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What $2.5 billion can buy: The effect of the Broadband Initiatives Program on farm productivity

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ABSTRACT

This paper investigates whether the Broadband Initiatives Program (BIP), implemented as part of the American Recovery and Reinvestment Act of 2009 (ARRA) had a positive impact on farm productivity, defined as farm sales per farm employment, in the counties that received any BIP funding. The effect of BIP on the growth of farm sales was examined for the 2008–2010, 2008–2011, 2008–2012 and 2008–2013 periods. The selection bias (the probability that a county received BIP funding) was accounted for using the inverse probability weighting regression method (IPW). The findings suggest that BIP funding had a significant but short-term impact on per employment farm sales.

1. Introduction

As a growing number of studies showing the stimulating effect of broadband Internet on the agricultural economy and farm profits (Kandilov, Kandilov, Liu, & Renkow, 2017; Lio & Liu, 2006), many government agencies have recognized the importance of broadband Internet in agricultural development, and several large-scale programs supporting broadband deployment and use in rural areas have been proposed and implemented. Particularly, the American Recovery and Reinvestment Act of 2009 (ARRA) appropriated a total of $7.2 billion to support broadband deployment and adoption, of which $2.5 billion was dedicated to the Broadband Initiative Program (BIP) to promote broadband infrastructure construction and services in underserved rural areas. Whereas the other program funded by ARRA, the Broadband Technology Opportunities Program (BTOP), is well-researched (Hauge & Prieger, 2015; LaRose et al., 2014), the BIP has garnered much less attention. This study seeks to fill this gap by providing a rigorous empirical analysis of the effect of the BIP program on the local agricultural economy.

Although the funding ended 10 years ago in 2010, to the best of our knowledge, no other study has investigated the economic impact of BIP. To provide a rigorous impact evaluation, we employ the Inverse Probability Weighting method to mitigate the selection bias in program coverage. The findings of the study can provide critical information and insights for BIP effectiveness assessment and future rural broadband program development.

The structure of the study is as follows. In the next section, the literature on the effect of broadband on agricultural economy and prior evaluation studies on rural broadband programs is reviewed, followed by a brief overview of the BIP program. The third section introduces the data and empirical strategy used in this study. The results of our analyses are summarized in the fourth section. The last section provides the main conclusion and implications of the study.

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2. Internet and rural development

Researchers have investigated the positive impact of the Internet, especially broadband, on general economic performance (Arvin & Pradhan, 2014; Bertschek, Briglauer, Hüschelrath, Kauf, & Niebel, 2015; Czernich, Falck, Kretschmer, & Woessmann, 2011; Katz & Callorda, 2018; Koutroumpis, 2019; Thompson & Garbacz, 2011). Despite this evidence, rural areas marked by "small markets, high transport costs and physical isolation," may suffer from a "rural penalty" (Kandilov & Renkow, 2010, p. 167), and rural communities have a long history of struggling with digital connectivity (Salemink, Strijker, & Bosworth, 2017).

However, research also shows that rural areas can catch up in development if broadband is made available. For example, Kolko (2012) identified a positive relationship between broadband expansion and employment growth, but also discovered, contradicting the literature, that the effect was stronger for the less populated areas. In effect, Kolko too found a spatial discrepancy in broadband impacts but in the opposite direction. Additionally, using a propensity score matching approach, Whitacre, Gallardo, and Strover (2014) used county-level data from the Federal Communication Commission's (FCC) National Broadband Map from 2001 to 2010 and found that a higher level of broadband adoption in rural areas positively impacted income growth, and negatively influenced the unemployment rate. Nevertheless, a county with a lower level of broadband adoption also tended to have a lower number of firms and total employment, which was consistent with previous studies (Jayakar & Park, 2013). Rural areas with a skilled and better educated workforce may perform better in employment growth if broadband is available (Forman, Goldfarb, & Greenstein, 2012).

Agriculture, one of the essential sectors of the rural economy, may be potentially benefited by digital technologies, especially through e-commerce platforms. For instance, the wholesale and retail food industries have improved their productivity with internet adoption (Beurskens, 2003; Stenberg et al., 2009). As the U.S. Department of Agriculture (USDA) points out in its 2019 annual report, e-connectivity would benefit agricultural industry. Specifically, within the agricultural production routine, American farmers and ranchers can utilize digital technologies, enhancing agriculture with data, increasing efficiency via automation, improving and augmenting supply chain management, and even expanding into new markets beyond geographical limitations (USDA, 2019, p. 17). In particular, digital technologies could benefit the production of various agricultural commodities, including row crops, livestock and dairy; and across different stages, such as planning, production and market coordination (USDA, 2019, pp. 22-23). Combining a census of agricultural activity from the USDA's National Agricultural Statistical Service (NASS) and broadband data from the FCC's Form 477, LoPiccalo (2021) found that increased Internet penetration rates on farms increased crop yields and reduced operating expenses. Specifically, LoPiccalo found that broadband improved farmers' access to pricing and marketing information, as well as comparison shopping for machinery, loans and credit and other agricultural inputs. Along with the development of Internet of Things, artificial intelligence and robotics, the digitalization of "agtech" continues to influence rural communities, industrial structure and labor economics nowadays (Rotz et al., 2019). Broadband is a key input into "precision agriculture," involving drone imaging, remote sensing, intelligent water management and fertilizer application, and environmental sustainability, that can have dramatic impacts on farm productivity and outputs (Sanders, Gibbs, & Lamm, 2022). However, not all studies have found positive broadband impacts on the agriculture sector. One recent study of rural broadband found that the economic effects were confined to the retail sector, with other sectors of the rural economy such as manufacturing or agriculture manifesting no significant impact (Aldashev & Batkeyev, 2021).

These documented broadband impacts on agricultural productivity make it imperative to study the effects of rural broadband investment programs such as the BIP, especially since the current literature offers few examples of program impact evaluations. Broadband investment programs may be conceived of as having two different types of impacts: the immediate impact in terms of increasing broadband availability, uptake and speeds and the ultimate (and more important) goal of better economic outcomes such as farm productivity, employment and payroll. On broadband connectivity impacts, the evidence is mostly positive. One study found that USDA programs (specifically the Pilot and Farm Bill loan programs) have fulfilled their purpose of enhancing connectivity in underserved rural areas (Dinterman & Renkow, 2017). A zip code area that received broadband loans had a statistically significant increase in the number of broadband providers from 1999 to 2008, compared to non-recipient zip codes (Dinterman & Renkow, 2017). The effect was also found to be stronger in rural locations than in urban locations.

On economic impacts however, the results are more equivocal. In an early study, Kandilov and Renkow (2010) found that the USDA's Pilot Broadband Loan Program had positive impacts on zip code-level economic outcomes, specifically on employment, annual payroll and the number of business establishments in the recipient communities between 2002 and 2003. They also found that the positive impacts of the Pilot program were mainly felt in communities that were close to urban areas. A follow-up study aimed to estimate a rate of return on broadband investment programs. It found that some of the USDA's smaller programs (the Pilot loan program and the broadband grants program) had no significant impact on payrolls; only the largest program (the broadband loans program) had a positive rate of return, with a one-time broadband investment of \$1 producing a \$0.92 annual increase in farm payrolls (Kandilov and Renkow, 2020).

To summarize the literature on broadband investment program impacts, effects on broadband availability and penetration have been well-demonstrated. At the same time, the economic impacts derivative of better broadband connectivity, in terms of higher farm productivity, output, employment and payrolls are more uncertain. To fill in this gap in the literature, we investigate the effect of BIP coverage on farm productivity at the county level.

3. Overview of the Broadband Initiatives Program

As discussed in the introduction, the ARRA (2009) allocated a total of \$2.5 billion via the Broadband Initiatives Program (BIP) to support broadband deployment and services in rural areas. The Rural Utilities Services (RUS) of the U.S. Department of Agriculture

(USDA) was designated to oversee the BIP. Three types of awards were made by RUS: grants, loans and loan/grant combinations. Full grants were awarded to applicants who proposed to serve exclusively remote, rural areas where more than 90% of the households lacked access to terrestrial broadband services. Loans and loan/grant combination were awarded to applicants serving non-remote, underserved areas where at least 75% of the proposed service area is categorized as rural. The BIP definitions of remote, rural, underserved and unserved areas are summarized in Table 1 (Committee on Small Business and Entrepreneurship, 2009).

Two rounds of applications were accepted from July 2009 to September 2010. According to Federal Grants Wire (2010), all approved funds were awarded by October 2010. During the first round of funding, $2 billion were allocated to three types of projects: Last Mile projects, Middle Mile projects and Last Mile projects for remote areas. Two new types of projects (Satellite and Technical Assistance) were added to the repertoire in the second round of applications. By the award appropriation deadline in October 2010, a total of $3.5 billion, $1 billion more than the initially planned $2.5 billion, was awarded by RUS to 320 projects. According to USDA (2014), of the 320 funded projects, 297 were last-mile and middle-mile infrastructure projects, 4 were satellite projects and 19 were technical assistance projects. Since most of the funded projects involve infrastructure construction, it is important to evaluate the potential effect of the program at different time points, which is further discussed in the next section.

Various entities are eligible to apply for BIP funding, which include state and local governments, Native American tribes, for-profit corporations and non-profit organizations. Funding decisions are made by RUS based on several factors. Applicants must demonstrate their technical capability and feasibility of proving broadband services in the proposed service areas. A system design and project timeline must be submitted and certified by a professional engineer if the proposed project requires over $1 million. 75% of the proposed service areas must be underserved or unserved rural areas based on the USDA criteria (Table 1).

4. Data and method

4.1. BIP coverage

Since there is no published record that lists the counties covered by the BIP-funded projects, the study relies on USDA's Telecommunications Program Funded Service Areas Map (Fig. 1) to determine the county coverage of the program. The map shows the service areas of BIP funds recipients. Based on the Map, we identified 758 counties in the United States that are covered by at least one BIP-funded project.

Although the funding decisions are made by RUS based on the applicants' qualifications and the proposed service areas rather than the counties they are located in or serve, this study chooses counties as the unit of analysis as it is the only geographic unit for which the data for both BIP coverage and agricultural economic indicators are available. The sample of this study includes all counties or county equivalents in the U.S. For each county, a dummy variable, *BIP*, is created (*BIP* = 1 for counties covered by at least one BIP-funded project; = 0 for counties not covered). An obvious limitation of such operationalization is that the dummy variable cannot capture the inter-project differences in the type and scale of funding. Should such data at the county level become available, further analysis with a more nuanced measurement would be a fruitful area for future research. Another limitation of this operationalization is that it is based only on the coverage of the program rather than the change in broadband connections directly related to it. In fact, how much of the change in broadband connection can be attributed to the BIP program is an important topic to explore on its own. Nevertheless, given the lack of detailed information for BIP-funded projects and the use of counties as the unit of analysis, it is impossible to determine how much of the change in broadband connections is for farm businesses, and how much of that change is a result of the program. Considering that the main treatment variable is the coverage of BIP, not the change in broadband connections attributed to the program, the interpretation of the study's findings should focus on the effect of the BIP funds on farm productivity, and caution must be used to interpret the findings as the effect of broadband connections.

4.1.1. The empirical strategy

We evaluated the impact of the BIP on regional agricultural economy based on the following production model:

$$farmsales\_pc = A * F\left(farmexpend\_pc\right), A = \exp\left(constant + \lambda 1 * BIP + \lambda 2 * proprietor\_emp + \lambda 3 * ISPs + \lambda 4 * inc\_pc + \lambda 5 * agricultural\_ests + \lambda 6 * regions\_dummies + \varepsilon\right) \tag{1}$$

Based on previous studies, our model estimates farm revenue per farm employment (*farmsales_ pc*) as a function of the farm production expenditure (excluding the expenditure on hired labors) per capita of farm employment (*farmexpend_ pc*), modified by a number of factors, including the percentage of sole-proprietor farm employment (*proprietor_emp*) in all farm employment, the number of Internet service providers (*ISPs*), per capita personal income (*inc_ pc*) and total number of agricultural establishments (*agricultural_ests*) for a given county. To control for the influence of the types of agricultural products on farm sales in different regions, 8 dummy variables (*regions_ dummies*)[1] were added to indicate the USDA-defined agricultural resource region each county is in. The focus of the study is the effect of BIP coverage, which is captured by the dummy variable, *BIP*. The data for farm sales, total farm employment, sole-

[1] USDA identifies 9 Farm Resource Regions: Basin and Range, Northern Great Plains, Heartland, Northern Crescent, Easter uplands, Southern Seaboard, Mississippi Portal, Prairie Gateway and Fruitful Rim. Each region produces distinct types of agricultural products. The Heartland region is used as the reference group and therefore not included in the model. See detailed information about USDA Farm Resource Regions at https://www.ers.usda.gov/publications/pub-details/?pubid=42299.

Table 1
Definitions of terms.

	BIP Definition
Remote	An unserved, rural area at least 50 miles away from a non-rural area
Rural	Any area, based on the 2000 decennial census of the Census Bureau, that is not located with 1) a city, town or incorporated area with a population over 20,000 or 2) an urbanized area contiguous and adjacent to a city or town that has a population over 50,000
Underserved	Any area that satisfies at least one of the three criteria: 1) at least 50% of the households lacks access to facility-based, territorial broadband service, 2) no service providers offer services with at least 3Mbps download speed and 3) no more than 40% of the households in the area subscribe to broadband service
Unserved	An area where at least 90% of the households have no access to territorial broadband service

Source: Broadband Initiatives Program (BIP) Guide (Committee on Small Business and Entrepreneurship, 2009)

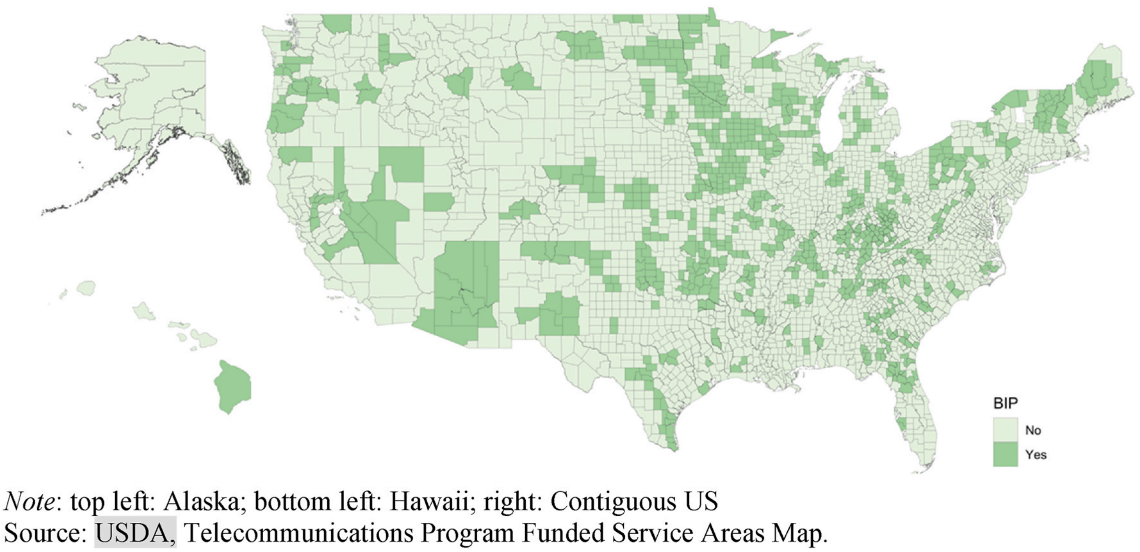

Fig. 1. BIP coverage.
Source: USDA, Telecommunications Program Funded Service Areas Map.

proprietor farm employment, per capita personal income and agricultural establishments are available from the Regional Data site of the Bureau of Economic Analysis. Noticeably, there are 22 counties in which the total farm sales remained 0 for all the years we examined. These counties are excluded from the regression analysis because the data suggest that there was no farming economy in those regions. The number of Internet service providers in each county is obtained from the Form 477 County Data on Internet Access Services database. County-level Farm Resource Region categorization can be found on USDA's Economic Research Service database.

Taking the natural log of the model gives a function that allows for linear regression analysis, and we further conduct the first-difference transformation so that any time-invariant fixed effect that could cause endogeneity issues is removed. The model used for the impact evaluation is:

$$\begin{gathered} \triangle ln(farmsales\_pc) = constant + \beta 1 * \triangle ln(farmexpend\_pc) \\ + \beta 2 * \triangle proprietor\_emp + \beta 3 * \triangle ISPs + \beta 4 * BIP + \beta 5 * inc\_pc \\ + \beta 6 * agricultural\_ests + \beta 7 * regions\_dummies + \varepsilon \end{gathered} \tag{2}$$

Given that the applications were accepted from May 2009 to September 2010, and all awards were made by October 2010 (Federal Grants Wire, 2010), the year 2008 is used as the base year for the model. Since no project-level information is available, how many of the projects funded in the first application round were operational by the end of round-2 application is unknown. Thus, the year 2010, when all the projects received funds, is used as the first year we test for the potential effect of BIP. Since many infrastructure projects did not start operation until the summer of 2013, we extended the analysis into the year 2013, by the end of which 55% of the infrastructure projects were operating (USDA, 2013). Admittedly, it is reasonable to expect that the effects of some infrastructure projects could take more than 3 years to manifest. Nevertheless, we decided to use 2013 as the last year we test for the potential effect of BIP because the more years after 2010 the analysis extends into, the more likely that the change in farm sales is caused by factors other than the BIP program which might be harder to control for in the current study. Table 2 summarizes the variables used in the estimation model for the BIP-covered and not covered counties in the base year of the study.

4.2. The issue of selection bias

The fact that the BIP awards were not randomly distributed across the counties poses a special challenge for the evaluation of its impact. Specifically, the factors that determine the receipt of the treatment, i.e., the BIP funding, could also influence the economic outcome. For example, a county with very few rural residents is less likely to have ISPs which applied for the funding to provide services in the that area. Therefore, it would be less likely that the county is covered by BIP. However, this same factor that there are very few rural residents could also influence the farm sales of the county. The existence of this selection bias means that the OLS regression would result in biased and inconsistent estimates not only for the BIP's effect but also for the influence of other explanatory variables. Thus, the bias must be addressed first before the evaluation of the program's effect.

To mitigate the selection bias, this study employs the inverse probability weighting method (IPW). This statistical method was recently introduced to the program effect evaluation literature by Busso, DiNardo, and McCrary (2014) and has been used in the evaluation of broadband infrastructure program (Kandilov et al., 2017). The IPW approach is similar to the more commonly used propensity score matching method (PSM) in that the first step requires explicit modelling of the selection process and the estimation of the likelihood of receiving the treatment (the propensity score) for each unit. In the context of this study, it means estimating the probability that a county is covered by the program. In contrast to the PSM method which then matches treatment units to non-treatment units with similar propensity scores, the IPW approach uses the estimated probability of treatment to construct a weighting matrix to be used in the impact evaluation model estimation. The weighting matrix is constructed as follows:

$$\begin{cases} For\ \ counties\ \ covered\ \ by\ \ BIP, w = \dfrac{1}{prob_{BIP}} \\ For\ \ counties\ \ not\ \ covered\ \ by\ \ BIP, w = \dfrac{1}{1 - prob_{BIP}} \end{cases}$$

where $prob_{BIP}$ is the estimated probability that a county is covered by at least one BIP-funded project.

The effect of applying this weighting scheme can be understood from a counterfactual perspective. In order to properly estimate the average treatment effect of the program, it is necessary to compare the observed outcome in a county to the one if the county was in a different situation. The issue is that the counterfactual condition is never observed in a non-experimental setting. Therefore, if a county has a small probability of being covered by the program but is in fact covered by it, this county is a valuable observation because it can serve as a counterfactual for the units not covered by the program. Therefore, such observations are given more weight in the sample. Similarly, if a county has a high probability of being covered but is in fact not covered, it can serve as a counterfactual for the counties covered by the program, and the county is given more weight in the sample.

Compared to the PSM method, the IPW approach as a selection bias correction strategy has several advantages. First, considerable loss of treatment units is a common issue in PSM because there might not be enough control units that have similar propensity scores (Guo & Fraser, 2010). Given that only 758 counties of over 3000 were covered by the program, the loss of treatment units could have a non-negligible impact on the estimation of the program's effect. Second, after estimating the propensity score, the PSM method matches units with similar scores and compares the outcomes. Thus, it is tricky to analyze the influence of factors on the outcome other than the ones determining the chances of receiving the treatment (Freedman & Berk, 2008). The study by Busso et al. (2014) further shows that in finite samples, the IPW approach works as well as even the most complicated PSM method in ameliorating selection bias particularly when there is good overlap between the propensity scores of the treated and control groups, which is the case with the current study. Based on these considerations, this study employs the IPW approach rather than the PSM method as the selection-bias mitigation strategy.

4.2.1. The selection model

Based on the eligibility criteria specified in the official Broadband Initiative Program Guide (2009), we construct the following logistic regression model to estimate the odds ratio of receiving the treatment for each county.

$$log\left(\frac{prob_{BIP}}{1 - prob_{BIP}}\right) = constant + \beta_1 * neighb\_bip + \beta_2 * btop2008 + \beta_3 * rural + \beta_4 * farm\_emp2008 + \varepsilon \tag{3}$$

where *neighb_bip* indicates whether any adjacent county is covered by the program to capture the potential spatial-clustering effect (Kandilov et al., 2017), *btop2008* is the availability of broadband Internet in the county in the year 2008, defined as residential fixed broadband connections per 1000 households and obtained from FCC 477 data, *rural* indicates the rural-urban status of a given county, following the definitions specified in the official program guide, and *farm_emp2008* is the total number of persons in farm employment in a given county, which could indicate the existence of an agricultural sector in the region.[2]

Although our selection model generates satisfactory prediction for the program coverage (see the detailed result in the next section), it is worth emphasizing again that the award decision was made based not on the rural/urban classification of a county but the eligibility of individual applicants and the proposed service areas. Thus, some discrepancies are possible where metropolitan counties

[2] According to BIP's definition of rural areas, a region with very few residents could be identified as a rural area. A service provider is less likely to propose to serve an area with very few residents since RUS requires proof of financial feasibility and sustainability in all BIP funding applications.

Table 2
Descriptive statistics of variables.

Variable	Definition	Counties covered by BIP	Counties not covered by BIP
farmsales_pc	Farm sales per farm employment ($1000)	132.8 (132.8)	125.2 (136.2)
farmexpend_pc	Farm production expenditure per farm employment ($1000)	115.4 (110.2)	110.5 (114.7)
proprietor_emp	% of sole-proprietor employment in all farm employment	80.9% (13.9%)	77.3% (16.6%)
ISPs	# of Internet service providers	11.8 (5.8)	12.5 (7.1)
inc_pc	per-capita personal income	32348.4 (6847.7)	33574 (9287.3)
agricultural_ests	# of agricultural establishments	7.9 (14.3)	8.6 (13.7)
regions_dummies	Dummy variables for USDA Farm Resource Region	/	/
BIP	Dummy variable for BIP coverage (=1 if a county has at least 1 BIP-funded project)	/	/

are still covered by BIP-funded projects. For example, even if a county as a whole can be classified as a metropolitan county and is in general sufficiently covered by broadband, there could still be some underserved or even unserved areas within the proposed service area of the ISP that qualify for BIP funding.

5. Analyses and results

5.1. The selection model and weights construction

Before the evaluation of the effect of the BIP, the propensity score of BIP coverage for each county is obtained by estimating the selection model. The result of the regression analysis is presented in Table 3. We used three different indicators for the goodness-of-fit of the selection model. The Omnibus test of model coefficients, χ^2 (4) = 933.76, $p < 0.01$, the Hosmer-Lemeshow test result, χ^2 (8) = 10.16, $p = 0.25$, and the Nagelkerke R^2 of 0.39 all indicate that the model fits the data well. Based on the regression result, the estimated probability of BIP coverage for each county is calculated. The estimated probability of BIP coverage for BIP-covered counties ($M = 0.45$, $SD = 0.09$) is significantly higher than that for counties not covered ($M = 0.19$, $SD = 0.21$), t (3045) = 32.53, $p < 0.01$.

According to the regression analysis, the probability that a county is covered by the BIP would be higher if any of its adjacent counties is covered by the program ($\beta = 3.59$, $p < 0.01$), indicating the presence of spatial-clustering effects in BIP coverage. In line with the official program guide, rural counties are more likely to have BIP-funded projects ($\beta = 1.36$ $p < 0.01$). Also, counties with more farm employment tend to have higher probabilities of receiving BIP funds ($\beta = 1.00$, $p < 0.01$). The availability of broadband is not a significant predictor for the receipt of BIP funds. This is likely due to the discrepancy between the overall broadband coverage in the county and the specific service areas of proposed projects, as discussed in the previous section.

Fig. 2 shows the distribution of propensity scores for BIP-covered and non-covered counties. As the figure shows, there is good overlap in the propensity score between the BIP-covered and non-covered counties. The overlap of the propensity score validates the use of the IPW approach as an appropriate selection-bias mitigation strategy.

Based on the estimated probability of each county being covered by the program, we constructed the weights to be used in the program evaluation. One common issue in the IPW method is that some observations could have extremely large weights so that they can impose unduly large influence on the estimated effect of the program (Lee, Lessler, & Stuart, 2011).

There are two common ways to address the issue of extremely large weights: trimming and truncation (Xiao, Moodie, & Abrahamowicz, 2013). Truncation refers to the method whereby all the weights larger than a specified threshold are replaced by the threshold, whereas in trimming, observations with extremely large weights are discarded. Although both methods have their merits and limitations, this study employs the trimming method as there is no consensus on which threshold should be used as the replacement for the large weights, and the use of different thresholds for truncation could have significant impact on the estimated effect. In order to discard as few observations as possible, the 99th percentile of the weights is identified, which is 20.305, and all observations (n = 30) with weights larger than that value are discarded in the program effect evaluation analysis. As Fig. 3 shows, after the extremely large outliers are deleted, the vast majority of the weights are between 1 and 3.

Noticeably, all the discarded cases are counties which are covered by BIP-funded projects but have very small probability of being covered. The average probability of the trimmed counties receiving BIP funding is 2.8% (SD = 0.5%, Min = 2.2%, Max = 4.9%). T-tests show that the growth of per-capita farm sales among the trimmed counties is not significantly different from that of the non-trimmed, BIP-covered counties. Therefore, deleting these observations is unlikely to result in the inflation of the estimated effect.

5.2. The baseline model

The result of the regression analysis without correcting for the selection bias is presented in Table 4. As the result shows, the change in per capita production expenditure and per capita personal income are consistently the significant predictors for the growth of per capita farm sales in all the time periods examined. The estimation shows that the BIP program has a positive impact on farm sales per employment for the 2008–2013 period. However, since the baseline models do not account for the selection bias in BIP coverage, the estimation and inferential statistics are likely to be biased and inconsistent.

Table 3
The BIP selection model.

	logit (BIP)
neighb_bip	3.59**
btop2008	0.96
rural	1.36**
farm_emp2008	1.00**
Obs	3047
LR Chi-sqr	933.76
Log Likelihood	−1240.21

Estimated odds ratios are reported. $^{**}p < 0.01$, $^{*}p < 0.05$.

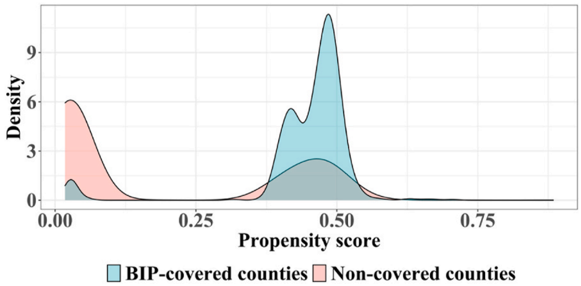

Fig. 2. Density distribution of propensity score.

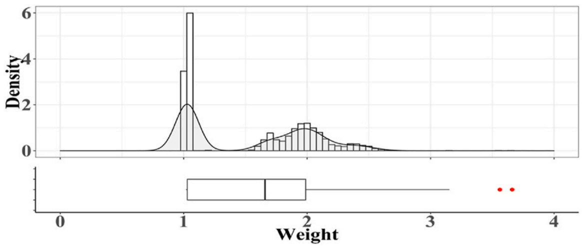

Fig. 3. Distribution of the weights (omitting 30 outliers).

5.3. *The IPW regression results*

Table 5 presents the IPW regression results. After correcting for the selection bias using Inverse Probability Weighting, the estimated effects of each variable changed slightly. The per capita production expenditure remains a significant contributor to the change in per capita farm sales. Specifically, a 1% increase in the growth of per capita production expenditure would result in 0.73%, 0.76%, 0.88% and 0.93% increase in the growth of per capita farm sales for the 08–10, 08–11, 08–12 and 08–13 periods, respectively. After the correction of the selection bias, the estimation reveals that if a county is covered by BIP-funded projects, the county would experience a

Table 4
The baseline models without selection bias correction.

	△ln(farmsales_pc)08-10	△ln(farmsales_pc)08-11	△ln(farmsales_pc)08-12	△ln(farmsales_pc)08-13
△ln(farmexpend_ pc)08–10, 11, 12 or 13	0.73**	0.75**	0.88**	0.94**
△ proprietor_ emp 08–10, 11, 12 or 13	0.33**	−0.05	−0.17*	0.21*
△ISPs 08–10, 11, 12 or 13	−0.003*	−0.002	−0.003^{+}	−0.005*
△inc_ pc 08–10, 11, 12 or 13	0.00001**	0.0001**	0.0001*	0.0001*
△agricultural_ ests 08–10, 11, 12 or 13	0.001	0.001	0.001	−0.0004
BIP	−0.006	0.008	0.001	0.02^{+}
constant	0.03**	0.05**	0.05**	0.06**
Observations	2514	2498	2494	2476
Adjusted R^2	0.31	0.34	0.47	0.48
F	80.51	90.84	161.58	162.43

Farm Resource Region dummies are included in the model. Unstandardized coefficients are reported. $^{**}p < 0.01$, $^{*}p < 0.05$,$+p < 0.1$.

greater growth in per capita farm sales in the 2008–2011 and 2008–2013 period. Specifically, counties covered by BIP had a 1% greater per-capita farm sales growth from 2008 to 2011 and a 2% greater growth from 2008 to 2013.

6. Conclusions and discussion

The Broadband Initiatives Program was implemented as part of a U.S. governmental response to an unprecedented financial crisis. In total, $3.5 billion of program funding was disbursed to promote broadband infrastructure construction and services in remote, rural, unserved and underserved areas. However, compared to other infrastructure investment programs such as BTOP, the BIP has garnered much less attention in terms of post-implementation studies and program evaluation. This paper is intended to address this gap in the literature. Our study analyzed the effect of the BIP program on the change in per capita farm sales from the base year, 2008 to 2010, 2011, 2012 and 2013, respectively. Since the factors that influence the coverage of BIP may also explain farm productivity changes, we employed the IPW method to mitigate the selection bias in program coverage.

The IPW regression results indicate that the primary driver of changes in per capita farm sales was production expenditure, with a 1% increase in per capita production expenditure resulting in approximately 0.7–0.9% increase in per capita farm sales. A small but significant positive relationship is found between the growth of per capita personal income and per capita farm sales growth in 3 out of the 4 periods examined.

The presence of BIP-funded projects in the county is a significant enhancer to farm productivity in only two of the periods, 2008–2011 and 2008–2013, during which the counties covered by BIP experienced a 1–2% increase in the per capita farm sales growth. The significant impact of the program in some but not all the time periods may be explained by many factors. Particularly, the final application round ended in September 2010 and all funds were awarded in October 2010 (Federal Grants Wire, 2010). Since infrastructure projects, which constitute over 90% of the funded projects, involve some time in planning and build-out, 2010 was probably too early for the impacts to manifest. Although there is a lack of reliable source of detailed project implementation and progress information, it can be confirmed that by August 2013, about 55% of the infrastructure projects were still under construction and not operational (USDA, 2013). Therefore, the significant impact noticed for the 2008–2011 projects is likely to be the initial effects of some of the early projects, particularly the technical assistance and satellite projects, which typically require much less time to complete and start operation. The increase in the completed and operational infrastructure projects is likely the cause of the significant impact observed for the 2008–2013 period. The fact that productivity growth was not sustained after the surge during the 2008–2011 and 2008–2013 may indicate that program effects are not robust and still within the margin of error. It is possible that an even longer period is needed for a robust effect of the projects to fully emerge.

Although the analysis shows the effects of the program were not sustained, it is noticeable that in the 2 time periods in which significant impact was observed, the program's effects on farm sale growth were 1.3–2.2 times larger than that contributed by the growth of production expenditure. Given that the purpose of BIP was to help the agricultural economy quickly recover from the Great Recession, an immediate boost of this magnitude in the three years after funds distribution is far from trivial. This finding can be used as the basis for a comprehensive estimate of the program's return, and it provides policymakers and evaluators with an evidentiary basis to determine whether the benefit of the program justifies its cost. Also, most of the existing studies evaluating rural broadband promotion programs tend to focus on the effect of the program itself (Kandilov et al., 2017; Kandilov & Renkow, 2020). However, if the effect of the program is not greater than that of increased production expenditure, it will be questionable whether the broadband program is a game-changing factor or simply another input that can be categorized as a production expenditure. Future studies can investigate if a stronger case can be made for rural broadband promotion programs by specifically comparing the effect of the program to the impact of increased production expenditures and other conventional production inputs.

The findings of the study can provide critical information and insights for not only the evaluation and impact assessment of the BIP, but also for future infrastructure programs especially in rural areas. The 2009 ARRA, of which the BIP was a part, was undertaken in the midst of an economic crisis, where the imperative was to stimulate the economy through government spending. The effectiveness and impact assessment of the specific programs undertaken was perhaps not a priority, so long as the spending helped to create jobs and rejuvenated the economy. However, prudent public policy requires that large scale stimulus programs—for which there may be need in the immediate future, in the context of the 2020 pandemic and the consequent economic contraction—should be based on a careful assessment of program outcomes.

There are several limitations to this study. First, counties that received BIP funding were identified from the USDA's Telecommunications Program Funded Service Areas Map and coded with a dummy variable. Dummy coding does not account for the quantum of funding each county received, which will impact the program outcome. However, data on the specific amounts allocated by county are not available. Also, it should be pointed out that BIP funding was allocated for specific projects and not by county. This too will affect the empirical analysis, since BIP-funding projects would not be implemented in all parts of a county, but only in areas that are rural and remote, or unserved or underserved by broadband. More granular data, perhaps at the zip code or census block levels, on the areas covered by BIP-funded projects would enhance the analysis. This too is currently unavailable.

Third, county-level broadband availability is obtained from FCC 477 data, which can be flawed in several ways. For example, if one location in an area is served, then the entire area will be classified as "covered." Some areas which are in fact served may be labeled unserved because small, rural service providers do not report their services. Future studies could use broadband availability data of higher quality to improve the measurement accuracy of the broadband coverage variable.

Finally, the coverage of this study was limited to four years in the immediate aftermath of BIP project implementation (2010–2013). A limited 4-year assessment window was a deliberate choice, since too many external factors may impact farm sales in the long-term, including the implementation of other broadband programs, international commodity prices, demographic changes and

Table 5
The IPW regression results.

	△ln(farmsales_pc)08-10	△ln(farmsales_pc)08-11	△ln(farmsales_pc)08-12	△ln(farmsales_pc)08-13
△ln(farmexpend_ pc)08–10, 11, 12 or 13	0.73**	0.76**	0.88**	0.93**
△ proprietor_ emp 08–10, 11, 12 or 13	0.33**	−0.001	-0.14^{+}	-0.16^{+}
△ISPs 08–10, 11, 12 or 13	−0.003*	-0.003^{+}	−0.002	−0.004**
△inc_ pc 08–10, 11, 12 or 13	0.00001**	0.0001**	0.0001*	0.0001*
△agricultural_ ests 08–10, 11, 12 or 13	0.005	−0.001	0.0001	0.0001
BIP	−0.003	0.01^{+}	0.005	0.02^{+}
constant	0.03**	0.05**	0.04**	−0.08
Observations	2488	2471	2467	2450
Adjusted R^2	0.31	0.34	0.49	0.48
F	81.92	91.86	168.21	165.05

Farm Resource Region dummies are included in the model. Unstandardized coefficients are reported. $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

climate changes. It, therefore, becomes more difficult to identify the causal impact of the BIP investments over the long term. Future research may also investigate the long-term impacts of the program using appropriate techniques to control for other factors.

Declaration of competing interest

None.

References

Aldashev, A., & Batkeyev, B. (2021). Broadband infrastructure and economic growth in rural areas. *Information Economics and Policy, 57*, Article 100936.

Arvin, B. M., & Pradhan, R. P. (2014). Broadband penetration and economic growth nexus: Evidence from cross-country panel data. *Applied Economics, 46*(35), 4360–4369. https://doi.org/10.1080/00036846.2014.957444

Bertschek, I., Briglauer, W., Hüschelrath, K., Kauf, B., & Niebel, T. (2015). The economic impacts of broadband internet: A survey. *Review of Network Economics, 14*(4), 201–227. https://doi.org/10.1515/rne-2016-0032

Beurskens, F. (2003). The economics of dot. Coms and E-commerce in the agrifood sector. *Review of Agricultural Economics, 25*(1), 22–28. https://www.jstor.org/stable/1349861.

Busso, M., DiNardo, J., & McCrary, J. (2014). New evidence on the finite sample properties of propensity score reweighting and matching estimators. *The Review of Economics and Statistics, 96*(5), 885–897. https://doi.org/10.1162/REST_a_00431

Committee on Small Business and Entrepreneurship. (2009). Broadband Initiatives program (BIP) guide: An overview of the US department of agriculture's rural Utilities. Available at: https://www.sbc.senate.gov/public/_cache/files/f/0/f0fc95ef-18ef-4f1b-a1cc-0cab31394b1c/11824FA937892AEF65A916A2803681F3.bip-grant-guide.pdf.

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal, 121*(552), 505–532. http://www.jstor.org/stable/41236989.

Dinterman, R., & Renkow, M. (2017). Evaluation of USDA's broadband loan program: Impacts on broadband provision. *Telecommunications Policy, 41*(2), 140–153. https://doi.org/10.1016/j.telpol.2016.12.004

Federal Grants Wire. (2010). Broadband Initiatives program. Available at: https://www.federalgrantswire.com/broadband-initiatives-program.html#.X9Z01dhKiHs.

Forman, C., Goldfarb, A., & Greenstein, S. (2012). The internet and local wages: A puzzle. *The American Economic Review, 102*(1), 556–575. https://doi.org/10.1257/aer.102.1.556

Freedman, D. A., & Berk, R. A. (2008). Weighting regressions by propensity scores. *Evaluation Review, 32*(4), 392–409.

Guo, S., & Fraser, M. (2010). *Propensity score analysis*. Los Angeles: Sage Publications.

Hauge, J. A., & Prieger, J. E. (2015). Evaluating the impact of the American Recovery and Reinvestment Act's BTOP on broadband adoption. *Applied Economics, 47*(60), 6553–6579.

Jayakar, K., & Park, E. (2013). Broadband availability and employment: An analysis of county level data from the National Broadband Map. *Journal of Information Policy, 3*, 181–200.

Kandilov, A. M. G., Kandilov, I. T., Liu, X., & Renkow, M. (2017). The impact of broadband on U.S. agriculture: An evaluation of the USDA broadband loan program. *Applied Economic Perspectives and Policy, 39*(4), 635–661.

Kandilov, I. T., & Renkow, M. (2010). Infrastructure investment and rural economic development: An evaluation of USDA's broadband loan program. *Growth and Change, 41*(2), 165–191. https://doi.org/10.1111/j.1468-2257.2010.00524.x

Kandilov, I. T., & Renkow, M. (2020). The impacts of the USDA broadband loan and grant programs: Moving toward estimating a rate of return. *Economic Inquiry, 58*(3), 1129–1145.

Katz, R., & Callorda, F. (2018). *The economic contribution of broadband, digitization and ICT regulation*. ITU Publications. Available at: https://www.itu.int/en/ITU-D/Regulatory-Market/Documents/FINAL_1d_18-00513_Broadband-and-Digital-Transformation-E.pdf.

Kolko, J. (2012). Broadband and local growth. *Journal of Urban Economics, 71*(1), 100–113. https://doi.org/10.1016/j.jue.2011.07.004

Koutroumpis, P. (2019). The economic impact of broadband: Evidence from OECD countries. *Technological Forecasting and Social Change, 148*, Article 119719. https://doi.org/10.1016/j.techfore.2019.119719

LaRose, R., Bauer, J. M., DeMaagd, K., Chew, H. E., Ma, W., & Jung, Y. (2014). Public broadband investment priorities in the United States: An analysis of the broadband Technology Opportunities program. *Government Information Quarterly, 31*(1), 53–64.

Lee, B. K., Lessler, J., & Stuart, E. A. (2011). Weight trimming and propensity score weighting. *PLoS One, 6*(3), e18174. e18174.

Lio, M., & Liu, M. C. (2006). ICT and agricultural productivity: Evidence from cross-country data. *Agricultural Economics, 34*(3), 221–228.

LoPiccalo, K. (2021). *Impact of broadband penetration on U.S. farm productivity*. OEA Working Paper 50. Washington, DC: Federal Communications Commission Office of Economics and Analytics. FCC. Available at: https://www.fcc.gov/reports-research/working-papers/impact-broadband-penetration-us-farm-productivity.

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., … Pant, L. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. *Journal of Rural Studies, 68*, 112–122. https://doi.org/10.1016/j.jrurstud.2019.01.023

Salemink, K., Strijker, D., & Bosworth, G. (2017). Rural development in the digital age: A systematic literature review on unequal ICT availability, adoption, and use in rural areas. *Journal of Rural Studies, 54*, 360–371. https://doi.org/10.1016/j.jrurstud.2015.09.001

Sanders, C. E., Gibson, K. E., & Lamm, A. J. (2022). Rural broadband and precision agriculture: A frame analysis of United States federal policy outreach under the Biden administration. *Sustainability, 14*, 460. https://doi.org/10.3390/su14010460

Stenberg, P. L., Morehart, M. J., Vogel, S. J., Cromartie, J., Breneman, V. E., & Brown, D. M. (2009). *Broadband Internet's value for rural America. Economic research report No.78*. United States Department of Agriculture. https://doi.org/10.22004/ag.econ.55944. Available at:.

Thompson, H. G., Jr., & Garbacz, C. (2011). Economic impacts of mobile versus fixed broadband. *Telecommunications Policy, 35*(11), 999–1009. https://doi.org/10.1016/j.telpol.2011.07.004

United States Department of Agriculture. (2013). *Rural Utilities service status of broadband Initiatives program as of 8/26/13*. Available at: https://www.rd.usda.gov/sites/default/files/broadband-initiatives-program-report-september-2013.pdf.

United States Department of Agriculture. (2019). *A case for rural broadband: Insights on rural broadband infrastructure and next generation precision agriculture technologies*. Available at: https://www.usda.gov/sites/default/files/documents/case-for-rural-broadband.pdf.

Whitacre, B., Gallardo, R., & Strover, S. (2014). Broadband' s contribution to economic growth in rural areas: Moving towards a causal relationship. *Telecommunications Policy, 38*(11), 1011–1023. https://doi.org/10.1016/j.telpol.2014.05.005

Xiao, Y., Moodie, E. E. M., & Abrahamowicz, M. (2013). Comparison of approaches to weight truncation for marginal structural cox models. *Epidemiologic Methods, 2*(1), 1–20.