Social Capital, County Information Networks and Poverty Reduction

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October 2014

Rural Development Paper no. 54
The power of social networks to change individuals’ fortunes has been recognized since the seminal work of Granovetter (1983), who showed that so-called weak ties (e.g., those that exist over a great distance) can be more important than strong or local ties in helping jobseekers find work. The primary reason for this is that contacts outside the local network usually have access to a different set of information (e.g., about job opportunities) than do contacts within the local network, because they are exposed to the same information sources as the jobseeker. Within the social sciences, network analysis has recently seen explosive growth with important principles such as preferential attachment (Barabási and Albert, 1999) or the importance of weak links (Csermely, 2009) finding universal applicability both in nature and society (e.g., Borgatti et al. 2009). To date, most of this work has focused on individual entities and their network connections (e.g., ants, bees, friends, jobseekers) rather than the explicit information networks that may exist among people living in different geographic entities such as counties or regions within a nation. In this sense, most previous network studies have not considered the role of space or spatial relationships in the formation and operation of human or social networks, that is, they have taken an aspatial approach. A parallel, more place-bound line of research draws on Putnam’s (2000) work on social capital, popularized in the book *Bowling Alone*, which considers trust and related connections among individuals as well as county-level spillovers, but without explicitly measuring the underlying networks. Rupasingha and Goetz (2007) operationalize a measure of social capital at the county-level and find, for example, that higher stocks of social
capital within US counties are associated with greater success in reducing poverty rates over time, as well as faster economic growth.

In this chapter we seek to merge these two disparate but related literatures by examining two distinctly different types of human networks. One is the network that is embedded within social capital, that is, the ties and bonds that exist among people living in a particular community or county. Even in this literature, a distinction is made between strong (usually frequent, local ties or connections) and weak ties, which can be contacts on the other side of the country that can be more useful to finding a job than the ties in one’s own labor market. The other is an explicitly spatial network of relationships among people that arises due to county-level commuting or migration flows. For example, when individuals migrate or commute from A to B they may bring with them new ideas and knowledge that do not already exist in B. This, too, is a form of information flow that exists within a (commuting or migration) network. For example, the information transmitted may represent ideas for new types of businesses or services that do not already exist in the community, or it may be ideas for solving problems of poverty or homelessness within a community. Migration and commuting are usually studied independently when in fact they may be connected (e.g., Renkow and Hoover, 2000; also see Renkow, 2003; Shuai, 2012; Han et al. 2013). We then examine the roles that these two different types of networks – commuting and migration on the one hand and social capital on the other – may play in changing county-level poverty rates over time.

We not only study the independent effects of social capital and county information networks on poverty reduction but also examine whether they support and reinforce or weaken one another, through interactions. For example, social capital could enhance the positive effects of new information helpful to ameliorating poverty that is transmitted via commuting or
migration flows. In particular, if a community is endowed with high levels of social capital, it may be more effective at disseminating new information that arrives with in-migrants or return-commuters. Or, if the social capital is of the negative variety, where newcomers or those who are “different” are excluded from communities or cliques, then it is possible that new information coming into a community never has a chance to be disseminated more broadly to the benefit of the community.

The notion that ideas and information flows are critical to human well-being, economic growth and innovation along with creativity is at the heart of the so-called Social Physics, which Pentland (2014) describes as a relatively new science that is being built on the newly available big data sets (such as cell phone calls, credit card purchases, etc.). Our contribution in this chapter is to examine how social capital, which itself may enhance flows of information that could bring about economic improvement, may interact with other forms of information flows – those embedded in migration or commuting networks – and enhance (or stifle) those flows.

We proceed by first briefly summarizing the literature on poverty determinants at the county-level and then reviewing the still nascent and sparse emerging literature on spatial information networks, and how these networks may affect socioeconomic well-being. We also very briefly cover the growing literature on social capital. This is followed by a discussion of a network-based entropy measure of information flows between nodes. We then discuss our empirical model and data in section 3, along with maps of the key variables. In section 4 we present the empirical results and discuss their potential implications for policymakers and community leaders. For example, if we find interaction effects between social capital and spatial networks, community leaders in places with more social capital could benefit by knowing this, and may seek to take advantage of any positive interactions, or they may be prepared to mitigate
the effects of any negative interactions. In section 5 we summarize and present ideas for further research.

1. Synopsis of Relevant Prior Research

We can divide the literature into studies that look at what drives migration (or commuting), on the one hand, and studies that examine the impacts of this migration (or commuting) both on the receiving and the sending communities, on the other hand. In the literature most of the work has been devoted to understanding the determinants or causes of migration (Goetz 1999; Grassmueck et al. 2008; Rupasingha and Goetz, 2004; Arzaghi and Rupasingha, 2013), rather than the effects or impacts of migration. Even so, both migration and commuting have important effects on local socioeconomic conditions, such as poverty, and there is growing interest in studying these effects, both for migration and commuting. For example, Partridge and Rickman (2006) find that a larger share of population living in the same house in the last five years (which implies less migration) was associated with a statistically significant higher poverty rate in US counties in both 1989 and 1999 regression models, after controlling for other salient factors. This would be symptomatic of communities that are in long-term economic decline or distress, where people are trapped because they do not have the skills or resources to move elsewhere in pursuit of new opportunities.¹

Net out-migration could also concentrate poverty in a community if those with fewer skills are more place-bound, thereby concentrating poverty. This has been argued to be at the core of the long-term persistence of poverty in entire regions, such as Appalachia or the

¹ Note that this measure only considers in-migrants; it does not count out-migrants, who by definition are no longer counted once they have left the community, and are therefore not available to answer the question. In that sense this measure is skewed.
Mississippi Delta. Commuting, on the other hand, has in recent research been found to reduce poverty rates, within the urban-suburban-rural spatial continuum, for counties that are not too distant from central business districts or downtown areas that offer agglomeration benefits and well-paying jobs (Partridge and Rickman, 2008a and b).

Eagle et al. (2010) are the first to explore the relationship between the structure of spatial networks using telephone communications as a proxy measure and the relative prosperity of communities, in the United Kingdom. While they do not claim causation, their results suggest that diversity of communication networks is significantly correlated with human socioeconomic well-being. The denser these spatial networks, measured through telephone network densities, the higher the economic well-being. Goetz et al. (2010), the only other related study we are aware of, examine the effect of information flows embedded within commuting networks on economic growth rates in the U.S., using two measures of network centrality. One is based on the commuting degrees (number of flows in and out) of a node and the other on the entropy of commuting flows, which can also be calculated as in- and out-flows for each county. They argue that the more central a county within a commuting shed, the faster the economic growth rate because of greater opportunities for information and knowledge spillovers. Their statistical analysis generally supports this hypothesis. While population density is often pointed to as a measure of spillovers and related externalities that produce agglomeration benefits, Gordon (2013: 672) suggests that “[n]etwork density and population density are not the same; the latter may be a poor proxy for the former.”

Despite the rapid expansion of interest in social networks as a dimension of social capital among researchers and practitioners, the potential role of networks in improving community-wide socioeconomic well-being has not been explored rigorously. From studies of international
migration it is well-known, for example, that remittances are sent back to home countries (e.g., Djajić, 1986; Russell, 1986; Adams et al. 2005). Less recognized, but we would argue more importantly from a development perspective, is the fact that these monetary flows are accompanied by flows of knowledge and ideas. The World Bank and other entities have recently suggested that international return migrants may carry with them knowledge about new legal institutions and business practices that they can introduce in their home countries. One example is relaxed licensing requirements for new businesses that are set up by returning Indian migrants from California. Likewise, a migrant from an economically depressed community in eastern Tennessee to New York City or San Francisco may be exposed to new business ideas that could be applied at the migration origin, or vice versa if the effect is experienced in the migration destination. The same may also be true of return migrants into rural communities who bring with them valuable skills and experience (von Reichert et al. 2014). In this context, we hypothesize that origin or destination counties that are better connected, in the sense of being more broadly linked within a county-level migration or commuting network, benefit more in terms of poverty reduction than those that are less connected. We define this notion of connectedness below in greater detail.

We examine the roles of two specific and distinct human networks in affecting wider socioeconomic well-being: county-level migration and commuting. Both of these networks have important spatial components. Previous county-level studies of migration or commuting have focused on gross (total) flows of migrants or commuters into and out of particular counties, and how they affect local economic well-being (e.g., Partridge et al., 2009). But studies that focus only on net or even gross in- or out-flows fail to exploit all of the information contained within the data, including migration efficiency, that is the number of gross in and out migrants that
generate a particular net migrant flow\(^2\) (e.g., Goetz, 1999). In particular, these studies ignore the fact that both migration and commuting flows represent network processes, with origins and destinations. By collapsing all flows into or out of a county into single variables (net or gross), important network features or characteristics are potentially missed.

As noted, we hypothesize that a county’s centrality or connectedness within a migration and commuting network affects important socioeconomic outcomes such as poverty changes over time. By measuring the networks at one point in time, and change in economic conditions or well-being over the ensuing period, we substantially mitigate any potential endogeneity bias. For example, a more central and wealthier county could receive quantitatively and qualitatively more diverse tacit knowledge spillovers and as a result experience greater improvements in socioeconomic conditions over time. In addition, if migrants (commuters) move to a more diverse array of destinations as opposed to a single major city, return knowledge flows useful for improving local economic conditions could be larger, and more diverse. An empirical question here is whether in- or out-flows are more important; for example, out-migrants may still send information back to their community of origin, while in-migrants may also bring new information with them. If new in-migrants are unable to apply that knowledge, however, it may be ineffective (e.g., if they are not trusted). From a policy perspective, our particular interest is also in determining whether migration or commuting is empirically more effective in improving the local economy, depending on how they interact with social capital.

To elaborate, two variables are said to interact with one another when changing (that is, increasing or reducing) one variable also changes the effect of the other variable on the

\(^2\) For example, 100 in-migrants and 50 out-migrants generate a net in-flow of 50 migrants, and the same is true of 100,050 in-migrants and 100,000 out-migrants. The first case is one of much greater efficiency, because far fewer migrants have to move to generate the net flow of 50 in-migrants.
dependent variable. For example, both educational attainment and experience are associated with earnings: higher levels of both lead to higher earnings. In addition, it is possible that individuals gain an additional boost to their earnings by having both more education and experience. This boost would be beyond the effects of education and experience alone. In this sense, higher levels of one variable (e.g., education) may compensate for lower levels of another variable, such as experience. Of course, two variables may also interact negatively with one another, so that higher levels of one reduce the effect of the other on a dependent variable.

Statistically, interactions are detected by multiplying the two candidate variables together and entering the product into the regression equation along with the non-interacted variables. If the coefficient estimate on the product statistically differs from zero, we conclude that an interaction effect is present.

While Rogers and Jarema (Chapter 2 of this volume) provide a broad discussion of the concept of social capital, the measure we use here is very specific and calculated for the county-level. In particular, our measure includes venues where social capital is often generated (such as bowling allies, chambers of commerce, social clubs, membership organizations etc.) and it also captures voter participation rates in the national presidential elections, as a measure of civic engagement. This is described in greater detail in Rupasingha, Goetz and Freshwater (2006). It is important to stress that our empirical measure of social capital is by construction closely tied to the community because it uses the density of local social-capital generating establishments; thus it is more of a strong tie rather than a weak tie that would exist across space. In some ways, then, by using statistical interaction terms, we seek to use our migration and commuting measures to extend the effect of this local social capital measure over space, i.e., across county borders.
Another large and growing literature examines the effects of social capital, at the county-level, on questions surrounding economic growth and other issues such as poverty reduction. Rupasingha and Goetz (2007), for example, find that counties with higher stocks of social capital also are more successful at reducing poverty rates over time, or achieving higher per capita income growth rates, again controlling for other factors associated with these dependent variables. There are many different ways in which we could explore the effects of social capital, as one dimension of a non-spatial, place-bound network, on different socioeconomic outcomes. In this chapter we chose to focus on the effect of social capital and other networks on poverty reduction, rather than employment or income growth. We are motivated to do this in part by the recent work of Chetty et al. (2014), who also look at the effect of social capital on economic mobility using the measure developed in Rupasingha et al. (2006), that is, the odds that a child born in the lowest quintile is able to reach the top quintile on the earnings distribution.

An even larger body of research has examined county-level determinants of changes in poverty rates over time. In this literature, race, educational attainment and access to work have consistently, and stubbornly, been shown to affect the path of poverty rates over time (e.g., Albrecht et al. 2000; Levernier et al. 2000; Gunderson and Ziliak, 2004; Partridge and Rickman, 2006). In addition, the age distribution of the population and the dominant employment sectors have been found to matter, especially in the latest Great Recessionary period, 2007-09, from which the nation still had not fully recovered as of 2011. These conventional individual- and community-level factors correspond to “cultural” and “ecological” schools or explanations of poverty. In county-level regressions, adjusted $R$-square values are 49% for the former and 44% for the latter, with combinations of both sets of regressors providing only small increases in $R$-squared values (Jensen et al. 2006).
2. Entropy Centrality: Definitions and Calculations

We next consider an entropy-based network measure that captures complex migration and commuting flows into and out of counties. Commuting and migration flows each form a network with origin-destination pairs representing nodes (counties). An important node (hub) in a migration or commuting network represents a central county in a spatial hierarchy, and the weighted flows of migrants or commuters between the nodes can be used to identify the underlying spatial structure. For example, as shown in Figure 1 a polycentric spatial structure may emerge through commuting flows. We suggest that commuters and migrants carry with them information as they cross county lines and our goal is to measure how much information a county receives, or loses, either through in- or out-movement of population through commuting or migration.

Figure 1 The concept of a polycentric spatial structure. Network flows create a self-similar fractal and self-organized spatial structure. The central node has large branches and achieves a star shape. This connectivity and spatial implication creates an influence space of central regions as well as a spatial structure.
Source: Authors

In information theory, entropy is a measure of the information contained in an element or a system of elements. Shannon (1948) measured the expected amount of information contained in a message transmitted through a telegraph line, which is known as information content or Shannon entropy. Today there is significant work in computer and communication technologies on how to maximize the rate of information transfer for a given infrastructure.
community economic development the notion of access to broadband brings notions of entropy to life.

When a message has \( N \) signals and the probability of a successful transmission of the \( i^{th} \) signal is \( p_i \), the information content of such a message is defined as in Eq. (1):

\[
H = -\sum_{i=1}^{N} p_i \log_2 p_i
\]  

(1)

Shannon entropy indicates the uncertainty or degree of freedom in a system. This information measure is useful for modeling complex systems (Gell-Mann and Lloyd, 1996), and it can identify important nodes in a large network as shown by Tutzauer (2007) and Volchenkov and Blanchard (2008). These authors measure signals by using the connections between nodes, and then quantify the nodes’ centrality within the network. We use this network-based entropy measure to estimate the centrality of counties for both commuting and migration flows.

Both migration and commuting flows have two directions, into and out of counties. Some residents commute out to work while others come into a county to work, and migrants similarly leave and move into counties. These two flows are conceptually different, with commuting occurring on a daily basis and migration usually occurring only once and over any possible range of distances, and yet both flows have the potential to carry information with them. We calculate two entropies: in-entropy \( e_{i}^{in} \) and out-entropy \( e_{i}^{out} \) of county \( i \) defined as in Eq. (2):

\[
e_{i}^{in} = -\sum_j \left( \frac{m_{ji}}{\sum_j m_{ji}} \log_2 \left( \frac{m_{ji}}{\sum_j m_{ji}} \right) \right), \quad e_{i}^{out} = -\sum_j \left( \frac{m_{ij}}{\sum_j m_{ij}} \log_2 \left( \frac{m_{ij}}{\sum_j m_{ij}} \right) \right)
\]  

(2)
Here, \( m_{ij} \) is the number of people who live in county \( i \) and work in county \( j \), and analogously for migrants. Ratio \( m_{ij} / \sum_j m_{ij} \) is the probability that one migrant (or commuter) in county \( i \) moves to county \( j \). If county \( i \) connects to all the other counties with equal flows of commuters (or migrants) to each county, the entropy is at a maximum. One way of thinking of this is that workers commute into a central business district, where they come up with new ideas due to the benefit of being together in a tighter space, which facilitates idea generation and information spillovers. Then, in the evening when they return home that knowledge flows back out into their communities with them, where it can potentially be applied to solve local problems. If region \( i \) links only to one other county (including itself), then it has minimum entropy, because \( \log_2(1) = 0 \). If interactions between any given counties depend on a few other counties, then the centrality is low even if the region has a high degree of connections. In the concept of entropy, a key factor of centrality is the diversity of connections in a network. Thus, the centrality of a county can increase either by adding more counties as commuting or migration origins or by including more equal shares of commuters (or migrants) from other counties, even though total employment (migrants) does not change (Fig. 2).

**Figure 2** In-entropy by type of connection. Each solid node \( i \) has the same number of in-flows (4) but the number of connected nodes and their weights are different. Therefore each node \( i \) has a different in-entropy value.

*Source: Authors*

Therefore a central idea associated with information entropy is that it is not just the total number of movers (migrants or commuters) that matters, but how evenly they are distributed across the commuting origins or migration destinations. The more evenly distributed are the flows from origins (to destinations) the greater the potential information content that is conveyed through the flow. Note that distance moved or commuted may also matter in that the
information content may increase with distance: spillovers of tacit knowledge are more likely the

closer together are the sender and receiver in space. This also suggests that a migrant moving

over a greater distance may bring different information than one moving into a nearby place.

3. Empirical Model and Data

We estimate a model with 2001-2011 simple change at the county-level in the percent poverty
rate ($Pov_{2011} - Pov_{2001}$) as the dependent variable. The evolution of the US poverty rate for all
ages over the period 2000-2012, which includes the Great Recession of 2007-09, as well as since
1959 (inset), is provided in Figure 3. County-level rates, and the changes in these rates as shown
in Figure 4, were available only through 2011 at the time of this study. This figure shows the
extensive and long-lasting effect of the 2001 so-called jobless recovery, which was compounded
by the 2007-09 recession. Underscoring the dramatic expansion of poverty over the last decade,
vast tracts of the country show higher poverty rates than a decade ago. The main exceptions
appear to be the energy-dependent counties in the nation’s center, which have benefited
enormously from recent expansion in unconventional forms of energy exploration. Otherwise
counties in Michigan, the remainder of the “rust belt” in Illinois, Indiana and Ohio (except for
Pennsylvania) and the southeast US Census region along with selected counties along the West
Coast that are generally not on the coast, appear to have borne the longer-lasting brunt of this
economic shock, in the form of a 5.9 percentage point increase in the poverty rate, or higher.

Regressors that we use in our analysis include the initial poverty rate in 2001 ($Pov_t$), as a
starting value that places all counties on the same playing field, along with standard determinants
of poverty familiar from previous work. Most notably, the “big four” determinants of poverty –
education, race, female (single) householder and access to work are included, with the latter
measured by the unemployment rate (we also consider, alternatively, the workforce/population ratio, with similar results).

**Figure 3** Poverty rates for the United States, 1959-2012  
Source: US Census Bureau Small Area Income and Poverty Estimates

**Figure 4** Change in Poverty Rate, the United States, 2001-2011  
Source: US Census Bureau Small Area Income and Poverty Estimates

We include population and population density as key controls for agglomeration effects as well as the fact that counties have vastly different sizes. Thus we can determine separately the effects of population size and population density, while controlling implicitly for land area. This is important because (see below) there is less commuting as defined by the Census in Western States simply because counties there are larger in terms of land area (so fewer county borders are crossed even though commuters may travel just as large a distance as Eastern seaboard commuters). This is shown in Figure 5, as the percent of non-movers and non-commuters in each of the U.S. counties in 2000.

**Figure 5** Map of percent (a) out-migrants and (b) out-commuters  
Source: Authors, using US Census Bureau, Census 2000 data

As additional regressors we include population age shares (15-24 and 65+ year olds), percent of adults with a college degree, percent African-American and Hispanic, employment shares in natural resource-based industries as well as manufacturing and construction. Reid et al. (2013) point out that African-Americans and workers in the construction and manufacturing
industries were especially hard-hit by the 2007-2009 recession. We also include the unemployment rate as a measure of access to work, which is expected to be associated with a higher poverty rate.

In addition, and as noted, we include as controls per capita migrants and per worker commuters in each county, as reported by the Census Bureau. These are measured separately for both in and out movers or commuters. Because we are also including population numbers, this fixes the number of residents who work in their county of residence, as well as the number of individuals living in the same house over the five years. Migration behavior is measured over five years (1995-2000) whereas commuting is measured in only one year, close to the Census year (1999). Our last basic but central measure in this benchmark equation is the social capital index compiled by Rupasingha, Goetz and Freshwater (2006), which we include along with regional fixed effects (RFE).

This empirical measure of social capital, which also is adopted by Markenson and Deller in Chapter 6 of this volume, is based on a range of variables from County Business Patterns that can be separated into those that are more Olson-type or rent-seeking, and those that are more in the spirit of facilitating social interaction, i.e., these are Putnam-type groups. Among the former are (see Rupasingha et al. 2006, p. 89) political, labor, business and professional organizations while the latter include civic organizations, bowling alleys, golf clubs, fitness and sports organizations, as well as religious groups. These organizations are calculated on a per capita (10,000) basis, and then the first principal component is used to create a constant aggregate measure of social capital at the county-level. This measure has been in a variety of subsequent studies and proven to quite reliably separate communities with low and high endowments of social capital, and it is remarkably consistent with the state-level measure of social capital.
reported in the General Social Survey (GSS), which is obtained using entirely different
techniques.

The migration ($\text{Mig}_t$) and commuting ($\text{Com}_t$) vectors are handled in parallel fashion, i.e.,
we calculate the same in- and out-entropy measures for each of these. This provides the
following equation to be estimated.

$$\Delta \text{Pov} = \alpha + \beta \text{Pov}_t + \gamma \Omega_t + \lambda \text{RFE}_t + \zeta \text{Mig}_t + \theta \text{Com}_t + \epsilon \quad (3)$$

Here, $\Delta \text{Pov}$ is the change in poverty rates between 2001 and 2011, $\text{Pov}_t$ is the poverty rate in
2001, $\Omega_t$ represents all the control variables described above, $\text{RFE}_t$ are the regional fixed effects,
and $\text{Mig}_t$ and $\text{Com}_t$ are our migration and commuting measures and are the primary variables of
interest. The error term ($\epsilon$) is assumed to be well-behaved. All of these variables are from the
U.S. Census Bureau except where noted. The variables calculated from the migration and
commuting data are by the authors, using Java software. Summary statistics for each of the
regressors are presented in Table 1.

In Figure 6 we illustrate how the raw migration and commuting flows appear in the
specific cases of Georgia and neighboring Alabama. In the migration network the central role of
Atlanta is clearly visible, primarily with outflows of residents into the suburbs. These flows are
then in a number of cases offset with reversed flows of in-commuting back into the central
business district. These two figures resemble patterns of a self-organizing fractal: even though
the commuting network looks quite different from the migration network, it also has features of a
fractal. Here we see four hubs in the Atlanta area, involving 100,000 or more daily commuters.
A visualization of our calculated migration and commuting entropy measures is provided in Figure 7 in the form of a map. The relative sizes of the in- and out-migration entropies are similar. It is worth repeating that these measures reflect entropies, in terms of diversity of migration origins and destinations, rather than gross or even net flows of people, which are implicitly controlled for in the regression equation. The relatively lower entropy values in the West especially are noteworthy, and largely relate to the larger land areas of the counties where greater geographic distances may minimize cross county flows.

**Figure 6** Movement of People in Alabama and Georgia; (a) migration and (b) commuting

Source: Authors using 2000 US Census data

**Figure 7** Migration and commuting entropy measures. Migration in terms of (a) in- and (b) out-. Commuting in terms of (c) in- and (d) out- (see explanation in text).

Source: Authors calculations, using US Census Bureau, Census 2000 data

4. **Empirical Results and Implications**

The regression results are shown in Table 2 in the first column, with region fixed effects but without the entropy-based information measures. The coefficient estimate for initial poverty rates in 2001 is consistently negative and highly significant statistically across all regressions. This indicates convergence in poverty rates over time, which means that counties that started out with higher poverty rates experienced smaller increases in poverty over the ensuing decade, while counties that started out with lower poverty rates experienced greater increases. The convergence just means that the counties are becoming more similar in terms of the poverty rate. Note that this is consistent with an overall increase in poverty. In general, the signs of the statistically significant regression parameters $\Omega (\gamma)$ are in the expected direction. In particular,
counties with larger shares of 15-24 year olds have higher poverty, while those with proportionately more retirees were similarly affected, suggesting that in this period retirement savings were perhaps insufficient to prevent poverty increases (possibly due also to large stock market losses).

Signs for the “big four” poverty determinants are as expected, and their statistical significance is robust across all of the equations, with the exception in this specification that communities with more African-Americans and Hispanic populations shares saw poverty rates decline (note that this effect remains robust even after we add the migration-related variables). College degrees provided strong protection against rising poverty rates, as did access to employment – or, for unemployment, the effect was strongly negative in the sense that more unemployment led to greater poverty. The female householder share was strongly associated with greater poverty increases, showing the largest standardized beta coefficient of all regressors (ahead even of the initial poverty rate).

Effects of the simple migration measures are statistically different from zero, with more in-migrants per capita leading to higher poverty increases and the converse for out-migrants. Only the number of out-commuters per worker is statistically significant, and negative, which is generally consistent with expectations based on previous research results. The effect of social capital is also pronounced and statistically robust: counties with higher stocks of this variable were better able to reduce poverty rates over this period, or at least prevent poverty rates from rising as rapidly as they did in communities with lower stocks. This finding is also generally consistent with the research results reviewed above, and it suggests that social capital can play an important role in improving local economic conditions (such as poverty) over time.
This is clearly an important finding and one that is central to this overall book. While we do not know the precise pathways through which this effect occurs, we can speculate on a few of them. For example, in counties with higher social capital residents may seek to work alongside one another both inside and outside of the political process, rather than putting up roadblocks, in finding and implementing local-level policies that create public benefits such as lowering the poverty rate. For example, they may subsidize the construction of low cost housing that gives the homeless a permanent address from which they can apply for employment. Studies have also found that counties with higher social capital the residents tend to be more supportive of locally-owned businesses (Kwon et al. 2014). In turn, small, locally-owned businesses tend to be associated with higher rates of per capita income growth over time (Fleming and Goetz, 2011; other).

Next we turn to the effect of information flows conveyed through migrants or commuters via the entropy-based measures. We also interact these with the social capital variable. In so doing, the earlier regression results are generally not affected. Migration in-entropy measured alone leads to higher poverty rates, but this is offset when the term is interacted with social capital. When migrants arrive from a greater variety of origins, receiving communities with higher stocks of social capital appear to be able to take advantage of the information flows that accompany these movers. The opposite is true for out-migrants: considering this term alone, a greater variety of destinations is associated with more poverty reduction, which is consistent with the idea that a more diverse information flow back into the origin is translated into poverty reduction. However, in this case social capital has the opposite effect, in that it reduces the beneficial effect on poverty reduction. Higher commuting out-entropy is associated with greater increases in poverty rates, but this is counteracted by social capital. This suggests counties that
send commuters to a greater variety of other communities, are penalized in the form of poverty increases unless they also enjoy higher social capital stocks that allow them to take advantage of new information or insights brought back by commuters. On the other hand, our results indicate that the effect of commuting out-entropy on poverty reduction is not distinguishable from zero. In other words, this type of information flow has no bearing statistically on poverty change over time in the community (ignoring the effect of the interaction with social capital).

In further analysis we examine whether the net effects of these entropies on poverty, after taking into account interactions with social capital, are still negative. Here we use the fact that

\[
\frac{\partial \Delta pov}{\partial entropy} = \alpha + \beta SOC
\]

on the interaction term, and we evaluate this relationship for different levels of SOC. The net effect on poverty depends not just on the parameters \(\alpha\) and \(\beta\) but also on the level or amount of social capital: the higher the level, the greater the effect. In this case we find that for about 92% of all counties the effect of migration in-entropy is to reduce poverty rates, holding social capital stocks constant at their mean. For the commuting out-entropy measure, social capital stocks are not high enough to translate into lower poverty rates.

5. Summary and Policy Conclusions

Our study confirms earlier research in that we find social capital within a county to reduce poverty rates in a statistically significant and important fashion. In addition, the directions of the effects of our other explanatory variables are in general consistent with prior expectations. A novelty of our work is that we apply and extend recent advances in network science to the question of information flows across county lines, and also test for potential interactions between these flows of ideas and community-level social capital stocks. In other words we examine if
social capital somehow enhances, or detracts from, any potential value that is contained in the information that is transmitted through cross-county border commuting or migration flows. Conversely, we also investigate whether the ideas that may be embedded within migration and commuting flows somehow amplify or reduce any positive effects of social capital. Here it is interesting to distinguish between migration and commuting because in the case of migration the new ideas may come from places that are further away while in the case of commuting a smaller distance is involved by definition, and thus the difference of novelty of the ideas may not be as pronounced. The migration and commuting phenomena also differ significantly in that migration tends to occur once or at least infrequently over a span of a few years while commuting usually occurs on a daily basis, allowing for repeated absorption of new ideas and their testing through a local application. To our knowledge, and as noted, commuting and migration have not previously been studied from this perspective.

Our results indicate that, without any interactions, only greater migration out-entropy is associated with poverty reduction. This would suggest that the benefit of new ideas and innovation occur only after a certain distance threshold between the origin and destination pair is exceeded, and it is consistent with the World Bank’s and others’ arguments that international migrants may do more to bolster economic growth in the place they left behind than only sending remittances. This particular finding is also consistent with the possibility that a poor county with a more balanced portfolio of other counties to which out-migrants move receives an additional boost over those counties where the out-migrants’ portfolio of destination counties and the migrants’ distribution across these is less well-balanced.

A related noteworthy result is that social capital appears to enhance both migration in-entropy and commuting out-entropy. This was found to be the case in over nine of every ten
counties, depending on the measure used. It is plausible that communities with more social
capital are more welcoming of new in-migrants, which in turns enhances their potential impact in
terms of reducing poverty. A similar effect could be in play for out-commuting, where any new
knowledge acquired outside the county by commuters is translated more readily into poverty-
reduction in their county of residence, if that county also enjoys higher stocks of social capital.
More generally, our results suggest that social capital and network-based information flows are
mutually reinforcing at the county-level.

In terms of implications for policy makers and practitioners we conclude that there are
strong tangible benefits in general to increasing social capital stocks along with human capital
within counties, if the goal is to reduce poverty rates. For example, the cooperative extension
system likely already plays an important role in many communities in terms of increasing social
capital through various interactions with community members, although this assertion merits
further analysis. This beneficial effect of primarily local social capital networks on community
socioeconomic well-being is perhaps the single most important conclusion and contribution of
this chapter.

We also find that social capital can reinforce the positive effects of ideas and information
flows that accompany occasional migrants and daily commuters across county lines. However,
here an important nuance emerges in that when we look at gross commuting and migration flows
(rather than net), higher stocks of social capital reinforce the out-migration entropy and the in-
commuting entropy in the direction of raising poverty rates over time. This negative (in the
sense of raising poverty) effect of social capital is worth further study and contemplation, before
blanket policy recommendations are made. In particular, this suggests that when more migrants
leave to a greater variety of destinations, those left behind may use their social capital to block
any poverty reduction efforts. Likewise, for reasons not yet fully understood, a community with higher social capital that receives a greater variety of in-commuters also somehow is more likely to see poverty rates increase rather than fall. This, too, is worthy of future study.

More generally, these nuanced findings suggest that before seeking to improve social capital stocks in a community, policy makers and practitioners are well-advised to contemplate how this increased social capital may interact with the migration and commuting characteristics of the community. Thus we cannot make a blanket recommendation that all communities seeking to lower their poverty rates adopt a strategy of raising social capital stocks. Instead, the devil as always is in the details, and all communities are not alike in the degree to which they would benefit from such a strategy, once we consider the cross-county information and idea flow networks that are layered on top of the social capital stocks.

References


Figure 1 The concept of a polycentric spatial structure. Network flows create a self-similar fractal and self-organized spatial structure. The central node has large branches and achieves a star shape. This connectivity and spatial implication creates an influence space of central regions as well as a spatial structure.
Source: Authors

Source: Authors

Figure 2 In-entropy by type of connection. Each solid node $i$ has the same number of in-flows (4) but the number of connected nodes and their weights are different. Therefore each node $i$ has a different in-entropy value.
Source: Authors
Figure 3 Poverty rates for the United States, 1959-2012
Source: US Census Bureau Small Area Income and Poverty Estimates

Figure 4 Change in Poverty Rate, the United States, 2001-2011
Source: US Census Bureau Small Area Income and Poverty Estimates
Figure 5 Map of percent (a) out-migrants and (b) out-commuters
Source: Authors, using US Census Bureau, Census 2000 data
Figure 6 Movement of People in Alabama and Georgia; (a) migration and (b) commuting
Source: Authors using 2000 US Census data
Figure 7 Migration and commuting entropy measures. Migration in terms of (a) in- and (b) out-. Commuting in terms of (c) in- and (d) out- (see explanation in text).
Source: Authors calculations, using US Census Bureau, Census 2000 data
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<th>Min.</th>
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Table 2 Regression parameter estimates

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Dependent variable = pov2011 - pov2001

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