Ann Reg Sci
DOI 10.1007/s00168-014-0637-x

ORIGINAL PAPER

Does rural broadband impact jobs and income? Evidence from spatial and first-differenced regressions

Brian Whitacre · Roberto Gallardo · Sharon Strover

Received: 19 April 2014 / Accepted: 26 August 2014
© Springer-Verlag Berlin Heidelberg 2014

Abstract In order to better understand the association between broadband and jobs/income in non-metropolitan counties, this study conducts spatial and first-differenced regressions using recent data from the Federal Communications Commission and the National Broadband Map. The relationships between broadband adoption/availability and jobs/income in rural areas are analyzed after controlling for a host of potentially influential variables such as age, race, educational attainment, transportation infrastructure, and the presence of natural amenities. Results from spatial error models using 2011 data provide evidence that high levels of broadband adoption in non-metro counties are positively related to the number of firms and total employees in those counties. The first-differenced regressions use data from 2008 and 2011 to suggest that increases in broadband adoption levels are associated with increases in median household income and the percentage of non-farm proprietors in non-metro counties. Interestingly, simply obtaining increases in broadband *availability* (not adoption) over this time has no statistical impact on either jobs or income.

JEL Classification R11 · O18

B. Whitacre (✉)
Oklahoma State University, 504 Ag Hall, Stillwater,
OK 74074, USA
e-mail: brian.whitacre@okstate.edu

R. Gallardo
Mississippi State University, Starkville, MS, USA

S. Strover
University of Texas, Austin, TX, USA

Published online: 09 September 2014

1 Introduction

Broadband, or "high-speed" Internet access, has become an integral part of the everyday life of many Americans. Household broadband adoption rates are above 60 % as of 2011, providing opportunities for communication, information, income, and entertainment. However, the persistence of a rural–urban "digital divide" in both broadband *availability* (including basic and higher speed broadband connectivity) and *adoption* has prompted concerns that rural areas might be left behind in terms of the benefits of this technology.

Scholars of economic development have been interested in broadband's potential since the early 2000s, when adoption rates of this "always on" type of Internet access began to rise.[1] Immediate attention was given to the "digital divide" between rural and urban areas, following in the footsteps of research examining similar divides in terms of first computer use and, later, Internet use (NTIA 1995, 1999, 2000). Researchers began to explore why broadband adoption rates were lower in rural areas and to suggest what the sources and the implications of these gaps might be (Malecki 2003; Mills and Whitacre 2003; Parker 2000; Strover 2001). Related work began to assess the relationship between broadband and economic growth, with some evidence linking higher levels of broadband infrastructure and adoption to improvements in economic outcomes (Czernich et al. 2011; Kolko 2012; Holt and Jamison 2009). These results led many rural advocates to highlight the importance of broadband as a tool for economic development. However, until recently, very little reliable and useable broadband infrastructure data have been available, and assessments of programs designed to improve broadband access and adoption are quite limited. Contemporary empirical evaluations of the economic impacts of broadband in rural areas are generally lacking.

This study uses recent data from the National Broadband Map (NBM) and the Federal Communications Commission (FCC) to assess the relationship between broadband availability/adoption and measures of jobs and income, specifically focusing on rural areas. Both spatial models and first-differenced regressions are used in an attempt to tease out the potential impacts of broadband on rural economies.

2 Literature review

Recent efforts in the economics literature have sought to document broadband's influence on productivity or economic gains. One of the earliest (and most widely cited) studies by Lehr et al. (2005) concluded that between 1998 and 2002 communities with consumer broadband experienced growth in employment, numbers of businesses, and businesses in IT-intensive sectors. However, their study also pointed out that the data available at that time were primarily supply-side and that better data on demand were sorely needed. Gillett et al. (2006) found similar results: Broadband availability

[1] The FCC's definition of broadband has changed over time. Historically, the definition has been 200 kilobits of data transfer per second (kbps) in at least 1 direction. The most recent (2010) definition is 4 megabits (mbps) download and 1 mbps upload. This report incorporates various thresholds, depending on the data used for analysis.

produces employment growth and business growth—especially growth in IT-related businesses. They found no relationship with wage levels.

Several more recent studies have focused explicitly on the linkages between broadband and businesses. Mack and Grubesic (2009) found that changes in broadband provision had no relationship with changes in firm locations for Ohio companies; however, Mack et al. (2011) found that broadband was an important location factor for knowledge-intensive firms. Kandilov and Renkow (2010) found no evidence that the current USDA Broadband Loan Program positively impacted the number of businesses in recipient communities. Kolko's (2012) study on broadband's contribution to local economic development examined broadband's causal relationship to employment, and specific industries likely to be affected by the presence of faster networks. Reasoning that broadband could have the effect of lowering communication costs, Kolko hypothesized that effects on employment could be either positive in terms of the need to hire more workers, or negative in terms of using technology to replace labor. His studies also examined specific locational effects, singling out the so-called "footloose" industries and rural places. Kolko's work integrated broadband supply data from the FCC with employment data from the National Establishment Time-Series database, Census information on employment and household income, and Forrester surveys in household technology adoption. Kolko's work focused on the USA during the time frame 1999 through 2006. He reported that broadband expansion is positively related to economic growth, with more strength in ICT-intensive industries. However, this study found only limited influence on household income. The Lehr et al., Gillett et al., Mack and Grubesic, Mack et al., and Kolko studies did not focus explicitly on rural parts of the country.

Stenberg et al. (2009) produced a thorough review of the value of broadband Internet for rural America, focusing on consumers, communities, and businesses. One finding, again using FCC data, is particularly noteworthy. Comparing non-metropolitan counties with relatively high levels of broadband in 2000 with otherwise similar non-metro counties, they found higher levels of growth in wage and salary jobs, non-farm proprietors, and private earnings between 2002 and 2006 for those counties with early access to broadband. They did caution, however, that their research did not necessarily imply causality. This report also summarized ways that rural communities and businesses could benefit from broadband, including research on distance education, telehealth, and telework. Along these same lines, Kuttner (2012) discussed the opportunity costs of *not* having broadband in rural areas for households, communities, and specific industry sectors. Others, however, have questioned the value of broadband access for rural economies, suggesting that accessibility for rural businesses is secondary to the lack of propensity for growth displayed by many rural businesses (Galloway 2007).

Calling attention to the significance of place-based analyses as opposed to sectoral analyses, Dickes et al. (2010) affirmed the need to examine both supply-side and demand-side policies in addressing the rural digital divide. A similar point is reinforced by Glasmeier and Greenstein in Strover (2011) when they state that while the most economic rural regions already have broadband connectivity, the remaining areas still could benefit in highly local ways; more granular approaches to the outcomes of broadband will be necessary to understand impacts. One such granular study is LaRose et al. (2011), who did not find strong evidence that local broadband availability produced greater community satisfaction or local individual economic development activities. They did find, however, that local community efforts to publicize and demonstrate broadband applications increased adoption. This finding reinforces some of Hauge and Prieger's (2009) suggestions regarding ways in which local organizations may be effective in stimulating adoption.

3 Data and methods

To assess the relationship between rural broadband and jobs/income, we combine recent data on broadband *availability* and *adoption* with county-level demographic and socioeconomic variables. We are particularly interested in which of the two broadband components (availability or adoption) is most highly correlated with levels of jobs and income—and whether this relationship holds true for both rural and urban areas. All of our data are collected at the county level, allowing informative maps to be drawn and spatial econometric tools to be used. In particular, we used:

1. FCC Form 477 broadband adoption data (residential broadband adoption rates). Each county is assigned a value between 1 and 5 based on the percentage of households with a broadband connection. Data from 2008 and 2011 are used.
2. National Broadband Map (NBM) infrastructure availability data. While this dataset is accessible at the census block level, we used a version that is aggregated to the county level in order to mesh with the dependent variables of interest. We utilized the 2011 version of this dataset.

These datasets are discussed in turn below.

3.1 FCC county-level data

The FCC has provided county-level data on household broadband adoption rates and number of broadband providers since 2008. As noted above, a particularly useful feature of this data is that it can be easily meshed with other county-level information, such as economic measures from the Bureau of Labor Statistics (BLS) or the Bureau of Economic Analysis (BEA), or demographic data provided by the Census. Counties are easily broken out into metro, micro, and non-core categories, allowing for more insight into the role that different levels of rurality might play.[2] Metropolitan counties typically have a core community with a population of at least 50,000 (or have 25 % of the workforce commute to a neighboring core), while micropolitan counties have an urban core of between 10,000 and 49,999 people (or again have 25 % of their workforce commute to one). Non-core counties do not have a core community with a population of at least 10,000. Of the 3,073 counties in each year of the FCC data, 2,037 are non-metropolitan (671 micropolitan and 1,366 non-core).[3] The definition of "broadband"

[2] We recognize the difference between rural/urban (defined at the community level) and metro/non-metro (defined at the county level). Our data are county oriented, so we generally speak in terms of metro/micro/non-core; however, we still use the term "rural" to connote a lack of population density.

[3] Initially, 3,109 counties were included, but Virginia independent cities were meshed with the counties where they reside to ultimately come up with 3,073.

for this dataset is an Internet connection having at least 200 kbps speeds in at least one direction. Data on a higher speed threshold (768 kbps download, 200 kbps upload) are also included.[4]

The most useful component of the FCC broadband data is the measure of residential broadband adoption. The data are split into five categories based on the proportion of households that connect to the Internet with a high-speed connection:

1) $<20\,\%$ adoption,
2) 20–39.9 % adoption,
3) 40–59.9 % adoption,
4) 60–79.9 % adoption,
5) $\geq 80\,\%$ adoption.

Although the lack of a point estimate for adoption is not ideal, the data are still quite useful for assessing the extent of the digital divide. It is worth noting that this broadband adoption variable only includes residential *fixed* (wireline) high-speed connections—wireless or mobile phone connections are not included. Data from 2008 to 2011 are used to model the impact of broadband adoption on county-level jobs and income measures.

3.2 National broadband map (NBM) data

While the FCC data do include some information about broadband availability, much more detailed data are available from the National Broadband Map. The NBM is an online database, collected from all broadband providers across the USA, which allows users to access availability information at a very low level of detail (neighborhood or census block level). The dataset also includes provider-level information about speed, such as maximum advertised upload and download speeds, and the type of technology utilized. NBM data became available starting in 2010, and we use the December 2011 version. There have been several critiques against the NBM data. These include the fact that the infrastructure carriers who provide the data have an incentive to overstate their service areas, that empty census blocks are sometimes handled illogically, and that the definition of "serving" a census block is if even one customer in that area has access to broadband (Grubesic 2012). This last issue may overstate some rural availability rates in cases where a small portion of the census block receives the same level of broadband service as a nearby urban neighborhood. Additionally, Ford (2011) shows that measurement errors or sample selection bias issues could cause serious problems. Regardless, the NBM data are a notable improvement from previous broadband supply data efforts because of their thoroughness and low level of geographic detail.

A particularly useful feature of the NBM data (available from 2011 on) is the "Analyze Table." Aggregated to different geography types (including counties), this table pulls information from all relevant providers to generate statistics such as the percentage of the population with access to wired and wireless broadband infrastructure,

[4] The FCC used this speed (768 kbps down, 200 kbps up) at one point as a definition for broadband, and it is also used by the Broadband Technology Opportunities Program (BTOP) for reporting purposes. The current broadband definition (enacted in 2010) from the FCC is 4 mbps download and 1 mbps upload.

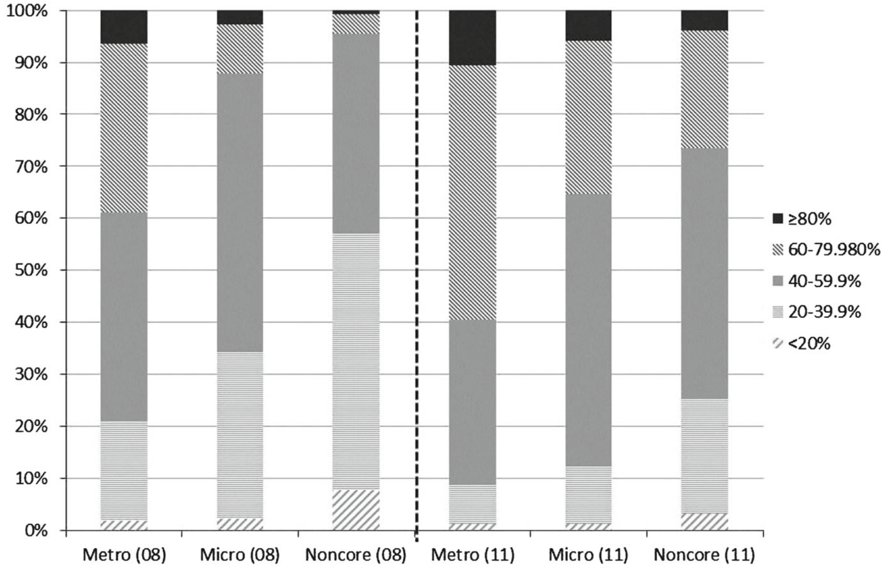

Fig. 1 County-level broadband adoption by metropolitan status, 2008–2011. *Source* FCC Form 477 Data, 2008 and 2011

the percentage of the population with access to a particular type of technology (for example, cable or fiber), or the percentage of the population with access to specific numbers of providers (ranging from 0 to 8 or more). This study focuses on NBM data related to the percentage of the population with access to some type of wired broadband. Because the FCC (2012) notes some concerns about the accuracy of the mobile wireless broadband data (including whether or not they truly meet the definition of broadband), only wireline technologies were used.[5] We do not use the wireless data in our analysis.

3.3 Descriptive statistics

The FCC county-level data demonstrate that rates of broadband adoption have increased significantly in non-metropolitan counties over the 2008–2011 time period. Non-core counties, in particular, saw large improvements in the percentage of households adopting broadband over this time (Fig. 1). While over 50 % of non-core counties had broadband adoption rates lower than 40 % in 2008, only 25 % met this criterion in 2011. Additionally, the proportion of non-core counties with relatively high levels of broadband adoption (>60 %) grew from only 4 % in 2008 to over 26 % in 2011.

To assess county-level broadband adoption gaps between metro/micro and metro/non-core areas, Fig. 2 presents means of the five adoption categories

[5] The FCC report notes that "…we have concerns that providers are reporting services as meeting the broadband speed benchmark when they likely do not. … although mobile networks deployed as of June 30, 2010, may be capable of delivering peak speeds of 3 Mbps/768 kpbs or more in some circumstances, the conditions under which these peak speeds could actually occur are rare." (FCC 2012, pp. 25–26).

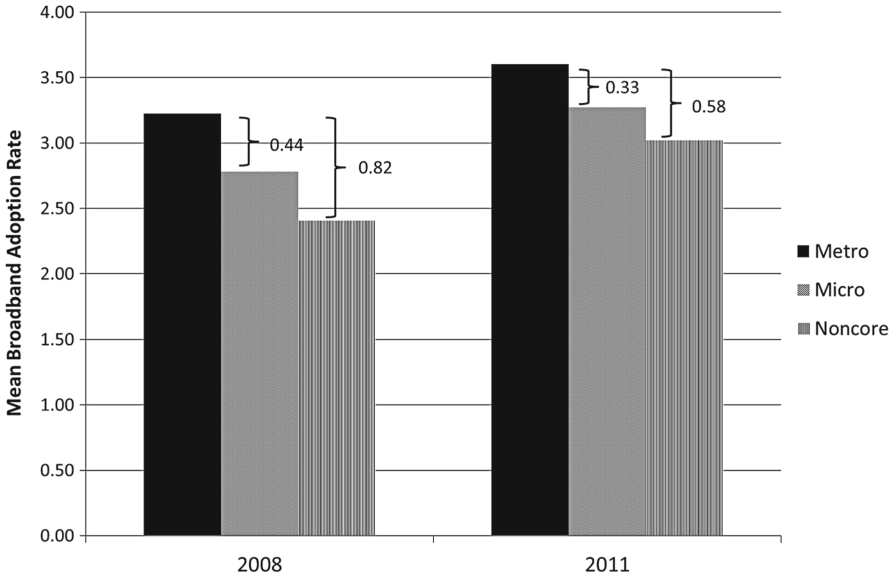

Fig. 2 County-level broadband adoption gaps, 2008 and 2011. *Source* FCC Form 477 Data, 2008 and 2011

(1 = <20 %, 2 = 20–39.9 %, 3 = 40–59.9 %, 4 = 60–79.9 %, and 5 = ≥80 %) for 2008 and 2011. Thus, a mean broadband adoption rate of 3.2 would suggest adoption rates in the 40–59.9 % range for the included counties. The results show a decline in both the metro–micro adoption gap (from 0.44 to 0.33) and the metro–non-core adoption gap (from 0.82 to 0.58) over this 3-year period. Thus, while broadband adoption rates continue to climb in metropolitan counties (nearly 60 % had county-level adoption rates of over 60 % in 2011), increases among micro and non-core counties with very low levels of adoption have reduced the gaps over time.

Figure 3 looks at the 2011 FCC data from a geographic perspective. Several states exhibit low levels of broadband adoption, notably those in the south (Georgia, Mississippi, and parts of Louisiana, Texas, and Oklahoma). Very high levels of broadband adoption exist in the northeast, and near Denver in Colorado. Interestingly, most states have pockets of counties with high levels of adoption, and a global Moran's I measure of 0.357 (p value 0.00) suggests that there is a general spatial trend among the data. Many of the counties with low levels of adoption are lightly populated and have lower-income levels. In fact, the average county population in 2011 for counties with the lowest adoption levels (<20 %) is 12,640, compared with the national average of 25,055 for all non-metro counties. Similarly, the average household income level in these counties is \$35,700 compared with \$39,500 for all non-metro counties.

Figure 4 depicts the percentage of county population without any type of broadband available to them in 2011, again using data from the National Broadband Map. Here, broadband is defined as 768 kbps down and 200 kbps upload. As expected, most metropolitan counties have very high levels of wired broadband availability (only about 2 % of the metropolitan population lack it), while the non-core areas have the worst (17 % of the non-core population lack availability). There are large pockets of

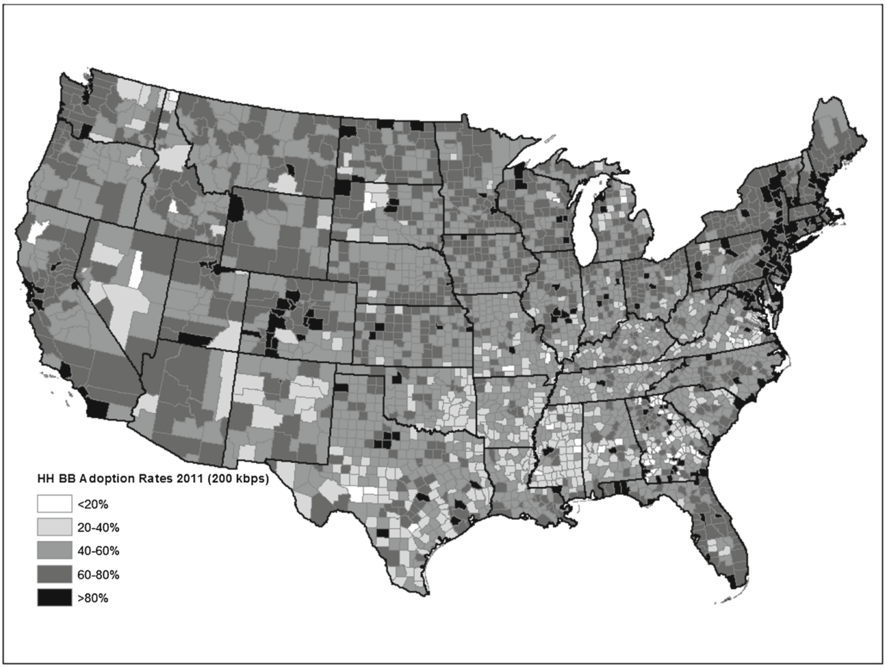

Fig. 3 County-level household broadband adoption rates, 2011. *Source* FCC Form 477 Data, 2011

micro and non-core counties with very poor levels of broadband availability in the south, perhaps contributing to the lower adoption rates seen in Figs. 2 and 3.

Additionally, Fig. 5 displays a spectrum of broadband availability categories for metro, micro, and non-core counties in 2011. It clearly demonstrates that the more rural areas are significantly worse off in terms of the availability of broadband infrastructure. In fact, over 20 % of all non-core counties have more than 30 % of their population lacking access to wired broadband infrastructure. Alternatively, only 10 % of non-core counties have the highest category of availability, compared with over 40 % of metro counties.[6]

3.4 Methodology

This paper seeks to answer the question of whether broadband availability or adoption is associated with jobs and income in rural areas. Recent studies (Stephens and Partridge 2011; McGranahan et al. 2011; Goetz et al. 2012) point to income levels, the number of businesses, total employment levels, and the percentage of self-employed (i.e., nonfarm proprietors) as important measures of rural economic health. We focus on the relationship between these measures and broadband adoption/availability.

[6] The highest level of broadband availability is where <2 % of the county's population lacks access to wired broadband.

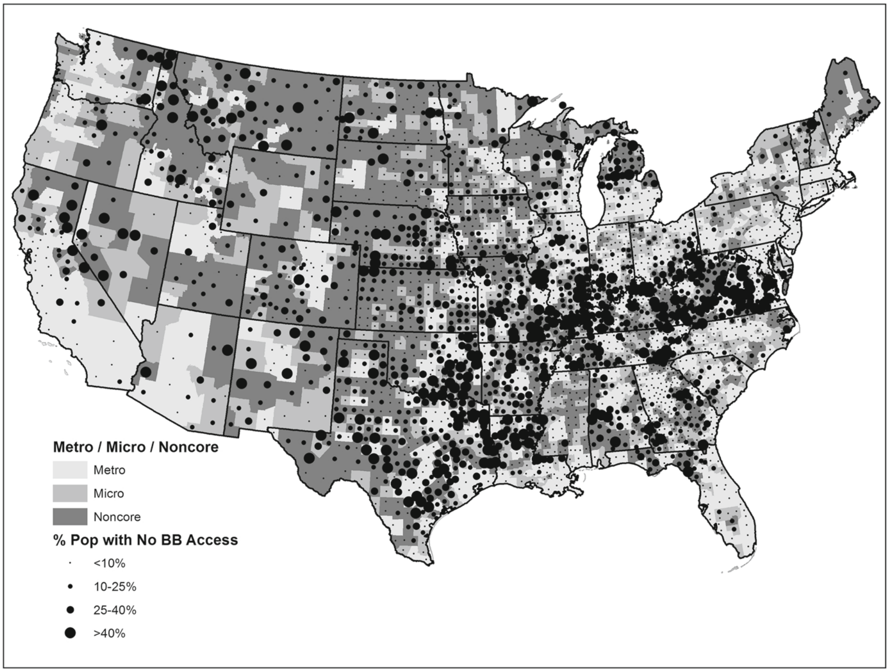

Fig. 4 Percent of population with no wired broadband availability by metropolitan status, 2011. *Source* National Broadband Map Data aggregated to County Level, 2011

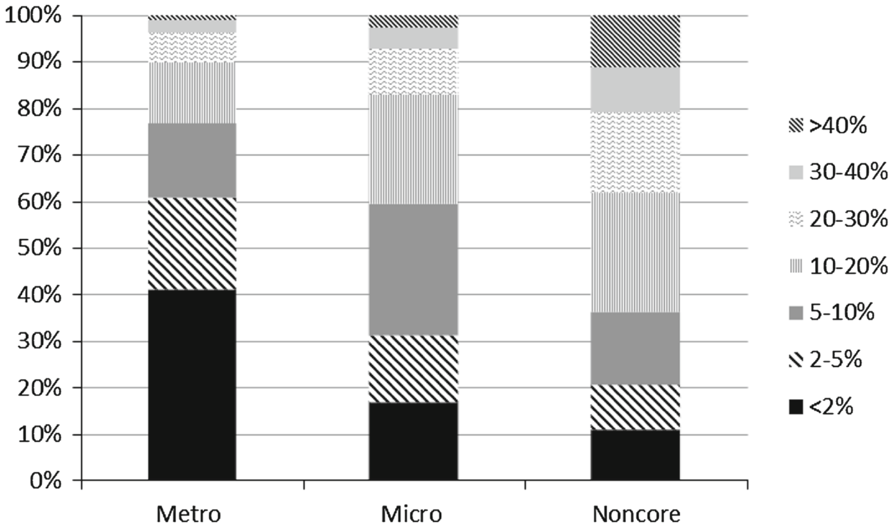

Fig. 5 Percentage of residents with no wired broadband availability by metropolitan status, 2011. *Source* National Broadband Map Data aggregated to County Level, 2011

In particular, we want to answer the question of whether more is better: do non-metro counties with high levels of broadband fare better in terms of jobs and income?

The following sections use the FCC data combined with National Broadband Map data to assess whether higher levels of broadband are positively related to the economic indicators noted above. The analytic techniques are discussed below and are included in order of increasing statements that can be made about causality:

- Cross-section spatial models
- First-differenced regression

3.5 Cross-section spatial models

A series of ordinary least squares (OLS) regressions with spatial dependency were conducted using the FCC county-level data. Spatial analyses are important because not accounting for spatial effects—spatial autocorrelation and spatial heterogeneity—can cause inaccurate interpretations of the associations between predictor and dependent variables (Anselin 1988; Anselin et al. 1996; Voss et al. 2006). The most frequently cited forms of spatial dependency are spatial lag and spatial error (Anselin et al. 1996; Chi 2010). Spatial lag refers to situations where the dependent variable of a particular geography might be affected by its neighboring values, while spatial error refers to spatially correlated model residuals—and is often due to spatial heterogeneity (Anselin et al. 1996; Chi 2010). Recent papers using similar dependent variables as ours have used spatial error models (SEMs), since theoretically spatial heterogeneity may be more of a factor than spatial autocorrelation (Wu and Gopinath 2008; Sobel and King 2008; Ferguson et al. 2007).

The models were run using GeoDa software and a first-order queen contiguity spatial weights matrix[7] to define the neighborhood structure. Queen contiguity considers neighbors of a particular county or polygon to be any other county that shares a common boundary or single point of contact in any direction (Anselin et al. 1996; Voss et al. 2006). For this reason, only counties within the continental USA were utilized. To test for the appropriate spatial model, we use spatial Lagrange multiplier (LM) tests (Anselin et al. 1996). The spatial dependency analysis results after running a standard OLS showed that, for each dependent variable, the LM statistic for a spatial error model was larger and more significant than the LM statistic for a spatial lag model. Further, the LM statistics for the combined spatial error and lag (SARMA) model were only slightly higher than those for the spatial error, providing further evidence that the error specification is the correct choice.[8]

More formally, the spatial error model is specified as:

$$y_i = X_i\beta + \varepsilon_i, \quad \varepsilon_i = \lambda W\varepsilon_i + \xi_i \tag{1}$$

[7] Multiple spatial weights matrices were tested before settling for the queen first order (including queen second order as well as rook first and second order).

[8] We note that the aggregate SARMA model can test for the inclusion of both spatial autocorrelation and spatial heterogeneity. However, the spatial structure of these models is complex and is more difficult to interpret than individual spatial error or spatial lag parameters. The focus of this paper is on the broadband component, and as such the easier-to-interpret SEM specification was chosen.

where y_i is a measure of county i's jobs or income in 2011, X_i is a vector of independent and control variables as of 2011, β is a vector of coefficients for X_i, λ is a spatial error parameter, W is a spatial weight matrix for the error term, and ξ_i is an error term that is independent and identically distributed.

Four specific dependent variables related to jobs and income in rural areas were used: (1) percent nonfarm proprietors of total employed (includes part time), (2) median household income, (3) number of firms with paid employees, and (4) total employed. The variables all display highly significant measures of spatial autocorrelation, as evidenced by global Moran's I values ranging from 0.13 (percent nonfarm proprietors) to 0.63 (median household income). All Moran's I values were significant at the $p = 0.01$ level. Maps of local Moran's I measures also displayed pockets of both low–low and high–high spatial relationships across the country for each dependent variable (Appendix).[9] Identifying such pockets of local clusters lends more support for the spatial error model (Anselin 2003). A total of eighteen (18) control variables are utilized in our modeling framework, including variables known to impact jobs and income such as population, educational attainment, age group composition, race breakdown, natural amenities, unemployment rate, state-level public expenditures, road conditions, and non-metropolitan status. Table 1 provides a summary of the dependent and control variables.

In addition to the 18 control variables summarized in Table 1, two distinct measures were used for broadband adoption/availability thresholds. Since the primary question of interest is whether high levels of adoption or availability matter, we devote most of our attention here. The thresholds used were:

- high broadband adoption rate (at least 600 residential fixed connections over 200 kbps in at least one direction per 1,000 households) (dummy)
- high broadband availability (more than 85 % of the county population has access to wired broadband) (dummy)

Table 2 includes a summary of the broadband adoption/availability used in the spatial specifications that follow. On average, less than 5 % of county residents do not have access to wired broadband—though this number is skewed by the high proportion of the population living in well-served metropolitan areas. Wired broadband availability varies greatly, specifically by geography (see Figs. 4, 5). About 39 % of counties can be classified as high adoption according to the definition above (26 % of non-metro counties). 66 % have high levels of broadband availability (58 % of non-metro counties).

Importantly, we follow the protocol laid out by Mack and Faggian (2013) to pinpoint the impact of *rural* broadband availability and adoption on the overall economy. In particular, we interact the broadband variables with a non-metropolitan dummy variable. The resulting coefficient on the interaction term will divulge the impact that non-metro levels of broadband have on the economic variables of interest for the overall economy. Thus, two distinct coefficients are of interest for each equation: the

[9] The Local Moran's I maps displayed in "Appendix" are compiled from a spatial weight matrix using 5 nearest neighbors, mitigating any potential geometric errors that may exist in the continental shapefile. Maps using a queen's contiguity matrix had similar quantitative and qualitative results.

Table 1 Summary of variables for spatial regression

Name	Description	Mean	Observations	Year	Source
Dependent variables					
NFP	% Nonfarm proprietors	25.29	3,073	2011	BEA
MHHI	Median household income	$43,673	3,073	2011	SAIPE
ESTPE	No. Estab. w/paid employees	2,370	3,073	2011	County Bus. Patterns
TOTEMP	Total Employed	56,962	3,073	2011	BEA
Control variables					
POP	Population	100,383	3,073	2011	Census
HS	% Pop 25+ with high school	35.24	3,073	2011	EMSI
SC	% Pop 25+ with some college	28.68	3,073	2011	EMSI
BACH	% Pop 25+ with bachelor's or more	19.02	3,073	2011	EMSI
AGE15–24	% Ages 15–24 years	12.95	3,073	2011	Census
AGE25–44	% Ages 25–44 years	23.48	3,073	2011	Census
AGE45–64	% Ages 45–64 years	28.28	3,073	2011	Census
AGE65+	% Ages 65 or more	16.25	3,073	2011	Census
BLACK	% Black non-Hispanic	8.59	3,073	2011	Census
ASIAN	% Asian non-Hispanic	1.11	3,073	2011	Census
HISP	% Hispanic	8.59	3,073	2011	Census
OTHRACE	% Other	3.09	3,073	2011	Census
NATAM	Natural Amenities Scale	3.49	3,072	2004	ERS
UR	Unemployment Rate	8.56	3,073	2011	BLS-LAU
PUBEXP_LN	Log of State and Local per Capita Expenditures	9.14	3,073	2010	Census of Government
RURROADS	Percent narrow lanes on rural roads	11.21	3,073	2006	Reason Foundation
URINTER	Percent poor miles urban interstate	4.26	3,073	2006	Reason Foundation
NM	Non-metropolitan county (1 = Yes)	0.66	3,073	2003	OMB
MICRO	Micropolitan county (1 = Yes)	0.22	3,073	2003	OMB
NONCORE	Non-core county (1 = Yes)	0.44	3,073	2003	OMB

Table 2 Summary of broadband adoption/availability measures included in spatial regression

Name	Description	Mean	Observations	Year	Source
HIADOPT	Hi adoption (>60 %) (1 = Yes)	0.39	3,073	2011	FCC
HIADOPTNM	Hi adoption in NM counties (1 = Yes)	0.26	2,013	2011	FCC
HIAVAIL	Hi availability (>85 % of population) (1 = Yes)	0.66	3,073	2011	FCC
HIAVAILNM	Hi availability in NM counties (1 = Yes)	0.58	2,013	2011	FCC

(general) impact of broadband on a particular job or income measure and the (non-metro-specific) impact of broadband on that same measure. A positive and statistically significant coefficient on the interaction term would suggest that broadband's impact is enlarged by its presence in non-metropolitan areas.

Separate regressions were run for specifications related to broadband availability and adoption. The result is eight SEM models (four dependent variables related to jobs and income, and two broadband variables to include for each) that test the importance of higher levels of rural broadband access and adoption on the overall economy. We use 2011 data from all relevant sources (NBM, Census, Bureau of Economic Analysis, Bureau of Labor Statistics).

3.6 First-differenced regression

Given the nature of the FCC data (with county-level observations in 2008 and 2011), another technique that can be used to evaluate the relationship between broadband availability/adoption and measures of jobs/income is first-differenced regression. This technique focuses on the impact of changing levels of broadband availability/adoption on shifts in various economic indicators over the same time frame. In this case, changes in the broadband adoption category or number of broadband providers are used as right-hand side (explanatory) variables. The dependent variables of interest are changes in different measures of jobs and income, and thus, the primary model can be written as:

$$\Delta Y_i = \beta_0 + \beta_1 \Delta X_i + \beta_2 \Delta BB_i + \varepsilon_i \tag{2}$$

where ΔY_i is the change to a specific economic measure such as median household income for county i, ΔX_i is a vector of changes to other county-level characteristics such as population, education, and age groupings, ΔBB_i is the right-hand side variable of interest denoting changes in broadband provider/adoption category, β_0, β_1, and β_2 are parameter vectors, and ε_i is the associated error term. The resulting models explore the role of increasing broadband providers or adoption rates on the measures of jobs and income, after controlling for other influential variables. The first-differenced technique is essentially a form of fixed effects modeling, with its primary benefit being the elimination of bias from time-invariant unobserved factors (Allison 1990). It also allows for some preliminary claims regarding causality, although endogeneity is still a concern. Each of the models that follow use the 2008–2011 time period since the FCC broadband data began in 2008 and 2011 was the most recent that was available. The models are restricted to non-metropolitan counties (which include both micro and non-core) and are also run solely on non-core counties.

4 Results

4.1 Cross-section spatial model results

A total of eight SEM models were run using the 18 criterion variables plus the two broadband adoption/availability variables (one general and one interacted with

Table 3 Spatial error regression results—broadband availability

	NFP		MHHI (LN)		ESTPE (LN)		TOTEMP (LN)	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
CONSTANT	76.850	12.231***	9.832	0.281***	−6.446	0.550***	−1.640	0.386***
POPLN	−3.935	0.162***	0.006	0.002**	1.081	0.006***	0.963	0.005***
HS	0.055	0.039	0.005	0.001***	0.003	0.001*	0.005	0.001***
SC	−0.072	0.034**	0.007	0.000***	0.008	0.001***	0.009	0.001***
BACH	0.180	0.033***	0.011	0.000***	0.019	0.001***	0.019	0.001***
AGE15_24	−0.399	0.075***	−0.018	0.001***	−0.009	0.002***	0.000	0.002
AGE25_44	−0.364	0.098***	−0.006	0.001***	−0.007	0.003**	0.004	0.003
AGE45_64	0.361	0.088***	0.000	0.001	−0.003	0.003	−0.005	0.003**
AGE65_	−0.112	0.077	−0.023	0.001***	0.019	0.003***	0.010	0.002***
BNH	−0.018	0.013	−0.006	0.000***	0.001	0.001**	0.003	0.000***
ANH	0.346	0.092***	0.003	0.001**	−0.014	0.003***	0.007	0.003**
HISP	0.028	0.016*	−0.002	0.000***	0.002	0.001***	0.004	0.000***
OTH	−0.086	0.023***	−0.005	0.000***	−0.008	0.001***	0.001	0.001
NATAM	1.544	0.172***	0.003	0.003	0.000	0.007	−0.015	0.005***
UR	0.348	0.064***	−0.015	0.001***	−0.031	0.002***	−0.030	0.002***
PUBEXPLN	−1.407	1.302	0.129	0.030***	0.142	0.059**	0.065	0.041
RURROADS	−0.052	0.015***	−0.001	0.000***	−0.003	0.001***	−0.001	0.000*
URINTER	−0.107	0.041***	−0.001	0.001	0.001	0.002	−0.002	0.001*
NM	−4.809	0.603***	−0.050	0.007***	0.171	0.018***	0.128	0.018***
HIAVAIL	−1.049	0.630*	−0.011	0.007	0.035	0.019*	0.057	0.019***
HIAVAILNM	0.253	0.689	0.012	0.008	0.001	0.021	−0.030	0.020*
LAMBDA	0.169	0.028***	0.781	0.014***	0.575	0.020***	0.237	0.027***
# Obs	3,073		3,073		3,073		3,073	
R^2	0.4054		0.8583		0.9784		0.9775	

*, **, and *** represent statistically significant coefficients at the $p = 0.10$, 0.05, and 0.01 levels, respectively

non-metropolitan status). Tables 3 and 4 present the full results of the models related to broadband availability and adoption, respectively.

Both tables provide many interesting results. We first note that the spatial error parameters (lambda) are highly significant in all models, and the Moran's I of the residuals are all close to zero and greatly reduced from their values for non-spatial OLS models (not shown in table). This suggests that the spatial modeling structure is an improvement over OLS. Most control variables demonstrate the expected relationships, such as higher levels of education being positively associated with income and higher population being positively associated with most job measures (with the notable exception of non-farm proprietors). Unemployment rates have the expected negative relationship with jobs, and natural amenities seem to be most influential for non-farm proprietors. We focus mostly on the broadband variables of interest. Turning first to broadband availability (Table 3), there is one case where the parameter on

Table 4 Spatial error regression results—broadband adoption

	NFP		MHHI (LN)		ESTPE (LN)		TOTEMP (LN)	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
CONSTANT	77.811	12.427***	9.916	0.280***	−6.257	0.550***	−1.429	0.392***
POPLN	−4.080	0.160***	0.004	0.002	1.085	0.005***	0.966	0.005***
HS	0.050	0.039	0.004	0.001***	0.002	0.001*	0.005	0.001***
SC	−0.082	0.034**	0.007	0.000***	0.008	0.001***	0.008	0.001***
BACH	0.160	0.035***	0.010	0.000***	0.019	0.001***	0.019	0.001***
AGE15_24	−0.371	0.075***	−0.018	0.001***	−0.011	0.002***	−0.001	0.002
AGE25_44	−0.348	0.098***	−0.007	0.001***	−0.008	0.003**	0.003	0.003
AGE45_64	0.399	0.088***	0.001	0.001	−0.004	0.003	−0.007	0.003***
AGE65_	−0.100	0.077	−0.023	0.001***	0.018	0.003***	0.010	0.002***
BNH	−0.018	0.013	−0.006	0.000***	0.001	0.001**	0.003	0.000***
ANH	0.338	0.092***	0.003	0.001**	−0.013	0.003***	0.008	0.003***
HISP	0.029	0.016*	−0.002	0.000***	0.002	0.001***	0.004	0.000***
OTH	−0.080	0.023***	−0.005	0.000***	−0.008	0.001***	0.001	0.001
NATAM	1.582	0.171***	0.003	0.003	−0.001	0.007	−0.017	0.005***
UR	0.346	0.064***	−0.015	0.001***	−0.031	0.002***	−0.030	0.002***
PUBEXPLN	−1.621	1.311	0.125	0.030***	0.134	0.059**	0.057	0.042
RURROADS	−0.049	0.015***	−0.001	0.000***	−0.003	0.001***	−0.001	0.000*
URINTER	−0.096	0.041**	−0.001	0.001	0.000	0.002	−0.002	0.001*
NM	−4.272	0.445***	−0.038	0.005***	0.150	0.014***	0.094	0.013***
HIADOPT	0.900	0.538*	0.030	0.006***	−0.014	0.016	0.010	0.016
HIADOPTNM	−0.997	0.618	−0.007	0.007	0.061	0.019***	0.038	0.018**
LAMBDA	0.171	0.028***	0.782	0.014***	0.570	0.020***	0.242	0.027***
# Obs	3,073		3,073		3,073		3,073	
R^2	0.4047		0.8600		0.9784		0.9776	

*, **, and *** represent statistically significant coefficients at the $p = 0.10$, 0.05, and 0.01 levels, respectively

the interacted variable has the opposite sign as the "base" broadband parameter. This suggests that it is possible for rural levels of broadband to sometimes act counter to the impacts of broadband in more urban areas (and providing evidence that it is important to differentiate between geographies). For example, the model for our measure of total employment (TOTEMP) has a positive and significant general parameter associated with high broadband availability. However, this association is switched for rural areas, as non-metro counties with high levels of broadband availability actually see lower levels of total employees (although this result is only significant at the $p = 0.10$ level). One interpretation of these results is that rural areas with higher levels of broadband availability may be more likely to outsource some categories of jobs.[10] For example,

[10] Kolko (2012) contains a useful discussion of how the relationship between broadband and employment could vary by location—and how it could hypothetically have a negative impact as technology is used as a substitute for labor.

accountants or tax preparers may not be necessary in some small towns with suitable access to online substitutes. Alternatively, the results may speak to the lack of familiarity with broadband in many rural businesses; simply having more of it available does not imply that the businesses know how to use it productively or even that they will choose to adopt it. This negative relationship between broadband availability and job growth has been previously documented, but was not broken out by geography (Mayo and Wallsten 2011). The results here suggest that the negative relationship holds solely in non-metro counties.

Interestingly, broadband availability seems to have a negative impact on the proportion of non-farm proprietors overall, and the non-metro shift is not significant. This suggests that high levels of broadband availability are actually associated with lower percentages of non-farm proprietors, perhaps speaking to the types of non-farm proprietors being considered (such as "entrepreneurs of last resort," who have turned to self-employment after losing other jobs and may not be likely to use broadband in their work). The lack of a significant non-metro shift in this instance implies that this relationship with broadband availability still holds for more rural entrepreneurs. In terms of income, none of the availability parameters is significant, which is surprising since we expected more well-off counties to be targeted for broadband investment.

When the focus turns to broadband adoption (Table 4), we see more evidence of important differences between the general broadband parameter and the interacted term. In this instance, however, measures of businesses and jobs (ESTPE and TOTEMP) only demonstrate positive and significant parameters associated with high levels of broadband adoption *for the non-metro shift*. This implies that, in urban areas, there is not a meaningful relationship between high levels of residential broadband adoption and jobs (after controlling for education, income, and other determinants). In non-metro counties, however, counties with residential broadband adoption rates of greater than 60 % will actually have more businesses and total employees. Hypothetically, as more rural individuals adopt broadband, job or business opportunities may arise due to increased access to ideas and markets. This result offers support for the argument that improving broadband adoption in rural areas can be a boon for local employment, and refutes the idea that some jobs in rural communities might be outsourced to a nearby urban center. This is notably different from the result for simple *availability* (Table 3).

In terms of income, there is a positive general relationship with broadband adoption rates overall, but no significant shift for rural areas. This same trend holds for the percentage of non-farm proprietors, suggesting that high levels of adoption are related to the presence of more entrepreneurs (though again, the non-metro shift is not significant). This implies that high levels of broadband adoption (but not availability) are particularly important for entrepreneurs in general.

Overall, these results reveal that broadband availability and adoption in rural areas are associated with several measures relating to jobs, including numbers of businesses and employees, even after controlling for spatial effects. The fact that many of the interacted parameters are shifts from a nonsignificant base or a base with a different sign implies that rural broadband does in fact have its own unique impact on the overall economy. The results imply that there is a positive relationship between high levels of broadband adoption and the number of businesses/jobs in non-metro counties.

Table 5 First-differenced regressions: broadband adoption impacts on jobs and Income (2008–2010)

	ΔNFP		Δln(MHHI)		Δln(ESTPE)		Δln(TOTEMP)	
	NM	Noncore	NM	Noncore	NM	Noncore	NM	Noncore
ΔBBadop	0.377***	0.442***	0.005***	0.006**	0.003	0.001	−0.001	−0.004
Δln(pop)	4.265**	5.725***	0.065**	0.045	0.481***	0.378***	0.285***	0.279***
Education								
ΔHS	0.138*	0.204**	−0.002	−0.003**	−0.002	0.010**	−0.002	−0.002
ΔSC	0.225***	0.141	0.000	−0.001	−0.007	−0.003	−0.001	−0.001
ΔBACH	0.444***	0.449***	−0.002	−0.004**	−0.013**	−0.003	0.002	0.003
Δunemp	0.258***	0.209***	−0.008***	−0.008***	−0.005	−0.007**	−0.018***	−0.019***
Δpov	−0.104***	−0.083	−0.013***	−0.012***	−0.006***	−0.002	−0.003***	−0.003***
ΔNFP			0.002***	0.002***	−0.005***	−0.004***	0.013***	0.014***
Age								
ΔAge15–24	−1.012***	−1.141***	−0.003*	−0.004**	−0.005	−0.009	−0.004**	−0.004*
ΔAge25–44	−0.385***	−0.486***	0.004**	0.005**	0.002	−0.003	−0.001	0.000
ΔAge45–64	−0.217**	−0.299**	−0.001	0.000	0.002	−0.001	−0.001	0.001
ΔAge65+	−0.356***	−0.419***	−0.006***	−0.003*	0.016***	0.005	−0.002	−0.001
Δblack	−0.123	−0.020	−0.002	−0.002	0.004	0.007	0.000	0.000
Δasian	0.490*	0.887**	−0.002	−0.013**	0.033**	0.023	0.005	0.007
Δhisp	−0.003	0.086	−0.004***	−0.004***	0.011***	0.005	−0.003**	−0.003**
Δothrace	−0.101	−0.013	−0.002	−0.001	−0.008	−0.017***	−0.005***	−0.006***
Constant	1.233***	1.588***	0.048***	0.046***	−0.034***	−0.032**	0.014***	0.014***
No. Obs	2,013	1,348	2,013	1,348	2,013	1,348	2,013	1,348
Adj R^2	0.0882	0.0849	0.3464	0.327	0.0434	0.0381	0.5331	0.5767

*, **, and *** represent statistically significant differences from 0 at the $p = 0.10$, 0.05, and 0.01 levels, respectively

A negative relationship exists between high broadband *availability* and total jobs in non-metro counties, demonstrating the importance of differentiating between availability and adoption. However, this type of cross-section model can make only very limited claims about causality. We turn to first-differenced regressions to focus more on how *changes* in broadband adoption/availability might impact jobs and income.

4.2 First-differenced regressions results

Table 5 provides the results for the same four measures of jobs and income: changes in the percentage of non-farm proprietors, changes in the log of median household income, changes in the log of the total number of firms, and changes in the log of total employment. Each dependent variable is modeled using two distinct subsets of data: all non-metro counties and only non-core counties. All models are run on changes over the 2008–2011 time period.

The results indicate that increasing levels of broadband adoption do impact several observed shifts in jobs and income for non-metro counties over the 2008–2011 time period.[11] Namely, changes in median household income and the percentage of non-farm proprietors are positively influenced by increases in broadband adoption over this time. Further, these increases are still seen when the analysis is restricted to non-core counties (i.e., those without a community of 10,000 or more). The finding related to median household income is particularly noteworthy given the non-existent relationship with broadband adoption documented in the spatial cross-section models. Thus, while overall income levels showed no association with high broadband adoption in non-metro areas as of 2011, rural counties that *increased* their adoption rates between 2008 and 2011 saw higher income growth. Changes to the other measures considered (total number of firms and total employment) do not show any impact from changing levels of broadband adoption. Overall, however, the results do suggest that increasing adoption levels positively impacts shifts to income and entrepreneurial activity in non-metropolitan areas. This finding is particularly impressive since it focuses on relatively recent increases in broadband adoption (since 2008) and looks over only a very short time period (4 years).

When similar regressions are run using changes in the number of residential providers over the 2008–2011 period as the independent variable of interest (replacing the changes in broadband adoption category), no statistical impacts are found for any measure.[12] These results are not reported for the sake of brevity. This suggests that increasing broadband adoption, rather than availability, is the more important factor for improving measures of jobs and income in rural areas.

5 Conclusion

This paper has attempted to use recent data on broadband availability and adoption to assess the relationship between broadband and economic health in rural parts of America. The data itself suggest that a digital divide still exists: Rural America still lags behind in terms of broadband adoption, and many of the most rural (non-core) counties still have significant portions of their population that lack access to wired broadband infrastructure. The modeling results demonstrate that relationships do exist between rural areas with higher levels of broadband availability/adoption and various measures of jobs and income. Importantly, these relationships are not always positive. The spatial models, in particular, show that non-metropolitan areas with high levels of broadband availability are associated with lower total employment, even after controlling for both demographic and spatial effects. This may be due to the propensity to electronically outsource work in rural areas with high levels of broadband. On the more encouraging side, high levels of broadband adoption in nonmetropolitan counties are positively associated with higher numbers of businesses and jobs, demonstrating the importance of distinguishing between access and adoption. However, these spatial models simply demonstrate correlations at a single point in time, and so first-differenced regres-

[11] Recall that a 1-unit increase in broadband adoption corresponds to a roughly 20 % increase in county household adoption rates due to the categorical nature of the FCC data.

[12] The FCC data do contain information on the number of residential providers in a county, though it is not as detailed as the NBM data. For this analysis, we use FCC provider data, since the NBM data were not available until 2010.

sions are used to model the impact of increases in broadband adoption/availability on changes to jobs and income over time. Focusing explicitly on non-metropolitan counties, the results show that increases in broadband adoption (but not availability) are associated with increases in median household income and the percentage of non-farm proprietors. Given that these increases in broadband adoption have only taken place recently (since 2008) and the period of evaluation is quite short (4 years), these results provide striking confirmation that levels of broadband adoption *do* have a role in rural economic development.

From a policy perspective, some options seem clear: to the extent that broadband capabilities are simply not present, the policies that can draw infrastructure to less economically robust regions lacking broadband must be supported. The data used here do not comment on the results of the infrastructure investments associated with the American Reinvestment and Recovery Act (ARRA) since they were under development from 2010 onward, but nevertheless it seems clear that the better data now available should be used to target the locations without services and infrastructure so that investment can do the most good. As a testament to this, the Government Accountability Office (2012) highlighted the need for better data to be able to fully evaluate the Broadband Technology Opportunities Program (BTOP) and Broadband Initiatives Program (BIP) projects that came out of the ARRA legislation.

Efforts to increase adoption in rural areas can be tailored to specific demographics that have tended to lag behind in terms of adoption rates—such as households with lower income, lower education levels, or elderly household heads. Strong relationships related to age and broadband adoption have been well documented in the past, especially populations over 45 years of age (Whitacre and Mills 2007; Goldfarb and Prince 2008). Policies might specifically target these groups for special attention to encourage adoption; arguably, the interests and abilities of an older population may differ from those of a younger one. Some programs doing exactly this are now underway through BTOP's Sustainable Broadband Adoption program, as well as its Public Computer Center program (which often includes training efforts). Systematic evaluation of these efforts would help to calibrate policy endeavors (Hauge and Prieger 2009). More fine-grained analysis that recognizes the multidimensionality of adopters would benefit the sponsored efforts to encourage people to use Internet resources to their advantage. These policy suggestions gain traction from recent findings regarding the link between broadband and productivity—in particular, the result that broadband impacts will vary based on the quality of the human capital stock (Mack and Faggian 2013).

Several limitations of this analysis are worth mentioning. While the inclusion of fixed effects via the first-differenced approach does allow for some limited claims about causality (Winship and Morgan 1999), the methodology for doing so is not optimal. Assessing strict causality is beyond the scope of this paper, but could be more effectively evaluated via techniques such as propensity score matching. Whitacre et al. (2014) use this technique and a similar dataset to take a step toward establishing a causal relationship between broadband and rural economic growth between 2001 and 2010. Further, more recent National Broadband Map and FCC adoption data are now available, and later NBM data represent an improvement from the 2011 version in terms of the percentage of providers reporting and overall reliability.

The results of this study represent an important element in establishing a link between broadband and jobs and income in rural areas. In particular, while cross-section spatial models document that broadband availability in non-metro counties can have different relationships with jobs/income than for the overall economy, only increases in broadband *adoption* are shown to impact changes over time. Thus, the demand-side programs espoused by many economists (Hauge and Prieger 2009; Dickes et al. 2010; Atkinson 2009) find significant support from this analysis.

Acknowledgments This study was supported by the National Agricultural and Rural Development Policy (NARDeP) Center under USDA/NIFA Grant no. 2012-70002-19385.

6 Appendix

See Fig. 6.

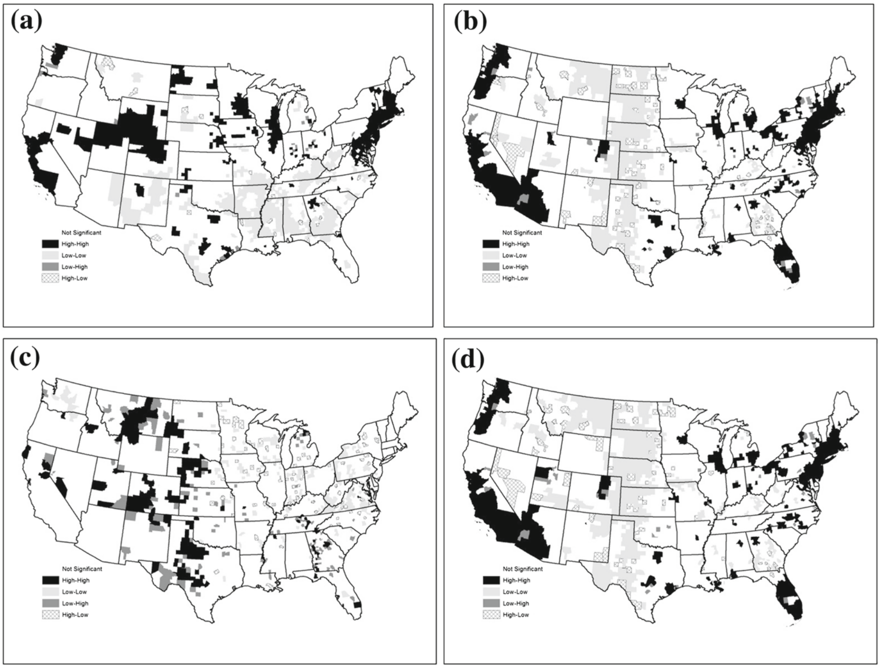

Fig. 6 Local Moran's I maps for dependent variables. **a** Median household income (MHHI), **b** establishments with paid employees (ESTPE), **c** % of non-farm proprietors (NFP), **d** total number of employees (TOTEMP)

References

Allison P (1990) Change scores as dependent variables in regression analysis. Sociol Methodol 20:93–114
Anselin L (1988) Spatial econometrics: methods and models. Kluwer Academic Publishers, Dordrecht

Anselin L (2003) Spatial externalities, spatial multipliers, and spatial econometrics. Int Region Sci Rev 26(2):153–166

Anselin L, Bera AK, Raymond F, Yoon MJ (1996) Simple diagnostic tests for spatial dependence. Reg Sci Urb Econ 26:77–104

Atkinson R (2009) Policies to increase broadband adoption at home. The Information Technology and Innovation Foundation. http://www.itif.org/files/2009-demand-side-policies.pdf

Chi G (2010) The impacts of highway expansion on population change: an integrated spatial approach. Rural Sociol 75(1):58–89

Czernich N, Falck O, Kretschmer T, Woessmann L (2011) Broadband infrastructure and economic growth. Econ J 121:505–532

Dickes L, Lamie D, Whitacre B (2010) The struggle for broadband in rural America. Choices 25(4). http://www.choicesmagazine.org/magazine/article.php?article=156

Federal Communications Commission (FCC) (2012) Eighth broadband progress report. http://www.fcc.gov/reports/eighth-broadband-progress-report

Ferguson M, Ali K, Olfert M, Partridge M (2007) Voting with their feet: jobs versus amenities. Growth Change 38(1):77–110

Ford G (2011) Challenges in using the National Broadband Map's data. Phoenix Center Policy Bull 27:1–21

Galloway L (2007) Can broadband access rescue the rural economy? J Small Bus Enterp Dev 14(4):641–653

Gillett S, Lehr W, Osorio C, Sirbu M (2006) Measuring the economic impact of broadband deployment. Economic Development Administration, Dept. of Commerce. http://cfp.mit.edu/publications/CFP_Papers/Measuring_bb_econ_impact-final.pdf

Goetz S, Fleming D, Rupasingha A (2012) The economic impacts of self-employment. J Agric Appl Econ 44(3):315–321

Goldfarb A, Prince J (2008) Internet adoption and usage patterns are different: implications for the digital divide. Inf Econ Policy 20(1):2–15

Government Accountability Office (GAO) (2012) Broadband programs are ongoing, and agencies' efforts would benefit from improved data quality. Report GAO-12-937. http://www.gao.gov/assets/650/648355.pdf

Grubesic T (2012) The U.S. National Broadband Map: data limitations and implications. Telecommun Policy 36:113–126

Hauge J, Prieger J (2009) Demand-side programs to stimulate adoption of broadband: what works? Social Sciences Research Network. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1492342

Holt L, Jamison M (2009) Broadband and contributions to economic growth: lessons from the US experience. Telecommun Policy 33:575–581

Kandilov I, Renkow M (2010) Infrastructure investment and rural economic development: an evaluation of USDA's broadband loan program. Growth Change 41(2):165–191

Kolko J (2012) Broadband and local growth. J Urb Econ 71(1):100–113

Kuttner H (2012) Broadband for rural America: economic impacts and economic opportunities. Report prepared for the Hudson Institute. http://www.hudson.org/files/publications/RuralTelecom-Kuttner-1012.pdf

LaRose R, Strover S, Gregg J, Straubhaar J (2011) The impact of rural broadband development: lessons from a natural field experiment. Gov Inf Q 28:91–100

Lehr W, Osorio C, Gillett S (2005) Measuring broadband's economic impact. Presented at the 33rd research conference on communication, information, and internet policy (TPRC), Arlington, VA. http://www.andrew.cmu.edu/user/sirbu/pubs/MeasuringBB_EconImpact.pdf

Mack E, Anselin L, Grubesic T (2011) The importance of broadband provision to knowledge intensive firm location. Reg Sci Policy Pract 3(1):17–35

Mack E, Grubesic T (2009) Broadband provision and firm location: an exploratory data analysis. Tijdschrift voor Economische en Sociale Geografie 100(3):298–315

Mack E, Faggian A (2013) Productivity and broadband: the human factor. Int Reg Sci Rev. doi:10.1177/0160017612471191

Malecki EJ (2003) Digital development in rural areas: potentials and pitfalls. J Rural Stud 19(2):201–214

Mayo J, Wallsten S (2011) From network externalities to broadband growth externalities: a bridge not yet built. Rev Ind Organ 38(2):173–190

McGranahan D, Wojan T, Lambert D (2011) The rural growth trifecta: outdoor amenities, creative class and entrepreneurial context. J Econ Geogr 11:529–557

Mills B, Whitacre B (2003) Understanding the metro-non-metro digital divide. Growth Change 34(2): 219–243

National Telecommunications and Information Administration (NTIA) (1995) Falling through the net: a survey of have-nots in rural and urban America. http://www.ntia.doc.gov/ntiahome/fallingthru.html

NTIA (1999) Falling through the Net: defining the digital divide. http://www.ntia.doc.gov/legacy/ntiahome/fttn99/contents.html

NTIA (2000) Falling through the Net: toward digital inclusion. http://www.ntia.doc.gov/legacy/ntiahome/fttn00/falling.htm

Parker EB (2000) Closing the digital divide in rural America. Telecommun Policy 24:281–290

Sobel R, King K (2008) Does school choice increase the rate of youth entrepreneurship? Econ Educ Rev 27(4):429–438

Stenberg P, Morehart M, Vogel S, Cromartie J, Breneman V, Brown D (2009) Broadband Internet's value for rural America. Economic Research Report No. 70 (ERR-78). http://www.ers.usda.gov/publications/err-economic-research-report/err78.aspx

Stephens H, Partridge M (2011) Do entrepreneurs enhance economic growth in lagging regions? Growth Change 42:431–465

Strover S (2001) Rural Internet connectivity. Telecommun Policy 25:331–347

Strover S (ed) (2011) Scholars' roundtable: the effects of expanding broadband to rural areas. Center for Rural Strategies, USA. http://www.ruralstrategies.org/sites/all/files/Broadband_Investment.pdf

Voss PR, Long DD, Hammer RB, Friedman S (2006) County child poverty rates in the US: a spatial regression approach. Popul Res Policy Rev 25(4):369–391

Whitacre B, Mills B (2007) Infrastructure and the rural–urban divide in high-speed residential internet access. Int Reg Sci Rev 30(3):249–273

Whitacre B, Gallardo R, Strover S (2014) Broadband's contribution to economic growth in rural areas: moving towards a causal relationship. Telecommun Policy. doi:10.1016/j.telpol.2014.05.005

Winship C, Morgan S (1999) The estimation of causal effects from observational data. Annu Rev Sociol 25:659–707

Wu J, Gopinath M (2008) What causes spatial variations in economic development in the United States? Am J Agric Econ 90(2):392–408