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U.S. Commuting Networks and Economic Growth: Measurement and Implications for Spatial Policy

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ABSTRACT Labor market areas (LMAs) have long been a staple of regional and urban analysis. As commuting patterns have expanded over time, these areas have become larger and more complex, and the dichotomous designation of a county either belonging to an LMA or not may no longer be adequate. We apply recent advances in network science to conduct a more refined analysis of U.S. commuting patterns, and examine their effects on local economic growth. Results show that network degree and entropy measures explain variations in county per capita income growth patterns. Higher in- and out-commuting entropies are associated with lower per capita income growth, but their interaction enhances economic growth in places simultaneously open to both in- and out-commuters. Using these results, common ground may be found for creating new forms of regional governance that better reflect local realities of cross-county border flows of workers and economic activity.

Introduction

Economists have analyzed commuting as a cost borne by workers (e.g., Quigley 1998), a disutility traded against amenities of larger homes and bigger backyards (Berliant and LaFountain 2008), and as an avenue for reducing poverty within the urban spatial hierarchy (Partridge and Rickman 2008). In a

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market economy, commuting raises aggregate utility and may be essential for labor market flexibility. Commuting, however, also creates important externalities: pollution from automobiles, congestion along with worker fatigue from daily commutes that can reduce worker productivity (van Ommeren and Gutierrez-i-Puigarnau 2009), and increased transmission of infectious disease (Balcan et al. 2009; Viboud et al. 2006). Glaeser and Kahn (2003:6) write that "increasing reliance on the automobile increases the costs of failing to properly address congestion externalities" while Putnam (2000:213) notes that "each additional ten minutes in daily commuting time cuts involvement in community affairs by 10 percent." From a central planning perspective, daily exchange of similar types of workers across county lines within the same megalopolis at least raises the prospect of waste, inefficiency, and creation of social problems. Understanding the full range of impacts of commuting and how to attenuate negative impacts through more effective governance and better policy is important, particularly given the persistence and continued growth of commuting. In rural policy analysis, the growing role of commuting is becoming more widely recognized (e.g., Johnson, Otto, and Deller 2006).

Commuting patterns are typically used by researchers and government agencies as the basis for defining local labor market areas (LLMAs or LMAs; OECD 2002; Tolbert and Killian 1987), commuting zones (Tolbert and Sizer 1996), and travel-to-work areas (Smart 1974). The delineation of nonoverlapping local labor market areas involves clustering of contiguous places largely on the basis of commuting patterns and often along jurisdictional lines. The boundaries of the LLMAs are updated as commuting data become available through, for example, a new Census (Coombes and Casado-Diaz 2005). The successive updating of the LLMAs' boundaries as commuting patterns change provides a snapshot of the spatial evolution of labor markets. However, over time urban labor markets have become much larger and more complex, spurring interest among urban planners, geographers, and regional scientists in understanding *intra*-LLMA dynamics and the characteristics of overlapping labor and commuter sheds within metropolitan areas.

Research is now beginning to emerge, largely in the urban literature, suggesting that commuting exhibits certain network properties (e.g., De Montis et al. 2005; Shearmur and Motte 2009). But the emerging science and tools of social and economic network analysis (e.g., Borgatti et al. 2009; Jackson 2008) have yet to be applied to fully understand and categorize commuting networks. Rural research generally has not considered the network properties of commuting, either rural-to-urban or rural-to-rural; rare exceptions include Green (2007) and Han, Goetz, and Lee (2009). Network analysis has the potential to provide important insights into the *characteristics*, *mechanisms*, and *evolution* of change as rural areas become more connected to each other through commuting or as rural areas transform to a more exurban-suburban-urban environment. As noted recently in *Congressional Quarterly Weekly* (Benson 2009), in the U.S. the line between rural and urban is becoming increasingly difficult to define, as sprawling urban areas "blur" the rural–urban threshold.[1] In fact, a surprising number of U.S. rural areas are already closely tied to suburban and urban places within commuting distance (Findeis, Brasier, and Salcedo Du Bois 2009; Partridge, Ali, and Olfert 2010).[2]

The presence of commuting *networks* and their effects on economic growth need to be explored to understand the implications of commuting for regional development policies, especially for rural areas. For example, environmental externalities associated with commuting could be more than offset by higher economic growth. If this is indeed the case, then it could make sense to assess options for developing well-designed regional systems that recognize the reality of cross-county commuting. This could enable planning for more environmentally balanced twenty-first-century transportation systems and related governance systems that reduce negative spillovers from commuting but capture the positive effects of potentially stimulating growth in networked rural counties while reducing congestion at the urban core.[3] Current discussions surrounding where infrastructure stimulus investments ought to occur make such an analysis even more important and compelling (see also Kandilov and Renkow 2010). A range of issues salient to policy makers and rural people can be addressed.

In this article we seek to understand commuting networks and how they influence local economic growth. Whether or not commuting conveys benefits in terms of higher economic growth within a county is an empirical question. For rural areas, commuting implies, on average, a greater variety of face-to-face contacts over the course of a work week. Commuters arriving at work from other areas may bring with them new ideas, and those returning to their homes may transmit tacit knowledge spillovers that facilitate economic growth locally. McCann and Simonen (2005:466) observe:

> It is now a standard theoretical assumption in the general literature on innovation processes and systems of innovation (Caniels 2000; Cantwell and Iammarino 2003; Acs 2002; Breshi and Lissoni 2001), that face-to-face contact between individuals promotes local innovation and growth via localized knowledge flow. Moreover, there is also much empirical evidence, which points to such localization tendencies.

But this is likely to be only part of the potential effect. Local consumption of goods and services, and the associated economic impacts of greater spending by new commuting residents or by long-time residents now able to access better jobs, may be influenced by commuting networks (Shearmur and Motte 2009). The result may be positive impacts on rural areas that become connected to the megalopolis or to each other (e.g., Partridge, Ali, and Olfert 2010 for the case of Canada), although Deller and Deller (2010) suggest that crime rates may also rise as a result of greater integration. Further, the potential for leakages also exists, i.e., spending elsewhere when local rural residents increasingly out-commute.

The greater connectedness between many places has implications for the debate about governance issues and the best balance between the responsibilities of the central cities and the suburbs (or in our case, places now or soon to be "connected" to commuting networks—rural-to-urban or rural-to-rural). This is particularly important today as there is evidence, presented by van der Laan (1998) and others, to suggest that newly emerging regional economic structures are horizontal as opposed to more traditional hierarchical organizations (Patuelli et al. 2009). From an understanding of the structure and implications of networks, best practice policy recommendations for increasingly "connected" rural counties can be developed.

Complex Networks: A Framework for Understanding Dynamic Ties between People and Place

Network science provides a unified framework for characterizing network structure. While not novel, network science has developed rapidly in recent years in both the natural and the social sciences (e.g., Barabasi and Albert 1999; Borgatti et al. 2009; Dorogovtsev and Mendes 2003; Jackson 2008; Wasserman and Faust 2007). The literature on urban commuting behaviors (e.g., Patuelli et al. 2009) is beginning to fill the void for urban places, focused on characterizing urban networks to understand overlapping urban labor sheds and urban–suburban linkages. Even as recently as 2005, McCann and Shefer concluded that few urban studies had focused on *intra*-metropolitan linkages, and Shearmur and Motte (2009) very recently concluded that surprisingly few studies have analyzed the economic mechanisms linking central city to suburb. The literature has given rise to the idea that commuting patterns are resulting in polycentricity, what are referred to by Batten (1995) as "network cities" or "city networks"; labor sheds and commuter sheds are found to be overlapping (Ali, Olfert, and Partridge 2008), and increasingly so. That is, an urban center can be tied to multiple other urban centers, creating overlapping labor sheds reflecting the reality of economic ties. Pumain (2004) convincingly shows how the once distinct labor markets in Germany's Ruhr region are now tied to each other by commuting flows, and Nordregio (1999) demonstrates this "merging" of cities for much of the EU.

Recent studies (e.g., Coombes and Casado-Diaz 2005; De Montis et al. 2005; Gorman et al. 2009; Shearmur and Motte 2009) are extending what is known about networks, and transportation systems (urban streets, airlines) networks have been studied in detail (e.g., Barrat et al. 2004; Jiang and Claramunt 2004). This literature has yielded interesting arguments and empirical results: Coombes and Casado-Diaz hypothesize that there are likely to be differences between workers on the basis of the structure of their jobs, with higher-wage workers making longer commutes (and probably engaging in more innovative patterns of work such as "split-site" and telecommuting) and workers employed in lower-paying jobs working closer to home. Of course, as also pointed out by Coombes and Casado-Diaz, working multiple part-time jobs also implies additional travel and tends to be concentrated among those with lower-wage employment. De Montis et al. (2005) find that "a constant fraction of the population of every city commutes to another town, irrespective of the size of the city" (p. 19). Throughout this literature there is also the general finding that suburban places are often interconnected, with each being connected in some way to the urban core.

But the implications of commuting for rural places using a network approach are virtually unexplored. Commuting is important within rural research, but researchers have tended to focus on net commuting (e.g., Partridge, Ali, and Olfert 2010; Partridge, Rickman, and Li 2009) rather than on gross in- or out-commuting flows, which may miss important relationships. The evolution of metropolitan networks can be expected to lead to transitions in adjacent rural places, and the impacts of and mechanisms underlying these transitions are not yet well understood. Understanding network evolution can contribute not only to understanding economic and cultural impacts but also help to answer questions relative to changing ecosystem function and land use along the rural-to-urban transition gradient, processes of critical importance to rapidly transitioning landscapes (Findeis, Brasier, and Salcedo Du Bois 2009). Additionally, commuting networks tie rural places to each other and rural "connectivity" continues to increase. As an example, since at least 1980, farms in the U.S. have seen substantial growth in rates of off-farm employment by family members (Findeis, Swaminathan, and Jayaraman 2005), with some very long commutes.

Commuting networks can be viewed as a frame for transmitting knowledge (e.g., Caragliu and Nijkamp 2008), information, and capital as well as people, and these in turn are keys to economic growth. County-to-county commuting patterns represent complex social and economic interactions between regions that involve workers, firms, industries, residential communities, transportation, and amenities, and they are influenced by strong forces including agglomeration economies. Patuelli et al. (2009) point out that while Krugman (1991) and others (e.g., Rossi-Hansberg and Wright 2006) have analyzed relationships between growth in urban areas, agglomeration economies, and commuting costs, "A point of concern is that, in these spatial (growth and interaction) models, the effects of spatial typology and connectivity are only implicitly included, but never explicitly considered and discussed" (Patuelli et al. 2009:257). We maintain that it is essential to analyze these commuting network patterns to understand the underlying social-economic systems and to evaluate their contributions to economic growth, including growth in rural counties.

In this article we explicitly measure the commuting network and use the network as a frame to examine the effect of commuting networks on economic growth. In the following section, we describe the network approach, focusing on two measures of centrality—degrees and entropy—used to characterize nodes within the network. These measures summarize two distinct ways of assessing in- and out-commuting patterns and serve as key variables within an economic growth model.

Network Characteristics and Commuting Flows: Measurement in a Complex Network

When commuting is viewed as a network, counties represent the organizational units that form the nodes (n) or vertices of the commuting network. The flows of commuters between counties are then the commuting network's links (l) or edges.[4] A number of different measures can be used to describe a network. These measures may describe the structure and characteristics of the network, as well as characteristics of individual nodes and ties among nodes (see, e.g., Jackson 2008; Wasserman and Faust 2007).

A key concept in network theory is that of a node's centrality (prominence or prestige). In directed and weighted networks—with a clear origin and a destination county for commuters, for example, and with data on the number of commuters—important measures of this concept include the in-degree and out-degree of a county in the commuting network. A county's in-degree is the total number of in-commuters into the county, and it reflects the commuting attractiveness or receptivity of the county. This may reflect the number of employment opportunities in the receiving county. A county's out-degree is the total number of commuters leaving the county and measures the degree to which a county supplies workers to other counties. Nodal degree is among the most commonly used centrality measure in network analysis and provides key information about a node's relative importance within a network. It is important to control for degrees in statistical analyses (Wasserman and Faust 2007:127).

Recently, Borgatti (2005) proposed a new typology for categorizing a node's attributes. The Borgatti typology goes beyond network measures of routes in the network to consider "the method by which the traffic spreads" (Tutzauer 2007:2).

The route that traffic follows includes such network measures as paths, geodesics, walks—each describes a specific pattern of the route. For example, a commuting path would describe the typical commute from residence to place of work, possibly passing through multiple nodes but not allowing for repetition of nodes. The shortest path is called a geodesic, and the walk allows for repetition of nodes. While measures of routes are well developed in the literature, measures of spread are not but are shown to be important in understanding networks by Borgatti's classification.

To fill this void, the relatively new centrality measure of entropy (including both in- and out-entropy) has been applied to social and economic networks (Tutzauer 2007); entropy in this context is a measure of spread consistent with the Borgatti typology. As described by Tutzauer (p. 3): "For a flow beginning at a specific node, the centrality of that node is related to the distribution of the probabilities that the flow stops at each of the nodes in the network and it is equivalent to the information content of a communication system. . . ." In many respects, the entropy measures capture the extensiveness of the network over which flows of information and communication can occur, and as described by Patuelli et al. (2009), the extent to which flows are more homogeneous and dispersed. In the case of commuting networks, consumer expenditures and flows of capital can also occur along the multiple links of the network.

Suppose that m_{ij} is the number of people who live in county i and work in county j. The information content of county j's commuter in-flows can then be calculated using the normalized entropy measure ε_j:

$$\varepsilon_j = -\left(\sum_i p_{ij} \log_2 p_{ij}\right) / \log_2 N \quad (1)$$

for $p_{ij} \neq 0$ and $i \in V = \{1,2, \ldots N\}$, which is a set of nonempty and finite nodes, with N representing the total number of relevant nodes (U.S. counties).[5] As noted, m_{ij} is the raw number of commuters from i to j, $p_{ij} = m_{ij}/\sum_i m_{ij}$ is the commuter-weighted probability that county j receives commuters from county i, and the sum runs over all counties that send commuters. Analogously, summing over j in (1) yields the out-entropy value for county i. Division by log N transforms this to a 0–1 scale and facilitates comparisons with other studies (Shannon 1948).

In-entropy or in-commuting entropy (ε^{in}) is highest when counties are "hubs" for commuters, receive those commuters from a diverse set of sending counties, and their commuter flows are spread unevenly across the sending nodes. Out-entropy or out-commuting entropy (ε^{out}) is highest when local out-commuters head out to multiple (work) locations in uneven numbers to more nodes within their commuting networks (i.e., entropy is higher for a county that sends a few workers to many counties compared with one that sends many workers to a few counties, but the relative distribution or shares of workers across the counties also matters, according to this equation). If a county receives commuters from only one other county, generally itself, then it has the lowest in-entropy value, 0. At the other extreme, a county may have zero residents working in the county (i.e., all workers commute in). Likewise, when a county receives workers from a number of different counties, then the in-entropy value is higher than if the county only draws in-commuters from one other county. Similarly, if a county sends commuters to multiple other counties, then it will have a high out-entropy value, holding constant total degrees. High values of ε^{in} identify a business hub (central business district) while high values of ε^{out} represent a bedroom community. Note that the two centrality measures used here—nodal degree and entropy—indicate two very different meanings of centrality. Nodal degree simply indicates centrality of a node in terms of the sheer volume of in- and out-commuters. Entropy indicates centrality to the network in terms of the relative spread of commuters into and out of the county. In both cases, higher values indicate greater centrality of the node or place.[6]

Application to Commuting Networks in the U.S.

Before analyzing centrality measures for specific U.S. counties, it is worth first asking whether commuting can even be considered a complex (interactive) network. Researchers often test for network structure by examining whether the degree distribution follows a power law (Barabasi and Albert 1999). The degree distribution of in- and out-commuting for U.S. counties provides a first clue that commuting is a complex network: it generally, although imperfectly, approaches a scale-free power law (Figure 1). A comparison of U.S. commuting flows between 1970 (not shown[7]) and 2000 reveals very large increases. Indeed, U.S. population mobility has increased markedly, as it has in many regions of the world (Findeis, Brasier, and Salcedo Du Bois 2009).

Figure 2 shows commuting in-entropy measures for U.S. counties, with counties categorized into quintiles and only the two highest quintiles shown. Figure 3 reveals patterns that are more dispersed (with clusters of, or contiguous counties with, similar values) in the case of out-entropy as compared with in-entropy. In other words, commuting destinations tend to be more highly concentrated than commuting origins, as is also evident in the maps in Chrest and Wheaton (2009). Finally, counties with high in-entropy, high out-entropy, or both are shown with increasingly darker shading in Figure 4.[8] Four distinct clusters or super-mega-regions emerge: New York City; Washington, DC; Atlanta; and Minneapolis-St. Paul. The two latter, especially, contain a high in-entropy core encircled by counties with both high in- and out-entropy.

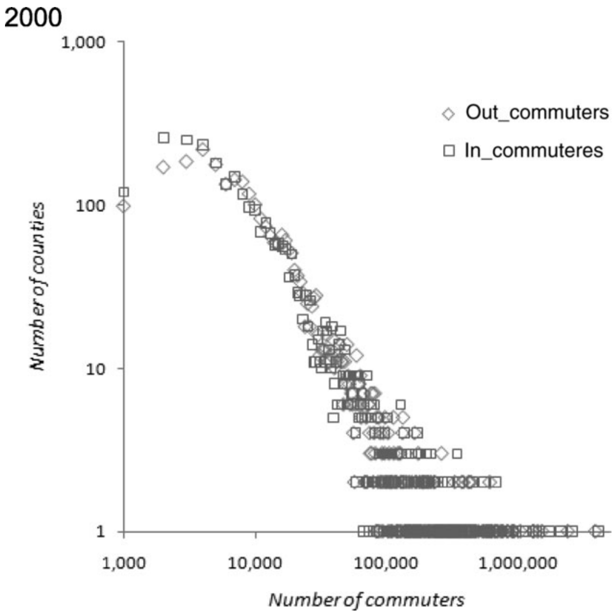

FIGURE 1. THE COMMUTING DEGREE DISTRIBUTION.
Note: The horizontal axis measures the number of commuters into and out of counties, and the vertical axis is the number of counties with the given number of commuters. (A pattern of straight lines in this log formulation suggests that commuting has features of complex networks, although the wide dispersion of points along the vertical axis—a few counties with a range of commuter numbers—indicates otherwise.).

Not surprisingly, New York City, Arlington, VA, and Fulton County, GA lead the list of counties ranked most highly by in-entropy (Table 1), with New York City having the highest value (0.294). Fifth highest is Scott County, KY, home to Toyota USA Motor Manufacturing Corp., which attracts workers from across the state as well as Indiana and Ohio. With the exception of Tunica, MS and Plaquemines Parish, LA, the remaining counties comprising the 20 highest-ranked counties are all around New York City, Washington, DC, or Atlanta, GA. At the other end of the distribution are two counties in Nebraska and one in Texas, each with in-commuting entropy values equal to zero. The 10 remaining lowest-ranked counties are all in the U.S. West, with the exception of Aroostook, ME.

As commuting is defined officially using cross-county flows, the measure is a function of a county's size. In the U.S. West, counties inherently cover more space,

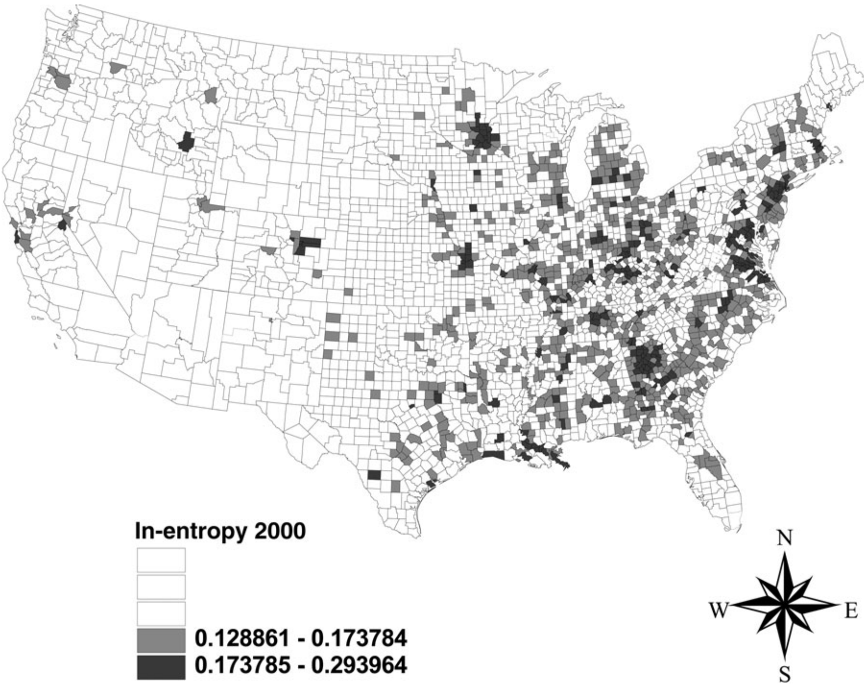

FIGURE 2. COMMUTING IN-ENTROPY VALUES (SHOWING THE TOP TWO QUINTILES ONLY).

and therefore western counties unsurprisingly do not appear on the list of high entropies. Ignoring this fact could lead to biased regression estimates, which would be an artifact of the definition. To alleviate this concern, we control for both county area and population density in the subsequent regressions (and also run separate regressions using only counties east and west of the Mississippi River).

Pike County, PA ranks highest, with a value of 0.322 on the out-commuting entropy measures. Pike is the fastest-growing county in the state, and it has large commuter out-flows to other counties proximate to New York City; in 2000 10.4 percent of Pike County residents commuted to Orange County, NY; 10.1 percent to Wayne County, PA; 9.6 percent to Monroe County, PA; 8.7 percent to Sussex County, NJ; 6.4 percent to Morris County, NJ; and 5.3 percent to New York, NY. Only 28.7 percent of Pike County residents worked within the county. In fact, the two highest in- and out-commuting counties are in each other's commuting sheds. Five of the eight highest-ranked counties on the out-commuting entropy measure are in Virginia, while the 20 lowest ranked are in the West, with

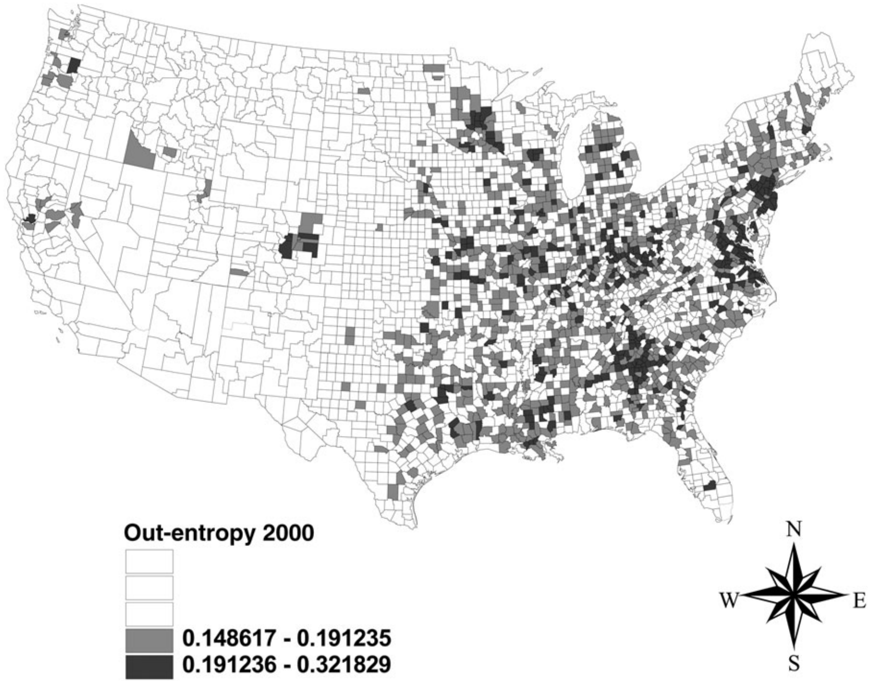

FIGURE 3. COMMUTING OUT-ENTROPY VALUES (SHOWING THE TOP TWO QUINTILES ONLY).

three important exceptions: Nantucket, MA (rank 2), Dukes, MA (14), and Monroe, FL (15). Shifts in the rankings of counties are evident across the 1970–2000 period as more counties became integrated into commuting networks that spread into adjacent counties.

The integrated in- and out-commuting patterns in Figures 2–4 suggest a system of highly connected and clearly delineated mega-regions in the U.S. Table 2 shows that even rural counties (Rural–Urban Continuum codes 4–9) can have relatively high in- and out-entropy values if they are adjacent to a metropolitan region. These counties particularly have high out-commuting entropy measures, reflecting their "sending" roles within commuting networks.

Income Growth Model

To assess whether and how commuting networks affect county-level economic growth, we follow in the long-established tradition of Barro-type growth models (e.g., Barro 1991). Based on earlier studies (e.g., Goetz and Hu 1996; Pagoulatos

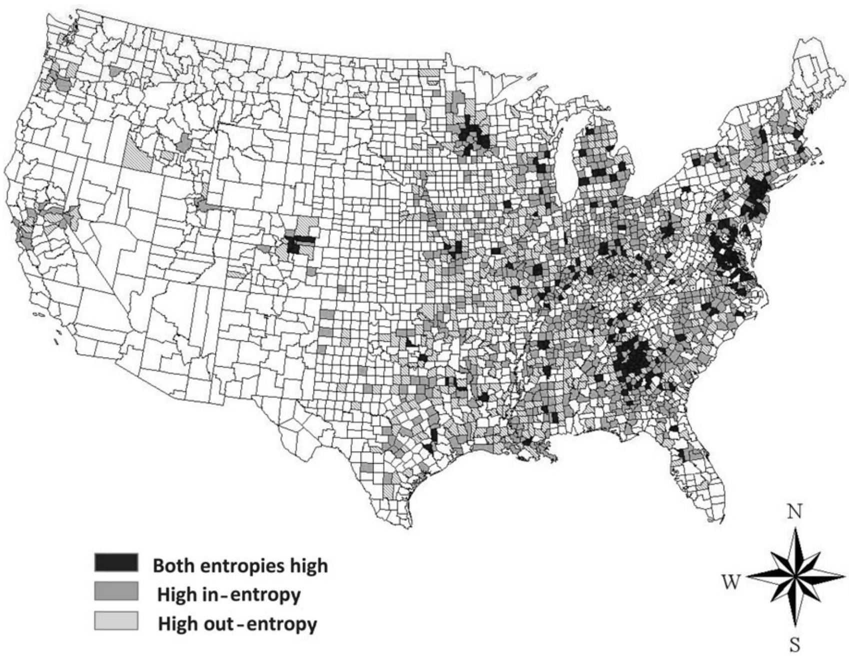

FIGURE 4. COUNTIES WITH HIGH IN- AND OUT-COMMUTING ENTROPY VALUES.

et al. 2004; Rupasingha, Goetz, and Freshwater 2002), county-level income growth (dy/dt) is hypothesized to depend on initial or beginning period per capita income levels (Y_0), stocks of human capital (H_k), agglomeration (a), and geographic area (g) effects, as well as a measure of industry diversity (id).

$$\mathrm{d}y/\mathrm{d}t = \mathrm{f}\left(Y_0, H_k, \mathrm{a}, g, id\right) \tag{2}$$

As predicted from the (conditional) β-convergence literature (e.g., Durlauf, Johnson, and Temple 2005), we expect a negative coefficient estimate on initial income, and that both human capital stocks and agglomeration economies are associated with faster income growth rates, *cet. par*. By regressing income growth over the period t_0 to $t_1 > t_0$ on regressors measured at t_0, we mitigate potential endogeneity bias (economic growth could be causing more commuting rather than the other way around).[9] Agglomeration in terms of population density is used as an independent factor in addition to income. As noted above, we include county area in miles squared as a regressor (g) to control for the fact that commuting is defined only when it occurs across county lines, and areas west of the Mississippi River inherently experience less commuting because they are larger in land area.

TABLE 1. 20 HIGHEST AND 10 LOWEST COUNTY RANKINGS ON COMMUTING ENTROPY VALUES (2000).

Rank	In-entropy ε_{in}			Out-entropy ε_{out}		
	Entropy	County	State	Entropy	County	State
High						
1	0.294	New York	NY	0.322	Pike	PA
2	0.280	Fulton	GA	0.289	Surry	VA
3	0.278	District of Columbia	DC	0.287	King and Queen	VA
4	0.275	Arlington	VA	0.272	Gates	NC
5	0.270	Scott	KY	0.271	Greene	MS
6	0.267	Somerset	NJ	0.266	Westmoreland	VA
7	0.258	Clayton	GA	0.264	Cumberland	VA
8	0.258	Essex	NJ	0.260	Louisa	VA
9	0.255	Morris	NJ	0.259	Jefferson Davis	MS
10	0.254	Alexandria city	VA	0.256	Caroline	VA
11	0.253	Plaquemines Parish	LA	0.256	Pike	GA
12	0.253	Surry	VA	0.255	Caldwell	MO
13	0.250	Tunica	MS	0.255	Isle of Wight	VA
14	0.250	Hudson	NJ	0.254	Switzerland	IN
15	0.245	Morgan	GA	0.254	Stafford	VA
16	0.243	Boone	KY	0.251	New Kent	VA
17	0.242	Union	NJ	0.250	Queen Anne's	MD
18	0.241	Isle of Wight	VA	0.250	Elliott	KY
19	0.239	Richmond city	VA	0.249	Orange	VA
20	0.238	Goochland	VA	0.249	Bracken	KY
Low						
1	0.000	McPherson	NE	0.000	Loving	TX
2	0.000	Arthur	NE	0.002	Nantucket	MA
3	0.000	Terrell	TX	0.009	Teton	WY
4	0.008	Carter	MT	0.011	Lemhi	ID
5	0.010	Wheeler	OR	0.012	Garfield	MT
6	0.011	Fremont	WY	0.013	Harney	OR
7	0.011	Harney	OR	0.014	Box Butte	NE
8	0.012	Lake	OR	0.014	Clark	NV
9	0.012	Aroostook	ME	0.015	Humboldt	CA
10	0.012	Lemhi	ID	0.016	Webb	TX

Note: to conserve space, only the bottom 10 counties are shown.

TABLE 2. AVERAGE COMMUTING IN- AND OUT-ENTROPY VALUES AND POPULATION DENSITY BY RURAL–URBAN CONTINUUM CODE.

Code#	Description for 2003 Rural-Urban continuum codes	Average		
		ε_{in}	ε_{out}	Pop_density
1	County in metro area with 1 million population or more	0.155	0.163	1,252.9
2	County in metro area of 250,000 to 1 million population	0.124	0.125	255.8
3	County in metro area of fewer than 250,000 population	0.112	0.117	130.7
4	Nonmetro county with urban population of 20,000 or more, adjacent to a metro area	0.108	0.121	101.1
5	Nonmetro county with urban population of 20,000 or more, not adjacent to a metro area	0.090	0.068	64.5
6	Nonmetro county with urban population of 2,500–19,999, adjacent to a metro area	0.110	0.143	42.1
7	Nonmetro county with urban population of 2,500–19,999, not adjacent to a metro area	0.094	0.102	30.8
8	Nonmetro county completely rural or less than 2,500 urban population, adjacent to metro area	0.107	0.164	21.6
9	Nonmetro county completely rural or less than 2,500 urban population, not adjacent to metro area	0.082	0.119	12.4

The descriptive results presented earlier in the article show the potential importance of controlling for this effect in the model (see Figures 2–4 and Table 1). Variable *id* captures the degree to which a county has a broad or narrow portfolio of industries. In past studies the effects of such a variable have varied with the type of data analyzed and the time period studied. In principle, greater concentration is consistent with benefits from specialization whereas greater diversity may imply more stability and resiliency of the county economy over time.

To this benchmark regression model we add measures of centrality, including degrees for U.S. counties (d), and commuting entropy (ε):

$$\mathrm{d}y/\mathrm{d}t = \mathrm{f}\left(Y_0, H_k, \mathrm{a}, g, id, d, \varepsilon\right) \tag{3}$$

As already noted, these additional variables represent a refinement over conventional measures of commuting, which are often represented in *net* terms (in-commuters minus out-commuters) and which do not consider the extensiveness of commuting networks in terms of origins and destinations (i.e., the entropy or spread measures). The net effects of commuting (both in terms of degrees and entropy) on economic growth are indeterminate *a priori*.

An important related issue arises in terms of how economic growth is measured.[10] The Bureau of Economic Analysis (BEA) reports per capita income by place of residence. This measure includes personal income which comprises 1) net earnings from labor, transfers, and property income; 2) personal current transfer receipts, which include income maintenance, unemployment insurance benefits, and retirement and other sources; and 3) dividends, interests, and rent payments. An alternative measure that could be used in this study is that of wage earnings. In contrast to income, per worker wages or earnings are calculated and reported by place of work rather than the residence of the worker. Clearly, this important place-dichotomy raises two critical questions in the context of this study: 1) whether to measure economic growth in terms of income (as is the convention in the economic growth literature) or in terms of wages (which is in line with the Mincerian literature on the returns to human capital), and 2) whether income measured at place of residence or place of work is the relevant measure of economic growth. Labor market areas span places of work and places of residence simultaneously to include both measures in the same LLMA or LMA. However, as previously discussed, the trend toward longer commuting distances is resulting in very large local labor markets that remain important but do not capture the heterogeneity within labor markets. It is these differences that are of particular interest to *intra*-metropolitan researchers and also have the potential to inform knowledge of economic growth in rural areas. It is the commuting phenomenon that drives a wedge between places of residence and places of work and gives rise to the possibility of network benefits accruing to rural places.

We use per capita income at the place of residence, from all sources, as our measure of income. This not only follows convention in the economic growth literature, but by using this measure we are also more consistent in the sense that variables such as educational attainment are reported in the Census by place of residence. In other words, because wages are measured at the place or county of work, and this place may differ from the place (or county) of residence where key demographic variables such as educational attainment are measured, important measurement errors may in principle be introduced into a wage earnings growth equation that contains educational attainment and other demographic factors as explanatory variables. Furthermore, in the economic growth context we are also interested in unearned income, such as dividends, rents, and interest payments, and these are reported by place of residence rather than by place of work—which is another argument in favor of an income by place of residence over an earnings by place of work approach.[11]

For the empirical model we therefore focus on growth in income per capita as the dependent variable (dy/dt), measured as the percent change in per capita income between 2000 and 2007, using BEA data. The independent variables are all measured in 2000 (although a few are constant over time, such as the regional designation). County-level per capita income ($Y_0 = PCPI2000$) in the starting period (i.e., year 2000) is included in the model. The land area of the county in square miles (*land area*) and population density (*pop_density*) capture county size and independent agglomeration spillovers, respectively. Variable $H_k = edu\_college+$ is the share of the adult population in 2000 with a 4-year college degree or more, based on U.S. Population Census data. Census definitions for U.S. regions are used to define binary variables controlling for region of the country. The Northcentral region is the base for comparison, i.e., the indicator variable for counties located in the Northcentral U.S. counties is excluded from the empirical model to avoid perfect collinearity. An industry-entropy variable (*indus_entropy*) separately measures economic growth effects potentially associated with greater industry diversity; this is calculated from Census data and individual industry employment numbers, also for 2000. A higher value of this number means greater diversity of industries, i.e., less local specialization. And finally, the commuting degree (*in-degree*, *out-degree*) and entropy (*in-entropy*, *out-entropy*) measures are included in the specifications, along with respective interaction terms (*in-degree* × *out-degree* = *in-degree* × *out-degree*; *in-entropy* × *out-entropy* = *in-entropy* × *out-entropy*). We allow for these interactions to assess whether joint in- and out-commuting reinforces or suppresses economic growth or has zero statistical impact.

Network characteristics, i.e., the degree and entropy measures, are hypothesized to exert an influence on local economic growth. While this exploratory empirical work does not allow us to sort out the *exact mechanisms* behind the hypothesized faster growth attributable to broader commuting network,[12] we suggest that (for example) greater local spending, a broader pool of ideas for entrepreneurship, and greater linkages to investment funds to support it, or

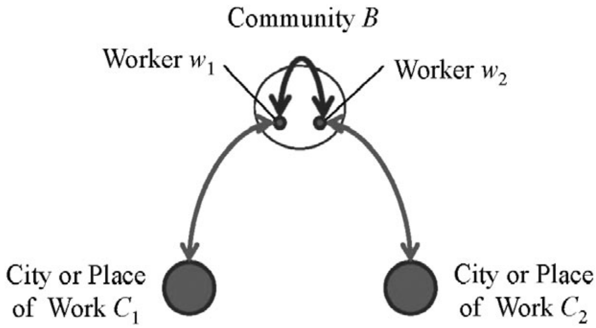

FIGURE 5. POTENTIAL SPILLOVER PATTERNS ACROSS COUNTIES OF WORK AND OF RESIDENCE.

spillovers created as a result of investment advice, are among the numerous important and plausible factors.

Knowledge and information spillovers through face-to-face interaction are often cited as contributors to innovation and economic growth (Krugman 1991; McCann and Simonen 2005). Focusing on the place of residence, consider community B in Figure 5. In the morning, workers w_1 and w_2 from two different households living in community B commute into places of work, C_1 and C_2. The three places (B, C_1, and C_2) are each located in a different county. After work, employees w_1 and w_2 reverse-commute, with new ideas and insights that they have gained through their interaction with others in the communities in which they work but also potentially in communities or places along their commute. Subsequently, the commuting workers from community B engage in their home local community—as neighbors, friends, volunteers, shoppers, or (local) investors. Within the home community, information and knowledge spillover occurs, consciously or subconsciously. The tacit information held within cities C_1 and C_2 is different than that found in B, and economic gains are realized when that information is shared by commuters within home community B.

Our maintained hypothesis is that the greater the opportunity for such spillovers to occur—via engagement with others attributable to the networks of commuting flows—the greater the economic benefit in terms of faster economic growth for rural areas, as they link to urban areas but also as they link to each other. This is in addition to the growth in income that occurs as new residents with higher average incomes become residents who now commute and as existing long-time residents now have access to a greater diversity of jobs (and also a greater likelihood of accessing jobs with higher wages). The downside, of course, is that this benefit is tempered by the increasing congestion and environmental costs associated with commuting that potentially reduce spillovers. But both of these costs are largely functions of transportation systems and technology options that can be influenced by smart policy.[13]

Regression Results

We first present the baseline growth model without commuting network variables (the first short set of columns of beta coefficients in Table 3). In comparison to previous studies, this basic model performs reasonably well and provides expected results for the conventional coefficients in predicting economic growth from 2000 to 2007—a period that was in many ways unique in American economic history. The absolute value of the standardized convergence parameter (i.e., the coefficient on initial or starting-period per capita income) is 0.209, and the

TABLE 3. U.S. COUNTY ECONOMIC GROWTH MODEL ESTIMATES, 2000–2007 (BETA COEFFICIENTS).

	Income per capita, by place of residence		Earnings per job, by place of work	
(Constant)	***	***	***	***
PCPY2000 (Y_0)	–0.209***	–0.144***		
ERPJ2000			–0.152***	–0.222***
Pop_density	0.048***	0.054**	0.032*	–0.001
Land area	0.125***	0.062***	0.065***	0.044**
Edu_college+	0.316***	0.247***	0.177***	0.136***
Indus_entropy	–0.295***	–0.261***	–0.179***	–0.177***
Northeast	0.104***	0.120***	–0.001	0.017
Southern	0.141***	0.162***	–0.087***	–0.090***
Western	0.011	–0.014	–0.116***	–0.106***
In_degree		0.157*		0.219**
Out_degree		–0.247***		–0.136
In*out degree		0.072**		–0.040
In_entropy		–0.198***		0.083
Out_entropy		–0.246***		–0.131**
In*out entropy		0.187***		0.000
Adjusted R-square	0.152	0.183	0.082	0.092

Significance levels: different from zero at *10%, **5%, and ***1% or lower.

agglomeration and education measures each have the expected positive signs. Over this time period, larger counties (in terms of geographic or land area) and the Northeast and Southern U.S. regions had more rapid economic growth relative to the Northcentral region. Counties with more diversified portfolios of industries—higher industrial diversity—grew *less* rapidly than more specialized counties, which potentially suggests a strength of clustering as an economic development strategy. In other words, a more concentrated set of industries leads to faster growth than a less specialized or concentrated set, which is consistent with current economic development thinking (e.g., Goetz, Deller, and Harris 2009). This result may also reflect the boom in commodity prices over this period in rural areas that are highly resource dependent.

The benchmark equation for earnings per job, measured by place-of-work, provides qualitatively similar results to the per capita income equation in Table 3 (the third shorter column of numbers in Table 3). The only important exceptions are the regional indicator variables: earnings growth in the Northeast is not statistically different from that in the Northcentral region, while the Western and Southern regions both experienced significantly slower earnings per job growth by place of work compared with the Northcentral region. This suggests that in the Western and Southern regions, growth was faster both in earned income (earnings from employment but also proprietor income) and unearned income (e.g., forms of asset income including interest, dividends, rent; retirement income; transfer income) than in the Northcentral region. For the Northeast, faster growth occurred in per capita income but not in earnings per job, relative to the Northcentral region, suggesting similar rates of return to labor from employment but higher growth rates of proprietor income, asset income, and other forms of unearned income taken together in the Northeast. Further, the industry diversity (entropy) effect is in the same direction as it was the case in the income growth model. We are not aware of previous studies that have compared economic growth by place of work as opposed to place of residence in this manner[14] and submit that differences in proprietor earnings and unearned income account for these regional differences.

We next (not shown) add the number of net commuters to this benchmark equation and obtain a negative and statistically significant coefficient estimate. This suggests that a relatively larger (net) number of out-commuters reduce the local income growth rate while more in-commuters raise the rate, all else equal. Using mean (out-) commuting time to work as a regressor likewise produces a negative coefficient estimate, suggesting that more time spent commuting suppresses per capita income growth over time, which is consistent with the reduced-productivity hypothesis.[15]

To the original benchmark economic growth model (both income per capita by place of residence and earnings per job by place of work) we then add commuting network variables: the gross in- and out-degrees of commuters, as well as their interaction, and also the in- and out-entropies and their interactions. One important first observation is that the (absolute) value of the convergence parameter in the income model declines as the sets of commuting network variables is added, indicating that exclusion of the commuting network measures leads to a biased coefficient estimate. In other words, ignoring the network effects of cross-county commuting produces an upward bias in the convergence parameter. In contrast, the convergence parameter for earnings per worker by place of work *increases* in absolute magnitude by nearly 50 percent.

The coefficient estimates for the commuting variables reveal that counties receiving a greater mass of in-commuters experienced faster economic growth for their residents over this period, while the opposite is true for counties sending out more commuters (although not in the earnings model). The result for in-degree centrality is important because it suggests that the benefits of in-commuting, conceivably in the form of growth-related spillovers (as one of a number of hypothesized mechanisms), are realized and can be measured in the destination county. Alternatively, for counties that are commuting origins, a greater mass of out-commuters is associated with a statistically significant lower economic growth rate as measured by per capita income growth. In effect, counties lose out in terms of economic growth by sending out workers, when we control for initial income, population density and land area, industrial diversification, and the other variables in the models. Finally, the degree interaction term is found to be important, with a positive coefficient estimate in the income by place of residence growth equation, but not in the wage earning equation (where it is again indistinguishable from zero). At least for income, this result is consistent with the observations of Patuelli et al. 2009 that more open places in Germany—i.e., those with both higher inward and outward "openness" to commuting—are emerging as growth poles. In our income growth model, the interaction term shows that the highest rates of income growth are expected under conditions of simultaneous high in-degree and high out-degree commuting, although overall rates also depend on the relative magnitudes of in- and outflows with a large outflow potentially resulting in lower growth rates.[16] These findings therefore lead us to not reject the key maintained hypothesis of tacit knowledge spillovers facilitated by commuting on the side of in-commuters and in terms of the joint (interaction) effect, but we *do* reject the hypothesis for out-commuters only (income model).

The entropy measures, which capture the centrality of a county in terms of the spread of flows through in- and out-commuting, and their interactions suggest that counties with greater in-commuting entropy (diversity, popularity, or attractiveness from multiple counties) experienced less income growth compared with counties that experienced commuting from just a few counties (i.e., from a more narrow geographic diversity). The same effect is observed for greater out-commuting entropy. Counties with higher out-entropy measures (that sent commuters to multiple counties in relatively unequal numbers) experienced less growth in per capita income. However, as indicated by the interaction term, the negative effects of the in- and out-entropy measures are offset by having both high in- and out-entropy. Thus we have the seemingly paradoxical result that counties that are predominantly a bedroom community *or* a business hub are penalized in the sense of enjoying less rapid income growth. However, counties that have the status of being both a bedroom community (high out-entropy or diversity) *and* a business hub (high in-entropy or diversity) receive a boost in economic growth.[17]

These results for the U.S. are consistent with the European and other North American experience. Green (2007) shows for the UK, Patuelli et al. (2009) demonstrate for Germany, and Shearmur and Motte (2009) find for Quebec (Montreal region) the emergence of hubs outside the urban core or central business district. Over the past decade at least, the spatial pattern of development in many places and perhaps even universally in most developed counties has evolved to be more dispersed, but with strong linkages between emerging places that are located at the periphery of the urban core and contribute workers to it or, even more likely, to each other. These hot spots of development contribute workers to connected communities that provide better jobs (resulting in high out-degree and high out-entropy) and also draw in workers from other places (high in-degree and high in-entropy). This form of development can give rise to new hubs that both give and take workers, some in the suburbs of long-standing urban centers but others in areas of the country—even more rural places—that are attracting those willing to commute what can be long distances to access the better jobs.[18] The commuting network is rapidly evolving, giving rise to new agglomerations with different structures than those that dominated in the past. The creation of knowledge and information spillovers across commuting networks, one potential mechanism that may stimulate growth, is likely to be a contributing factor to this growth, although more detailed data and different methods should be used to clearly identify how the spillover mechanism(s) actually works.

Conclusion

For rural policy to be properly designed, implemented, and evaluated it is essential to define and use appropriate units of analysis. Here we propose the use of commuting *networks* as an innovative approach to measure the multidimensional and complex interactions between rural and urban areas, as opposed to relying only on net commuting flows. We introduce a new method for measuring the characteristics and effects of commuting networks, i.e., that of entropy measures, and show how these measures vary over the rural–urban continuum. Our approach builds on the literature on spillovers, and recognition that tacit flows of knowledge embodied in workers may be as important as flows of codified knowledge.

We find marked increases in commuting, which is in agreement with Coombes and Casado-Diaz (2005), who observe that we are seeing "dramatic changes in levels of personal mobility in many areas of the developed world" (p. 20). Importantly, for the U.S. our analysis shows that even rural counties in the most rural places (rural–urban continuum codes 6 and 8) can have high out-centrality scores, comparable with those found in urban core areas (code 1). This finding may provide some common ground in the future for creating new regional forms of public governance (regionalism) that better reflect the local realities of cross-county and cross-state border flows of workers and economic activity. From a policy perspective, commuting will continue to occur and exert important influences on all counties, metropolitan and otherwise, even if commuting is not planned or preferred by individuals or by governmental units. As Green (2007) concludes, "The clusters [that we empirically observe] show little respect for administrative boundaries" (p. 2081).

The emerging science of social networks has yet to be deployed to assess economic growth dynamics along the rural–urban continuum and from more micro-behavior oriented to macroeconomic growth models. Yet shaping future commuting patterns based on knowledge of impacts across the full rural–urban continuum will be critical. Otherwise, the result could well include unintended consequences. For urban systems, Shearmur and Motte (2009: 516) note that "[i]f theory and evidence can be brought forward that clearly explain the mechanisms by which the constituent parts of a metropolitan area depend upon each other, then it may become easier to persuade suburban constituents of the merits of metropolitan-level governance." A similar argument can be made for regional governance. Clearly understanding the components of the commuting network system helps to clarify impacts to yield improved policy.

And, of course, we have not yet been able to satisfactorily answer the question of whether rural communities should facilitate out-commuting by supporting infrastructure development to better link themselves to urban areas, or seek to promote economic development locally through business formation, investments in human capital, or building a broadband infrastructure. Nevertheless, we believe that expanding the analysis of economic growth by explicitly modeling commuting behavior and the spillovers that it allows is a fruitful new area for research. Further, jointly analyzing commuting networks and physical infrastructure may help to identify bottlenecks in the system (Coombes and Casado-Diaz 2005) or to find potential alternatives to reduce the negative spillovers of commuting. Understanding the implications of commuting networks for ecosystem function and services should also be fruitful territory for research; environmental impacts constitute an important issue that often requires assessment at scales that transcend the borders of LMAs.

Finally, our work suggests the need for more investigation at the micro level into the underlying mechanisms of settlement patterns and economic activity along the rural–urban continuum. In addition to spillovers due to access to more ideas, we postulate the following three additional categories of impacts on growth associated with commuting networks: 1) changes in income due to wealthier/ poorer people moving in and out, 2) changes in income due to greater access to (better) jobs elsewhere, in some cases reducing job mismatch and the rural underemployment problem, and 3) consumption expenditures driving multiplier effects. We are not able to determine the relative importance of these; this is a question that awaits further study from researchers interested in rural and urban development.

NOTES

1. Raising concerns about the century-old rural/urban threshold now used, demographer John Cromartie of the Economic Research Service, USDA, observes, "With all the urbanization that's taken place, you'd think that maybe that threshold should be raised, . . . , [b]ut there's no real methodology to say where that cutoff should be" (Benson 2009:2228).
2. Increases in commuting distances over the last two decades have been documented (van Eck, Ritsema, and Snellen 2006); longer commuting distances in part reflect the fact that it costs less in real terms to get from one place to another now than in the past, and it takes less time. This has resulted in a larger commuting network, i.e., one reaching farther into the countryside.
3. Corcoran, Faggian, and McCann (2010) describe spatial policy in Australia that is designed to address some of these issues.
4. For a formal statement of a social network structure see, e.g., Wasserman and Faust 2007:90.
5. Our computations of the entropy measures use Java software, following Han, Goetz, and Lee 2009. See also Tutzauer (2007:251, 258).
6. As a reviewer pointed out, other measures can be constructed that combine the absolute levels and shares of commuter flows. While Diana and Mokhtarian (2008:13) develop and apply such a measure to multimodal commuting behavior, such an extension is beyond the scope of the current article.
7. Figures and maps for 1970 are available from the authors upon request.
8. Color versions of all maps and figures are available from the authors (as well as in the online version of this article).

9. Note that *changes* in variables over time (dy/dt) are more difficult to model empirically than *levels* of the same variables (e.g., Y_1 as a function of its lagged value, Y_0).
10. We are thankful to an anonymous reviewer for strongly encouraging us to address this issue.
11. It is less obvious, *a priori*, how other types of unearned income such as welfare payments or retirement benefits may be affected by commuting network flows. Also, there are interesting research questions related to retirees (moving into rural areas) and needing access to health-care facilities not available locally. Rural places with greater network centrality may also be more attractive to this population.
12. The urban literature has focused to date on characterizing and visualizing urban commuting networks, suggesting that testing should be undertaken to understand the processes at play in that literature as well.
13. In recognition of the fact that network spillovers may directly affect wages per worker, we also estimate auxiliary equations with growth in wage earnings as the dependent variable, recognizing the potential measurement error associated, for example, with educational attainment. These estimation results are reviewed below.
14. The only article that to our knowledge touches on this subject is Partridge, Rickman, and Li (2009), who examine changes in *net* commuting as one of four different labor supply responses associated with economic development in a community.
15. These results are available from the authors upon request.
16. Note that the positive sign on the in-degree variable could denote reverse causation; however, as stated earlier, we are estimating this model using the effect of in-degrees in 1999–2000 on subsequent (2000–2007) economic growth to mitigate potential endogeneity.
17. It is interesting to note the *positive* albeit statistically insignificant coefficient estimate for earnings per job and the fact that the interaction term for the entropies is not distinguishable from zero. Further, the adjusted R-square statistics are nearly twice as high for the per capita income growth model as for the earnings per job growth model.
18. Our regression results are remarkably robust when we restrict our sample to the counties east of the Mississippi River (results available from the authors upon request).

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