroids via highway (divided by 100). Following Davies, Greenwood, and Li (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 as increasing numbers of baby boomers reach 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 (*elder*) 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 percentage 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, Levine, and Price 1996) and post 2000 period have bolstered certain rural economies. To test the validity of these claims, we incorporate the average county wage (*wage*) and industry-mix employment growth rate (*indusmix*). Empirical results on the relationship between per capita income or earnings and in-migration have been mixed; some studies found a positive link (Davies, Greenwood, and Li 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—that is, relative wage levels are a compensating differential.[7] Due to these offsetting effects, the expected effects of the wage variable are ambiguous.

As a sign of employment availability, for both periods we use the 1990–2000 and 2000–2007 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, which 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 the four-digit level with the corresponding national U.S. industry growth rates, thus producing an exogenous 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 (*mhv*) and volatility of local economies (*cvurate*), as well as government policy variables such as per capita taxes (*pctax*) and government expenditures (*pcgexp*). Higher housing prices may discourage in-migrants, though they also may reflect unmeasured amenities (Jeanty, Partridge, and Irwin 2010; Murphy, Muellbauer, and Cameron 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

[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 3,000 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. 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).

[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 proprietary employment data from the EMSI consulting company. Note that we end the 2000–2007 industry mix variable before the Great Recession in order to not mix the cyclical effects of the recession with the persistent growth effects reflected in the 2000–2007 period beforehand.

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, while government expenditures are positively associated with in-migration.

This article utilizes county-to-county migration data from the 2000 decennial census for the population aged 5 and over for the period between 1995 and 2000, and the same data 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 five years prior, while the ACS asked where a resident lived one year prior. Therefore, the 2000 Census data include those who moved over the previous 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, these authors 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," (Benetsky and Koerber 2012). 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, Loayza, and Beck (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 more than 3,000 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 by taking advantage of the equivalence relation between the log-likelihood functions of the CLM and the PRM (Guimaraes, Figueirdo, and Woodward 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, Figueirdo, and Woodward 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 leads 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 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 overdispersion, 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, as well as 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 being constant, for one standard deviation increase in the natural amenity index, a nonmetro county's in-migration increases by 23% for the full sample from 1995–2000.[11] However, the effect seems to have weakened in the second period in all samples. The value of the amenity coefficient for the full sample 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 they are 0.100 and 0.088. Accordingly, for a one standard deviation increase in the natural amenity index, a nonmetro county's in-migration increases by 16% 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%, respectively, for the 1995–2000 and 2005–2009 models. For example, for a given average metropolitan-nonmetropolitan county pair between 2005–2009, table 1 shows that on average, about 0.86 migrants moved from the nonmetropolitan county to the metropolitan county. Thus, a one standard deviation increase in amenities would lead to an increase of 58% in migration, or there will be an additional one-half of a migrant moving to the metropolitan county from each nonmetropolitan county annually over the five-year period (or by about 1,000 new migrants in total from the approximately 2,000 possible nonmetropolitan counties).

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

[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. One reviewer pointed out that bias may be introduced from the differences in the way the migration question was posed. For instance, young people may make several moves over a 5-year period as they search for jobs they like, making yearly rates more responsive to area employment opportunities than 5-year rates. People may move more often in short-distance moves than long-distance moves.

[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).

Table 1. Variable Description and Descriptive Statistics: Metro to Nonmetro vs. Nonmetro to Metro Migration Full Samples

		Metro to Nonmetro Migration				Nonmetro to Metro Migration			
		1995–2000		2005–2009		1995–2000		2005–2009	
Variable	Description	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 - 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	Percentage 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

Note: Robust standard errors appear in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

locating in nonmetro adjacent counties may have grown, *ceteris paribus*. A nonmetro-adjacent county has a 38% greater number of expected in-migrants, holding all other variables constant from 1995–2000. The respective number for the latter period is 43%.

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%. Comparing the two sub-samples in metro-to-nonmetro flows, the nonmetro-nonadjacent sample seems to have a 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 increases in the second period for all samples. This result may conflict with some of the claims in the previous literature (e.g., Juarez 2000) that distance may be less of a migration barrier than in the past, but supports the view that the cost of moving to remote locations increases because technological advances may increase the value of other types of agglomeration economies found in metro areas (Partridge et al. 2008). This result may also be at odds with the argument that telecommuting has aided longer rural-urban commutes. 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 magnitude, a 50-person increase in population per square mile is associated with a 48% increase in a nonmetro county's in-migration rate in the first time-period. The effect is even more notable for remote nonmetro counties when comparing 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% increase in a nonmetro county's in-migration. The temporal differences are 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%) for a 50-person 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 a 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

[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.

(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 $1,000 increase in nonmetro county salary is associated with a 1% increase in in-migration to that county, and the same increase in a metro county is associated with a 10% increase in in-migration to that county.

The results between two time periods in the 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 determinant of migration from metro to nonmetro counties in the 2000s than in the 1990s, downplaying the claim that economic factors may have become less important in metro-to-nonmetro migration. For example, a $1,000 increase in nonmetro salary is related to a 4% 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 (at 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 being equal, a one standard deviation increase in industry mix employment growth in a given nonmetro county was related to a 19% increase in the population moving to that county from a given metro county between 1995–2000, and the corresponding figure for nonmetro-to-metro model was 44%. 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 that job availability is a key factor in rural areas, perhaps due to thin labor markets. There are also noticeable differences with regard to the magnitude of the coefficient of this variable between samples in the first period in the metro-to-nonmetro model: the coefficient for the 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 the 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 they were concerned with net migration from all sources (especially metro-to-metro). In summary, the effect that industry mix employment has 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

[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.

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 those aged over 64 with the percentage 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 the USDA Economic Research Service (the number of residents 60 and older grew by 15% or more between 1990 and 2000 due to in-migration). Not surprisingly given its construction, 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: the estimated coefficient is not significant for the full sample, is negative and significant for the nonmetro-adjacent sample, and is 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 the 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] Indeed, 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, which supports 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 between long- and short-distance moves from metropolitan to nonmetropolitan locations. 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 locations would have similar packages of natural amenity bundles, even if the amenity scores differ between two relatively nearby

[14] Jeanty, Partridge, and Irwin (2012) contend that a positive migration coefficient on median housing values may suggest that there are omitted amenities capitalized into housing values. These authors 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.

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

Note: Robust standard errors appear 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

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

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 add both interactions of industry mix job growth and the amenity score with distance; the respective results are reported in tables 3 and 4.[16]

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 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 including the Great Recession, perhaps due to greater risk aversion (though we caution that the coefficient is imprecisely measured in the metro to nonadjacent model). Nonmetro-to-metro results suggest that local job market conditions can be an attractive force for migration regardless of the distance in the first time-period, but they matter more at short distances in the second time-period.

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. The fact that the interactive variable in the second time period is not statistically significant relative to the slope of distance indicates that distance was not an intervening factor when migrating for amenity purposes in the second time period.

Conclusions

The study provides new insights into the changing U.S. migration patterns, where migration has historically been from nonmetro areas to metro areas, but has changed to show more migration from metro to nonmetro areas during the 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 aged over 64 are shown 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 responds to agglomeration economies even in nonmetro areas, suggesting that some threshold of agglomeration economies are necessary, though it is also contrary to the claims made by the deconcentration perspective that these movers prefer less dense areas. This may be due to the people enjoying easy access to rural amenities, but at the same time enjoying some level of urban amenities, including access to technology. The effects seem to be somewhat muted over time. We also find

[16] We did not include the respective interactions with distance squared because it would have greatly complicated the interpretation of the results. In sensitivity analysis, we included the distance-squared interaction with amenities and industry mix job growth. In this case, the marginal effect of amenities and industry mix was mostly unaffected by including their respective interaction with distance squared. However, when we included these interactions with distance squared, the resulting coefficients on the distance squared interaction were negative and statistically significant, suggesting some attenuation at greater distances regarding how amenities and industry mix job growth affect migration.

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, which downplays 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 rate (15% 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 the economic restructuring argument has some validity in metro-to-nonmetro migration and that labor market opportunities play a significant role. The effect of the industry mix variable seems to be unchanged in nonmetro-to-metro migration over the two periods, but this effect has clearly increased in metro-to-nonmetro migration, indicating that successful 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 a similar analysis, the draw of natural amenities also increased with distance, thus 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.

Finally, it is important to draw attention to the role of context in shaping the substantial changes in coefficients over time. For instance, the coefficients of several variables that measure economic restructuring, such as variability of unemployment, wage rates, and job growth or industry mix, increased in magnitude between the periods. Even though the general patterns of migration stayed the same as indicated above, economic shocks such as the significant drop in employment in both metropolitan and nonmetropolitan areas in 2007–2009 seem likely to make economic factors more relevant to migration patterns in the second period.[17]

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[17] We are thankful to an anonymous referee for raising this point.

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