Locally Owned:

Do Local Business Ownership and Size Matter for Local Economic Well-being?

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Abstract: The concept of "economic gardening"—supporting locally owned businesses over nonlocally owned businesses and small businesses over large ones—has gained traction as a means of economic development since the 1980s. However, there is no definitive evidence for or against this pro-local business view. Therefore, I am using a rich U.S. county-level data set to obtain a statistical characterization of the relationship between local-based entrepreneurship and county economic performance for the period 2000–2009. I investigate the importance of the size of locally based businesses relative to all businesses in a county measured by the share of employment by local businesses in total employment. I also disaggregate employment by local businesses based on the establishment size. My results provide evidence that local entrepreneurship matters for local economic performance and smaller local businesses are more important than larger local businesses for local economic performance.

About the Author: Anil Rupasingha is a research adviser and economist in the community and economic development (CED) group at the Federal Reserve Bank of Atlanta. His major fields of study are microbusiness and small business, entrepreneurship, self-employment, regional income growth and poverty, internal migration, and social capital. Prior to joining the Atlanta Fed in 2011, Rupasingha was a faculty member in the Department of Agricultural Economics at New Mexico State University, and prior to that in the Department of Economics at American University of Sharjah in the United Arab Emirates, a senior research associate in the Northeast Regional Center for Rural Development at Pennsylvania State University, and a postdoctoral fellow in TVA rural studies at the University of Kentucky.

He has published his research in various journals, including *American Journal of Agricultural Economics*, *Annals of Regional Science*, *Economic Development Quarterly*, *Journal of Economic Behavior and Organization*, *Papers in Regional Science*, and *Review of Agricultural Economics*. A native of Sri Lanka, Rupasingha received a BA in economics from the University of Peradeniya (Sri Lanka). He earned his PhD in agricultural economics at Texas A&M University.

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Introduction

In most counties in the U.S., the percent of workers employed by locally- or resident-owned businesses outweigh the percent of workers employed by nonresident-owned businesses. But this number varies widely among counties (see Figures 1 and 2). For example, the share of employment in resident businesses varies from 10.7 percent in Loving County, Texas to 87.2 percent in Franklin County, Texas in 2007. The share of employment in nonresident businesses varies from zero percent in 24 counties across the nation to 85 percent in Tunica County, Mississippi. This spatial variation is ideal for assessing whether such variation explains the inter-county variation in economic well-being. The objective of this paper is twofold: (1) to assess if locally-owned businesses improve local economic performance, and (2) to I investigate whether the size of the locally-owned businesses affects local economic well-being. I

Figure 1. Spatial variation of workers employed by resident businesses, 2007
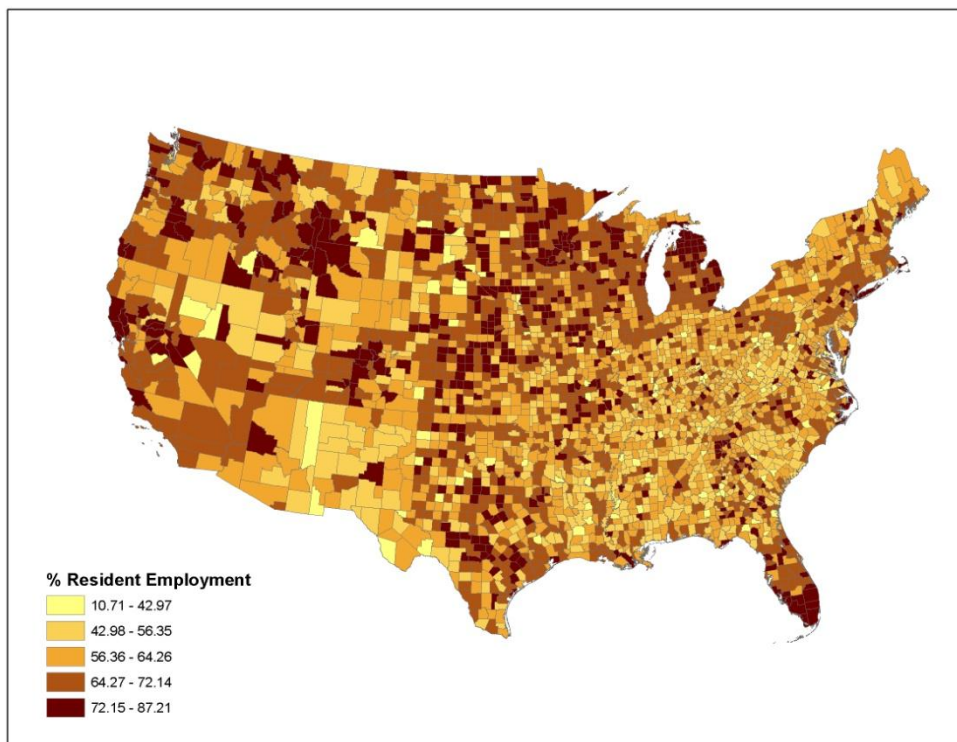
Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 2. Spatial variation of workers employed by nonresident businesses, 2007
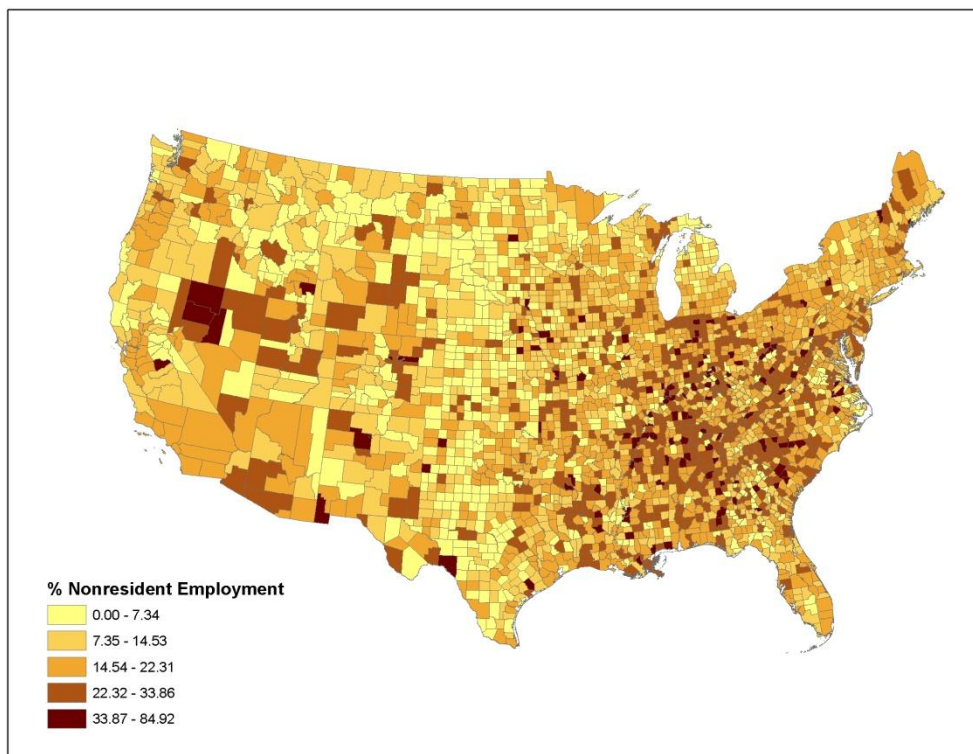
Source: Author's calculation using NETS Database, Edward Lowe Foundation

Historically, the most popular local economic development approach was to attract businesses from outside a particular municipality, state or region, which was commonly known as industrial recruitment or "smokestack chasing." State and local policy makers have been giving numerous incentives including tax subsidies, low-rent land, and job training subsidies to attract existing firms from elsewhere. This includes relocation of existing plants or expansion of existing firms. These incentive policies resulted in fierce competition among states to attract various big plants and large employers to respective states. For example (see Rork, 2005, for more details), General Motors received offers consisting of tax breaks and cash subsidies from over 35 different states before choosing to locate its Saturn plant in Tennessee (1985). Toyota received such incentives from over 30 states before settling one of its plants in Kentucky (1985). Similar competitions took place before BMW settled in South Carolina and when Alabama successfully lured Mercedes-Benz (1990s).

This economic development strategy of industrial recruitment presents several challenges and limitations, especially in terms of a local area's ability to sustain economic activity. One main problem with industrial recruitment is that policy makers had little influence over if or when the recruited establishments wanted to leave. A case in point is labor intensive companies such as call centers.[1] The policy of industrial recruitment may also have led to a tax competition between states that led to a "race

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[1] Call centers are kind of "foot-loose" businesses due to less capital intensive nature and less intensive labor skill requirements. It is easier for them to relocate to an alternative location that offers attractive incentives once the incentive structure in the current location is exhausted.

to the bottom."[2] Furthermore, local small businesses, or mom-and-pop stores, face stiff competition from big firms locating in local communities. On a more positive note, as a companion activity to recruiting particular plants, some states took steps to improve general business climate in their respective states using different fiscal incentives to create an environment beneficial to all firms in the state.

However, approaches to local economic development have evolved in the recent past and economic development based on local entrepreneurship is increasingly gaining traction in the research, policy, and practice spheres. This approach is a subset of the broader concept of sustainable development and more generally known as "development from below" or "bottom-up development" (Coffey and Polese, 1984) or more recently as "economic gardening" (Barrios and Barrios, 2004). The idea is that directing economic development resources to support local businesses over outside businesses and local small businesses over big businesses will be beneficial for the local community in number of ways. One concern is that outside corporations will be less environmentally sensitive to local communities. Outside firms are also subject to global economic outlook and therefore more amenable to relocation in other areas than local businesses. Also by favoring local businesses, local communities are more likely to keep the economic and political power within the local community (Barrios and Barrios, 2004). The development of local entrepreneurship can lead to a diversified economic structure that will protect the local economy from being overly dependent on one firm or establishment, or one industry. The result of local entrepreneurship, it may be presumed, is increased trade within the local economy, greater export of goods and services out of the local economy, and improved quality of life. The idea of locally-owned business development is especially favorable for economically distressed rural areas when it is difficult for these communities to attract outside businesses.

Pro-local business supporters also argue that more local businesses enhance healthy competition due to the fact that most local businesses are smaller scale operations, increase efficiency, and increase entrepreneurship in local communities. Kolko and Neumark (2010) argue that locally-owned firms are more likely to internalize the costs of job loss to communities by not relocating and closing. There may be other considerations such as "…loyalty toward the headquarters' hometown or a desire for better public relations in the headquarters' hometown, perhaps for political reasons" (Kolko and Neumark, 2010, p. 103). In addition to these, Kolko and Neumark (2010) point out other specific economic arguments such as small businesses start-up opportunities for local residents, preserving businesses in downtown and cultural districts, economic multiplier effects by local businesses spending more in local communities, local innovation and long-term economic stability in localities. To take advantage of all these benefits, many local, state and federal governments are initiating numerous policy approaches to promote locally grown businesses. Numerous localities have enacted policies favoring locally-owned businesses such as implementing restrictions on formula businesses, store size cap, local purchasing programs, and set asides for local retail (Kolko and Neumark, 2010). But these arguments are not without criticisms. For example, some argue that businesses coming from outside to a locality have been around for a while, are more stable, and may bring higher quality jobs compared to jobs coming from locally-based firms.

There is no definitive evidence for or against the pro-local business view. For example, numerous papers (discussed below) suggest that local economic performance in general and employment growth in

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[2] The phrase "race to the bottom" is commonly used in regional studies literature to convey the behavior of states that compete with one another by lowering taxes and reducing environmental regulations to attract businesses, which often reduces public revenues for infrastructure, education, and healthcare, for example, and strains environmental conditions.

particular is strongly associated with smaller average establishment size, but little or no evidence exists whether these small establishments are resident versus nonresident-owned. The objective of this paper is to provide such evidence using a new data set. Based on aforementioned claims I investigate whether the relative size of the locally-owned business sector has a positive association with local economic well-being. To assess this, I examine the relationship between the percent of establishment-level employment and local economic indicators such as income and employment growth and change in poverty. I also investigate whether the different sizes of local businesses have different effects on local economic well-being. There is evidence on how the size of businesses affects local economies, but not based on whether the businesses are local or non-local. With the exception of Kolko and Neumark (2010) and Fleming and Goetz (2011), I am not aware of any research that studies directly the relationship between local businesses and local economic well-being. One main difference between Kolko and Neumark (2010) and the present study is that while they look at employment within business establishment, I focus on general employment growth, income growth and change in poverty in a county. By doing this I am able to capture the positive externalities of local ownership due to multiplier effects. To capture these effects, I rely on county-level aggregates rather than establishment-level data. Fleming and Goetz (2011) study the effects of local and nonlocal businesses on county income growth using establishment counts. In this study I use employment data as opposed to establishment counts and expand the analysis to study the effects on employment and poverty.

My resident business measure is the share of the employment in resident business establishments in total employment by all establishments (resident, non-resident, and noncommercial) in a county. I assess the relationship between the size of the local business sector and the local income and employment growth and the change in poverty as measured by the per capita real income growth, the change in full- and part-time employment, and the change in poverty rate, respectively, averaged over the period 2000 to 2008.[3] Next I disaggregate the measures of percent of employment in resident establishments into different sizes based on the categorization provided by the data developer Edward Lowe Foundation (youreconomy.org) and examine the relationship between these various categories on measures of county economic performance.

The rest of the paper is structured as follows. Section 2 provides a summary of related existing literature. Descriptive evidence on resident and nonresident employment is provided in Section 3. Section 4 presents methodology and Section 5 presents descriptive statistics and correlations. Section 6 presents my main results. Section 7 concludes the paper.

Existing Literature

The local entrepreneurship approach is not new and dates back to Schumpeter. Schumpeter (1934) saw the technological innovation introduced by the entrepreneur playing a central role in economic growth and development. However, there is a dearth of research that speaks directly to the question of how locally-owned businesses affect local economic performance. Michelacci and Silva (2007) study factors affecting the local bias in entrepreneurship (LBE), measured as a fraction of entrepreneurs working in the region where they were born, including the effects of local unemployment rate and per capita Gross Domestic Product (GDP). Utilizing data from the United States and Italy, they find a negative relation

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[3] Poverty rate up to 2009.

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between LBE and local unemployment rates and LBE is higher in more developed regions. A special issue of the *Journal of Urban Economics* (67(1), 2010) brings together papers that specifically focus on the local dimensions of entrepreneurship. The first paper of this issue (Glaeser, et al., 2010) sheds light on core questions[4] that researchers face when studying local causes and consequences of entrepreneurship, presents a model to incorporate entrepreneurship in urban settings, and offers an agenda for future work on the spatial aspects of entrepreneurship. They also point out that although nonresident firms may bring new employment opportunities and economic activities to a region, they may be less effective in providing local economic impact because of vertical and horizontal integration with other non-local (subsidiary) firms. Kolko and Neumark (2010) assess the argument that local businesses are more likely to internalize the costs to the community regarding decisions to reduce employment, thereby helping cities to absorb adverse economic shocks. They find that some types of local ownership do protect regions from economic shocks, but this protection mainly comes from corporate headquarters rather than from small independent businesses. Fleming and Goetz (2011) study the effects of local ownership of businesses on income growth using the establishment data from Edward Lowe Foundation and find evidence that local ownership matters for income growth. Several sociological studies have identified local ownership as a key factor in a community's long-term economic viability and resilience against shocks (Varghese, et al., 2006). Tolbert (2005) argues that locally-based businesses, along with civic organizations, associations, and churches, have a positive impact on community quality of life and these entities have a strong capacity for local problem-solving.

Small business and job creation

David Birch (Birch, 1987, 1979) pioneered the idea that small firms are an effective engine for job creation. The main finding of Birch's research was that small firms are the most important source of job creation in the U.S. economy. He claims that 66 percent of all net new jobs in the United States were created by firms with 20 or fewer employees and 81.5 percent were created by firms with 100 or fewer employees during 1969-1976. The pro-small firm idea was immediately embraced by the U.S. Small Business Administration and they implemented numerous policies and programs to promote small business development.

Subsequent researchers have found fault with Birch's findings. Biggs (2003) cites a number of studies that dispute the findings by Birch. Among the criticisms: not controlling for many new or small establishments that are owned by large firms such as Wal-Mart (Armington and Odle, 1982); many jobs created by small firms are destroyed due to high failure rate of new small firms (Dunne, Roberts and Samuelson, 1987); and statistical errors in Birch study (Hamilton and Medoff, 1990; Davis, Haltiwanger and Schuh, 1993). Davis et al. (1996) argue that Birch's conclusion is flawed and concluded that there was no relationship between establishment size and net job creation using improved methods and data for the manufacturing sector. Using the National Establishments Time Series (NETS) data, Neumark, et al. (2008) present evidence that small firms and small establishments create more jobs, on net, although the difference is much smaller than what is suggested by Birch's methods. They also find a negative relationship between establishment size and job creation for both the manufacturing and services sectors.

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[4] For example: What is the impact of entrepreneurship at the local level? What are the causes of spatial variations in entrepreneurial activity? To what extent do social interactions in a place create a local multiplier in entrepreneurship? See Glaeser, et al., (2010) for details.

Descriptive Evidence on Resident and Nonresident Employment

This study uses data from NETS Database provided by the Edward Lowe Foundation (). The NETS is a unique data set that describes the type of ownership, the size of firms, and geographic location. It was constructed using the most recent waves of the Dun and Bradstreet (D&B) data. The Edward Lowe Foundation organizes NETS business establishments in a county into unique sectors as follows:

- Resident — either stand-alone businesses in the area or businesses with headquarters in the same state.
- Nonresident — businesses that are located in the area but headquartered in a different state.
- Noncommercial — educational institutions, post offices, government agencies and other nonprofit organizations.

These categories were then subdivided into stages based on employment size. They are self-employed (1 employee), stage 1 (2-9 employees)[5], stage 2 (10-99 employees), stage 3 (100-499 employees), and stage 4 (500 or more employees). This categorization, the Edward Lowe Foundation claims, reflects "operational and management issues establishments face as they grow from startups to mature companies". Following Fleming and Goetz (2011), I name these four stages respectively as *micro*, *small*, *medium*, and *large*.

County-level analysis show that there were nearly 100 million workers employed by resident establishments and a little over 31 million workers employed by nonresident establishments in the United States in 2007. As a percent of total employment, 59 percent were employed by resident establishments and 22 percent were employed by nonresident establishments. The remaining employees were in the noncommercial sector. One noticeable feature is that these proportions between resident and nonresident employee categories do not vary much and stay more or less stable during the time period considered, 1997 to 2007 (Figure 3). The figures for metro areas in 2007 were 86 million resident employees (57 percent) and 27 million nonresident employees (18 percent) and for nonmetro areas, there were 14 million resident employees (52 percent) and 4 million nonresident employees (15 percent) (Figure 4).[6]

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[5] The data that I received from the Edward Lowe Foundation had the self-employed category included in stage 1.
[6] I use USDA-ERS rural urban continuum codes to classify counties as metro (codes 1 through 3) and nonmetro (codes 4 through 9) counties.

Figure 3. Resident and nonresident employment shares for all counties in the U.S., 1997-2007

All establishments
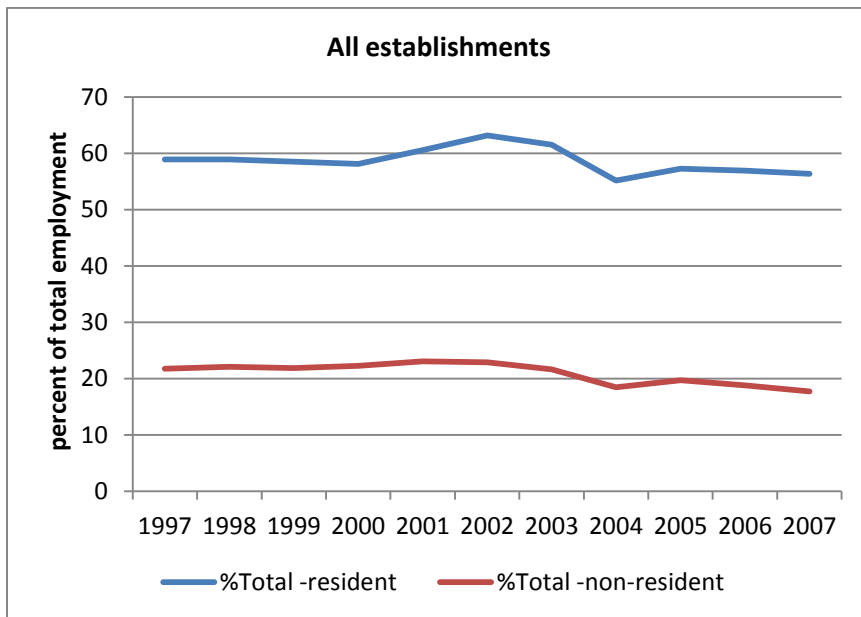
Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 4. Resident and nonresident employment shares for metro and nonmetro counties in the U.S., 1997-2007

All establishments
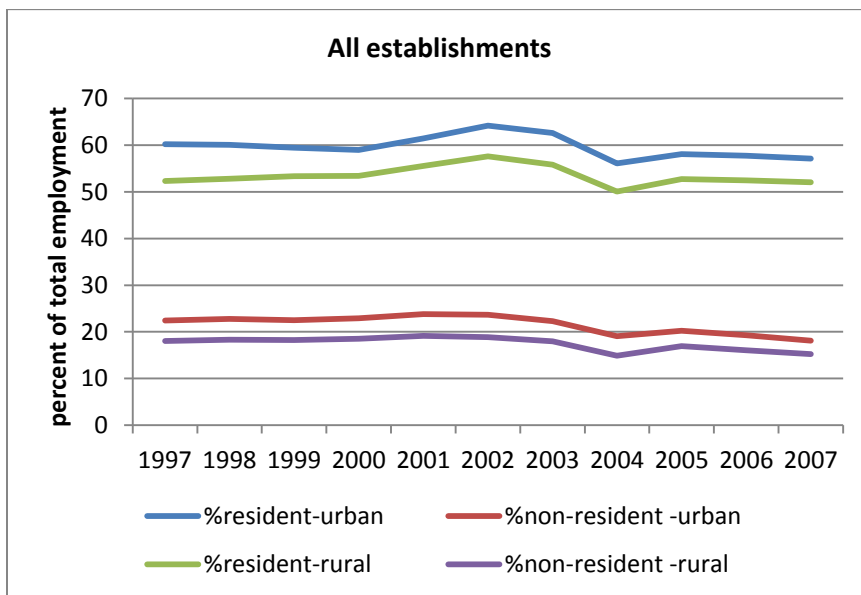
Source: Author's calculation using NETS Database, Edward Lowe Foundation

The share of workers employed by resident establishments is substantially greater compared to those employed by non-resident establishments in all size (stage) categories. Figures 5.1 through 5.4 show that the distribution of workers (as a percent of total employment) among the four stages described above for all counties in the United States, from 1997 through 2007. Casual examination of figures 5.1 through 5.4 shows that the nonresident shares of employment is very low (less than 2 percent) for micro businesses and gradually starts to go up for small and medium size businesses.

Another notable feature is that employment shares for micro and small businesses stay somewhat stable during the time period considered, but starts going down for both resident and nonresident types for medium and large businesses after 2001.

Figure 5.1. Resident and nonresident employment shares for all counties in the U.S., 1997-2007

1-9 employee establishments

Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 5.2. Resident and nonresident employment shares for all counties in the U.S., 1997-2007

10-99 employee establishments
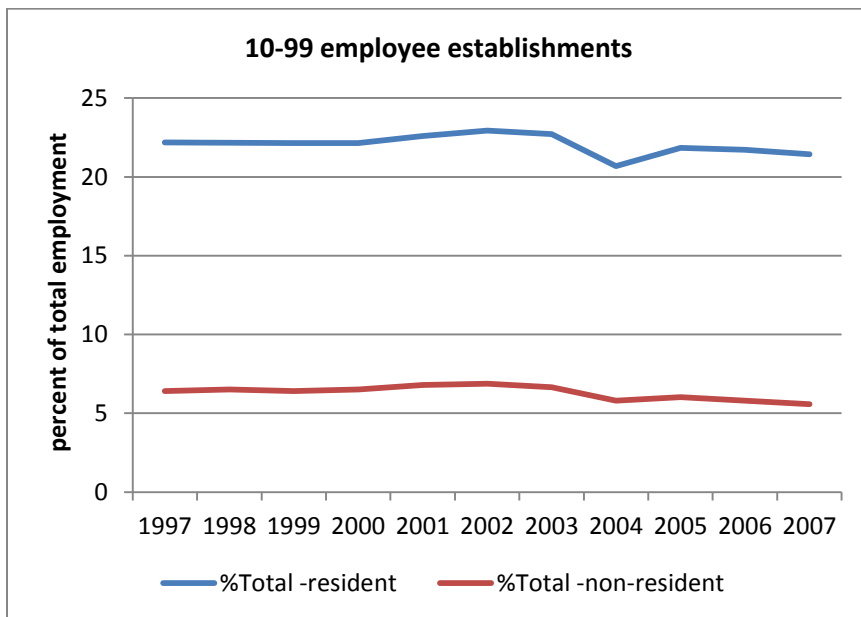
Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 5.3. Resident and nonresident employment shares for all counties in the U.S., 1997-2007

100-499 employee establishments

Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 5.4. Resident and nonresident employment shares for all counties in the U.S., 1997-2007

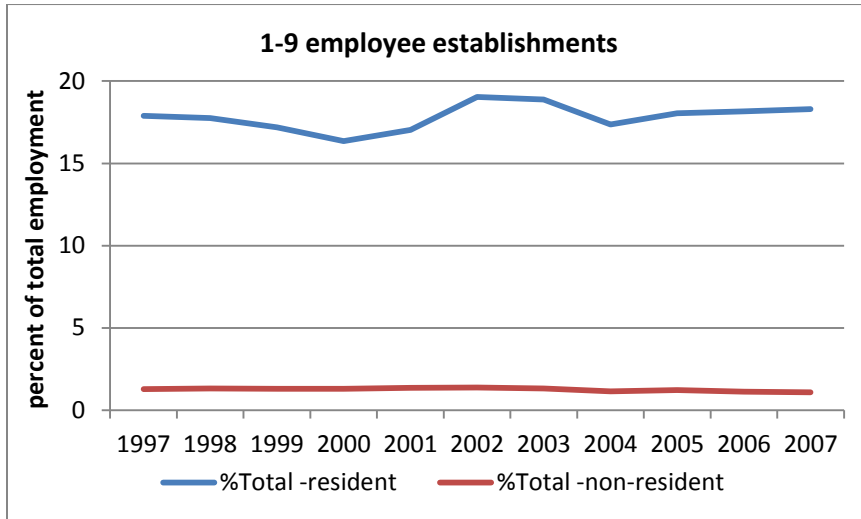**500 and above employee establishments**

Source: Author's calculation using NETS Database, Edward Lowe Foundation

A similar graphical analysis for metro and nonmetro counties separately shows some notable differences between the two types of counties. Figure 6.1 shows that nonmetro areas have a higher percent of people employed by resident, micro establishments (20 percent in 2007) than metro counties (18 percent in 2007), but the share of nonresident employees in this stage is very low (1 percent in 2007) and about the same for both nonmetro and metro counties. These respective shares stay about the same throughout the time period considered with some minor fluctuations in the resident employment category. Figures 6.2 through 6.4 show that the employment shares for resident and nonresident establishments were higher in metro areas than nonmetro areas for small, medium,

and large establishments. Figure 6.4 shows that employment shares of large establishments for nonmetro areas for both resident and nonresident establishments stay between 4 and 6 percent and both types are lower than those in metro areas. Overall, nonmetro employment is dominated by small and medium-sized resident establishments.

Figure 6.1. Resident and nonresident employment shares for metro and nonmetro counties in the U.S., 1997-2007

Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 6.2. Resident and nonresident employment shares for metro and nonmetro counties in the U.S., 1997-2007
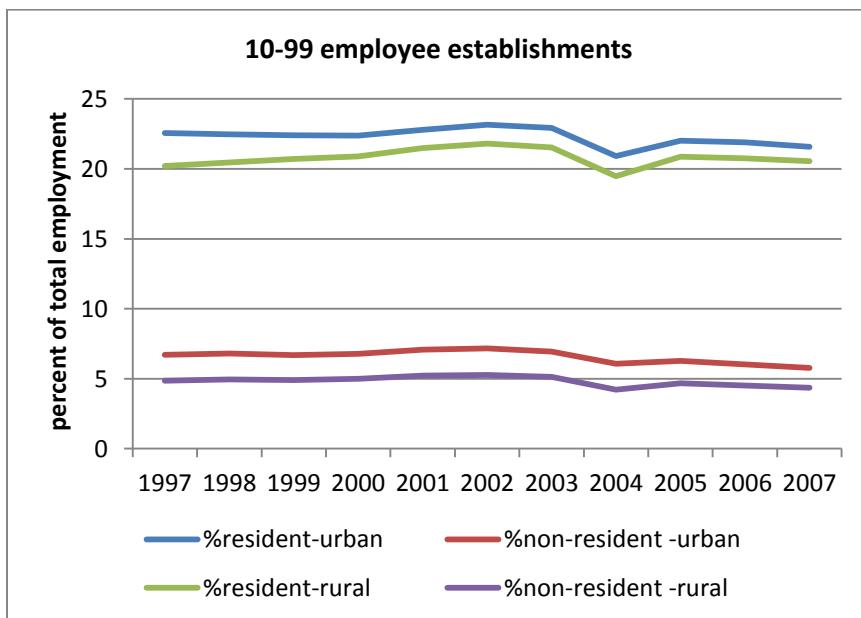
Source: Author's calculation using NETS Database, Edward Lowe Foundation

Figure 6.3. Resident and nonresident employment shares for metro and nonmetro counties in the U.S., 1997-2007
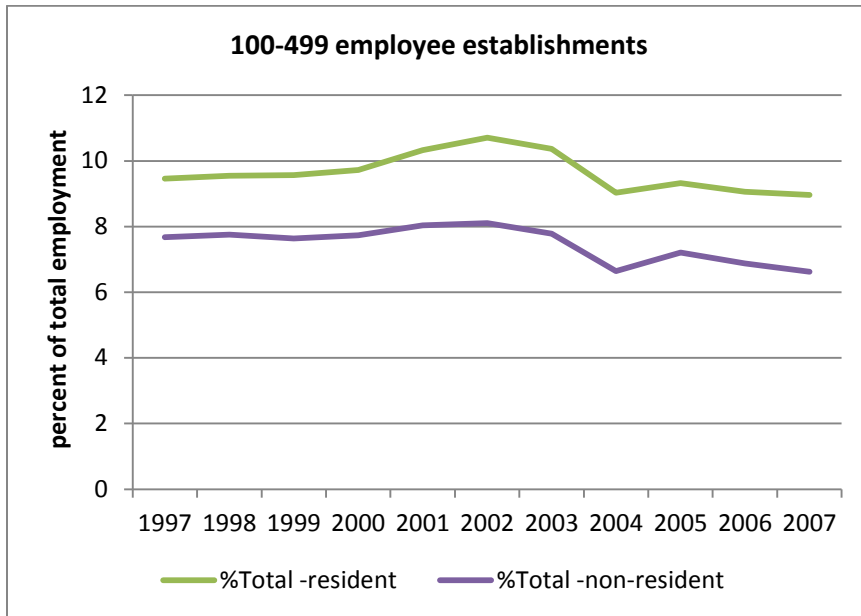
100-499 employee establishments
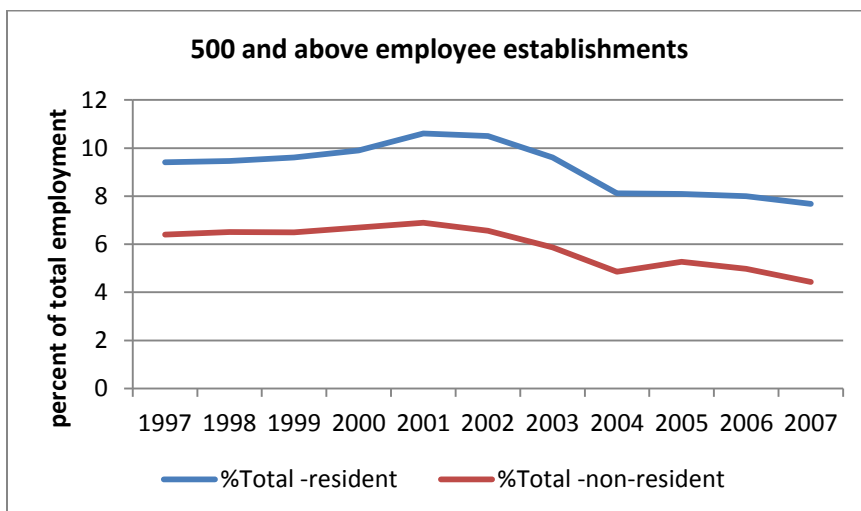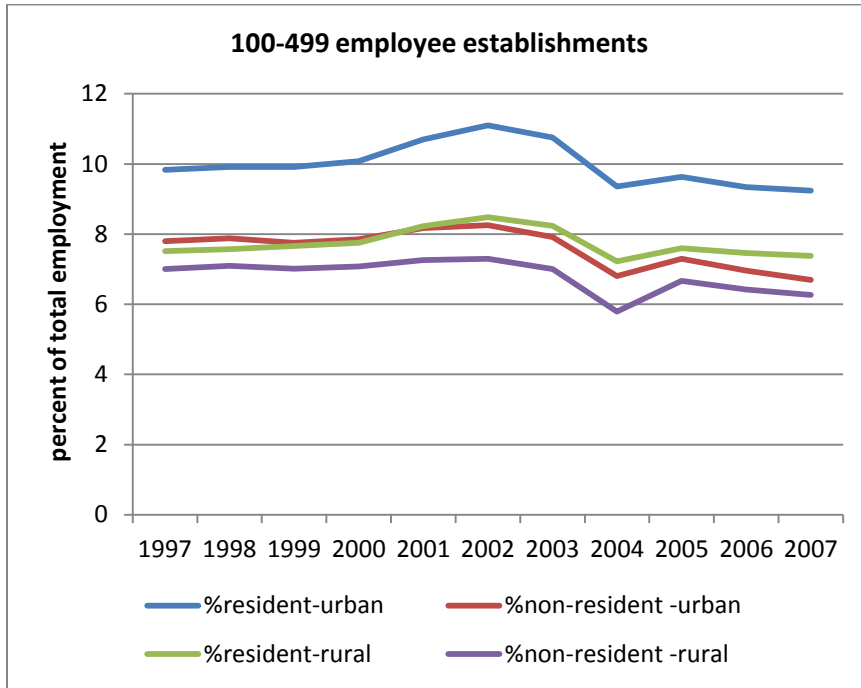

Source: Author's calculation using NETS Database, Edward Lowe Foundation

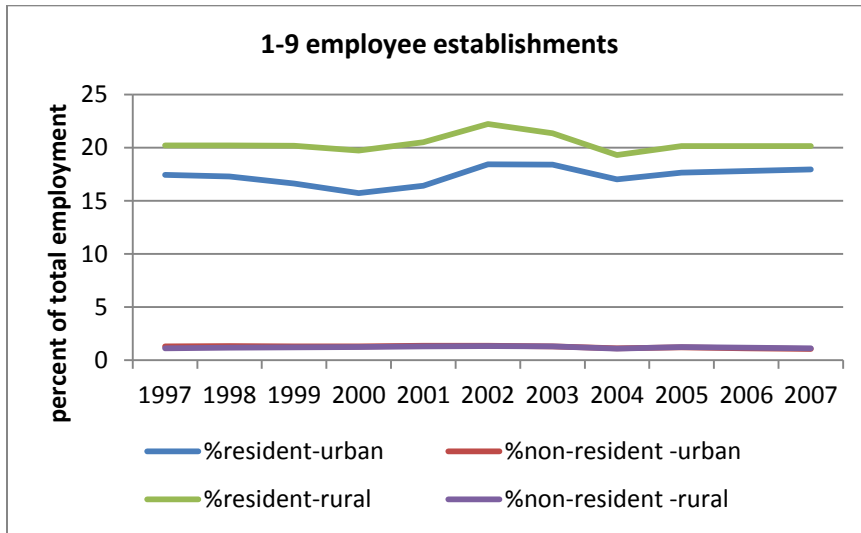Figure 6.4. Resident and nonresident employment shares for metro and nonmetro counties in the U.S., 1997-2007

500 and above employee establishments
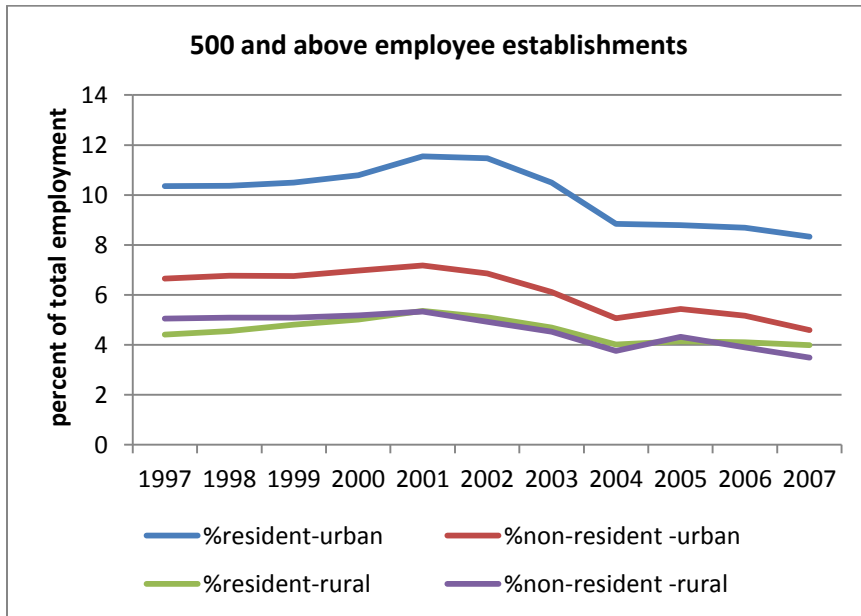
Source: Author's calculation using NETS Database, Edward Lowe Foundation

Methodology

The empirical framework for the analysis is based on Mankiw, et al (1992), but I use a more ad hoc regression equation (Temple, 1999) that includes a wider set of factors that affect local economic performance. To evaluate the relationship between local entrepreneurship and economic performance over the period 2000-2008, I use the following regression equation:

$$(1) \qquad y_i = \alpha_i + \beta y_{it-T} + \gamma estab_{it-T} + \delta X_{it-T} + \varepsilon_i$$

where y_i is the dependent variable under consideration for economy i during the time period T, y_{it-T} is a convergence variable, $estab_{it-T}$ is a vector of the initial employment share of resident establishments (or a vector of their subcategories based on employment size of establishments), as a percent of total employment, X_{it-T} is a vector of other initial conditions, and ε_i is the error term. For the dependent variables I use county per capita real income growth, employment growth, and change in poverty rate, between 2000 and 2008 (2009 for poverty rate). For the employment rate, I use total full- and part-time employment in a county. What follows is a brief description of the variables used in the estimation and their measurement.

To measure the role of resident businesses in a county, I use the NETS database on the share of total employment accounted for by these businesses.[7] In one specification of the equation (1), I use the total employment in resident establishments as a percent of total employment by all establishments (*resall*). In another specification of equation (1) I use a disaggregated shares of total resident employment based on establishment size. I control for eight initial conditions. As in most regional growth regressions, I include initial per capita income (*rlinc*), initial total full-and part-time employment (*temp*), and initial poverty rate (*indpov*) in each of the regression equations respectively to control for convergence effects. Other control variables include percent of people who have a college degree or more (*college*) to capture human capital, local government property taxes per capita (*pcptaxt*), and expenditures on education (*edexp*) and highways (*hyexp*) as policy variables, nonwhite minorities (*nonwhite*) to capture recent labor market trends, population density (*popden*) as an agglomeration variable and natural amenity index (*amnscale*).

Based on previous literature on local entrepreneurship and small business, I test the following two major hypotheses in this study:

(1) local entrepreneurship has a positive effect on county per capita income growth and employment growth and a negative effect on change in poverty in counties; and

(2) smaller local businesses have a more positive effect on local economic performance (measured as per capita income growth, employment growth, and change in poverty) than larger local businesses.

Estimation issues: endogeneity and spatial dependence

My analyses may be prone to biases resulting from endogeneity. For example faster per capita income and employment growth might encourage the entry of more local businesses to the locality. Michelacci and Silva (2007) find that local bias in entrepreneurship is associated with a region's level of

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[7] One shortcoming of this measure, as observed by Beck et al (2005), is that it is a static measure. My data do not take into consideration the entry of new firms, firm deaths, or growth of firms.

economic development. This scenario would bias, usually upward, the parameter estimates and explanatory power (Glaeser and Kerr, 2009). I use lag values for local entrepreneurship variables and spatial econometric methods (described below) to mitigate the endogeneity bias in the data.

Lesage and Fischer (2008) present a strong case for using a spatial econometric approach to estimate regional growth models. There is also a sizeable and growing literature in regional science showing that regional growth rates exhibit spatial dependence and Abreu et al. (2004) summarizes over 50 such studies. The present study uses county-level data in the United States and many county- and state-level studies that have been conducted to investigate income growth, poverty, and employment in the United States use spatial econometric approach (see for example Rey and Montouri, 1999; Rupasingha et al., 2002; Rupasingha and Goetz, 2007). Previous growth studies have used competing spatial models to address various forms of spatial dependence. For example, some studies consider only spatial dependence in the dependent variable using spatial lag model (SAR) and others examine only spatial dependence in the error term using spatial error model (SEM) (Abreu, et al., 2004). Abreu et al. (2004) also refer to studies that use both error and lag dependence in the same model using general spatial model (SAC) as well as spatial dependence in the independent variables. Lesage and Fischer (2008), based on the results derived in Lesage and Pace (2009), suggest that the appropriate spatial regression model for regional growth regressions is the Spatial Durbin Model (SDM). The SDM includes a spatial lag of the dependent variable as well as spatial lags of the explanatory variables.

The SDM for the growth model in equation (1) can be written as:

$$(2) \qquad y_i = \alpha_i + \rho W(y_i) + \beta Y_{it-T} + \mu W Y_{it-T} + \sum_{j=1}^{k} \delta_j X_{ij,t-T} + W \sum_{j=1}^{k} \gamma_j (X_{ij,t-T}) + \varepsilon_i$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

where y_i denotes an $nx1$ vector of the dependent variable (income growth, employment growth or change in poverty in the present case) as in equation (1), Y_{it-T} is the convergence variable, X represents an nxk matrix containing the determinants of the dependent variable including variables for local entrepreneurship and W is an nxn spatial weights matrix. The terms $\rho W(y_i)$, $\mu W Y_{it-T}$, and $\gamma W \sum_{j=1}^{k} (X_{it-T})$ in the equation adds dependent variable, convergence variables, and explanatory variables respectively from neighboring counties. ρ, β, μ, δ, and γ denote the parameters to be estimated. The coefficients ρ, μ, and γ pick up the extent to which the dependent and independent variables of nearby counties influence economic performance in the original county.

One motivation for using the SDM for growth regressions is that it is the only spatial model that nests spatial dependence in the dependent variable, independent variables and error term that will produce unbiased estimates (Lesage and Pace, 2009). The setting parameters $\mu = 0$ and $\gamma = 0$ in equation (2) leads to the SAR specification that includes a spatial lag of the dependent variable from neighboring regions. Imposing the common factor parameter restriction $\gamma = -\rho\delta$ and $\mu = -\rho\beta$ yields the SEM specification (LeSage and Pace, 2009). Also, imposing the restriction that all spatial parameters are equal to zero yields the standard OLS regression model. Another motivation for using the SDM is that an omitted variables problem likely arises when handling regional data samples and Lesage and Pace (2009) demonstrate that parameter estimates of the SDM are not affected by the magnitude of the spatial dependence in the omitted variables.

Descriptive Statistics and Correlations

Table 1 presents summary statistics of the variables used in the analysis for all counties, metro counties, and nonmetro counties.[8] There is a wide variation in average annual real per capita income growth across the counties in my sample over the period 2000–2008, ranging from –10.0 percent in Slope County, North Dakota to 12 percent in Hayes County, Nebraska, with a mean of 0.8 percent and standard deviation of 2 percent. Average annual employment growth varies from –6.0 percent in St. Bernard Parish, Louisiana to 11 percent in Storey County, Nevada and average annual individual poverty rate changes from –1.3 percent in Starr County, Texas, to 2.3 percent in Irwin County, Georgia. I generally observe substantial county-level variation in the measures of initial conditions. For example, the share of the population who have a college degree or more range from 5 percent (Edmonson County, Kentucky) to 61 percent (Los Alamos County, New Mexico), with a mean of 16 percent and standard deviation of 7.63 percent. The natural amenity index varies from -6.40 in Red Lake County, Minnesota to 11.17 in Ventura County, California, with a mean of 0.27 and standard deviation of 2.4. There is also substantial variation across counties in local government taxes and expenditure on education and highways.

Table 2 presents the correlations between the dependent variables and the variables of interest in this study which are percent of employment in total resident establishments and the establishment categories based on employment size described above. For the sake of conciseness, only the statistically significant correlations for all counties sample are discussed here. Simple correlations indicate that the total employment share in resident establishments is positively correlated with real per capita income and employment growth and negatively correlated with change in poverty, indicating that the resident establishment employment share is clearly favorably correlated with local economic performance measures. Results are mixed with respect to employment size (stages) categories. The share of employment in micro businesses is positively correlated with income growth, negatively correlated with change in poverty, and not significantly correlated with employment growth. The share of employment in small resident establishments is positively correlated with income and employment growth and negatively correlated with change in poverty. The resident share of employment in medium businesses is negatively correlated with income and employment growth and positively correlated with change in poverty. The resident share of employment in large establishments is negatively correlated with income growth, positively correlated with change in poverty, and not significantly correlated with employment growth.

Econometric Estimation Results

I use three samples to estimate the model presented in equation 1 for each of my local economic performance measures. The three samples are all counties of the United States, both metro and nonmetro counties. For all three samples, I obtained two sets of estimates as follows. First, I include all the initial conditions and aggregated resident employment share (*set one*). Second, I include all the initial conditions and disaggregated resident employment shares based on employment size (*set two*). Results are organized as follows.

I first present and discuss income growth results, followed by employment growth and change in poverty. Each dependent variable is featured in two separate tables, one for the set-one and another

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[8] See Appendix for all tables.

for the set-two variables. Each table has three samples: all counties, metro counties, and nonmetro counties. Multicollinearity across the independent variables was not found to be an issue, as variance inflation factors were consistently below 2 for all variables in income and employment growth and all variables in change in poverty equation with the exception of 2.1 for one variable in the set-two regression.

OLS results

Tables 3-5 presents results of OLS estimations of equation (1) and the consistent estimates were produced using White procedure. The results for the income growth equation with set-one and set-two results are presented in Table 3. The resident share of employment was highly significant and positive in all counties and nonmetro counties samples but not significant in the metro sample. Next I estimate the income growth equation with set-two variables. Results for all counties show that among resident employment sizes, micro business share has a positive and significant association with income growth (significant at 1 percent), but the small business share has a negative and significant (at 10 percent) association. Medium and large employment shares are not significant. Results for the metro sample show that the micro establishment share is positive and significant at the 6 percent level, but medium and large shares are negative and significant (at 1 percent and 5 percent respectively). In the nonmetro sample only the micro employment share is significant (1 percent) and positively associated with income growth. Other sizes are not statistically significant.

The model represented in Equation (1) is used to analyze employment growth in all U.S. counties, metro counties, and nonmetro counties, from 2000 to 2008 and results are reported in Table 4 for set-one and set-two variables. The resident share of employment was highly significant (at 1 percent) and positive in all samples. Next I estimate the employment growth equation with set-two variables. Results for all counties show that among resident employment sizes, micro and small business employment shares were significant at 1 percent and large business share was significant at the 10 percent level. All three of these parameters are positive, indicating a favorable association with employment growth in counties. Results for the metro sample show that micro and small employment shares have a positive and significant (at 1 percent level) association with employment growth. Medium employment share is negative and significant (at 1 percent), indicating an unfavorable association with employment growth in metro counties. In the nonmetro sample only micro and small employment shares are significant (1 percent) and positively associated with employment growth. Other sizes are not statistically significant.

Next I estimate the model represented in Equation (1) to analyze change in poverty from 2000 to 2009 and results are reported in Table 5. Regression results with set-one variables show that resident share employment is negatively associated with change in poverty in all three samples. Estimated parameters were significant at 1 percent for all samples. Table 5 also reports the results for set-two variables. The share of micro and small employment shares are negative and significant (1 percent) for all counties and nonmetro counties samples. The share of micro employment share is negative and significant (1 percent) for the metro sample. The medium employment share is positive and significant (10 percent) for all counties and nonmetro counties samples.

Spatial model results

As pointed out above, growth models with county-level data may exhibit spatial dependence. In this section, following Lesage and Fischer (2008) and others (Fischer, et al., 2009, LeSage and Pace, 2009), I estimate a series of SDM specifications and show that the SDM is the suitable choice among competing spatial specifications. The estimation of the SDM is the same as the spatial lag model (SAR), through maximum likelihood procedure, the difference being that the SDM procedure doubles the number of independent variables in the model with the inclusion of spatially lagged independent variables. Results presented in Tables 6-11[9] show that all the spatial lag parameters are statistically significant at the 1 percent level, indicating spatial dependence in the dependent variables and therefore the simple restriction that spatial lag parameter is equal to zero does not hold. The likelihood ratio tests conducted to discriminate between unrestricted SDM and the SEM (Fischer, et al., 2009) reject the common factor restriction at the 1 percent level for all specifications in all samples and therefore the SEM specification. The significant spatial parameters in all specifications for all samples also show that my results based on OLS may be biased, inefficient, and inconsistent (Anselin, 1988).

Also notable in Tables 6-11 is that there are many statistically significant spatially-lagged initial conditions in all specifications, indicating that characteristics of neighboring counties do play a role in explaining the economic performance of a particular county. If the coefficients of my variables of interest in the OLS model and the SDM are to be compared, the parameter estimates for most of the resident employment shares were not changed in terms of signs and general significance levels. Affected resident employment shares were as follows. In the income growth model, medium employment share is significant and large employment share is not significant in the OLS for all counties, micro and large employment shares were significant in the OLS for metro counties, and medium share is not significant in the OLS for nonmetro counties. In the employment growth model, large share is not significant for metro counties. In the change in poverty model, total resident share and medium share of employment are significant in the OLS model. Overall, the estimation results on resident employment shares support my *a priori* hypothesis that resident/local establishment employment shares are associated with better local economic performance and when disaggregated, higher shares of smaller resident businesses are associated with better county economic performance.

The interpretation of estimated parameters in the SDM estimation is richer and more complicated due to the fact that spatial models expand the information set to include the information on neighboring regions (LeSage and Pace, 2009). Therefore the least squares simple partial derivative interpretation of regression parameters does not hold any more in the SDM context. For example, in my SDM setting, the per capita income growth in county *i* depends on the income growth of county *i*'s neighboring counties, county *i*'s initial per capita income, initial per capita income of neighboring counties, county *i*'s other initial conditions including local entrepreneurship shares, and other initial conditions of neighboring counties. LeSage and Pace (2009) demonstrate that a change in a single explanatory variable in region *i* has a 'direct effect' on region *i* as well an 'indirect effect' on *i*'s neighboring counties. Lesage and Pace (2009) point out that there are two ways to interpret indirect impacts: the impact a region has on all other regions and the impact of all other regions on a particular

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[9] I standardized each dependent and independent variable by subtracting its mean and dividing by its standard deviation to avoid badly conditioned variables and negative definite matrices.

region. I rely on LeSage and Pace (2009) to interpret correctly the impact of local entrepreneurship on measures of county economic performance.[10]

Tables 12-17 present the summary direct and indirect impact measures for my SDM specification for set-one and set-two variables for all samples. A comparison between the model average estimates presented in Tables 6-11 and the direct impact estimates presented in Tables 12-17 shows that in some cases these estimates are similar in magnitudes, while others are different in magnitude. The reason for these differences is due to feedback effects (Lesage and Fischer, 2008). For example, while the coefficient estimates seem to be similar in magnitude for amenity scale in income growth equation for all counties model (-0.088 and -0.088, respectively for average estimate and direct estimate), they seem to differ in magnitude for per capita property taxes (0.139 and 0.170, respectively for average estimate and direct estimate).

Income growth

The direct and indirect impact measures for the income growth equation for all samples are presented in Table 12 for set-one variables and Table 13 for set-two variables. Turning to the direct impact of total resident employment share on county real per capita income growth, it has a positive and significant impact for all counties and nonmetro samples, but has no significant effect for metro sample. When disaggregated to establishment size, the share of employment in micro establishments is positive and significant for all counties and nonmetro samples. The medium share is negative and significant for metro sample and positive and significant for the nonmetro sample. While I do not observe any significant indirect impact of aggregate resident employment share, few estimates in set-two regression are significant. The micro share is positive and medium and large shares are negative in the all counties sample and medium share is negative in the nonmetro sample. The positive and significant indirect impact of the micro share in the all counties sample can be interpreted as: one percent increase in the share of micro employment in a county will on average result in all other counties collectively experiencing a 0.23 percent increase in real per capita income. This can also be interpreted as a one percent increase in micro share in all other counties will on average lead to a 0.23 percent increase in real per capita income for a particular county.

The direct impacts of the rest of the control variables[11] have generally been as expected. Initial per capita income is negative and highly significant for all samples in both set-one and set-two regressions. The estimate for the percentage of the population with at least a bachelor's degree is positive and significant in all samples and highly significant for all samples in both set-one and set-two regressions. The estimate for the per capita property tax variable is significant with an unexpected positive sign for all samples in both set-one and set-two regressions. While the estimate for government expenditure on education is not significant in any of the specifications, the estimate for per capita expenditure on highways is positive and significant for the all counties and metro samples in set-one regression and positive and significant for metro sample in set-two regression. The nonwhite estimate is significant and negative for the all counties and nonmetro samples, but significant and positive for metro counties in set-one regression. This estimate in significant only in the metro sample and is

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[10] See LeSage and Pace (2009) and others (Fischer, et al., 2009; Lesage and Fischer, 2008) for details regarding the specific calculations.

[11] For the sake of brevity, we only discuss here the direct effects of these variables and interested readers may consult Tables 12-17 for details.

positive in set-two regression. The estimate for population density is only significant for nonmetro sample in set-one regression and is negative. The estimate for natural amenity index is negative and significant for the all counties and nonmetro samples in set-one and set-two regressions.

Employment growth

The direct and indirect impact measures for the employment growth equation for all samples are present in Table 14 for set-one variables and Table 15 for set-two variables. The aggregate resident share of employment has a positive and significant impact for all samples. When disaggregated to establishment size, the shares of employment in micro and small establishments are positive and significant for all samples. The medium share is negative and significant for the metro sample and the large share is positive and significant in the all counties and metro samples. Indirect impact estimates for all employment shares, except the micro share, in employment growth equation for the all counties model are not significant. The micro share in employment growth equation for the all counties sample is negative and significant indicating that the feedback effects of this particular variable are negative from a particular county to rest of the counties and vice versa.

I now turn to a brief discussion of the direct impacts of the rest of the control variables in employment growth equation. The estimated convergence parameter (initial employment level in a county) has the expected negative sign and is significant in all specifications except for the nonmetro sample, where it is not statistically significant. The estimated parameter for the education variable is positive and significant in all regressions. Per capita property taxes enter negatively and significantly for the all counties and metro samples, but not for the nonmetro sample. The direct impact estimate for per capita education expenditure indicates no significant association with employment growth in any specification. A negative and highly significant association is shown for per capita government expenditure on highways for the all counties and nonmetro samples. The direct impact estimate for the nonwhite variable is negative and significant in the all counties and metro samples and positive and significant in the nonmetro sample. Population density estimate shows no statistically significant association with employment growth in any sample. The natural amenity scale estimate is significant and positive for the nonmetro sample only.

Change in poverty regressions

The direct and indirect impact measures for change in the poverty equation for all samples are present in Table 16 for set-one variables and Table 17 for set-two variables. The aggregate resident share of employment has a negative and significant direct impact for the all counties and nonmetro samples, indicating that this measure has a favorable association with poverty reduction in respective regions. This estimate is not significant in the metro sample. As for the direct impact of disaggregated resident employment shares, the micro share is negative and significant for all samples. And the small share is negative and significant for the all counties and nonmetro samples. Turning to indirect effects of the variables of interest, only the medium share estimate is significant, and that is for the all counties and nonmetro samples. This estimate has a positive sign, showing that the feedback effects of this particular variable from a particular county to rest of the counties and vice versa are not favorable for poverty reduction.

Signs and significant levels of the direct impact measure for rest of the control variables in the poverty regressions, in general, are as expected except for the initial poverty level (convergence

variable) and education variables. The parameter estimates for both of these variables are consistently significant across all specifications for all three samples, but have a positive sign. A positive and significant initial poverty rate estimate indicates that counties that had higher initial poverty have gotten poorer over the study period. The positive sign for the estimate for the education variable is against the conventional belief. The direct impact of per capita property taxes is negative and significant in the all counties and nonmetro samples. The estimate for per capita expenditure on education is negative and significant for all specifications. The highway expenditure estimate is negative and significant only for the metro sample with set-one variables. The estimate for the nonwhite variable is positive and significant for all samples with set-one specification and for the all counties and nonmetro samples with set-two specification. The estimate for population density is not significant in any of the specifications and the estimate for the natural amenity index is positive and significant for the metro sample.

Endogeneity bias

As mentioned above, my results could be subject to endogeneity bias and I have attempted to address this issue in my estimation methods. First, I use initial or beginning period values of resident and nonresident businesses, which is known as a weakly exogenous regressors approach (Levine, et al., 2000). Lagged values from year 2000 were also used for other explanatory variables in order to mitigate the potential endogeneity issues associated with those variables. I also test this further by including lagged employment shares of 1997, which is prior to my initial year of 2000, considering the fact that my initial employment shares may be subject to a greater level of stochastic disturbance over short time period. The results (not reported here) remained unchanged for coefficients and significance levels with the use of 1997 values for local employment shares. Another way that I correct the endogeneity bias in my data is with the use of SDM. A main concern for endogeneity arises when there are omitted variables that exhibit non-zero covariance with variables included in the model. The use of the SDM for the analysis minimizes this problem (Brasington and Hite, 2005) because the SDM controls for the influence of omitted variables, thus alleviating the need to instrument for endogenous variables.

Summary and Conclusions

This study presents preliminary evidence on the effects of local entrepreneurship on local economic performance. Exploiting a rich county-level variation in locally-owned businesses and economic performance variables, I conducted a systematic investigation into the significance of local entrepreneurship for local economic performance in the United States at the county-level. The conceptual framework followed a conventional conditional growth model to study the effects of local entrepreneurship on real per capita income growth, employment growth, and change in poverty for all counties in the United States. I also estimated the models for metro and nonmetro. The estimation approach used an OLS, corrected for heteroskedasticity, and spatial econometric method that utilizes a Spatial Durbin Model. I addressed possible endogeneity bias in my data. Two main hypotheses were tested with the estimation. They are: (1) local entrepreneurship in general has a positive effect on county per capita income growth and employment growth and a negative effect on change in poverty in counties; and (2) smaller local businesses have a more positive effect on local economic performance (measured as per capita income growth, employment growth, and change in poverty) than larger local businesses.

My results in general support the two main hypotheses and provide evidence that local entrepreneurship matters for local economic performance and smaller local businesses are more conducive than larger local businesses for local economic performance. Results are quite robust to the inclusion of other commonly used control variables in regional growth models, the incorporation of spatial dependence in the data, and the estimation of sub-samples for metro and nonmetro counties. I find that the percent of employment provided by resident, or locally-owned, business establishments has a significant positive effect on county income and employment growth and a significant and negative effect on change in poverty in the all counties and nonmetro counties samples. When disaggregated the employment share of resident businesses to establishment size, the results show that smaller resident establishments are more favorable for county economic performance. For example, the micro employment share is positive and significant for income growth for the all counties and nonmetro counties samples. The same estimate is positive and significant in employment growth and negative and significant in change in poverty for all samples that I estimated. The share of employment in small establishments has a positive and significant association with employment growth for all samples and a negative and significant association with change in poverty for the all counties and nonmetro samples. The effects of the employment shares in medium and large businesses are mixed. For example, the medium share is negative and significant on income growth for the metro sample and positive and significant on income growth for the nonmetro sample. In the employment growth equation, the medium share is negative and significant for the metro sample and the large share is positive and significant for the all counties and metro samples. The poverty regressions show no clear effects of medium and large establishments. These findings clearly show that employment in micro and small-sized local establishments are favorable for county income and employment growth and poverty reduction. However, the effects of employment in larger resident establishments on local economies are mixed.

Supporting the expectations of policy makers, some researchers and economic development practitioners, I find evidence that locally-based business development may be a viable local economic development approach. More specifically, I find evidence that higher percentages of employment in locally-based, micro and small-sized businesses are more favorable for local economies. Based on my results, the evidence for the effects of medium- and large-sized establishments is ambiguous. My results suggest that fostering smaller local businesses may be good local economic development policy. While more research is needed to identify the primary needs of local entrepreneurs, local policy makers and economic development practitioners may want to consider strategic interventions to help local small business owners by addressing barriers such as access to technology and capital by building and investing in entrepreneurship-friendly ecosystems. Though, my study does not shed light on the efficacy of specific policies to stimulate local entrepreneurship. Of course, my findings are only preliminary and additional studies are necessary to substantiate these findings. This may require conducting panel studies, establishing stronger causal relationships, and also examining the industrial composition and dynamics of these local businesses.

APPENDIX

Table 1. Descriptive statistics

	All Counties		Metro counties		Nonmetro counties	
Variable	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
lgrwth	0.034	0.012	0.032	0.010	0.035	0.012
chgemp	0.008	0.015	0.014	0.017	0.005	0.013
chgpov	0.303	0.269	0.302	0.232	0.304	0.286
resall	61.305	10.653	60.006	9.701	61.984	11.059
micro	25.268	9.501	21.143	7.549	27.424	9.703
small	23.697	5.719	23.612	4.787	23.742	6.151
medium	7.867	5.248	8.614	4.128	7.477	5.709
large	4.473	7.458	6.638	7.603	3.341	7.126
linc	10.019	0.225	10.154	0.232	9.949	0.185
temp	53595	188117	132172	305482	12445	12335
indpov	13.353	5.595	10.885	4.477	14.646	5.688
colleg	16.383	7.632	20.257	9.221	14.354	5.682
pctax	989.26	737.92	1046.98	584.02	959.06	805.31
edexp	1457.12	487.47	1438.83	425.87	1466.69	516.62
hyexp	240.57	201.65	164.21	127.66	280.37	220.79
nonwhite	18.32	18.77	20.51	17.69	17.18	19.21
popden	228.49	1675.12	591.63	2822.27	38.31	39.70
amnscale	0.053	2.294	0.265	2.360	-0.057	2.252
Obs.	3053		1048		2005	

Table 2. Correlations.

	Income growth	Employment growth	Change in poverty
resall	0.067***	0.093***	-0.202***
micro	0.214***	0.015	-0.311***
small	0.068***	0.180***	-0.122***
medium	-0.140***	-0.046***	0.125***
large	-0.130***	0.008	0.113***

Notes: ***, ** and * stand for significance levels at 1, 5 and 10 percent, respectively.

Table 3. OLS estimation results - income growth

variable	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Set-one regressions						
resall	0.00021	6.409	-0.00002	-0.334	0.00017	4.057
Set-two regressions						
micro	0.00060	15.78	0.00013	1.893	0.00048	9.311
small	-0.00009	-1.864	0.00007	0.782	-0.00005	-0.802
medium	-0.00006	-1.094	-0.00038	-4.087	0.00004	0.599
large	-0.00001	-0.142	-0.00013	-2.147	0.00005	0.792

Table 4. OLS estimation results - employment growth

variable	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Set-one regressions						
resall	0.00015	5.224	0.00028	3.876	0.00014	5.047
Set-two regressions						
micro	0.00009	2.645	0.00049	5.404	0.00011	2.868
small	0.00038	8.166	0.00046	3.923	0.00030	6.516
medium	-0.00004	-0.780	-0.00036	-2.893	0.00003	0.654
large	0.00007	1.711	0.00009	1.209	0.00006	1.382

Table 5. OLS estimation results – change in poverty

variable	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Set-one regressions						
resall	-0.00380	-7.911	-0.00215	-3.014	-0.00319	-5.157
Set-two regressions						
micro	-0.00782	-12.961	-0.00858	-6.979	-0.00570	-7.180
small	-0.00278	-3.478	0.00012	0.076	-0.00374	-3.966
medium	0.00144	1.608	0.00304	1.783	0.00040	0.377
large	0.00011	0.155	0.00156	1.479	-0.00073	-0.835

Table 6. SDM estimation results - income growth – set-one variables

variable	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
cons	0.000	-0.003	-0.006	-0.108	0.001	0.026
rlinc	-0.214	-14.740	-0.263	-9.896	-0.160	-9.220
resall	0.070	2.345	-0.004	-0.072	0.083	2.631
college	0.112	7.333	0.163	5.853	0.111	5.831
pcptax	0.139	6.156	0.082	1.797	0.146	5.872
edexp	-0.011	-0.601	-0.029	-0.760	0.004	0.168
hyexp	0.024	1.457	0.123	3.713	-0.004	-0.183
nonwhite	-0.068	-3.813	0.056	1.704	-0.069	-3.283
popden	0.026	0.930	0.035	0.868	-0.047	-1.291
amnscale	-0.088	-4.394	-0.015	-0.419	-0.094	-3.490
W-rlinc	0.031	0.877	-0.234	-3.893	0.087	2.123
W-resall	-0.013	-0.302	0.016	0.162	-0.068	-1.476
W-college	-0.027	-0.933	0.072	1.284	0.012	0.310
W-pcptax	0.097	2.358	0.243	2.631	0.014	0.338
W-edexp	0.002	0.064	-0.087	-1.048	-0.0002	-0.004
W-hyexp	0.058	1.916	-0.039	-0.632	-0.023	-0.610
W-nonwhite	0.085	3.171	-0.007	-0.144	0.075	2.183
W-popden	-0.042	-1.249	-0.031	-0.559	-0.166	-3.746
W-amnscale	0.057	1.904	0.042	0.741	-0.003	-0.067
rho	0.633	14.656	0.561	7.652	0.547	10.899

Table 7. SDM estimation results - income growth – set-two variables

variable	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
cons	0.0002	0.006	-0.007	-0.128	0.001	0.036
rlinc	-0.180	-12.750	-0.245	-9.383	-0.146	-8.528
micro	0.157	5.178	0.059	1.090	0.144	4.457
small	-0.009	-0.391	0.010	0.273	0.014	0.530
medium	0.024	1.653	-0.076	-2.553	0.045	2.553
large	0.012	0.803	-0.031	-1.173	0.023	1.251
college	0.128	7.922	0.177	5.620	0.115	6.073
pcptax	0.123	5.421	0.096	2.096	0.141	5.634
edexp	-0.011	-0.593	-0.034	-0.863	0.002	0.095
hyexp	0.008	0.504	0.105	3.161	-0.006	-0.282
nonwhite	-0.012	-0.676	0.115	3.440	-0.026	-1.234
popden	0.026	0.873	0.039	0.883	-0.023	-0.602
amnscale	-0.081	-4.101	-0.023	-0.661	-0.088	-3.226
W-rlinc	0.066	1.856	-0.222	-3.718	0.064	1.579
W-micro	0.004	0.096	-0.076	-0.776	-0.008	-0.180
W-small	-0.037	-1.025	0.108	1.552	-0.079	-1.678
W-medium	-0.098	-3.326	-0.071	-1.162	-0.106	-2.910
W-large	-0.062	-1.932	-0.032	-0.524	-0.021	-0.512
W-college	-0.052	-1.422	0.035	0.507	-0.006	-0.144
W-pcptax	0.056	1.349	0.230	2.485	0.018	0.426
W-edexp	-0.008	-0.219	-0.060	-0.729	-0.011	-0.261
W-hyexp	0.055	1.795	-0.034	-0.552	0.011	0.297
W-nonwhite	0.054	1.996	-0.075	-1.489	0.050	1.429
W-popden	-0.014	-0.391	-0.011	-0.181	-0.102	-2.220
W-amnscale	0.047	1.564	0.038	0.664	0.004	0.096
rho	0.587	13.779	0.534	7.318	0.528	10.583

Table 8. SDM estimation results - employment growth – set-one variables

variable	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
cons	0.002	0.048	0.004	0.060	0.0002	0.004
temp	-0.123	-7.961	-0.154	-5.640	-0.001	-0.044
resall	0.098	4.902	0.126	3.566	0.103	3.120
college	0.227	12.894	0.227	7.685	0.170	7.746
pcptax	-0.071	-3.212	-0.111	-2.883	-0.013	-0.453
edexp	-0.008	-0.395	0.054	1.295	-0.038	-1.509
hyexp	-0.078	-4.207	-0.030	-0.844	-0.073	-3.203
nonwhite	-0.144	-7.223	-0.303	-7.994	0.050	1.998
popden	-0.024	-0.815	-0.002	-0.049	0.028	0.694
amnscale	0.001	0.025	-0.046	-1.130	0.085	2.144
W-temp	0.165	4.045	0.168	2.543	-0.035	-0.742
W-resall	-0.055	-1.456	-0.065	-0.953	0.033	0.542
W-college	-0.089	-2.705	-0.164	-2.806	-0.108	-2.457
W-pcptax	0.065	1.795	0.136	1.902	0.033	0.747
W-edexp	-0.020	-0.539	-0.130	-1.568	0.068	1.475
W-hyexp	-0.010	-0.287	0.021	0.323	0.034	0.758
W-nonwhite	0.188	6.174	0.424	7.526	-0.024	-0.585
W-popden	-0.012	-0.342	-0.069	-1.109	0.049	1.028
W-amnscale	0.141	3.866	0.125	1.903	0.166	2.584
rho	0.443	9.409	0.418	5.337	0.367	6.450

Table 9. SDM estimation results - employment growth – set-two variables

variable	all counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
cons	0.002	0.042	0.002	0.036	0.0004	0.010
temp	-0.116	-7.596	-0.133	-4.996	0.009	0.477
micro	0.089	4.520	0.163	4.615	0.078	2.303
small	0.122	5.034	0.106	2.602	0.126	4.087
medium	-0.022	-1.300	-0.065	-1.984	0.009	0.453
large	0.032	1.940	0.065	2.232	0.024	1.134
college	0.235	12.599	0.253	7.546	0.166	7.538
pcptax	-0.066	-2.852	-0.087	-2.204	-0.007	-0.265
edexp	-0.002	-0.090	0.046	1.110	-0.029	-1.134
hyexp	-0.082	-4.460	-0.047	-1.313	-0.072	-3.165
nonwhite	-0.113	-5.619	-0.232	-6.213	0.061	2.431
popden	-0.021	-0.672	-0.003	-0.062	0.033	0.789
amnscale	-0.008	-0.328	-0.065	-1.616	0.078	1.977
W-temp	0.147	3.649	0.194	2.950	-0.057	-1.213
W-micro	-0.108	-2.759	-0.116	-1.656	-0.007	-0.114
W-small	-0.015	-0.381	0.047	0.621	0.021	0.379
W-medium	-0.010	-0.302	-0.063	-0.948	0.028	0.653
W-large	-0.001	-0.032	-0.112	-1.730	0.052	1.122
W-college	-0.101	-2.486	-0.180	-2.477	-0.099	-1.989
W-pcptax	0.056	1.516	0.112	1.554	0.017	0.386
W-edexp	-0.011	-0.293	-0.105	-1.291	0.074	1.608
W-hyexp	0.001	0.022	0.009	0.138	0.029	0.648
W-nonwhite	0.145	4.717	0.336	5.990	-0.047	-1.153
W-popden	-0.013	-0.339	-0.053	-0.833	0.036	0.721
W-amnscale	0.143	3.967	0.120	1.850	0.167	2.589
rho	0.446	9.517	0.392	5.059	0.360	6.355

Table 10. SDM estimation results – change in poverty – set-one variables

	All counties		Metro counties		Nonmetro counties	
variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
cons	-0.001	-0.029	-0.001	-0.024	0.001	0.017
indpov	0.386	22.768	0.365	12.248	0.266	14.520
resall	-0.090	-2.442	-0.076	-1.325	-0.084	-1.960
college	0.242	13.638	0.278	8.658	0.186	9.115
pcptax	-0.035	-1.669	-0.012	-0.298	-0.051	-2.108
edexp	-0.070	-3.828	-0.117	-2.949	-0.048	-2.248
hyexp	-0.015	-0.930	-0.072	-2.118	0.004	0.226
nonwhite	0.108	5.965	0.097	2.766	0.122	5.813
popden	-0.030	-0.873	-0.059	-1.074	0.024	0.548
amnscale	0.028	1.372	0.111	2.883	-0.016	-0.635
W-indpov	-0.492	-12.760	-0.580	-8.365	-0.263	-6.535
W-resall	0.036	0.769	0.061	0.696	0.048	0.860
W-college	-0.305	-9.869	-0.381	-6.344	-0.217	-5.725
W-pcptax	-0.158	-4.428	-0.150	-1.909	-0.071	-1.887
W-edexp	-0.002	-0.071	0.066	0.818	-0.045	-1.122
W-hyexp	-0.008	-0.248	0.085	1.385	0.049	1.315
W-nonwhite	-0.078	-2.904	-0.085	-1.639	-0.113	-3.338
W-popden	0.023	0.556	0.029	0.381	0.127	2.433
W-amnscale	-0.066	-2.209	-0.156	-2.562	-0.016	-0.422
rho	0.568	12.931	0.453	5.830	0.566	11.464

Table 11. SDM estimation results – change in poverty – set-two variables

variable	all counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
cons	-0.001	-0.025	0.001	0.010	0.0004	0.011
indpov	0.417	23.944	0.375	12.611	0.288	15.464
micro	-0.137	-3.616	-0.197	-3.323	-0.103	-2.370
small	-0.049	-2.222	-0.001	-0.031	-0.063	-2.477
medium	-0.020	-1.382	0.007	0.242	-0.027	-1.565
large	-0.017	-1.143	0.010	0.377	-0.016	-0.930
college	0.225	13.007	0.231	7.106	0.186	9.564
pcptax	-0.027	-1.282	-0.040	-1.008	-0.046	-1.898
edexp	-0.072	-3.975	-0.105	-2.672	-0.052	-2.392
hyexp	-0.004	-0.229	-0.036	-1.069	0.007	0.350
nonwhite	0.050	2.745	-0.003	-0.088	0.084	4.030
popden	-0.035	-0.966	-0.068	-1.184	0.008	0.171
amnscale	0.024	1.192	0.124	3.237	-0.018	-0.669
W-indpov	-0.435	-11.497	-0.553	-8.071	-0.244	-6.103
W-micro	0.049	1.007	0.072	0.823	0.069	1.222
W-small	0.007	0.188	0.016	0.222	-0.018	-0.402
W-medium	0.123	4.113	0.051	0.839	0.104	2.884
W-large	0.058	1.743	0.057	0.923	0.026	0.648
W-college	-0.270	-7.229	-0.327	-4.551	-0.189	-4.485
W-pcptax	-0.112	-3.080	-0.121	-1.538	-0.051	-1.325
W-edexp	-0.007	-0.193	0.021	0.262	-0.055	-1.360
W-hyexp	-0.003	-0.086	0.064	1.044	0.034	0.899
W-nonwhite	-0.064	-2.347	-0.001	-0.028	-0.093	-2.715
W-popden	-0.001	-0.033	0.008	0.110	0.118	2.162
W-amnscale	-0.067	-2.211	-0.166	-2.754	-0.021	-0.498
rho	0.538	12.364	0.429	5.566	0.553	11.191

Table 12. Direct and indirect effects - income growth – set-one variables

	all counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
	Direct effects					
rlinc	-0.232	-12.463	-0.318	-8.302	-0.162	-8.420
resall	0.075	2.495	-0.005	-0.092	0.081	2.564
college	0.119	7.301	0.184	5.801	0.121	5.845
pcptax	0.170	7.220	0.122	2.530	0.158	6.325
edexp	-0.012	-0.632	-0.043	-1.047	0.006	0.242
hyexp	0.035	2.086	0.127	3.578	-0.007	-0.369
nonwhite	-0.061	-3.457	0.058	1.776	-0.064	-3.089
popden	0.021	0.846	0.031	0.810	-0.071	-2.015
amnscale	-0.088	-4.684	-0.011	-0.321	-0.101	-3.936
	Indirect effects					
rlinc	-0.286	-1.903	-0.881	-2.520	-0.008	-0.081
resall	0.088	0.927	0.037	0.180	-0.042	-0.510
college	0.114	1.460	0.365	2.345	0.150	1.683
pcptax	0.484	4.231	0.639	2.731	0.197	2.389
edexp	-0.014	-0.172	-0.238	-1.262	0.004	0.047
hyexp	0.192	2.357	0.075	0.561	-0.055	-0.660
nonwhite	0.111	1.905	0.058	0.574	0.080	1.199
popden	-0.065	-1.109	-0.028	-0.300	-0.409	-4.560
amnscale	0.001	0.022	0.079	0.746	-0.111	-1.537

Table 13. Direct and indirect effects - income growth – set-two variables

	all counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
			Direct effects			
rlinc	-0.186	-10.817	-0.291	-7.895	-0.148	-7.919
micro	0.171	5.788	0.052	0.972	0.152	4.885
small	-0.014	-0.647	0.024	0.648	0.006	0.215
medium	0.012	0.778	-0.088	-2.780	0.036	1.956
large	0.003	0.212	-0.036	-1.260	0.022	1.143
college	0.131	7.082	0.193	5.545	0.122	5.960
pcptax	0.142	6.202	0.134	2.807	0.151	5.992
edexp	-0.013	-0.683	-0.044	-1.052	0.002	0.089
hyexp	0.017	1.004	0.108	3.104	-0.005	-0.270
nonwhite	-0.005	-0.300	0.114	3.483	-0.021	-0.983
popden	0.027	0.977	0.041	0.991	-0.034	-0.946
amnscale	-0.083	-4.248	-0.020	-0.595	-0.094	-3.599
			Indirect effects			
rlinc	-0.101	-0.890	-0.767	-2.578	-0.032	-0.324
micro	0.226	2.234	-0.085	-0.433	0.137	1.602
small	-0.100	-1.323	0.234	1.558	-0.142	-1.570
medium	-0.193	-2.800	-0.235	-1.584	-0.167	-2.206
large	-0.134	-1.823	-0.101	-0.785	-0.013	-0.158
college	0.054	0.609	0.277	1.657	0.109	1.160
pcptax	0.296	3.242	0.583	2.766	0.186	2.390
edexp	-0.029	-0.391	-0.164	-0.876	-0.016	-0.194
hyexp	0.137	1.999	0.056	0.417	0.015	0.201
nonwhite	0.111	1.987	-0.020	-0.209	0.073	1.129
popden	0.0003	0.005	0.020	0.219	-0.232	-3.295
amnscale	-0.001	-0.011	0.049	0.519	-0.084	-1.066

Table 14. Direct and indirect effects – employment growth – set-one variables

	all counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Direct effects						
temp	-0.113	-6.974	-0.146	-5.059	-0.004	-0.215
resall	0.097	4.640	0.125	3.573	0.105	3.118
college	0.228	12.928	0.221	7.371	0.167	7.916
pcptax	-0.069	-3.087	-0.105	-2.774	-0.010	-0.355
edexp	-0.010	-0.491	0.046	1.114	-0.034	-1.331
hyexp	-0.082	-4.301	-0.030	-0.840	-0.073	-3.245
nonwhite	-0.132	-6.782	-0.278	-7.478	0.048	1.921
popden	-0.026	-0.908	-0.009	-0.204	0.033	0.873
amnscale	0.014	0.600	-0.036	-0.916	0.101	2.495
Indirect effects						
temp	0.181	2.662	0.155	1.337	-0.057	-0.744
resall	-0.021	-0.338	-0.022	-0.196	0.111	1.292
college	0.021	0.353	-0.111	-1.209	-0.066	-0.978
pcptax	0.055	0.953	0.148	1.282	0.039	0.631
edexp	-0.038	-0.652	-0.176	-1.335	0.080	1.200
hyexp	-0.076	-1.296	0.011	0.107	0.010	0.144
nonwhite	0.215	4.617	0.491	5.633	-0.006	-0.103
popden	-0.041	-0.848	-0.117	-1.284	0.088	1.645
amnscale	0.244	4.078	0.177	1.833	0.299	3.023

Table 15. Direct and indirect effects – employment growth – set-two variables

	Direct effects					
	All counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-prob	Coefficient	t-prob
temp	-0.108	-6.660	-0.122	-4.436	0.006	0.290
micro	0.084	4.389	0.158	4.338	0.081	2.442
small	0.126	5.299	0.116	2.783	0.132	4.380
medium	-0.024	-1.425	-0.074	-2.263	0.010	0.492
large	0.034	1.996	0.058	1.858	0.029	1.301
college	0.236	11.801	0.246	6.954	0.163	7.019
pcptax	-0.063	-2.778	-0.081	-2.034	-0.007	-0.262
edexp	-0.003	-0.153	0.039	0.965	-0.023	-0.901
hyexp	-0.084	-4.483	-0.047	-1.328	-0.072	-3.141
nonwhite	-0.103	-5.292	-0.212	-5.776	0.059	2.366
popden	-0.026	-0.835	-0.006	-0.142	0.037	0.900
amnscale	0.006	0.264	-0.056	-1.437	0.092	2.356
	Indirect effects					
temp	0.158	2.281	0.210	2.096	-0.086	-1.105
micro	-0.117	-1.873	-0.083	-0.789	0.022	0.238
small	0.069	1.067	0.143	1.155	0.102	1.220
medium	-0.034	-0.606	-0.147	-1.327	0.043	0.688
large	0.023	0.389	-0.134	-1.265	0.099	1.374
college	0.011	0.147	-0.124	-1.055	-0.054	-0.697
pcptax	0.043	0.756	0.118	1.099	0.023	0.378
edexp	-0.020	-0.335	-0.136	-1.096	0.097	1.452
hyexp	-0.062	-1.044	-0.009	-0.089	0.008	0.125
nonwhite	0.160	3.488	0.389	4.643	-0.036	-0.641
popden	-0.040	-0.797	-0.090	-1.034	0.073	1.256
amnscale	0.242	4.191	0.151	1.663	0.303	3.051

Table 16. Direct and indirect effects – change in poverty – set-one variables

	all counties		Metro counties		Nonmetro counties	
	Coefficient	t-stat	Coefficient	t-prob	Coefficient	t-prob
Direct effects						
indpov	0.348	19.408	0.323	9.887	0.250	12.502
resall	-0.093	-2.604	-0.073	-1.325	-0.087	-2.128
college	0.219	12.755	0.251	7.611	0.171	8.282
pcptax	-0.059	-2.730	-0.025	-0.630	-0.065	-2.692
edexp	-0.075	-4.020	-0.116	-2.980	-0.059	-2.779
hyexp	-0.018	-1.052	-0.066	-1.989	0.012	0.580
nonwhite	0.106	5.821	0.092	2.840	0.118	5.498
popden	-0.029	-0.887	-0.061	-1.145	0.045	1.071
amnscale	0.020	1.027	0.101	2.748	-0.020	-0.808
Indirect effects						
indpov	-0.608	-5.902	-0.738	-4.070	-0.251	-2.833
resall	-0.034	-0.453	0.046	0.342	0.003	0.029
college	-0.366	-5.822	-0.451	-4.036	-0.237	-2.888
pcptax	-0.393	-4.396	-0.274	-1.818	-0.224	-2.692
edexp	-0.094	-1.316	0.020	0.144	-0.160	-1.818
hyexp	-0.034	-0.516	0.092	0.887	0.116	1.375
nonwhite	-0.036	-0.707	-0.068	-0.853	-0.093	-1.369
popden	0.012	0.195	-0.0001	-0.001	0.307	3.562
amnscale	-0.113	-2.184	-0.181	-2.044	-0.053	-0.797

Table 17. Direct and indirect effects – change in poverty – set-two variables

	all counties		Metro counties		Nonmetro counties	
Direct effects						
	Coefficient	t-stat	Coefficient	t-prob	Coefficient	t-prob
indpov	0.390	21.107	0.339	10.810	0.276	13.952
micro	-0.142	-3.904	-0.196	-3.456	-0.103	-2.576
small	-0.051	-2.294	0.002	0.057	-0.070	-2.744
medium	-0.007	-0.442	0.010	0.319	-0.016	-0.838
large	-0.011	-0.701	0.015	0.543	-0.013	-0.688
college	0.207	11.619	0.208	6.229	0.175	8.159
pcptax	-0.043	-2.009	-0.051	-1.255	-0.055	-2.263
edexp	-0.080	-4.337	-0.107	-2.656	-0.063	-2.954
hyexp	-0.004	-0.244	-0.032	-0.956	0.012	0.614
nonwhite	0.046	2.617	-0.004	-0.127	0.079	3.811
popden	-0.037	-1.047	-0.072	-1.306	0.025	0.595
amnscale	0.017	0.902	0.113	3.119	-0.022	-0.818
Indirect effects						
indpov	-0.436	-5.391	-0.668	-4.468	-0.187	-2.358
micro	-0.055	-0.714	-0.026	-0.199	0.023	0.261
small	-0.041	-0.621	0.027	0.221	-0.115	-1.258
medium	0.229	3.635	0.090	0.882	0.191	2.364
large	0.099	1.473	0.109	1.030	0.035	0.404
college	-0.304	-3.889	-0.383	-3.106	-0.182	-1.973
pcptax	-0.265	-3.578	-0.232	-1.628	-0.164	-2.036
edexp	-0.095	-1.356	-0.040	-0.295	-0.183	-2.104
hyexp	-0.010	-0.157	0.076	0.749	0.083	1.045
nonwhite	-0.075	-1.491	-0.005	-0.060	-0.097	-1.442
popden	-0.041	-0.657	-0.033	-0.325	0.263	3.125
amnscale	-0.110	-2.232	-0.190	-2.226	-0.066	-0.860

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