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SPREAD AND BACKWASH EFFECTS FOR NONMETROPOLITAN COMMUNITIES IN THE U.S.

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ABSTRACT. Few studies empirically estimate the effects of metropolitan growth on nonmetropolitan communities at a national scale. This paper estimates the growth effects of 276 MSAs on population in 1,988 nonmetropolitan communities in the United States from 2000 to 2007. We estimate the distance for growth spillovers from MSAs to nonmetropolitan communities and test the assumption that a single MSA influences growth. We compare three methods of weighting cities' influence: nearest city only, inverse-distance, and relative commuting flow to multiple cities. We find the inverse-distance approach provides slightly more reliable and theoretically supportable results than the traditional nearest city approach.

1. INTRODUCTION

Integration of cities with their exurbs can be viewed negatively as sprawl or positively as rural integration. For researchers studying rural development, the simple fact that growth cannot be understood as isolated from urban fates leads to the study of urban–rural linkage models (Partridge et al., 2007). That urban development can affect rural population through growth or decline is captured by the terms spread and backwash effects.

The recent growth in literature around agglomeration economies and amenities relates the growth in cities to growth in outlying areas. These studies consistently highlight the variation caused by local context (Barkley, Henry, and Bao, 1996; Zhang, 2001; Partridge and Rickman, 2003b). However, they tend to incongruously impose an assumption across all study sites: that outlying areas enjoy the growth benefits of only the closest city.

In contrast to this assumption, descriptive statistics reveal the multi-city access available to rural residents in the United States. On average, while the nonmetropolitan places studied in this manuscript are 46 miles from the nearest central city, they also fall within 100 miles of four central cities. In this paper, we test whether spread-backwash effects in nonmetropolitan U.S. communities are affected by only the closest city or also by multiple nearby cities. Additionally, we test and compare two methods of selecting the pool of multiple influential cities.

First, we use the traditional method of relating each nonmetropolitan place to only its nearest city (Metropolitan Statistical Areas/Consolidated Metropolitan Statistical Areas,

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MSAs). Second, we use an inverse-distance method of weighting cities' influence on nonmetropolitan places, with a maximum threshold distance imposed. This second method assumes that while the nearest city has the strongest influence on the nonmetropolitan place, other proximate cities are also recipients of rurally produced goods and commuters. Third, we weight cities' influence on nonmetropolitan places' growth according to the commuting flow between each nonmetropolitan place and each MSA. This approach focuses on the role of labor mobility and less on the flow of goods from nonmetropolitan to metropolitan places.

This paper's primary contribution is the comparison of three alternative structures of the spread-backwash effects for 276 MSAs on population growth in 1,988 nonmetropolitan Census places across the U.S. from 2000 to 2007 to understand the potential contributions of multiple cities to nonmetropolitan spread effects. Theoretically, the inverse-distance model of multiple cities is attractive, as the nearest city model is inflexible to market shifts that change commuter behavior and the commuting-weighted model potentially overstates the spread effects gained through commuting (versus the flow of goods or proximity to urban amenities). Moreover, MSAs are defined partially by commuting flows, so by default nonmetropolitan places are unlikely to reflect true spread or backwash effects. The commuting approach does capture the explicit employment connections between urban and rural areas and the relative market potential of each influential city, and is therefore a tempting approach.

Second, this study lends itself to generalization more convincingly than many existing spread-backwash studies. In a response to the call from Partridge et al. (2007) for studies inclusive of more variation in urban and rural characteristics, our sample includes nonmetropolitan places and MSAs across the United States, where previous studies have generally been limited to urban areas within small regions (e.g., Henry, Schmitt, and Piguet, 2001; for a notable exception, see Partridge et al., 2007). The inverse-distance model also fills another gap identified by Partridge et al. (2007, p. 129): the measurement of "a continuous influence of distance on urban growth spillovers."

2. BACKGROUND ON SPREAD-BACKWASH CONCEPT

The spread-backwash concept was introduced in the 1950s with the nearly simultaneous publications of Hirschman (1958) and Myrdal (1957). Hirschman's "trickling down" of urban influence on outlying areas is conceptually analogous to Myrdal's spread effects. According to Hirschman (1958, p. 188), the most important of the positive effects are the more developed region's "purchases and investments" in the less developed region. In contrast, Hirschman's negative (backwash or polarization) effects include migration from the rural area to the more developed region, especially of the more skilled and trained workers, and weak production in the outlying region, caused by superior urban competition.

As summarized by Barkley, Henry, and Bao (1996), the flow of investment funds, spending for goods and services, people, firms and employment, knowledge and technology, and government outlays result in positive and negative growth implications for rural areas. These implications range from the life-cycle theory movement of firms to the fringe (providing spread effects) to the investment of rural funds in expanding urban markets (backwash effects). Whether these flows occur, or to what extent they occur, relies on a range of factors, including production methods, distance, and the context of the outlying locations, such as whether the locations offer high quality public services and lower public sector costs (Henry, Barkley, and Bao, 1997). While most research, including that presented here, favors the predomination of spread effects, the range of flows and the preconditions guiding the magnitude of flows presents the possibility that backwash effects could dominate (e.g., Barkley, Henry, and Bao, 1994).

At its simplest, spread and backwash can be measured by either population change or income change as a function of distance to and growth in the nearest city (Berry, 1970; Gaile, 1980). Regardless of a town's economic structure or amenities (though these features certainly matter, as discussed below; see also Blank, 2005), it is possible for the community to grow if its excess labor can access the city, or if the community can access the urban service and recreation sectors. As Partridge et al. (2007) describe, the concept of population growth effects that are solely attributable to distance to the urban center can be called the urban distance discount (UDD). In addition to the UDD, several factors may influence spread and backwash effects, most notably, the income and population growth rates of the nearest city or set of cities, and the characteristics of the nonmetropolitan community, such as age and economic structure.

The transition from theory to empirics began in earnest in the late-1980s when Carlino and Mills (1987) explored exogenous determinants of county-level growth by simultaneously estimating employment and population growth. In 1994, Hughes and Holland provided the first effort to systematically evaluate spread and backwash effects in the United States, using input–output (I–O) models to examine core-periphery relationships for Washington State. A simpler approach of comparing population densities over time was used by Henry, Barkley, and Bao (1997) for eight Functional Economic Areas in the Southeast U.S. Intra-metropolitan growth was taken up by Boarnet's (1994) econometric model of spread-backwash effects introducing the spatial lag of population and employment change. The model has since been extended in various directions. Yet the mainstream research question has remained focused on how the proximity and magnitude of urban economic activity collectively impact nonmetropolitan growth (Henry, Barkley, and Bao, 1997; Henry et al., 1999; McMillen, 2004; Partridge et al., 2008; Wu and Gopinath, 2008; Portnov and Schwartz, 2009; Saito and Gopinath, 2011; for a broader discussion of this sub-topic, see Partridge and Rickman, 2007, 2008; Ali, Olfert, and Partridge, 2011). This body of literature tends to find that proximity to both central cities and to clustered economic centers outside the central city positively influence growth beyond the metropolis.

Scholars have researched a range of related questions less germane but still relevant to the spread-backwash topic. Popular areas of focus have included the roles of agglomeration economies, amenities, and the rural labor force. Few papers deal solely with the role of agglomeration economies in delivering spread-backwash effects. One exception is Partridge and Rickman (2008), who find that the benefits of urban agglomeration diminish with distance (see also van Soest, Gerking, and van Oort, 2006), resulting in insufficient rural labor responses to labor demand. In brief, they find that in response to a one standard deviation increase in the industry growth rate of the nearest city, poverty rates decrease three times more in urban-adjacent rural counties (−0.3 percent) than in counties 90 km away (−0.1 percent). Agglomeration studies otherwise tend to focus on causes of agglomeration, such as clustering of production (Puga, 2010) and metropolitan skill level (i.e., Glaeser and Resseger, 2010). The question of agglomeration as a driver for economic growth is taken up most notably in the New Economic Geography (NEG) literature (e.g., Krugman, 1991; Overman, Rice, and Venables, 2010) and spatial econometrics (e.g., Storper, 2010), which theorize and model the rise of industrial centers. Krugman's original formulation for NEG combines agglomeration forces from monopolistic competition models of firms and dispersion forces from transport costs to an immobile rural population to solve for the optimal size of urban centers. In other words, urban and rural places are connected by proximity and supply and demand of goods and labor.

More recent work explores the effect of amenities versus agglomeration on growth (e.g., Park and von Rabenau, 2011). Its outcomes reveal significant aspects of path-dependent development (Portnov and Schwartz, 2008). This literature finds that across the U.S. and Canada, amenities rather than agglomeration drive urban growth, while the opposite is true for nonmetropolitan areas (Adamson, Clark, and Partridge, 2004; Ferguson et al., 2007). Even so, amenities appear to drive migration more in the U.S. than in Canada, where the population centers parallel the country's southern border (Partridge, Olfert, and Alasia, 2007)—a historical pattern that has continued to influence development patterns.

A large body of work focuses on the development roles of natural resource-based amenities and public services in the New West (e.g., Carruthers and Vias, 2005) and elsewhere (Deller et al., 2001; Kim, Marcouiller, and Deller, 2005; Deller and Lledo, 2007; Deller, Lledo, and Marcouiller, 2008; Chi and Marcouiller, 2011). However, this work does not focus on the ties between urban and rural regions. Papers such as Nzaku and Bukenya (2005) look more holistically at place-based amenities, but focus primarily on natural resource and climate-based amenities. Deller et al. (2001) advance this work, expanding the Carlino and Mills (1987) model to assess amenities' role in economic growth. Their model includes previous population size and measures of market size and labor supply, but focuses on neither agglomeration nor urban–rural linkages. Henry, Barkley, and Bao (1997) consider place-based amenities factoring into business and household location decisions, such as school quality, labor force quality, housing age, etc. McGranahan and Wojan (2007) relate amenities to the creative class to model economic growth for urban and rural counties.

Commuting is a key delivery mechanism of spread effects. Though they do not frame their work as a spread-backwash study, Moss, Jack, and Wallace (2004) study the economic effect of urban proximity through the use of rural-to-urban commuting as a means of sustaining rural communities. Partridge, Ali, and Olfert (2010) and Renkow (2003) explore the issue of rural commuting, finding that while in-county job growth reduces out-commuting, job employment growth in nearby cities remains the larger contributor to nonmetropolitan growth. Yet even with growing job accessibility, selective out-migration remains an important demographic force for nonmetropolitan places experiencing spread effects (Corcoran, Faggian, and McCann, 2010).

Studies explicitly focused on spread-backwash effects are more limited. Most focus on growth within a single region (e.g., Henry, Schmitt, and Piguet, 2001) to expand our empirical frameworks. Partridge et al. (2007) explicitly consider spread-backwash effects in a multi-region sample over a sustained period of time. As they state, they are the first to employ a national scale and a Canadian setting. Rural policy development with similar data work also appears in Partridge, Olfert, and Ali (2009) and Partridge and Rickman (2003b). Given the magnitude of spread-backwash effects for rural economic growth, we believe having measurements of these effects throughout the United States can help inform rural development policy.

3. U.S CONTEXT AND SAMPLE

Given descriptive statistics about U.S. nonmetropolitan places, nonmetropolitan residents likely commute to urban labor markets and often have access to multiple cities. The vast majority of nonmetropolitan places are relatively close to an MSA. Of the 1,988 nonmetro communities studied, 59 percent are within fifty miles of the primary central city of an MSA, and 13 percent are within 25 miles (Figure 1). On average, each place is within 100 miles of four central cities. Despite the proximity, these places are in nonmetropolitan counties, meaning that there is not a strong commuting tie to the MSA's central county.

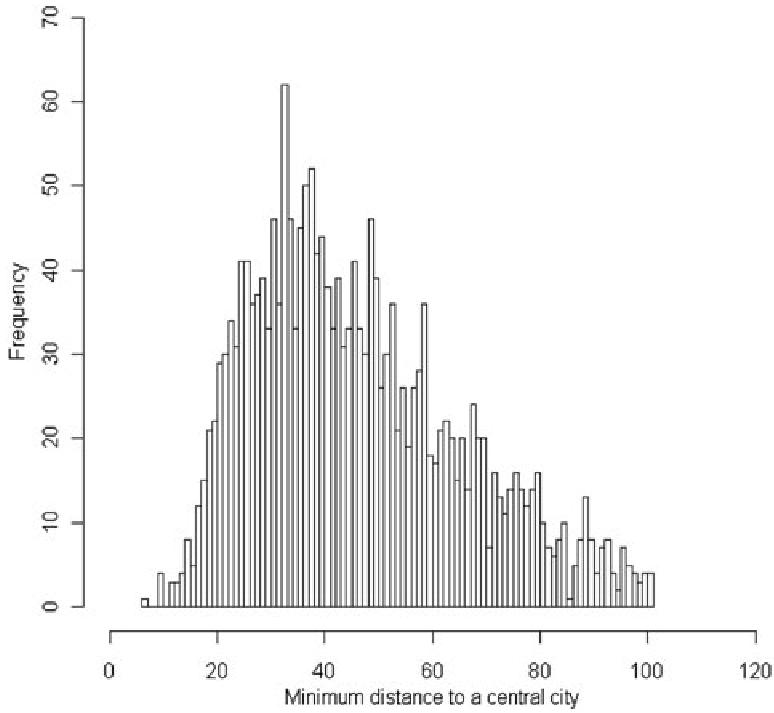

FIGURE 1: Distribution of Distance (miles) between Communities and Nearest MSA.

Our sample includes 276 MSAs and 1,988 nonmetropolitan communities (incorporated Census places[1]) across the U.S. (Figure 2). Nonmetropolitan communities include places outside central or outlying metropolitan counties using the 1999 Office of Management and Budget (OMB) definition for MSAs (Office of Management and Budget, 2009). The sample is restricted to Census Designated Places that are incorporated or are minor civil divisions in selected states. Many MSAs changed boundaries between 2000 and 2007. Places that were nonmetropolitan in 2000 and metropolitan in 2007 were not excluded from the sample. Excluding these places would prevent observation of the places that are gaining dramatic spread effects via commuting. Table A1 provides a comprehensive list of the variables with data sources.

4. EMPIRICAL SPECIFICATION AND DATA

The model's structural form follows the literature (Greene, 1997; Partridge and Rickman, 2003a; Rappaport, 2004a, 2004b; Partridge et al., 2007). These papers develop and build on a partial adjustment model using population change as the dependent variable. Population density in year t is assumed to be a weighted average of the actual population in year 0 and the equilibrium population density demanded by the representative household. As noted by Partridge et al. (2007), the equilibrium density is assumed to be a function of location-specific amenities and economic characteristics of the region

[1]Roughly 400 Census Designated Places had to be removed from the sample because population estimates for 2007 were not available. The Census Bureau provides population estimates for all incorporated places and minor civil divisions in selected states; not all Census Designated Places are incorporated.

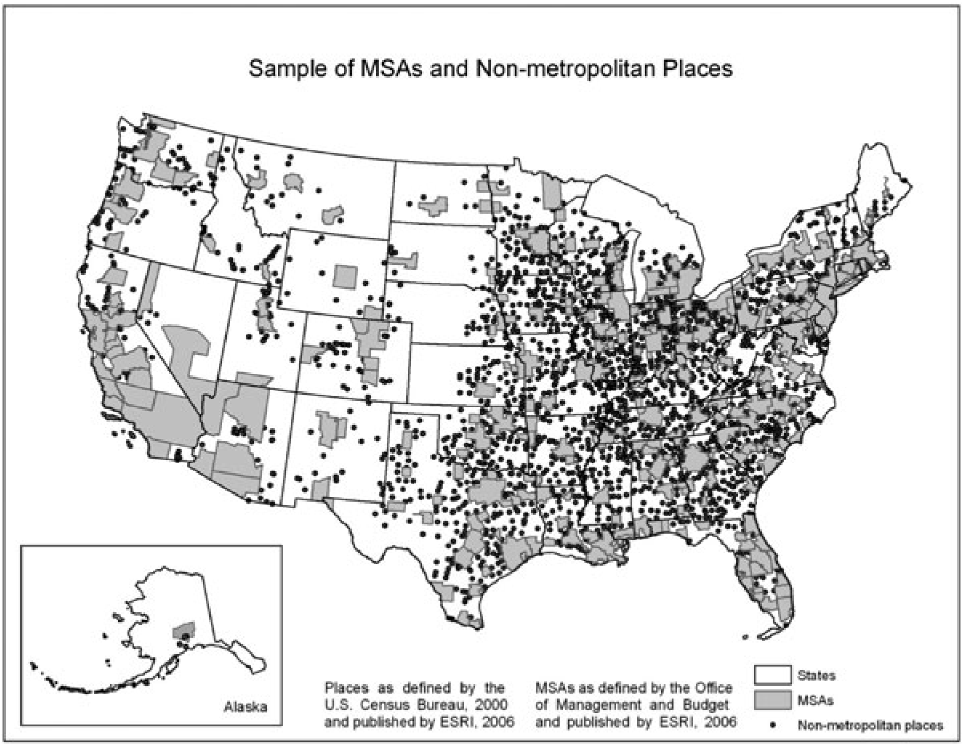

FIGURE 2: MSAs and Nonmetropolitan Places Used in Study.

(X). The parameter λ reflects the adjustment speed.

$$PD_{it} - PD_{i0} = \lambda \beta X_{i0} - \lambda PD_{i0}, \quad (0 \le \lambda \le 1). \tag{1}$$

The left-hand side can be represented by the percentage change in population, since the land area, which would make the left-hand side a density calculation, is differenced away. For a fuller discussion of the appropriateness of using partial adjustment models, see Partridge et al. (2007). We measure spread and backwash effects by modeling the community population change between 2000 and 2007. This time period was selected to reduce changes in the boundaries of MSAs and community definitions which could result in population growth by annexation. The independent variables are measures of economic and other location-specific characteristics from the initial year (2000), and are assumed to reflect household utility and firm productivity over time. Our goal is to estimate the effect of the nearby city or multiple cities on population growth.

The specification of the full models follows from the reduced form partial adjustment model given in Equation (1) and the three approaches to conceptual measurement: using the nearest city only, weighting cities by inverse-distance, and weighting cities by commuting flow from nonmetropolitan place to MSA. The full specification for each conceptual measurement includes three groups of variables, *spatial*, *control*, and *state*.

The *spatial* variables include the key spread-backwash variables. Spread-backwash theory revolves primarily around the growth benefits of urban proximity, urban income growth, and urban population growth. Therefore, the *spatial* variables include distance (not inverse) to the nearest MSA, income (average annual pay) growth and population growth in the nearest MSA. Starting year population and income values were included to

TABLE 1: Summary Statistics for Key Spread-Backwash Variables

	Nearest city		Inverse-distance		Commuting weighted	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
Place-level population, 2000	8,410	7,662	8,410	7,662	8,410	7,662
Place-level % change in population*	1.42%	10.68%	1.42%	10.68%	1.42%	10.68%
Distance to nearest central city (miles)	45.97	19.47	61.38	14.96	124.63	152.66
Distance to nearest medium tier MSA	32.80	9.37	35.74	32.11	18.55	105.35
Distance to nearest large tier MSA	25.87	20.77	23.7	31.2	47.73	156.89
Nearest MSA population, 2000	461,351	841,286	579,057	564,790	1,632,672	2,152,533
Nearest MSA % population change*	6.47%	6.75%	6.81%	5.28%	8.07%	5.89%
Nearest MSA income, 2000	$25,989	$3,651	$26,270	$2,649	$28,591	$3,610
Nearest MSA income change*	29.63%	8.27%	29.62%	6.59%	29.16%	7.00%
Nearest MSA industry mix component	0.098	0.017	0.098	0.01	0.1	0.01

*Change between 2000 and 2007.

account for urban hierarchy effects; larger cities likely have spread effects over longer distances than small cities (Ali, Olfert, and Partridge, 2011). Distance squared to the nearest MSA is included to detect nonlinearities. Finally, the *spatial* set includes a dummy variable indicating the urban tier level of the nearest city (population <100,000, 100,000–500,000, and >500,000) and its interaction with its distance to the nonmetropolitan center. Urban tier information is incorporated as a measure of market potential, as discussed further below, and as a means of incorporating the interaction of distance and city size into the model, following Partridge et al. (2010).[2] The urban tier information also provides a test of Central Place Theory (Christaller, 1966), which states that the highest order places provide markets and goods that lower order places cannot supply. Thus, the stronger markets of higher order places should have stronger spread effects on nonmetropolitan places.

All measures of distance were constructed using Census point data for places, provided through ESRI, to define the coordinates of each community and the central city of each MSA. For MSAs with two central cities, the x and y coordinates of the principal city were used. The distance was then taken using the great circle distance between the points.

Table 1 gives summary statistics for the key *spatial* variables. As the summary statistic of nearest MSA population and its growth shows (rows 6 and 7, Table 1), the commuting-weighted model reflects nonmetropolitan commuters' access to much larger and faster growing cities than do the other two models. The difference in population size is the result of a very few large MSAs that are heavily weighted in the commuting model.

We hypothesize that coefficient signs will be consistent across models. The inverse-distance models use the inverse distance only for weighting the sample of influential cities. The distance and distance squared terms in the models, for both distance to the nearest city and the urban tier cities are not inverse distance, to ease interpretation.

The *control* variables account for the industry mix effect, economic and demographic characteristics, and recreation amenities of MSAs, as well as demographic and economic conditions in the observed nonmetropolitan communities. The industry mix effect captures changes in the employment demand over the period in the MSAs, since labor demand is central to the decision to commute rather than migrate from the nonmetropolitan

[2]To clarify, Partridge et al. (2010) use an incremental measure of distance to the nearest medium and large city, meaning that they subtract the distance to the nearest city from the distance to the medium or large city. Here we use continuous, total distance in all applications. In our application, this was done to allow the UDD calculation for each tier of city.

community. To reduce multicollinearity, for each model the *control* variables were weighted using the respective weighting scheme then put into a principal components analysis. The factor scores for components with an eigenvalue of at least 1.00 were used.

Finally, state-level fixed effects were incorporated using Missouri as the reference state. These *state* fixed effects control for large-scale migration patterns, thereby controlling for otherwise undistinguished climate, lifestyle-based amenities, and regional economic and housing market conditions (such as the effects of land use regulations on housing, that is, Glaeser, Gyourko and Saks, 2005). These fixed effects also help control for variation in county size across the U.S.; counties in the American West are much larger than those east of the Mississippi River. Consequently, Western nonmetropolitan places are likely farther from central cities than are eastern nonmetropolitan places, since the county is the building block of MSA definitions.

In general, the models are specified as given below (2).

$$
\begin{aligned}
(2)\qquad G_{i(t-0)} &= \alpha + \theta \mathrm{POPDEN}_{i0} + \psi\,\mathrm{SPATIAL}_{i0} + ß_1X_1 + ß_2X_2 + ß_3X_3 \\
&\quad + ß_4X_4 + \gamma\,\mathrm{STATE}_{i0} + \varepsilon_{i(t-0)},
\end{aligned}
$$

where G_i = percent population change in community i; $X_{1\ldots4}$ terms represent the components (constructed from the *control* variables), defined in the principal components analysis. The specification in Equation (2) illustrates the functional form in generalities.

For the nearest MSA models, the specification in Equation (2) is straightforward. The second and third models assume that nonmetropolitan places realize spread and backwash effects from multiple MSAs. Consequently, the *spatial* and *control* variables must be constructed from the multiple MSAs that are assumed to influence each nonmetropolitan place. The inverse-distance model uses a row-standardized weights matrix consisting of the inverse distance between each nonmetropolitan place and the MSAs within the selected distance band (101 miles) of each place to construct one composite city with a population, distance from each nonmetropolitan place, and other characteristics. The 101-mile threshold represents the distance of the nonmetropolitan community from the nearest MSA at one standard deviation greater than the mean distance to an MSA. The commuting model uses a row-standardized weights matrix of commuting flows from each nonmetropolitan place to each MSA within the same spatial limits to construct its composite cities.

The distance term and its square are calculated by multiplying the respective weights matrices with the great circle distances between each MSA and nonmetropolitan place to calculate one composite distance. This approach has the benefit of capturing influence from multiple MSAs, where traditional models (and a limitation of Central Place Theory) would neglect a city one mile farther away than the nearest city, regardless of size. The downside, however, is that if two cities, one small and one very large, are 20 and 22 miles, respectively, from a nonmetropolitan place, the inverse-distance model will favor the smaller MSA, which is likely inappropriate. The commuting-weighted model was devised to overcome this problem, by weighting cities according to relative market potential for each nonmetropolitan place, in absence of complete nonmetropolitan I–O data. Nevertheless, both weighting approaches obscure the extent of the increased economic potential of having multiple proximate cities. The inclusion of the urban tier distances allows larger cities to have different effects on growth than smaller centers. In both the inverse-distance and commuting-weighted models, the interaction of the urban tier dummy with the distance term is constructed in a parallel fashion to the Nearest City models, replacing the "real" nearest city with the composite city made from weighting multiple influential cities.

Nine models are presented. For each approach (nearest city, inverse-distance, and commuting-weighted), the full model was arrived at in three stages, the first including

TABLE 2: Nearest City Models

	Model of key variables with distance interaction terms	Model of key variables with distance interaction terms plus control variables	Full model
Intercept	13.34**	28.79***	33.22***
	(5.531)	(6.198)	(6.815)
Log of population density in 2000	−1.986***	−3.814***	−2.516***
	(0.615)	(0.734)	(0.656)
Distance to nearest MSA central city centroid	−0.132*	−0.0247	−0.0748
	(0.0773)	(0.0716)	(0.0630)
Squared distance to nearest central city centroid	0.00159***	0.000504	0.000623
	(0.000557)	(0.000522)	(0.000502)
Dummy variable for medium urban tier MSA	3.524	4.405**	4.606***
	(2.508)	(2.169)	(1.429)
Dummy variable for large urban tier MSA	3.946	5.702*	8.053***
	(3.511)	(2.930)	(2.636)
Distance to medium urban tier MSA	−0.0859*	−0.0924*	−0.0625**
	(0.0470)	(0.0478)	(0.0296)
Distance to large urban tier MSA	−0.0754	−0.104*	−0.104*
	(0.0670)	(0.0600)	(0.0529)
% population change in nearest MSA	0.407***	0.252***	0.114*
	(0.0425)	(0.0578)	(0.0648)
% change in average annual pay in nearest MSA	0.0480	0.0194	0.109***
	(0.0424)	(0.0356)	(0.0406)
Population in nearest MSA, 2000	0.00137***	0.000760	0.00122**
	(0.000515)	(0.000567)	(0.000539)
Average annual pay in nearest MSA	−0.0130	−0.131	−0.169*
	(0.134)	(0.138)	(0.0953)
Adjusted R^2	0.108	0.197	0.295

Note: Significance symbols are: $*P < 0.10$; $**P < 0.05$; $***P < 0.01$.

only *spatial* variables, the second adding the *control* variables, and the third adding the *state* fixed effects. Other models were run as robustness checks, as discussed in the results.

5. RESULTS AND DISCUSSION

Tables 2–4 show the results for the period 2000–2007. These results are strongly similar to those from 2000–2006, which was included as a robustness test. The *state* variables are omitted due to space constraints. Those fixed effects generally reflect the Midwest's population decline and population growth along the coasts. The place-level and MSA-level controls, which are generally statistically significant and with the expected sign, are given in Table A2. For all three weighting approaches, the full models are reported with standard errors clustered by BEA economic region.[3]

None of the models can be rejected based on model strength; all three show reasonable and similar levels of fit. Therefore, we use tests of external validity to differentiate our interpretation of the models.

[3]The BEA economic areas are collections of counties that constitute the regional market of an MSA. Our assumption is that nonmetro areas within these regions may face common shocks, leading their error terms to be correlated. For details on the areas, see www.bea.gov/regional/docs./econlist.cfm

TABLE 3: Inverse-Distance Weighted Models

	Model of key variables with distance interaction terms	Model of key variables with distance interaction terms plus variables	Full model
Intercept	29.88***	40.16***	41.63***
	(8.316)	(8.341)	(7.666)
Log of population density in 2000	−1.922***	−3.489***	−2.198***
	(0.566)	(0.703)	(0.645)
Distance to nearest MSA central city centroid	−0.461***	−0.248*	−0.238
	(0.164)	(0.147)	(0.149)
Squared distance to nearest central city centroid	0.00344***	0.00175	0.00177*
	(0.00125)	(0.00114)	(0.00102)
Dummy variable for medium urban tier MSA	−2.892	−0.258	3.341
	(6.176)	(5.556)	(4.235)
Dummy variable for large urban tier MSA	1.292	4.282	7.713*
	(6.317)	(5.645)	(4.024)
Distance to medium urban tier MSA	−0.0232	−0.0330	−0.0401
	(0.0690)	(0.0653)	(0.0537)
Distance to large urban tier MSA	−0.0447	−0.0631	−0.0771
	(0.0715)	(0.0651)	(0.0529)
% population change in nearest MSA	0.518***	0.347***	0.240**
	(0.0625)	(0.0978)	(0.115)
% change in average annual pay in nearest MSA	0.0252	0.0355	0.250***
	(0.0548)	(0.0568)	(0.0823)
Population in nearest MSA, 2000	0.00192***	0.00156*	0.00369***
	(0.000671)	(0.000874)	(0.000970)
Average annual pay in nearest MSA	−0.0987	−0.339	−0.722***
	(0.195)	(0.233)	(0.190)
Adjusted R^2	0.148	0.22	0.305

Note: Significance symbols are: $^{*}P < 0.10$; $^{**}P < 0.05$; $^{***}P < 0.01$.

A negative sign on the distance term provides the first test of external validity. We expect nonmetropolitan growth to be slower with increasing distance from an MSA. All three sets of models pass this test. Next, regarding the baseline (year 2000) variables, we anticipate that larger metropolitan populations (congestion) drive nonmetropolitan growth. Theory is unclear on hypothesized signs for income and income growth. NEG suggests that higher metropolitan incomes and thus larger market potential draw people to the city. Empirical evidence argues that higher urban incomes drive increased nonmetropolitan tourism and purchase of rural goods, potentially resulting in rural growth (Partridge, Olfert and Alasia, 2007). Glaeser, Gyourko, and Saks (2005) offer a third argument, that land use regulations and density, rather than income, push urban population growth. Finally, some research indicates that migration is driven more by differences in price indices than by income differentials between places (Lange and Quaas, 2010). In other words, we hypothesize a positive sign on population but lack a clear hypothesis for income effects. Income and income change are included to build on precedent and as tests of the NEG theory.

All nine models find that population and population change in the nearest or weighted MSAs are positively related to nonmetropolitan population growth, as anticipated. In general, the models show that income change is positively related to nonmetropolitan growth while initial year income is negatively related to growth. This suggests that people

TABLE 4: Commuting Weighted Models

	Model of key variables with distance interaction terms	Model of key variables with distance interaction terms plus control variables	Full model
Intercept	2.204	22.98***	10.49
	(5.616)	(6.142)	(6.583)
Log of population density in 2000	−1.805***	−3.456***	−2.394***
	(0.524)	(0.644)	(0.659)
Distance to nearest MSA central city centroid	−0.0162***	−0.0209***	−0.0129***
	(0.00313)	(0.00319)	(0.00397)
Squared distance to nearest central city centroid	5.69e−06**	7.28e−06***	7.96e−06***
	(2.83e−06)	(2.59e−06)	(2.62e−06)
Dummy variable for medium urban tier MSA	1.550	4.226***	7.606***
	(1.238)	(1.523)	(2.634)
Dummy variable for large urban tier MSA	2.712**	5.177***	9.091***
	(1.282)	(1.553)	(2.505)
Distance to medium urban tier MSA	0.00493	0.00413	−0.00296
	(0.00520)	(0.00515)	(0.00592)
Distance to large urban tier MSA	0.00638**	0.00517**	−0.00354
	(0.00266)	(0.00235)	(0.00319)
% population change in nearest MSA	0.461***	0.353***	0.230***
	(0.0552)	(0.0738)	(0.0784)
% change in average annual pay in nearest MSA	0.0717	0.0471	0.174***
	(0.0535)	(0.0476)	(0.0645)
Population in nearest MSA, 2000	0.000407*	−0.000116	0.000379
	(0.000212)	(0.000251)	(0.000266)
Average annual pay in nearest MSA	0.146	−0.150	−0.179
	(0.140)	(0.143)	(0.134)
Adjusted R^2	0.1	0.207	0.289

Note: Significance symbols are: $^{*}P < 0.10$; $^{**}P < 0.05$; $^{***}P < 0.01$.

TABLE 5: Tipping Point Where Spread Effects Diminish to Zero, Backwash Effects Dominate

	Nearest City	Inverse Distance	Commuting
Tipping point for small city	60.04	67.12	811.34
Tipping point for medium city	110.22	78.42	997.56
Tipping point for large city	143.32	88.86	1033.51

choose to migrate to the city based on relative wages, but that growth in urban income results in spread effects.

The distance and distance squared terms primarily serve to calculate the urban distance discount (pure distance effect), or UDD. Clearly, urban proximity produces spread effects for nonmetropolitan places. Using the Full models, the tipping point was calculated where spread effects are overwhelmed by backwash effects (Table 5). This tipping point was calculated for each class of urban tier city, small (<100,000 people), medium (100,000–500,000) and large (>500,000). All three weighting schemes show that larger cities' spread effects have a broader spatial reach. Table 5 indicates reasonable ranges for the nearest city and inverse-distance models, but shows that the commuting models over-estimate the distance of spread effects.

Taken collectively, these results outline positive and negative aspects of each conceptual measurement of spread-backwash effects and all three sets of models are reasonably robust. Tradition stands behind the nearest city model. Nevertheless, the distance squared term is not statistically significant beyond the basic model, where we observe an insignificant linear distance effect. An otherwise benign multicollinearity problem[4] may prohibit the rejection of the null hypothesis regarding the base year income variables, which is also problematic. Finally, the UDD calculation ranging from 60 miles for small centers to 143 miles for large centers is likely reasonable (Table 5).

By contrast, the inverse-distance weighted models do not share these problems. Both the distance and distance squared terms are significant across the models, the urban tier and population variables show statistical significance and the anticipated signs, and the models show marginally greater strength than the nearest city models. The smaller UDD range (67 miles for a small city, 89 miles for a large city) seems reasonable and leaves the possibility that a nontrivial number of places fall beyond the reach of spread effects. An inverse-distance model includes nearby cities to which workers undoubtedly commute, as well as cities farther off (in this case up to 101 miles away) which likely receive more nonmetropolitan goods than workers. Consequently, an I–O approach may be appropriate in the selection of a distance band or sample selection of MSAs assumed to influence growth for each nonmetropolitan place. Previous work in using I–O to estimate metropolitan growth linkages (i.e., Hughes, 2009) suggests that industrial linkages and strength of ties vary by urban area size; the nuance of this work should be used to calibrate an I–O approach to selecting a distance band.

The commuting-weighted model shows reasonable model strength and the anticipated signs for distance and distance squared. Of concern here, the UDD calculation ranges from 811 miles to 1,033 miles. Speculating that the bandwidth used (101 miles) implied an impractically large labor shed, the commuting-weighted models were tested using both 50- and 75-mile bandwidths. These models yielded similarly unrealistic calculations of the UDD. MSA definitions are partly to blame, as tight commuting flows largely define metropolitan regions for the OMB. Therefore, nonmetropolitan places are by definition weakly linked to MSAs via commuting. Second, these models may suffer from having both the major determinants of commuting included (population, distance, etc.) then weighting cities by commuting flows, creating an exponential effect. Third, by focusing on the positive economic flow associated with commuting, as opposed to migration, this model may mask backwash effects. We submit the argument that models based on commuting weights may be useful, but only when implemented using a theoretical framework focused on the spread effects generated through commuting. These models should focus on municipal service provision, transportation costs, and other place-based factors that influence household location decisions.

6. CONCLUSION

This paper seeks to quantify spread and backwash effects of MSAs on population growth in nonmetropolitan communities in the U.S. and compares results generated through three approaches. We find that while all three models perform well, the inverse-distance model provides the most reliable, robust results. This finding indicates

[4]Multicollinearity here presents a nonissue, as its presence only increases the standard errors, which increases the likelihood of accepting the Null hypothesis that a given variable is statistically insignificant. As the variables in this model show statistical significance even with multicollinearity, we can be certain that any bias strengthens rather than depletes our argument.

that nonmetropolitan places may develop their local economies around multiple cities rather than only the nearest city, suggesting a collaborative approach to regional and nonmetropolitan development. Consistent with theory, the results indicate that nonmetropolitan places might benefit from urban congestion, which drives residents to seek space in nonmetropolitan places, and that urban income growth causes nonmetropolitan spread effects. The addition of state-level fixed effects strengthens the models and shows the anticipated general geographic patterns of U.S. population growth and decline.

From a policy perspective, these results imply that nonmetropolitan places should have flexibility in their planning efforts, allowing them to strategically pursue goals with different cities according to the markets, characteristics, goals, and strengths of each city. This work reinforces the growing body of literature suggesting that nonmetropolitan places must understand the geographic reach of their economic linkages to have effective growth policies (Ganning and McCall, 2012; Partridge, Olfert, and Ali, 2009; Pezzini, 2001). Importantly, work remains to be done to understand the relative influence of the nearest city versus other proximate cities. Until future research addresses that question, nonmetropolitan planning efforts should proceed with caution. For a discussion of policy implications for nonmetropolitan places with linkages to urban centers, see Ganning and McCall (2012, p. 329).

Additionally, nonmetropolitan places must be the center of their planning efforts, rather than existing as participants in one city's plan. For instance, Minneapolis' Metropolitan Council sets the policy framework for the region, including nonmetropolitan places that may not always agree with the framework. The finding that nonmetropolitan places are influenced by multiple cities implies that planning for nonmetropolitan places should be centered in each place, rather than controlled by only one of its influential cities. This policy implication is true not only for managing growth, but also for managing backwash effects of individual cities on nonmetropolitan places, especially in cases where those backwash effects overwhelm spread effects, which may be a function of distance or nonmetropolitan place characteristics.

Finally, this work implies that competitive bidding for industry may produce no net gains for nonmetropolitan places located between the competing cities. For example, despite being closer to one MSA, a nonmetro area may redirect commuters when an industry moves from the nearest MSA to a regional MSA. That this paper uses a nationwide sample helps to establish generalizable tipping point estimates which may be useful in determining the net gains associated with industrial bidding between cities for nonmetropolitan areas.

Future work could be extended along three lines. First, while the commuting-weighted model does not yield externally reliable results, it remains an important step toward weighting multiple cities in a way that captures market potential. Second, understanding the effects of urban income and income growth on nonmetropolitan growth should be examined in more depth. Our results indicate that relative income drives migration decisions, while urban income change results in spread effects, but these mechanisms deserve more attention. Third, as mentioned, work should be done to better understand the relative influence of each of a nonmetropolitan place's influential cities.

In sum, this paper compares results of a spread-backwash model using three approaches to conceptual measurement. This research has developed robust, generalizable results based on a broad, national sample and produced realistic estimates of the distance at which backwash effects overwhelm spread effects. Based on empirical findings, the inverse-distance model appears to be the best choice, though potential advancements remain. One potential advancement is a model that could distinguish between the spread and backwash effects that act through commuting and those permitted by the flow of goods. A better approximation of the level of infrastructure that permits commuter and goods flows would also enhance future research in this area.

APPENDIX

TABLE A1: Variables in Analysis

Variable name	Data source	Description
Key Variables		
Log of population density	Census 2000	Using land area only, population per mile squared
Distance to nearest central city	Census 2000 TIGER/Line shapefiles, ArcMap 9.3	Used x, y coordinates to calculate the great circle distance between each nonmetropolitan place and the first central city for each MSA
MSA-level population and population change	Census 2000 and Census Bureau Population Estimates, 2007	Level variable is divided by 1000
MSA-level income and income change	Bureau of Economic Analysis, REIS Tables	Per capita personal income, 2000 and 2007. Level variable is divided by 1000
Place-level controls		
Nonwhite	Census 2000	Percent of the population reporting multiple races or any nonwhite race
Elderly	Census 2000	Percent of the population that is age 65 or older
Education attainment	Census 2000	Percent of the population age 25+ that has at least a bachelors degree
Labor force participation rate	Census 2000	Percent of the population age 16+ that is in the labor force
Unemployment	Census 2000	Percent of the population that is in the labor force and unemployed
Urban	Census 2000	Percent of the population that is classified as urban
MSA-level controls		
Elderly	Census 2000	Percent of the population that is age 65+
Labor force participation rate	Census 2000	Percent of the population ages 16+ that is in the labor force
Afford	Census 2000	Percent of households paying less than 35% of monthly income on selected housing costs
Nonwhite	Census 2000	Percent of the population reporting multiple races or any nonwhite race
Foreign	Census 2000	Percent of the population that is foreign born
Education attainment	Census 2000	Percent of the population age 25+ that has at least a bachelors degree
Industry Mix	Census 2000, American Community Survey 2007	Sum of shares of employment in each industry multiplied by its national growth rate from 2000 to 2007. Thirteen industries used.

TABLE A2: Control Variable Results

	Model of key variables with distance interaction terms plus control variables	Full model
Nearest City Models		
MSA controls, general: housing affordability, nonwhite population share	−0.0618 (0.234)	1.441*** (0.325)
MSA controls for labor force: labor force participation rate, population share that is elderly, and education attainment (four-year degree or higher)	−1.367*** (0.295)	−1.309*** (0.275)
Place controls: population shares of elderly, educated (four-year degree or higher), and labor force participation rate	2.175*** (0.303)	1.852*** (0.327)
MSA controls: industry mix and share of the population that is foreign born	1.174*** (0.290)	0.537* (0.317)
Inverse-distance Models		
MSA controls, general: housing affordability, nonwhite population share, labor force participation	0.346 (0.303)	2.135*** (0.406)
MSA controls: population share that is elderly, and education attainment (four-year degree or higher)	−1.383*** (0.293)	−1.215*** (0.331)
Place controls: population shares of elderly, educated (four-year degree or higher), labor force participation rate, and urban population	2.017*** (0.288)	1.706*** (0.296)
MSA controls: industry mix and share of the population that is foreign born	−0.476 (0.316)	−0.0487 (0.401)
Commuting Models		
MSA controls, general: housing affordability, nonwhite population share, labor force participation	−0.323 (0.273)	0.855** (0.371)
MSA controls: population share that is elderly, and education attainment (four-year degree or higher)	−1.790*** (0.305)	−1.584*** (0.342)
Place controls: population shares of elderly, educated (four-year degree or higher), labor force participation rate, and urban population	2.330*** (0.306)	2.050*** (0.319)
MSA controls: industry mix and share of the population that is foreign born	−1.466*** (0.299)	−1.218*** (0.390)

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