The Impact of the USDA Broadband Loan Program on U.S. Agriculture: Reference Document

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Data

Information on which counties obtained loans under the pilot broadband loan program and the current broadband loan program was obtained from the USDA's Rural Development broadband program website (*http://www.usda.gov/rus/telecom/broadband.htm*). A Pilot Broadband Loan Program was introduced in 2000, while the current Broadband Loan Program started after the 2002 Farm Bill took effect. Therefore, no counties had received any loans by 2000. By 2007, loans from the current Broadband Loan Program were administered as well. For each county, we construct four treatment variables that show if a given county has received at least one of either the pilot or the current broadband loans. The first two variables, $Pilot\_BBLP_{ct}$ and $BBLP_{ct}$ are indicator variables equal to one in year t and afterwards if county c has at least one community which has received a pilot or a current broadband loan in year t, respectively.[1] The other two variables, $N\_Pilot\_BBLP_{ct}$ and N_BBLP_{ct}, show the exact number of communities in county c that have received a pilot or a current broadband loan, respectively.

To estimate the impact of a broadband loan receipt on farming activities, we used county-level data from the Bureau of Economic Analysis. The county is the smallest level of geographic disaggregation for which data on both receipt of broadband loans and farm performance is publically available. While the USDA does, with some exceptions, provide data on the actual communities that received broadband loans, comprehensive (nationwide) agricultural performance data is only available at the county level. We used data on farm sales – in aggregate and broken down into crop and livestock sub-categories – and farm expenditures from 2000 (just before the Pilot Broadband loan program started) and 2007 (after both the Pilot and the current Broadband loan programs were established). We also used data on county population and income per capita from the U.S. Census of Population.

Econometric Strategy

Our strategy for identifying the impact of the USDA's Broadband Loan programs is rooted in the following reduced-form first-differenced model:

$$(1)\quad \Delta ln(\Psi_c) = \beta_0 + \beta_1 \Delta BBLP_c + \beta_2 \Delta Pilot\_BBLP_c + \Delta \mathbf{X}_c \boldsymbol{\beta}_3 + \varepsilon_c$$

where $\Delta ln(\Psi_c) = ln(\Psi_{c,2007}) - ln(\Psi_{c,2000})$ and $\Delta BBLP_c$, $\Delta Pilot\_BBLP_c$, and $\Delta \mathbf{X}_c$ are similarly defined as the difference between 2000 and 2007 values. The dependent variable $\Delta ln(\Psi_c)$ is the difference between years 2007 and 2000 in the natural logarithm of one of a set of agricultural performance measures for a given county c. We investigated how increased access to high-speed internet affects four different agricultural performance measures – total farm sales, total expenditures, livestock sales, and crop sales. Taking first differences eliminates county-specific characteristics that are time-invariant, affect the outcome of interest, and may even be correlated with broadband loan programs if they were not randomly distributed. Also, any aggregate

[1] For the pilot broadband loan program, we assigned 2002 as the start year for all counties that received such a loan. If a county received a loan from the current broadband loan program before June 1 of a given year, we consider that year as the start year; otherwise, we take the following year as the start year.

economy-wide shocks between 2000 and 2007 that affect all counties are subsumed in the constant term. Note that there were no federal broadband loans distributed in 2000, and both types of loans were distributed by 2007. The Pilot loans were distributed in 2002 and 2003, so by 2007 about five years had passed since they have been first received. On the other hand, the current broadband loans were distributed starting after 2003, so by the end of our sample in 2007, current broadband loans have only been in effect for 1 to 3 years.

In our econometric specification, $Pilot\_BBLP_{ct}$ and $BBLP_{ct}$ are indicator variables equal to one if a county c has received at least one pilot broadband loan (current broadband loan) by year 2007. The coefficients of interest therefore are β_1 and β_2. Under random assignment of the broadband loans, these coefficients would measure the causal impact of the current program (β_1) and the pilot program (β_2). The vector $\Delta\mathbf{X}_c$ includes changes in any time-varying county-specific covariates, such as county population and income per capita, that may affect the dependent variable and may potentially be correlated with broadband loan receipt if the loan distribution is not random. Finally, ε_c is a classical error term.

Inferring causality of $\Delta BBLP_c$ and $\Delta Pilot\_BBLP_c$ on the outcome of interest $\Delta ln(\Psi_c)$ is a challenging task, even after we have eliminated the unobservable, time-invariant, county fixed effects. If the USDA's broadband loans were randomly distributed across U.S. counties, one would easily be able to identify the impacts of the loan programs by estimating equation (3) directly via Ordinary Least Squares. However, whether or not a county receives a broadband loan (the treatment) depends on a number of factors that include both the outcome variables of interest (county-level farm sales and expenditures) as well as other factors (such as the county's entrepreneurial/pro-growth spirit) that would contribute to internet service providing firms within the county to apply for a loan and/or the firms' success in securing a loan.

To avoid the selection bias associated with using OLS under these circumstances, we employed an inverse probability weighting (IPW) procedure.[2] Widely used to estimate causal effects in public health and clinical medicine, IPW estimators rely on modeling selection in terms of confounders. A confounder is simply a variable that is causally related to the outcome in question, is also associated with the treatment, but is not a consequence of the treatment. The IPW approach views confounding as a mechanism leading to nonrandom selection from the population of potential outcomes. This provides a natural motivation for the use of inverse weighting – a staple in the design of sample surveys – as a method to correct selection bias. Essentially, confounding is viewed as an omitted variables problem that leads to a correlation between the error and the right-hand side variables (endogeneity).

Inverse probability weighting involves weighting the observed data by the reciprocal of the probability of treatment. As this probability is generally unknown, it therefore must be

[2] We chose to employ IPW instead of Propensity Score Matching based on recent evidence in Busso, DiNardo, and McCrary (2011) showing that in finite samples, IPW tends to perform as well as or better than even the most sophisticated PSM estimators, especially when there is a good overlap in the distribution of the propensity score between the comparison and treatment groups. As noted above, given that PSM tends to be more difficult to implement empirically and standard errors are available only for some of the existing PSM estimators, IPW emerges as the natural candidate for evaluating the causal effect of broadband loan receipt on farm outcomes. Note that as with PSM, the central identifying assumption of the IPW estimator is the assumption of ignorability given confounders – i.e., treatment is assumed to be random conditional on the observed confounders (Hogan and Lancaster 2004).

estimated. To estimate the probability of treatment, we followed the standard approach of assuming that the treatment selection model is a logistic regression such that the log-odds of treatment are linear in the confounders, Z:

$$p_c(BBL_c = 1) = \frac{1}{1 + e^{-Z_c\gamma}} \tag{2}$$

Here $p_c\,(BBL_c{=}1)$ is the probability (i.e., the propensity score) that county c received either a Pilot or a current broadband loan by 2007, and the vector Z_c contains the set of confounding variables that are associated with the treatment. These confounders are measured as of 1997, which is before the start of our sample used in equation (1) and before the broadband loan programs were initiated.

We used a number of confounders that are believed to be associated with treatment. These included a dummy variable indicating if a neighboring county has already received a broadband loan (to account for neighbor effects); changes in the county per capita income from 1992 to 1997 (a period just prior to our sample period) as a proxy for county entrepreneurial (pro-growth) spirit; county population at the beginning of our sample period (1997) in order to account for the likelihood that providers from more populous counties have a larger profit incentive to apply for the loans because they would supply to larger markets; a number of county-level agricultural performance measures in 1997 – farm sales, expenditures, other farm-related income, acreage, and number of farms with positive sales; indicator variables that show the county position in the rural-urban hierarchy (i.e., each county's rural-urban continuum code as designated by the USDA); and indicators for the nine ERS U.S. farm resource regions.

Once the selection model (2) is estimated, one can compute the predicted probability of treatment, $\hat{p}_c$, for each county and use its inverse, $\frac{1}{\hat{p}_c}$, as the sampling weight in the main equation (1). The estimated coefficients of the weighted regression equation (1) are then consistent estimates for the causal impact of the broadband loans on agricultural performance.

Finally, note that equation (1) does not allow for spatial spillovers – either in the dependent variable or in the error term. One can account for such effects by including a spatial lag dependent variable and a spatial autoregressive error term on the right-hand side.[3] In this case, each observation of the spatial lag variable is a weighted average of the values of the dependent variable observed for all counties that share a common border with county c. The spatial-weighting matrix would assign a weight equal to one for all geographically neighboring counties and zero for the rest. Allowing for both spatial lag dependent variable and spatial autoregressive error term is often referred to as a SARAR model (Anselin and Florax 1995). The model can then be augmented as follows:

$$\begin{aligned} \Delta ln(\Psi_c) &= \beta_0 + \lambda \sum\nolimits_{i=1}^{N} w_{ic} \Delta ln(\Psi_i) + \beta_1 \Delta BBLP_c + \beta_2 \Delta Pilot\_BBLP_c + \Delta \mathbf{X}_c \boldsymbol{\beta}_3 + \varepsilon_c, \\ \varepsilon_c &= \rho \sum\nolimits_{i=1}^{N} m_{ic} \varepsilon_i + u_c \end{aligned} \tag{3}$$

Spatial interactions in equation (3) above are modeled through spatial lags. This specification is general enough to allow for spatial interactions in both the dependent variable and the error term.

[3] Note that these spatial lags are not causal variables. Rather, they control for omitted variables – e.g., weather and geographical factors – that are spatially correlated such that they produce similar outcomes in neighboring counties.

As in most other applications, the spatial-weighting matrices for the spatial lag dependent variable and the spatial autoregressive error term are the same, i.e. w_{ic} is equal to m_{ic}. The spatial-autoregressive parameter λ measures the extent of the spatial interactions between county c and all of its geographic neighbors. The error terms u_c are assumed to be independent but they can be heteroskedastically distributed; hence we estimated (3) using Generalized Spatial 2SLS, which produces consistent estimates even in the case of heteroskedasticity.

Results

We first estimated the selection equation (2) via logistic regression in order to compute the weights for use in implementing our empirical model (equation 3).[4] Using these weights, we first estimated a cross-sectional version of equation (3) to ascertain that receipt of broadband loans has in fact contributed to increased high-speed internet use among U.S. farmers (data on use of high-speed internet on farms is only available for 2007 – the last year of our sample period). We then estimated the impacts of program participation on total farm sales and expenditure, as well as livestock and crop sales.

The Impact of USDA Broadband Loans on High-speed Internet Use

Only in the 2007 Ag. Census was specific information on the number of farms with high-speed internet connection recorded. We took advantage of this limited data on access to high-speed internet to determine whether counties that had received a loan by 2007 (through either the pilot or the current broadband loan program) do in fact have a higher fraction of farms with access to high-speed internet vis-a-vis non-recipient counties.

Table 1 presents these results. The estimated model implies that, on average, there is no association between broadband loan receipt (either the Pilot or the current loan) and the fraction of farms in the county with access to high-speed internet. The coefficients on the categorical variables $BBLP_c$ and $Pilot\_BBLP_c$ are both negative, but economically small and not statistically significantly different from zero. Note that while the average effect is estimated to be zero, we show in Table 3 that there is substantial heterogeneity in the impact of the broadband loans on the fraction of farms with access to high-speed internet. The first column in Table 3 suggests that there was a positive effect in rural counties adjacent to metropolitan counties, but there are likely no impacts in metropolitan counties and in rural counties that are not adjacent to metropolitan counties.

The Impact of the Broadband Loans on Farm Sales, Farm Expenditures, and Farm Profits

Table 2 presents the results for the average impact of the broadband loans at the intensive margin. The estimates in the first column imply that total commodity sales increased in counties which received at least one loan – by 11.2 percent for counties receiving a current loan, and by 17.3 percent for counties that received a Pilot loan.[5] These impacts are both economically and

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[4] For brevity, we do not present these results here; a full discussion may be found in Kandilov, et al. (2012). In general, the results conformed with prior expectations in terms of goodness of fit (pseudo-R^2 = 0.30) as well as the signs and significance of covariates.

[5] The percentage change in total commodity sales resulting from a broadband loan receipt – i.e., increasing $BBLP_{ct}$ from 0 to 1 – is computed as $\exp(\beta) - 1$. In practice, however, for small β's the difference between $[\exp(\beta) - 1]$ and β is trivial.

statistically significant. As we have no information on average prices received or production quantities, it is not possible to assess directly how much of these increased sales are due to increased output (perhaps due to an expanded customer base) or higher prices obtained as a result of better and/or more timely information. Note, however, that to produce the same quantity after they gain increased access to high-speed internet, farmers would at most face the same level of expenditure and would likely experience lower unit production costs. If farm expenditures rise following the receipt of broadband loans, then it must be the case that input use, and therefore production quantity, increased.

The second column of Table 2 reveals that farms' total expenditure in counties that have received a current or Pilot broadband loan did in fact increase – by 6.6 percent and 9.6 percent, respectively. In combination with the positive impact on sales, this signals that the loans led to an increase in overall agricultural output in the counties in which they were received. Moreover, the fact that these estimates are only about half the size of the impacts on total commodity sales suggests that farm profits increased in counties receiving loans by 4.6 percent (= 11.2 – 6.6) and 7.7 percent (= 17.3 – 9.6) for the current and Pilot programs, respectively.

Finally, the last two columns of Table 2 shed light on whether the growth in commodity sales for counties receiving a broadband loan was the result of increased sales of crops or livestock products (or both). The estimates indicate sizeable and significant positive impacts of the Pilot loans on both crop and livestock sales. The estimated impact on crop sales from receipt of a loan under the current program, i.e. the coefficient on $\Delta BBLP_c$, is nearly identical to that estimated for the Pilot program (although it is no longer statistically significant). In contrast, the estimated coefficient for $\Delta Pilot\_BBLP_c$ in the livestock sales regression is very close to zero (with a very large standard error). The implication here is that the impacts on the livestock sector have effectively disappeared with changes made between the Pilot and current programs, whereas positive impacts on crop sales have remained quite stable across both programs.[6]

Difference in Impact Due to Counties' Position in the Rural-Urban Continuum

Previous research has found a positive relationship between the economic impacts of broadband and proximity to densely populated urban areas (see, for example, Gillett et al. 2006; Shideler et al. 2007; Mack and Grubesic 2009; Kandilov and Renkow 2010). This may be a result of economies of density in broadband supply and/or agglomeration economies affecting broadband demand. To check whether a similar spatial gradient of the impacts on farm-related outcomes exists in the case of the broadband loan program, we re-estimated equation 3 by adding terms interacting the loan participation variables ($BBLP_c$ and $Pilot\_BBLP_c$) with dummy variables for rural counties adjacent to metro counties and rural counties that are not adjacent to metro counties. (We used the USDA's Rural-Urban Continuum codes to delineate these groupings). A positive (negative) coefficient on these interaction terms indicates greater (smaller) impacts of the relevant loan program *vis-à-vis* impacts in metro counties (the omitted category).

These results are displayed in Table 3. The first column presents the estimates for the program impacts on the number of farms with high-speed internet. It is evident that the Pilot program had much more profound impacts on metro counties than rural counties. The

[6] In all regressions the coefficients on the spatial lag and spatial error terms are significant, indicating that spatial spillovers exist. The estimated impacts of the broadband loans, while somewhat larger when we allow for spatial effects, are quite similar in statistical significance across specifications with and without spatial effects.

coefficients for both rural adjacent and rural non-adjacent interaction terms for the Pilot program were negative, sizeable, and (in the case of non-adjacent counties) statistically significant. The implication here is that the Pilot program did a relatively poor job of boosting high-speed internet access in the remote rural counties that the program was intended to help (*vis-à-vis* more populous and less remote counties). These targeting issues are consistent with changes made in the program design following audits of the Pilot program.[7] Consistent with this result, no significant impact of the Pilot program on sales or expenditures in rural counties is evident in Table 3.

The results for the impacts of the current program are markedly different. Significant positive impacts of the current program on the number of farms with high-speed internet are evident for both adjacent and non-adjacent rural counties. Moreover, significant and positive coefficients on sales and expenditure for both types of rural counties indicate that the impacts of the current program on these variables are similarly more profound in rural counties than in metro counties. However, comparison of the implied sales and expenditures figures suggests that only in rural adjacent counties did the current program give rise to statistically significant positive impacts on farm profits.

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[7] For example, a 2005 audit by the USDA's Inspector General found that nearly 12 percent of the value of total Pilot loans went to suburban communities located near large cities (USDA, Office of Inspector General 2005).

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Table 1. The Impact of the Broadband Loan Program (*$BBLP_{ct}$*) and the Pilot Broadband Loan Program (*$Pilot\_ BBLP_{ct}$*) on High-speed Internet Use in 2007

Variable	Fraction of Farms with High-speed Internet
$BBLP_c$	-0.019
	(0.023)
$Pilot\_BBLP_c$	-0.001
	(0.035)
ln(Population)	0.007*
	(0.004)
ln(Income per capita)	0.031***
	(0.005)
Lambda	0.030
	(0.012)
Rho	1.479***
	(0.135)
No. Obs.	3,006

Note. The Dependent variable is the fraction of farms reporting use of high-speed internet in 2007. Constant is suppressed. Robust standard errors are reported in parentheses. *** indicates $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 2. The Impact of the Broadband Loan Program and the Pilot Broadband Loan Program on the Change in Livestock and Crop Sales between 2000 and 2007

Variable	***Δln*(Total Sales)**	***Δln*(Total Expenditures)**	***Δln*(Livestock Sales)**	***Δln*(Crop Sales)**
$\Delta BBLP_c$	0.112*	0.066	0.035	0.169
	(0.067)	(0.054)	(0.085)	(0.118)
$\Delta Pilot\_BBLP_c$	0.173**	0.096*	0.291***	0.174**
	(0.078)	(0.051)	(0.088)	(0.070)
Δln(Population) x 10^8	0.242***	-0.017	0.264***	0.205***
	(0.067)	(0.040)	-0.095	(0.069)
Δln(Income per capita)	0.451***	0.167*	-0.044	0.633***
	(0.126)	(0.099)	(0.149)	(0.231)
Lambda	0.826***	1.784***	1.527***	1.643***
	(0.295)	(0.230)	(0.423)	(0.150)
Rho	-0.381	-1.387***	-1.352***	-1.257***
	(0.369)	(0.275)	(0.316)	(0.285)
No. Obs.	3,015	3,015	3,015	3,015

Note. Robust standard errors are reported in parentheses. *** indicates p<0.01, ** p<0.05, * p<0.10.

Table 3. Differences in the Impact of the Broadband Loan Programs across the Rural-Urban Hierarchy

Variable	**Fraction of Farms with High-speed Internet**	**Variable**	***Δln*(Total Sales)**	***Δln*(Total Expenditures)**
$BBLP_c$	-0.010	$\Delta BBLP_c$	-0.297***	-0.147***
	(0.014)		(0.040)	(0.020)
$Pilot\_BBLP_c$	-0.018	$\Delta Pilot\_BBLP_c$	0.260**	0.085
	(0.071)		(0.131)	(0.166)
$ln(\text{Population})_c$	0.007	$\Delta log(\text{Population})_c$	0.000***	-0.000
	(0.008)		(0.000)	(0.000)
ln(Income per capita)	0.030***	$\Delta ln(\text{Income per capita})_c$	0.235*	0.066
	(0.010)		(0.132)	(0.124)
$BBLP_c*RURAL\_ADJ$	0.053***	$\Delta BBLP_c*RURAL\_ADJ$	0.408***	0.167***
	(0.018)		(0.052)	(0.056)
$BBLP_c*RURAL\_NONADJ$	-0.032	$\Delta BBLP_c*RURAL\_NONADJ$	0.408***	0.254***
	(0.032)		(0.078)	(0.062)
$Pilot\_BBLP_c*RURAL\_ADJ$	0.245***	$\Delta Pilot\_BBLP_c*RURAL\_ADJ$	0.071	0.089
	(0.072)		(0.137)	(0.171)
$PilotBBLP_c*RURAL\_NONADJ$	-0.020	$\Delta PilotBBLP_c*RURAL\_NONADJ$	-0.137	0.021
	(0.072)		(0.141)	(0.174)
Lambda	-0.019	Lambda	1.813***	1.921***
	(0.125)		(0.210)	(0.335)
Rho	1.475***	Rho	-1.915***	-1.310***
	(0.139)		(0.244)	(0.279)
No. Obs.	3,006	No. Obs.	3,015	3,015

Note. Robust standard errors are reported in parentheses. *** indicates p<0.01, ** p<0.05, * p<0.10.