Does Broadband Access Impact Population Growth in Rural America?

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Introduction

According to neoclassical economics, geographic differences in the supply of and demand for labor are a primary cause of population migration (Todaro and Maruszko, 1987). People who live in labor-surplus areas, which usually have lower wages, tend to migrate to labor-scarce areas, which usually have higher wages. Generally, the labor-scarce areas have relatively higher economic growth with more industries and manufacturing concentration than the labor-surplus areas. In a neoclassical world, these differences in supply and demand cause immigration, as areas with high economic growth tend to experience in-migration (Hendrink, 2001).

In recent years new concepts have altered the neoclassical view of migration theory. These concepts center around the idea that people not only consider economic activity factors but also the infrastructure and amenity factors that can improve their quality of life (Greenwood, 1985).[1] Few people make a location decision without considering topics such as public schools, hospitals, transportation availability, and general quality of life. The existing literature on this topic has consistently demonstrated that communities with a higher quantity and quality of infrastructure and amenities showed increases in population, mostly from in-migration, while communities with lower level of infrastructure and amenities tended to lose their population (Aschauer, 1989; Gramlich, 1994; and Deller et al., 2001).

The availability of broadband, or high-speed Internet access, is a relatively new addition to the spectrum of infrastructure services a community can offer.[2] Since its introduction in the late 1990s, broadband has been widely touted as an instrument to benefit a wide cross-section of

[1] Amenities can be separated into two categories. The first category is natural amenities such as weather, mountains, and ocean. The second category is human-built amenities such as golf courses, tennis courts, and parks.
[2] Broadband access, also called high-speed access or advanced service, is defined by the Federal Communications Commission as 200 Kilobits per second (Kbps) (or 200,000 bits per second) of data throughput in at least one direction.

the economy and society in general (Whitacre and Mahasuweerachai, 2008). The Bureau of Economic Advisors (2003) estimates that for each $1 invested in broadband, the economy benefits nearly $3. Other recent studies on broadband found that its presence increases industrial effectiveness and economic growth in certain sectors of the economy (Leh et al., 2005; Ford and Koutsky, 2005; Shideler et al., 2007). Moreover, broadband access has the potential to increase the quality of life through enhanced education, improved health care, instant connection across the country and around the globe, e-government, and employment generation (Warren, 2007; Intelligent Community Forum, 2008). These positive impacts of broadband access on the economy and society could improve the quality of life of residents living in communities where this technology is available. Hence, the availability of broadband access could represent a new wave of infrastructure that could play a role in an individual's location decision. This may be particularly true for rural and remote areas. Some anecdotal studies suggest that broadband access may potentially solve the current problem of population decline in these areas (McGranahan and Beale, 2002; William, 2008). However, to our knowledge, no empirical work has surfaced on this topic. While many rural areas lagged behind their urban counterparts in the availability of broadband, those areas fortunate enough to offer this type of infrastructure may have had an advantage in attracting residents.

This paper attempts to answer the question of whether areas, especially rural ones, with access to broadband infrastructure relatively early on (by the year 2000) had higher levels of population growth than those without it. We attempt to answer the question in two distinct ways: (1) regression analysis on population change over the period 2000-2006; and (2) average treatment effects. Various specifications are explored (including spatial econometric models) and results from the two methods are compared in order to make stronger statements about the impact that broadband access has had on population growth. These results will be of interest to individuals involved in community development, given the relationship between population change and economic growth (Deller et al., 2001).

Methodology

In order to make stronger statements about the impact of broadband on population growth, both regression analysis and the average treatment effects method are employed.

Spatial Regression Model

We develop a model to explain the factors that cause migration in the U.S. This model will dictate the econometric framework that should shed light on the role of broadband infrastructure in the migration decision.

Suppose that the expected utility of an immigrant to migrate to county j can be defined as

$$U_j\left(Y_j, I_j, C_j, Q_j\right) \tag{1}$$

where Y_j is the expected income that an immigrant expects to earn in county j; I_j is the vector of infrastructure available in county j; C_j is cost of living in county j; and Q_i is the vector of quality of life in county j. An immigrant will migrate to the county that maximizes his/her expected utility. By applying the migration model developed by Treyz et al. (1993) and Dust et al. (2008), people will have a reference utility that reflects the expected utility across all possible locations, denoted by $\overline{U}$. Whether or not an individual will move to county j is dependent upon the difference between the utility received from moving to county j and the reference utility. If the utility received from moving to county j is higher than the reference utility, this individual will move to county j. If the utility received from moving to county j, on the other hand, is less than the reference utility, an individual will stay where he/she is or move to another county that maximizes his/her utility. This relation is represented by:

$$\Delta P_j = f(U_j - \overline{U}) \tag{2}$$

where ΔP_j is the population change for county j, indicating net immigration, and $f(\cdot)$ is the function aggregating migrants' decision into county j.[3]

To operationalize the model for empirical work, we specify the elements of Y_j, I_j, C_j, and Q_j. We proxy expected wages in county j using the median county income, since the wage data for each sector in each county are not available. In addition, we include measures of a county's industrial composition (percent employment by industry) and employment level to proxy for the potential demand for labor in county j.

We expect higher wages and employment levels to increase population change, while the industrial composition variables control for the relative labor-intensity of local firms. Immigrants also consider the cost of living in each county when they make their location decision. We use the average housing value in each county as the proxy for this variable, C_j. A lower cost of living should increase one's expected utility in a location, so lower housing values should increase population change. Moreover, a rural dummy variable, R_j, is included to capture the difference in migration pattern between rural and urban areas.[4] Previous studies indicated that the quality of life is also an important factor considered by people before making the decision to settle in a particular area. Per capita crime rate, per capita social security benefit, poverty rate,

[3] The reference utility of each individual is unobservable. We can observe the difference between expected utility and reference utility by examining a county's characteristics and migration pattern.
[4] The rural dummy is created by using Rural-Urban Continuum Codes provided by the USDA; counties with codes greater than 4 were deemed rural.

and an amenities score, which was developed by the USDA Forest Service's Wilderness Assessment Unit, are used to represent the level of quality of life in each county.

The vector of infrastructure, I_j, includes per capita local government expenditures and broadband access. An immigrant would prefer to live in areas with more extensive government support, so areas with high per capita local government expenditures would be more likely to attract immigrants (although, high government expenditure is typically associated with high taxes). For broadband infrastructure, we create a dummy variable to represent the availability of broadband access in the year 2000. The dummy variable denotes areas with at least Cable or DSL available as equal to one and zero otherwise.

Putting these variables into the expected utility function of an immigrant, and specifying the utility function in the form as following, we get

$$U_j = \beta_Y lnY_j + \sum_{l=1}^{k} \beta_l \frac{E_{lj}}{E_j} + \beta_m lnM_j + \beta_I I_j + \beta_c lnC_j + \beta_Q Q_j \quad (3)$$

By substituting (3) into (2), we get empirical model as

$$\Delta P_j = \beta_0 + \beta_Y lnY_j + \sum_{l=1}^{k} \beta_l \frac{E_{lj}}{E_j} + \beta_m lnM_j + \beta_c lnC_j + \beta_q Q_j + \beta_i I_j + \beta_{bb} BB_j + \beta_r R_j + \varepsilon_j \quad (4)$$

For industrial share in employment, E_{ij}/E_j, the industrial sectors used are agriculture, construction, manufacturing, wholesale, retail, finance, and public administration.[5] BB_j is the broadband dummy variable, and M_j is the employment level in county j.

An additional consideration in that the pattern of immigration and population growth may extend beyond a single geographical observation; papers such as Boarnet (1994) and Boarnet et al. (2005) have documented the spatial interdependence of population growth. This issue creates a pattern of spatial dependence that requires a spatial econometric approach. The general spatial econometric model can be represented as:

$$\Delta P = X\beta + \rho W \Delta P + u; \quad u = \lambda W u + \varepsilon; \quad \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n) \tag{5}$$

where X is the vector of explanatory variables shown in (4); W is a known spatial weight matrix[6], which captures spatial dependence between each geographic area (counties in this analysis) and its neighbors; ρ is a coefficient on the spatially lagged dependent variable; and λ is a coefficient on the spatially correlated errors. Ordinarily, one would use the LM-test developed by Anselin (1988) to determine whether there is spatial dependence in the residuals of our model to justify use of the general spatial form. However, this test is not easily performed when large data sets are involved, so we justify our use of this form based upon the significance of both spatial parameters and likelihood ratio test results that suggest spatial correlation among the residuals exists in a spatial lag model.

[5] We also included other industrial shares for employment reported by the U.S. Census into the model, but they are not statistically significant.
[6] The weight matrix was constructed using the Delaunay triangulation algorithm in MATLAB from latitude and longitude coordinates of the geographic centroid of each county.

If broadband access does have an impact in the migration decision, we would expect to see a positive and statistically significant value for our estimated broadband coefficients after controlling for all other variables in the specification.

Treatment Effects

Even though regression can verify whether broadband is correlated with the population growth, we cannot establish causation. In addition, because regression relies on the assumption of functional form, which is rarely justified theoretically, misspecification of the functional form may result in unsolved endogeneity problems, which cause biased estimates. Matching techniques, on the other hand, could avoid these problems. They are not model-based and hence do not depend on any functional form assumptions.

To measure the effect of broadband on population growth, we are interested in the difference in the population growth between areas with and without broadband. This is known as the "treatment effect" because those areas with broadband are considered to have been "treated". Let ΔP_{j1} and ΔP_{j0} be the population growth of the areas with and without broadband, respectively. The average treatment effect on treated (ATET) can be represented as

$$ATET = E\left(\Delta P_{j1} | T_j = 1\right) - E\left(\Delta P_{j0} | T_j = 1\right) \quad (6)$$

where T_j equals one for areas with broadband (treated) and 0 for areas without broadband (non-treated). However, we can only observe either ΔP_{j1} or ΔP_{j0} for a particular area, but not both, since each county will either have or lack broadband access. In other words, there is self-selection into the treatment group (Wooldridge, 2002). Typically, this would cause biased estimates of the broadband effect. To yield unbiased estimates of broadband impact, an assumption of "conditional independence" or "exogeneity" is applied (Imbens, 2004). This assumption implies that there are no unobservable differences between areas with broadband (treated) and areas without broadband (non-treated) after conditioning on observable characteristics. Based on this assumption, the population growth from areas without broadband could represent what the areas with broadband would have experienced if they did not have broadband (potential outcome). Hence, to solve the problem of missing data, we have to "match" areas with broadband with one or more areas without broadband that have similar observable characteristics.

Fortunately, a number of methods for estimating ATET relying on the conditional independence assumption (CIA) have been introduced that may result in unbiased estimates. Simple matching estimator and propensity score matching techniques have been widely used in many recent studies (Dehejia and Wahba, 1999; and Antonio et al., 2005). However, simple matching estimators may still provide biased estimates especially when the matching is not exact (Imbens, 2004).

Unlike the simple matching estimator, the propensity score method does not directly adjust for all covariates. Instead, it focuses on adjusting the propensity score, which is the conditional probability of receiving the treatment (i.e. having broadband access). This method uses the propensity score, which is based on observable predictors, to group treated and non-treated units that have similar propensity scores. This would prevent the bias from poor matches, especially when we have many observable characteristics.

We apply a logit model to estimate the propensity score, which will then be used to match treated and non-treated units by creating blocks that contain units with similar propensity scores. To avoid bias in estimation of the ATET due to an incorrect specification of the propensity score, we use an algorithm developed by Becker and Ichino (2002) to test whether the logit model meets a specific balancing property. This tests whether the treated and non-treated groups of each block have the same distribution of covariates, and ensures that the components of covariates are balanced. By using this test, we can calibrate the logit model until the balancing property is satified. Even though we have a propensity score that satisfies the balancing property, the continuous nature of the propensity score variable prevents us from having units in the treated and non-treated groups with exactly the same value. The question is then how to match observations from the various blocks. In order to ensure robustness of our results, both nearest neighbor matching and kernal matching techniques will be employed to estimate broadband's effect on population growth.[7]

The nearest matching technique matches the treated unit with non-treated units for each potential outcome by taking each treated unit and searching for the non-treated unit with the closest propensity score. However, sometimes these matches may be poor because the difference between propensity scores treated and nearest non-treated units are huge. Kernel matching may solve this problem because instead of searching for nearest neighbors to match with each treated unit, all treated units are matched with a weighted average of all non-treated units with weights that are inversely proportional to the distance between the propensity scores of treated and non-treated units. This effect controls for the problem faced by the nearest matching technique (Becker and Ichino, 2002).

Unlike the spatial econometric analysis, which focuses on a single aggregate model, we estimate ATET of broadband on population changes in several distinct cases. We first compare

[7] Details of propensity score technique and the balancing algorithm used are provided in Becker and Ichino (2002) and Dehejia and Wahba (2002).

the areas with at least one type of broadband to areas with none of them. We then restrict our observations to areas with both types of broadband and areas with no broadband available at all. We also allow the ATET to differ by rural and urban location.

Data Description

The data used in this study come from a number of publicly available secondary sources. The population changes at the county level in the U.S. between 2000 and 2006 are obtained from the U.S. Census Bureau. We include both total and domestic population change in various specifications. Industrial shares in employment, the employment level, average housing value, and the poverty rate are also collected from the U.S. Census Bureau. The rural dummy variable is created by using Rural-Urban Continuum Codes for 2003 provided by the USDA. County and City Data Book 2000 edition provide information on per capita crime rate and per capita social security benefit. We use State and Local Government Finances provided by the U.S. Census to collect the county level government expenditure. The broadband data set is taken from sources dealing with the two dominant types of broadband infrastructure in 2000: the Cable TV Factbook, which lists all counties with cable Internet availability, and the FCC's Tariff #4 dataset, which also lists all cities with DSL capability.[8]

Empirical Results

Spatial Regression results

The spatial regression results for total and domestic population growth are presented in Table 1. Because of the importance of preserving the spatial relationships among observations, only two

[8] More detailed information on these sources can be found in Whitacre and Mills (2007).

sets of results are presented. The results reflect the dataset containing all observations (urban and rural) and include the broadband variable that denotes at least one broadband platform is present in the county. Because the results of total and domestic population growth are almost the same, we discuss them together. Of utmost importance is the sign and significance of the broadband dummy variable, which suggests that the presence of some type of broadband (DSL or Cable) had a negative but not statistically significant impact on both population changes holding all other factors constant. Income and housing value have opposite signs than hypothesized; the results suggest that population change was higher for counties with lower wages or higher property values. One explanation for these results might be that higher wages and lower housing values might discourage residents from leaving the community (i.e., they have a higher reservation utility), rather than higher wages and lower housing values attracting migrants to a community. Alternatively, the positive and significant parameter on employment levels may imply that the potential for employment might drive migration decisions more so than expected wages and/or cost of living of the location. Several of the industrial employment shares parameters were significant: construction, manufacturing, wholesale trade, retail trade and finance. The parameters on manufacturing, wholesale trade and finance were negative, suggesting that higher proportions of employment in these sectors lead to lower population growth possibly due to their capital intensity. Construction and retail trade, on the other hand, realized positive parameter estimates suggesting that higher employment shares in these sectors induce population growth. Given that these industries are labor-intensive, these results are intuitive. Counties with higher per capita local government expenditures, higher per capita social security benefits, and lower crimes per capita, as well as rural counties, will experience lower population growth, according to the results. While the results for per capita social security benefits and rural counties were as hypothesized, the signs for the parameters of per capita local government expenditures and crimes per capita were opposite of our hypotheses.

Treatment Effect

Propensity Score Models

Unlike the spatial model, we utilize two distinct cases to clarify the effect of broadband on population growth. For the first case, we compare counties with at least one type of broadband to those with no broadband. The second case compares counties with *both* Cable and DSL access (a more intensive measure of broadband access) to counties without any type of broadband. This requires two sets of propensity score models to be estimated.[9] The matching strategy relies on the conditional independence assumption (CIA). In the case of the propensity score matching method, there is some debate about whether variables included in the propensity score model should affect both the availability of broadband (participation decision) and the migration decision (outcome variables) (Ham et al., 2005; Caliendo and Kopeinig, 2008). Hence, our propensity score specifications include one model that incorporates only the variables that affect both the availability of broadband and migration, and another model that incorporates the former variable and the variables that influence only migration decision.

The true functional forms of propensity score models are not known. We apply the algorithm developed by Becker and Ichino (2002) to test the necessary condition for the balancing property, which ensures that the estimated propensity scores and observable characteristics between treated and non-treated units are statistically identical. This test allows us

[9] Following Rosenbaum and Rubin (1985), even though we also estimate the effect of broadband on population changes for rural and urban areas by themselves, the propensity score estimated by the entire sample can be used to get the ATET for area groups.

to calibrate the logit models until the balancing property is reached. This is why some variables are not included in certain specifications.

Table 2 reports four sets of logit estimates for the availability of broadband. The dependent variable in models 1 and 2 is coded to one if a county has at least one type of broadband and zero otherwise. The difference between model 1 and model 2 is that model 1 contains not only variables that affect both availability of broadband and migration decision but also variables that may only influence the migration decision by itself, such as amenity score, per capita social security income, and per capita crime rate. Model 2 only contains variables that may affect the availability of broadband and migration decision such as the share of employment in particular industries, education, and rural location. The coefficients of these two logit models are consistent with most broadband studies. For example, counties with higher income and population density are more likely to have broadband available, while the digital divide between rural and urban areas still exists (i.e. the rural dummy is negative and significant).

Turning now to models 3 and 4, the dependent variable is switched to a more in-depth measure of broadband availability. Counties with *both* Cable and DSL are coded to one and are zero otherwise - effectively leaving out approximately 1,300 counties with just one type of broadband. The difference between these two models is the same as that between model 1 and model 2. Namely, model 3 contains two types of variables, which are the variables affecting the migration decision only, and the variables influencing both the migration decision and the availability of broadband. Model 4 includes only the latter type of variable. Similar to the model 1 and model 2 results, most coefficients have the expected sign and are consistent with previous broadband studies. However, most coefficients of model 4 are significantly larger than those in model 3. This may be a sign of biased estimates from omitting important variables (Heckman et al., 1997; Dehejia and Wahba, 1999).

Estimates of Broadband Effects on Population Change

Table 3 represents the effects of availability of at least one type of broadband on total population and domestic population changes estimated by both the kernel matching method and the nearest matching method. The standard errors of those two methods are calculated with 1,000 bootstrap repetitions. Starting with the kernel matching method, when all areas are estimated together, the effects of the availability of at least one type of broadband are positive in both total population and domestic population changes. These effects, however, are only statistically significant for the domestic population – suggesting that areas with at least one type of broadband experience domestic population growth 0.7% higher than those without it. In addition, the estimates from model 1 and model 2 are very similar in terms of both the broadband effects and standard errors. This would also imply that the variables that are expected to influence the migration decision only (amenity score, per capita social security income, and per capita crime rate) may not provide extra information regarding the migration decision after controlling for other county characteristics. When we disaggregate our sample into rural and urban areas, the effect of availability of at least one type of broadband on population change is still positive in both cases. However, these effects are very small and are statistically insignificant in all rural cases. For urban areas, on the other hand, the results are larger and generally significant – suggesting population growth rates that were 1.5% to 2% higher in urban areas with access than in urban areas without access.

When the nearest matching method is applied, the effects of having at least one type of broadband available are relatively larger than those from the kernel matching technique for almost all cases. Generally the results are similar to those from the kernel method, with differences in domestic population change being positive and significant for all areas and urban areas. In addition, total population change is now positive and significant for the models using all counties and urban counties, with results ranging from an expected increase of 0.8% - 1.0% (all areas) to 1.5% - 3.1% (urban areas). However, in the case of rural areas, this effect is still not significant for all cases, and actually turns to negative (although not significant) in model 2.

We also estimate the effect of broadband on population growth by comparing areas with *both* Cable and DSL to areas with no broadband at all. The estimation strategies of this case are the same as the former case. The only difference is that the observations are restricted to areas with both types of broadband and those without any types of broadband. Table 4 presents the estimates based on these observations. In the kernel matching panel, the effects of having both types of broadband on population growth are positive and statistically significant for the cases of all areas and urban areas. Counties with both types of broadband tend to have 1.2% to 1.9% higher level of total population growth and 1.5% to 2.3% higher level of domestic population growth than those without them. In a similar manner, urban counties with both types of broadband also experience an increase in total population growth (1.5% to 2.9%) and domestic population growth (2.3% to 3.5%). In addition, rural areas with availability of both types of broadband may attract domestic immigrants because the effect of broadband is positive and statistically significant at 10% level. Rural areas with both types of broadband tend to have levels of domestic population growth 1.1% higher than those without them.

When the nearest matching method is used, the results are similar to those obtained under the kernel matching method. The effects, however, are generally bigger than those from the kernel matching method. Namely, the effects of both types of broadband on total population change and domestic population change for all observation and urban observation are about range from 1.2% to 2.9%. The interesting result from this estimation is that the availability of both types of broadband in rural counties not only affects the domestic population change but also affects the total population change because the effects are statistically significant for both cases. This is shown in model 3 in the rural area column. Rural counties with both types of broadband have 1.4% higher total population growth and 1.6% higher domestic population growth than those without any types of broadband.

Discussion and Conclusion

The spatial econometric model estimates the effect of broadband on domestic population change for the entire data set of both rural and urban counties. The results suggest that spatial interdependence of population growth exists given the statistical significance of spatially lagged coefficients and spatially correlated errors. Most coefficients of the spatial model are consistent with the previous migration studies. However, the dummy variable for having at least one type of broadband access is negative and is statistically insignificant. Thus, the takeaway result from the spatial econometric model is that the availability of broadband access may not be a key factor in attracting new residents.

However, the spatial econometric model may not provide the best assessment of the impact of broadband on population growth because it relies on the assumption of a specific functional form. Misspecification of the functional form may result in unsolved endogeneity, which results in biased estimates. In addition, the spatial econometric model is limited by the assumption of interdependence among the observations. This limits the insights we can gain regarding the impact of broadband on population growth by location. It also limits our ability to measure the impact of broadband in the case of a more intensive measure of broadband access. Hence, the average treatment effects are employed to avoid these problems.

The propensity score matching estimates show several important results. The first one is that generally, we do not find a strong impact of broadband on population growth – particularly for rural areas. Even though most estimates show a positive impact of broadband on population growth, most of the statistically significant values are fairly small. In addition, when we consider this impact for rural counties only, the impact of the availability of at least one type of broadband on population growth is never statistically significant, and is actually negative in some cases.

This result may give further credence to the idea that rural broadband is not a one-way street for attracting residents. In particular, some rural areas with at least one type of broadband may actually experience outmigration when compared to rural areas that lack broadband access. This evidence has also been found by Egan (2002), and LaRose et al. (2008). In the LaRose study, broadband access in rural areas actually encouraged outmigration because residents used broadband to search for jobs in nearby cities online and then moved away. This situation, however, may not hold absolutely true for all cases. When we restrict our observations to rural areas with *both* Cable and DSL (a more intensive measure of broadband access), the impact on population growth turns to positive and significant for both total and domestic population.

Our results are somewhat tempted by the fact that the broadband variable only considers counties with infrastructure prior to 2000. Given the dramatic rise of both supply and demand for broadband since that time, our analysis of the period 2000-2006 potentially misses the impact of those counties who added broadband later on (2001-2006). Without a comprehensive list of where each county obtained its broadband infrastructure (which to our knowledge does not exist) the current study provides a starting point for analyzing broadband's impact on population growth.

Overall, our attempt to determine whether the presence of broadband access by the year 2000 had an impact on population growth find no support from the spatial econometric model used, and only slightly support from the matching methods. The matching method suggests that all counties, and specifically urban counties, with broadband access saw population increase roughly 1% to 4% higher than similar counties without broadband access. For rural counties, only those counties having *both* Cable and DSL access available in 2000 saw population increases higher than similar counties without broadband experienced.

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Table 1. Spatial Regression Results[10]

Variable	Δ Total Population	Δ Domestic Population
Ln(Employ)	0.006***	0.006***
	(3.097)	(3.095)
Ln(Income)	-0.034***	-0.034***
	(-4.827)	(-4.792)
Ln(Housing Value)	0.035***	0.035***
	(5.749)	(5.745)
Poverty Rate	0.036	0.036
	(1.488)	(1.494)
Agriculture	0.008	0.008
	(0.294)	(0.296)
Construction	0.178**	0.178**
	(2.567)	(2.571)
Manufacturing	-0.031**	-0.031**
	(-1.979)	(-1.970)
Wholesale Trade	-0.552***	-0.552***
	(-4.472)	(-4.469)
Retail Trade	0.127*	0.127*
	(1.694)	(1.693)
Finance	-0.407***	-0.407***
	(-4.414)	(-4.139)
Public Administration	0.016	0.016
	(0260)	(0.262)
Per Capita Crimes	0.188**	0.188**
	(2.167)	(2.165)
Per Capita Social Security Benefits	-0.082***	-0.082***
	(-3.179)	(-3.175)
Per Capita Local Gov't Expenditures	-0.007***	-0.007***
	(-6.479)	(-6.474)
Amenity Score	0.002	0.002
	(1.079)	(1.083)
Rural Dummy	-0.017***	-0.017***
	(-5.289)	(-5.285)
Broadband Dummy	-0.001	-0.001
	(-0.315)	(-0.317)
ρ (spatial lag parameter)	0.226***	0.224***
	(8.734)	(8.113)
λ (spatial error parameter)	-0.084***	-0.081***
	(-10.510)	(-4.718)
Constant	-0.025	-0.026
	(-1.167)	(-1.095)
R^2	0.216	0.216
Adjusted R^2	0.211	0.211
No. of Observations	2987	2987

Notes: ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.

[10] The reported t-statistics reflect heteroskedatically-corrected standard errors; heteroskedasticity was detected in earlier versions of the model using the Breusch-Pagan test statistic. For this model, the test statistic had a value of 89.9.

Table 2. Logit Models to Estimate Propensity Score for Areas with at least One Type of Broadband and both Types of Broadband

	Broadband		Cable & DSL	
Variable	Model 1	Model 2	Model 3	Model 4
Ln(income)	0.944**	0.398	1.516***	0.887**
	(0.395)	(0.392)	(0.547)	(0.427)
Ln(popdensity)		0.580***	2.263***	
		(0.064)	(0.259)	
Ln($popdensity^{\wedge 2}$)			-0.185***	
			(0.029)	
Agriculture		2.339**	4.664**	
		(0.974)	(2.065)	
Construction	-7.493***		-12.169***	
	(2.264)		(3.381)	
Manufacturing	2.768***	0.552	-1.535	7.217***
	(0.719)	(0.856)	(1.213)	(0.836)
Wholesale trade	8.991*	5.888		25.427***
	(4.967)	(4.886)		(5.968)
Transportation	-5.021		-10.688**	
	(3.393)		(4.711)	
Finance	4.610	-6.196	0.841	13.894***
	(4.308)	(4.261)	(5.768)	(4.998)
Public Administration		-1.239	-5.901**	
		(1.902)	(2.631)	
High school	-0.276	0.270	0.639	
	(1.198)	(1.155)	(1.581)	
College	-0.763	3.057***	4.060***	2.931***
	(0.954)	(1.010)	(1.440)	(1.030)
Graduate degree	3.742	-6.024*	-10.914**	8.007**
	(3.433)	(3.374)	(4.235)	(3.475)
Amenities	-0.216***		-0.114	
	(0.058)		(0.079)	
Per capital social security income			1.010	
			(1.460)	
Per capita government expenditure	0.062			
	(0.054)			
Per capita crime rate	20.741***		23.091***	
	(3.639)		(4.384)	
Rural dummy	-0.810***	-0.387**	-0.425**	-1.051***
	(0.152)	(0.157)	(0.192)	(0.161)
Constant	-7.454**	-5.374	-20.363***	-11.850***
	(3.636)	(3.658)	(5.065)	(4.184)
Pseudo R^2	0.108	0.116	0.328	0.198
Log-likelihood	-1297.407	-1285.118	-722.209	-861.296
No. of Observation	2987	2987	1677	1677

Notes: ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.

Table 3. Average Effect of having at least Cable or DSL on Population Growth based on Two Alternative Logit Models

	All Area		Rural Area		Urban Area	
Population Change	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
			Kernel matching method			
Total population	0.006	0.006	0.001	0.001	0.012	0.015*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.008)
Domestic population	0.007*	0.007*	0.002	0.002	0.016*	0.020**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)
			Nearest matching method			
Total population	0.008*	0.010**	0.001	-0.003	0.015*	0.031***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)
Domestic population	0.013***	0.014***	0.003	-0.003	0.024***	0.042***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)	(0.011)

Notes: Standard errors calculated from 1,000 bootstrap repetitions are in parentheses.

***, **, and * represent significant level at 1%, 5%, and 10%, respectively.

Table 4. Average Effect of having both Cable and DSL on Population Growth based on Two Alternative Logit Models

	All Area		Rural Area		Urban Area	
Population Change	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
			Kernel matching method			
Total population	0.019***	0.012**	0.009	0.007	0.029***	0.018*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)
Domestic population	0.023***	0.015**	0.011*	0.008	0.035***	0.023**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.010)
			Nearest matching method			
Total population	0.025***	0.012**	0.014**	0.010	0.029*	0.020**
	(0.008)	(0.006)	(0.007)	(0.007)	(0.016)	(0.009)
Domestic population	0.028***	0.015**	0.016**	0.010	0.027**	0.025**
	(0.009)	(0.007)	(0.007)	(0.007)	(0.016)	(0.010)

Notes: Standard errors calculated from 1,000 bootstrap repetitions are in parentheses.

***, **, and * represent significant level at 1%, 5%, and 10%, respectively.