Do public libraries impact local labor markets? Evidence from Appalachia

B Ferreira Neto, Amir

Florida Gulf Coast University

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Amir Borges Ferreira Neto

Regional Economic Research Institute
Lutgert College of Business
Florida Gulf Coast University
10501 FGCU Boulevard South
Fort Myers, FL 33965-6565
em: aborgesferreiraneto@fgcu.edu
ORCID: 0000-0001-9369-4854

Abstract

This paper investigates the effect of public library programs and participation on unemployment and labor force participation in Appalachia. Appalachia is an economically distressed area, mostly rural, and with a sustained lower level of labor force participation and a higher level of unemployment. As public library programs can be cyclical to business cycles, i.e. labor market outcomes, I use public library staff and the amount and computers available as instruments. While OLS estimates show no effect of adult or children's programs and participation on local labor market outcomes, spatial econometric estimates provide evidence of indirect effects of adults programs and children participation on labor force participation.

Keywords: Local Labor Market, Labor Force Participation, Public Library, Unemployment, Appalachia
JEL Classification: R59, J64, L39, H40

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1 Introduction

The idea that public libraries are only about books amid advances in technology, such as computers and the internet, has reduced the perceived importance of public libraries to local communities. Yet, in 2014, there were 9,305 public libraries in the United States, 3.9% more public libraries than in 2010. Public libraries in the United States received an overall yearly, non-unique, 4.6 in-person visits per capita and $12.1 billion in revenue in 2014, which, compared to 2010, represents a 12% increase in yearly in-person visits and 7% increase in revenues.

To remain relevant, public libraries have been adapting their services to match a new demand for services and materials (Goulding, 2006; Jerrard, 2009; Hunt, 2017). For example, public libraries have been expanding the number of programs and resources offered. In 2014, there were a total of 4.5 million programs offered to adults and children, with 101.9 million non-unique attendees in the country. This represented a 20% increase in the number of programs and 17% increase in the number of attendees compared to 2010. In terms of collection materials, in 2014 there were over 1.2 billion materials covering books, e-books, video, and audio. This corresponded to an increase of 29% of collection materials from 2010. The composition of these materials also changed. In 2014, books were 66.1% of the materials and e-books were 18.4%, while in 2010, books represented 86.4% of the materials and e-books 2% (The Institute of Museum and Library Services, 2017).

Library programs can be roughly divided into those for children and those for adults. Children's programs usually focus on book-related activities, educational and entertainment activities. Adult programs focus on book activities, development of skills, and job search services.[1] This paper investigates the impact of these public library programs for children and adults and their participation on local labor markets outcomes, in particular, unemployment and labor force participation. To evaluate the impact of the public library programs on local labor market outcomes, I combine datasets on county demographic characteristics and labor statistics with a novel dataset on public libraries. The Public Library System (PLS) dataset is an annual survey considered to be the census of public libraries in the United States. From the PLS, I collect data on the number of programs and program participation, as well as a variety of information about each public library system.[2]

By focusing on public library programs, this paper first contribute to the literature of urban amenities and its effect, in particular, the effect of library use. The most relevant work in this literature is Bhatt (2010). She finds that an increase in library usage increases time spent reading, decreases time spent watching TV, and, for school-age children, increases homework completion rates. Betts (1995) and Farber and Gibbons (1996) utilize the possession of a library card at age 14 as a proxy for innate ability, but they did not evaluate the impact of library programs directly on wages. Further, Liu (2004) uses cross-section of countries and find that public libraries' literacy programs affect economic productivity measured by gross domestic product per capita.

This paper also contributes to the local labor market literature, in particular, to the active labor market programs(ALMP) (Ashenfelter, 1978) which has been summarized by

[1] For a complete list of programs for school-age children visit http://www.ala.org/alsc/kickstart. For a list of services and programs for adults visit http://www.ala.org/tools/atoz/adultservices/adult_lib_svcs.

[2] A public library system is composed of a central library and its branches and bookmobiles.

Heckman et al. (1999), Card et al. (2010), and Card et al. (2018), among others. The ALMP literature mostly focuses on the government programs created by the Area Redevelopment Act in 1961 (LaLonde, 2003), and its most relevant results shows ineffectiveness of public sector employment programs, and the positive impact of job search assistance programs. In addition, there is some heterogeneity in the results depending on the investigated outcomes, the program type, and the treatment groups, with larger effects for women and those who were unemployed longer (Heckman et al., 1999; Kluve, 2010; Card et al., 2010, 2018). Also, Card et al. (2018) argue that ALMP have larger effects during recession times, i.e., low growth and high unemployment.

Similar to some of the government programs, most public library adult programs have a focus on employment by helping develop new skills and finding jobs (Bertot et al., 2012; Rainie, 2016). Children's programs, on the other hand, can have an impact on local labor markets since parents may see public libraries as possible substitutes for daycare services (Smith and Rivera, 2004; Parrish, 2013). Thus, I contribute by focusing on overlooked labor market programs and rural areas, which have lower levels of private and public provided labor market programs.

I restrict my analysis to the Appalachian region. Appalachia is comprised of 420 counties across 13 states[3] covering remote rural, and urban areas as well. However, the region is mostly rural as 70% of its counties are non-metropolitan areas hosting 42% of its population (Appalachian Regional Commission, 2018; Stephens and Partridge, 2011). Appalachia is, and has been, a systematically lagging region associated with lower levels of labor force participation and higher levels of unemployment (Dorsey, 1991; Isserman and Rephann, 1993; Stephens and Deskins, 2018). For instance, this is the only region in the US with a dedicated policy-making commission, the Appalachian Regional Commission, which has been in place for over 50 years (Isserman and Rephann, 1993; Sayago-Gomez et al., 2017).

Library programs and program participation, however, can be endogenous to local labor markets. If public library programs are used as counter-cyclical policies, areas with high unemployment and low labor force participation may be more likely to have more adult programs and less children's programs, for example, rendering OLS estimation biased. Hence, I make use of an instrumental variable (IV) approach, thus contributing by extending the Halleck Vega and Elhorst (2016) model to account for endogeneity. More specifically, I use the number of librarians without master's degree and the amount of computers for public use as instruments for the number of programs and the participation in these programs.

Libraries need both monetary and physical resources to promote programs and to attract patrons. Because public library funding comes mostly from local government, this is likely to be contemporaneously correlated with local labor markets. In turn, physical resources, such as computers and books for instance, are less likely to be contemporaneously associated to local labor markets outcomes. On the one hand, although the flow of purchases of books and computers may change during recessions and booms, the volume of these resources in the library is less likely to change over time. This should be especially true for rural areas given historical building constraints, and the reduced access to the internet and newer technologies such as e-readers and computers by patrons (Swan et al., 2013; Real and Rose, 2017).

[3] List of states that comprise Appalachia: Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia, and West Virginia.

On the other hand, librarians without master's degree are less likely to take on managerial positions hence being responsible to offer and run programs, which should influence the quantity and the selection into specific programs.Since most public librarian positions require a Master of Library Science (MLS) or a Master of Library and Information Science (MLIS) degree, preferably from a school accredited by the American Library Association (ALA), the number of librarians without a Master degree can is the result of past public library employment policies that are uncorrelated with current labor market outcomes.

Spatial econometric estimations that account for spatial dependence and possible spillovers find suggestive results that there are some direct and indirect effects from adult programs and participation on the labor force participation. These results are consistent with those in the active labor market program literature in that programs are largely ineffective. Data limitation in the lack of participants data on public library programs and on the programs themselves do not allow for additional analysis closer to those in the ALMP literature that explore both individual or program heterogeneous effects. Hence the analysis at an aggregate level. The spatial econometric results are especially important in light of evidence that job search service assistance benefits participants at the expense of those who do not participate in such programs (Gautier et al., 2017).

With the recent trend of budget cuts to public library and the shift on public library focus to programs to help local communities, it is important to understand the effectiveness of public library programs. This is the first attempt to explore such questions, even though, data limitations prevents the analysis on a more granular level.

2 Public Library in the US

Public libraries are usually taken for granted (Dubner, 2007). In the US, they started as privately-financed institutions that offered book-lending services. Public libraries have been, and are still, valued by patrons (Wiegamd, 2015). According to the Pew Research Center, black and Hispanic populations, as well as students, job seekers, people without internet access at home are those who value public libraries services the most (Pew Research Center, 2013b, 2014). In turn, parents, more educated people, and the high income population are more likely to utilize public library services (Pew Research Center, 2013c, 2014). However, there is an overall lack of knowledge of the services public libraries offer (Bertot et al., 2012; Pew Research Center, 2013a,b; Rainie, 2016).

Nevertheless, public libraries are little studied by economists and policy scholars.[4] The first economic study on public libraries is Tiebout and Willis (1965) who discuss the public nature of public libraries. Most studies that followed can be classified into two strands: one focusing on demand, unit-costs and cost-benefit analysis (Pfister and Milliman, 1970; Goddard, 1970; Feldstein, 1976; Stratton, 1976; Getz, 1980; DeBoer, 1992; Hammond, 1999); and another focusing on the technical efficiency of public libraries (Sharma et al., 1999; Vitaliano, 1997, 1998; Hemmeter, 2006; Ferreira Neto and Hall, 2018).

On the other hand, there are few studies that analyze the impact of public libraries on

[4]For instance, Knight and Nourse (1969) commission's report asked for further studies on public libraries instead of providing recommendations per se. Even though there are numerous journals specialized on libraries, a focus on the impact or policy outcome of libraries is scarce.

different outcomes. For instance, using an instrumental variable approach, Bhatt (2010) finds that an increase in library use increases time spent reading, decreases time spent watching TV and for children at schools, it increases homework completion rates. Fujiwara et al. (2017) use a survey of users and non-users of public libraries in the UK showing a positive association between public library use and self-reported happiness and health status. Conversely, Ferreira Neto (2018) studies the impact of government funding on private donations to public libraries in the US, finding suggestive results of a crowd-in effect. In terms of the labor market, the research on the impact of public libraries is scarce. For instance, Stine (2008) investigates the effect of volunteer workers on public libraries' demand for labor, and finds a complementary relationship between volunteer work and library staff.

3 Data

3.1 Labor Market Outcomes

Unemployment and labor force participation data come from the Local Area Unemployment Statistics (LAUS) provided by the Bureau of Labor Statistics (BLS). I follow the BLS and define the labor force participation rate as the ratio between labor force status and population over 15 years old. Table 1 provides summary statistics for all counties in the US (Panel A) and those in Appalachia (Panel B).

Similar to previous studies Appalachian counties have lower labor force participation and higher unemployment compared to other counties in the US. Table 1 also splits the counties into those with and without a public library system. In both Appalachia and the US, counties with a public library system have, on average, lower unemployment. However, while in the US these have higher labor force participation, in Appalachia they have lower labor force participation. Although these groups are not directly comparable, this shows suggestive evidence on the uniqueness of Appalachia with respect to its labor market.

This uniqueness of Appalachia is multifaceted. Durlauf (2012) points to poverty traps to explain Appalachia's persistent poverty and inequality, in particular he focus on educational attainment and migration pattern issues. Betz and Partridge (2012) point that migration in Appalachia has different effects compared to the rest of the United States in that economic growth attracts lower skilled migrants. As pointed by James and James (2015), Appalachia has been dependent of its natural resources, however, it can be a heterogenous region with subregional differences and concentration of self-employment (Stephens and Partridge, 2011). Kahn (2009) adds that Appalachia misses large cities, and its urban centers are far from high amenity areas. In addition, the region has difficulties in attracting firms and retaining talent. Lastly, Bollinger et al. (2011) concludes that Appalachia suffer from "missing markets" i.e., the lack of high skilled labor and low returns to skill.

Thus, according to the ALMP literature, labor market programs should be effective in areas like Appalachia, with low skilled workers and those who have been unemployed for longer times. However, rural areas have a lower number of private and public labor market programs (Whitener, 1991; Green et al., 2003; Dunham et al., 2005). In addition, rural areas have lower levels of internet access, which is an important tool in today's labor market (Stenberg et al., 2009; Hampton, 2018). Thus, in such areas, public libraries could bridge this gap by offering both some labor market programs and internet access.

3.2 The Public Library Survey

Information from public libraries come from the Public Library Survey (PLS). The PLS has been collected annually since 1988 covering approximately 9,300 public library systems comprising over 17,000 individual public library outlets (central library, branches, and bookmobiles). The survey covers all 50 states, the District of Columbia, and outlying territories and has over a 98% rate of response. As such it is considered the census of public libraries in the US (The Institute of Museum and Library Services, 2018).

The Institute of Museum and Library Services (IMLS) reports that no governmental program is attached to the PLS, and it is not mandatory. Therefore, there are no incentives for over or underreporting information provided, which covers several features including location, administrative data such as staff information, revenue by source, expenditures, among others; and service and use, such as circulation, visits, programs, materials, among others. Until 2005, the PLS was collected by the Institute of Education Sciences and the US Department of Education. Since 2006, the survey has been collected by the IMLS. Since 2009 the PLS has reported the rate of response per state. Appalachian states have a 100% response rate, with the exception of Pennsylvania that had an average response rate of 99.6%.

The variables of interest are the adult and children library programs. The PLS collects data on the number programs and participation in these programs, and reports these data for all (total) programs, children's programs, and since 2009 young adult programs. Ideally the PLS would record not only the total number of programs and participation, but also the repeated participation in these programs. Unfortunately, as this is not the case I am unable to differentiate between extensive and intensive margins of public library use.

For my analysis, I calculate the number of adult programs as the difference in total programs from children's programs. Similarly, the participation in adult programs is the difference in total program attendance minus children's program attendance. Further, because data on these programs largely begins in 2006, I restrict my sample to the years from 2006 to 2015. Figures 1 and 2 show the average number of adults and kids programs in 2006 and 2015 for Appalachia.

Because the number of programs and participation are likely endogenous to labor market outcomes I use other library information as instruments for the number of programs and participation. More specifically, I use the number of computer with internet access for public use, and number of librarians without an American Library Association certified Master's degree. The number of librarians without a Master's degree is the difference between the number of librarians and those with a Master's degree. These variables proxy for quality and capacity of running programs and attracting patrons. To take into account the heterogeneity due to location and density, library programs and participation are scaled by county population. The instrumental variables, number of computers and librarians without Master's degree are scaled by the unduplicated service population, which is calculated by the IMLS and represents the service area population without overlapping state service areas.[5]

[5]The analysis with library population scaled by unduplicated service population yields similar results in terms of magnitude, sign and statistical significance and is available upon request.

3.3 Demographic and Industry Characteristics

Other independent variables used are demographic and industry controls. Demographic control, namely, race, gender, age composition comes from the Census Bureau through the Area Health Resource Files. Ideally, I would like to incorporate some measure of education. However, there is no dataset that I know of that systematically collects education attainment at the county level on a yearly basis. The average weekly wage for total manufacturing and total services come from the Quarterly Census of Employment and Wages (QCEW) provided by the BLS.

Table 2 provides the descriptive statistics for the variables used in the econometric model. In terms of demographics, most of the population is white (91%), female (50.5%), and between 15 to 64 years (65.5%). For industry and employment, the weekly wage in manufacturing ($779) is larger than the weekly wage in services ($528). With regards to library programs and participation, there are on average more than two times the number of children's programs (277) than adult programs (135). Also, the participation in children's programs (7,269) is on average about three times the participation in adult programs (2,290).

4 Empirical Strategy

Halleck Vega and Elhorst (2016) note three stylized facts about local unemployment rates: the strong correlation over time (Blanchard and Katz, 1992), the parallel to national trends (Pesaran, 2006), and the correlation across space (Patacchini and Zenou, 2007; Manning and Petrongolo, 2017). Two methods to take the three features of local labor market outcomes into account have been proposed: on the one hand, Bailey et al. (2016) suggest a two-step procedure, in which the aggregate shocks are de-factored from local labor market outcomes, and the resulting variables modeled using spatial econometrics. On the other hand, Halleck Vega and Elhorst (2016) argue against this method presenting an alternative that deals with the three issues concomitantly.

Therefore, since the approach described by Halleck Vega and Elhorst (2016) is able to account for all three stylized facts at the same time, I follow their approach more closely, and use different local spatial econometric model specifications. This approach has also been followed by Zeilstra and Elhorst (2014) and Rios (2017) analyzing unemployment across European regions using a hierarchical model and a spatial Durbin model, respectively.

A general formulation of spatial econometric models is

$$\begin{aligned} y &= \rho W y + X\beta + WX\gamma + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + \upsilon \end{aligned} \tag{1}$$

where W is the spatial weight matrix used to spatially lag the variable of interest. The spatial autogressive model (SAR) includes only the ρ parameter, the spatial error model (SEM) includes only the λ parameter, and the spatial lag of X model (SLX) includes only the γ parameter. LeSage (2014) argue that most applied works such as this, should focus on two models only: the spatial Durbin model (SDM), which is the linear combination of SAR and SEM models, and the spatial Durbin error model (SDEM), which is the nested version of the SEM and SLX models. The former includes both ρ and γ parameters, while the latter includes λ and γ parameters.

The key difference between the SDM and SDEM models is that, while the SDM is a global spillover specification, the SDEM is a local spillover one. Global spillover implies an endogenous feedback effect, which are spillovers from higher-order neighbors as well (LeSage, 2014). LeSage (2014) argue that global spillover phenomena should be rarer than local spillovers. For the case of local labor markets, local spillovers should be more likely (Patacchini and Zenou, 2007; Halleck Vega and Elhorst, 2016), as these spillover effects would work through commuting patterns, for example, and would not generate further spillovers from neighboring regions. An extra benefit of local spillover models lies in the fact that the spatially-lagged variables can be interpreted as the indirect effect while the non-spatially-lagged are the direct effect. Therefore, I estimate both an SDEM model and a SLX model for robustness.

Therefore, to investigate the effects of public library programs on the local labor market outcomes, I estimate the following model:

$$
\begin{aligned}
y_{ct} &= Lib_{ct}\beta_1 + WLib_{ct}\beta_2 + X_{ct}\delta_1 + WX_{ct}\delta_2 + \mu_c + \varepsilon_{ct} \\
\varepsilon_{ct} &= \lambda W \varepsilon_{ct} + \upsilon_{ct}
\end{aligned}
\tag{2}
$$

where y is either the unemployment rate (UR) or labor force participation rate ($LFPR$) in county c and year t. W is the spatial weight matrix, Lib is a vector with the library program variables: average adult and children number of programs per capita, or average adult and children participation per capita. The vector X contains relevant control variables following the previous literature (Halleck Vega and Elhorst, 2016; Stephens and Deskins, 2018) that explains local labor market outcomes such as demographic controls (race, gender and age composition), industry controls (average weekly wage in manufacturing and services as a whole), the time-lagged unemployment rate or labor force participation rate, and contemporaneous and time-lagged national unemployment rate. μ_c, are county fixed effects; and ε_{ct} is an error term. All regressors are spatially-lagged including the time-lagged dependent variable. As noted by Halleck Vega and Elhorst (2016), the inclusion of the common factors (national unemployment rate) precludes the use of time fixed effects due to perfect collinearity. Appendix A show the results using time fixed effects and the results are similar to those in the main analysis. All variables included in the regression are presented in Table 2 and are described in the table notes.

The inclusion of the time-lagged dependent variable imposes a dynamic setting which is biased under least squares estimation. For the spatial specifications, we use the estimator described by Millo and Piras (2012) which relies on a generalized moments estimator (GM) based on Kapoor et al. (2007) and Mutl and Pfaffermayr (2011) and based on the full set of moments conditions to address any issues with the initial condition. The estimation procedure described in Kapoor et al. (2007) is a generalization of the GM estimator, allowing the definition of feasible GLS estimator which is "identical to an OLS calculated on the "doubly" transformed model (Millo and Piras, 2012, Page 17). Also, as noted by Millo and Piras (2012), in a local spillover model a within estimator will produce consistent estimates.

The coefficients of interest in this model are β_1 and β_2, which should be interpreted as the percentage point impact of the additional program or participation per person on the unemployment rate and labor force participation rate. If β_1 and β_2 are positive, this suggests that public library programs have a negative impact on the unemployment rate as larger participation and more programs would be associated with a higher unemployment rate. Conversely, a negative sign would suggest positive impact on the unemployment rate. The opposite is true for the labor force participation rate. That is, if β_1 and β_2 are positive (negative), then public library programs will have a positive (negative) impact on the labor force participation rate.

However, OLS estimations are likely biased due to an endogeneity problem. As the local labor markets changes, i.e., unemployment rate and labor force participation rate increase (decrease), libraries can respond to these changes by offering (cutting) programs or by incentivizing (discouraging) participation (Jerrard, 2009; Hunt, 2017). If there is a procyclical relationship between public libraries programs and unemployment rate the OLS estimates would be biased upward, or vice versa.

Therefore, I use an instrumental variable (IV) approach. Because I have two endogenous variables, adult and children's programs, at least two instruments are needed for proper identification. The two instruments used are: the average number of computers with internet for public use and the average number of librarians without a Master's degree per served person for program participation. The unbiased effect of public library programs on the local labor markets is estimated using a two-stage least square framework, in which in the first stage, the instruments are regressed on the endogenous variables, also controlling for other control variables used in the second stage, as well as the regional fixed effects.[6]

4.1 Instrument Validity

There is a possible simultaneity of the unemployment rate and labor force participation rate with the number of public library programs and their attendance. Public libraries are not randomly assigned to location throughout the country; however, most of them have been in place for over five decades at minimum. According to Stratton (1976), in 1972 there were 7,109 public libraries in the country which corresponds to over 78% of the libraries that existed in 2014 according to the Institute of Museum and Library Services (IMLS, 2017). Further, public libraries can be used as a policy instrument providing more or fewer programs in response to changes in the local labor markets.

To properly identify the effect of public library programs on local labor markets, I need a set of instruments that are uncorrelated with the local labor markets, but highly correlated with the number of programs and participation in these programs. I argue that the capacity of offering a program and attracting patrons meet both criteria.

To offer a program, public libraries require both an appropriate level of funding and availability of resources for the programs. According to the IMLS, in 2014, approximately 85.2% of public library funding came from local government, while the remaining part comes from state government (7%), federal government (0.4%), and other sources (7.4%) (The Institute of Museum and Library Services, 2017). Since most revenue stems from local government, this funding is expected to be contemporaneously correlated with regional business cycles

[6] Further, conditioning on county fixed effects and lags of characteristics should be enough to mitigate the issue that neighborhood target variables can be endogenous to labor market outcomes and correlated with county-level target variables.

and local labor markets. This is corroborated by several reports of public libraries across the country losing part of their revenue due to struggling local governments (Blau, 2011; Warburton, 2013; Smith, 2015; Kelley, 2015; Davis, 2015; Stepleton, 2015; Woods, 2015; Cleaver, 2015).[7]

Public libraries also require trained staff, physical space, and materials (print and computers), at a minimum, in order to offer such programs. A priori, because these variables are related to the capacity of the library, they should not be contemporaneously correlated with regional business cycles, but they should be strongly correlated to the programs offered by the library. Such features make these variables good candidates for instruments.

Exclusion criteria: According to the American Library Association (2018) there are six occupations in a public library: pages, library assistants or technicians, librarians, library managers, library directors and other professionals.[8] Librarians should be less susceptible to business cycle fluctuations since education (bachelors and masters degree) is shown to be a determinant in job security (Hashimoto and Raisian, 1985; Kambayashi and Kato, 2017). Librarians *without* a Masters degree should be the result of past decision-making, thus uncorrelated with current regional business cycles, as most public librarian positions require a Masters degree, preferably from a school accredited by the American Library Association.

The number of computers can be considered a stock variable. Even though the flow[9] of purchases of (upgrade) computers by libraries vary with budgetary allocation, libraries have physical constraint for storage and use of their materials. This physical constraint from the public library building is likely to be historically determined, thus contemporaneously uncorrelated to both unemployment rate and labor force participation rate.

Relevance criteria: The set of variables chosen also proxy for the quantity and quality of programs and number of programs. According to the American Library Association[10] a Masters degree is required by employers for most librarian positions. Given the different occupations in public library, one should expect that the librarians with a Masters degree to take on administrative duties as managers and directors, while those without masters degree to be more likely responsible for library programs. Additionally, people, may select into those programs in which the librarian is better prepared, more approachable, or have a better reputation, making it good predictors for participation as well.

On the other hand, computers and internet access are usually required for adult programs focused on job seekers. Also, the amount and quality of inputs (books and computers) available should make it easier to provide more and better programs for both children and adults.

[7]In response to budget cuts, several proposal for levies have the introduced in the ballots to specifically fund public libraries, either creating, renewing or increasing existing levies. These proposals have been mostly successful in the ballots (Howard Fleeter & Associates, 2017; Spokane Public Library, 2017; Hrin, 2018; Fallows, 2014).

[8]A *page* is usually a part-time job and is responsible to keep items in order. A *library assistant* can be either part-time or full-time job and generally performs clerical duties. *Librarians* are full-time employees that decide the items that are needed, offer programs and training, and help people in general. *Library managers* are middle managers responsible for daily operations, while *library directors* are the main leadership in the library. For more details on visit http://www.ala.org/educationcareers/careers/librarycareerssite/typesofjobs.

[9]The Institute of Museum and Library Services (2017) and The Institute of Museum and Library Services (2019) show that for the period in study there is no big change in the kind of collection hold by public libraries, even though changes in the collection have occurred over time.

[10]http://www.ala.org/educationcareers/libcareers/become

Tables 3 and 4 report the First Stage F-Statistics and the Wu-Hausman F-Statistics. The first stage F-Statistics are mostly above 18 suggesting the set of instruments used are good instruments (Stock and Yogo, 2005). These results are corroborated by the Wu-Hausman Test, especially for the unemployment rate results.[11]

5 Results

Tables 3 and 4 show the OLS and IV results for two sets of regressions. The first two columns report the results for the unemployment rate, while the last two columns report the results for the labor force participation rate. Table 3 focuses on the number of programs and Table 4 focuses on the participation.[12]

The OLS results show no statistical significant correlation between adult's programs and participation with the unemployment rate and the labor force participation rate. Children's programs are also not statistically correlated unemployment rate, but are positively and statistically associated with labor force participation rate. Children's participation has no statistical significant association with neither unemployment rate nor labor force participation rate.

As previously discussed, the OLS estimations are likely endogenous to labor market outcomes, hence the instrumental variable approach. The IV results show that neither adult nor children's programs and participation affect unemployment rate, similar to the OLS results, but also do not affect the labor force participation. However, the results in Tables 3 and 4 are likely to be biased given the dynamic specification and the omission of spatial dependence. Therefore, I address both of these issues in Table 6 which reports both SLX and SDEM models using an IV approach and a GM estimator.[13]

The first empirical step in the estimation of the a spatial econometric model is the determination of spatial dependence and the spatial weight matrix. From Patacchini and Zenou (2007) and Halleck Vega and Elhorst (2016) we should expect spatial dependence on local labor market outcomes. I test this hypothesis for the case of Appalachia calculating the Moran's I statistic for each year in my sample for both unemployment rate and labor force participation rate, and using $k = 1, \ldots, 10$ nearest neighbors weight matrix since not all counties with public library in Appalachia are contiguous. I report the Moran's I statistics on Table 5, which shows evidence of spatial dependence for every year and regardless of the spatial weight matrix and sample. Given these results I use a spatial weight matrix of $k = 1$ nearest neighbor.[14]

[11]One concern may be adult and children programs should be considered separately. Appendix B present the spatial econometric analysis considering adults' and children's programs and participation separately, relying on the number of computers as instrument. The results are in line with those in the main analysis.

[12]One possible concern is the heterogenous effects across the conditional distribution of labor force participation and unemployment given differential costs associated with the labor market. Appendix D shows results for quantile regressions without the spatial dependence and show no difference across the conditional distribution of labor market outcomes.

[13]Because the estimation of spatial panel models rely on balanced panels only, the results presented in the main text consider only the 360 counties with public libraries during the all the period of analysis. Appendix C provides estimates considering counties with no public libraries as zero programs and participation. The results are consistent in terms of sign, magnitude and statistical significance.

[14]LeSage and Pace (2014) argue that the specification of the weight matrices should not have large impact

The CD Test (Pesaran, 2015, 2021) for all spatial regressions rejects the hypothesis of weak cross-sectional dependence. Hence, neither the estimation including common factors in the form of contemporaneous and time-lagged national unemployment rate, nor the estimation including time fixed-effects, account for all cross-section dependence. While this is undesirable from an empirical standpoint, this is not unexpected given the setting under investigation. The CD Test may underperform given small time dimension, suggesting evidence that some strong cross-section dependence remains. Spatial methods to approximate it are the best available option.

The results in Table 6 are similar to those in the non-spatial setting for unemployment rate. Mostly there is no statistical significant association between adults' and children's program and participation on local unemployment rate. However, for both SLX-IV and SDEM-IV, the results suggest a negative association between adult's programs and participation on local labor force participation rate in terms of direct and indirect effects. Children's program and participation effect on labor force participation rate are not different from zero.

The additional adults' program per 1,000 served people decreases the labor force participation by approximately 0.27 percentage points, while the additional neighboring adults' program per 1,000 served people decreases the labor force participation by approximately 0.10 percentage points. The additional adults' participation per 1,000 served people and neighboring adults' participation per 1,000 served people decrease labor force participation by approximately 0.03 and 0.005 percentage points, respectively.

Public library programs (and participation) may not help people find jobs, however they should reduce the cost of joining the labor market, especially for adult programs. Adults programs focus on job services and skills training (Bertot et al., 2012; Hunt, 2017). These programs are designed to help adults find and keep their jobs which should positively impact labor force participation and negatively impact unemployment. This should be particularly true in Appalachia, where people have less access to formal training (Haaga, 2004; Pollard and Jacobsen, 2017) and to the internet at home (Stenberg et al., 2009). However, if adults are selecting into (participating) programs in their own county and neighboring counties, they may opt out of the labor market or not accept jobs they would otherwise.

Similar to active labor market programs (Heckman et al., 1999; LaLonde, 2003; Card et al., 2018), these programs may suffer from a selection bias. In other words, these programs target low-skilled and/or first-time workers (Goulding, 2006; Jerrard, 2009) who may have a higher cost of joining the labor market, especially in rural areas such as Appalachia. Hence, individual level data would be ideal to disentangle these heterogenous effects, but it is not available for public library programs.

Finally, in this setting I am not able to explicit account for other programs similar to those from public libraries that can be offered by private agents, government, and not-for-profits such as Goodwill for instance. On the one hand, these programs can be considered substitute to library programs offered to adults. However, more likely, these are programs are complementary to both adults and children program. Although each of these agencies focus on different issues (skillset, wrap-around, etc.), all of them aim at lowering the cost of access to labor market. Therefore, while they likely do not influence the number and the participation on library programs, they can influence individual outcomes, however, the

on estimates and inferences.

ALMP literature suggests they are ineffective.

6 Conclusion and Policy Implication

The objective of this paper is to investigate the effect of public library programs in local labor markets. More specifically, I focus on the impact of the number of children's and adult programs and participation on unemployment and labor force participation. I restrict my analysis to the Appalachian region because: it is a lagging region, suggesting a high level of unemployment and poverty; mostly rural, which implies fewer private and public labor market programs and lower levels of internet access; and with unique features in terms of labor market outcomes, in particular, lower levels of labor force participation.

Since the provision of public library programs can be endogenous to local business cycles, I use an instrumental variable approach. Spatial econometric estimates, show suggestive result that there is some negative direct and indirect effects of public library adults' programs and participation on local labor market outcomes. As indirect effects follow the same pattern as direct effects, in setting such as that of Appalachia, public library programs evaluation may be underestimated.

Therefore, in light of the spatial econometric models, the results suggest that public libraries may provide not only education services, but also can create other direct and indirect effects to local communities. Some library programs aim at reducing cost of (re-)joining the labor market, but other programs target local community leisure. While I don't expect that library programs alone to change local labor markets outcomes, they may add incentives and costs that need to be taken into account to better understand observed outcomes.

Although there is no statistically effect for children's programs and participation, they may have both a short- and long-term effects on labor market outcomes (not in the time-series sense). In the short-term they may be used by parents to join the labor market, while also being important for educational outcomes, which is an important predictor of long-term employment and income (Bhatt, 2010; Karger, 2021). In addition, if adult's are selecting into programs that allow them to find better job opportunities these should spillover into other outcomes such as income and health, for example.

These results should be taken with a grain of salt as they may vary within the population (gender, race, education level, etc.) and across programs. From Active Labor Market Program literature similar programs are largely ineffective but for some subpopulation groups and for some types of programs (Card et al., 2018). In this paper, however, I am unable to test for these heterogenous effects. The differential effects from types of programs and across subpopulation groups precludes some generalization of the results, especially in light of the uniqueness of Appalachia, previously discussed. However, this paper adds to the understanding of how these programs affect labor market outcomes on this unique setting, and how public libraries can affect local economy such as Karger (2021)and Gilpin et al. (2021).

Future studies should focus on acquiring, ideally, data at the individual level, and identifying the patrons that participate in each library program. Also, focusing on the type of library programs is important to make results more comparable to studies on private and publicly provided active labor market programs. Lastly, extending a mean group approach as described in Aquaro et al. (2021) and a partial identification approach in the spirit of

Manski and Pepper (2000, 2018) to incorporate the spatial spillovers can help improve the understanding and identification of the effect of the library programs given its aggregate nature.

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Tables and Figures

Table 1: Summary Statistics for Local Labor Market Outcome Variables

Statistic	All Counties	With Libraries	Without Libraries
Panel A: *United States*			
Unemployment Rate	6.96	6.82	7.52
	(2.98)	(2.95)	(3.06)
Labor Force Participation Rate	54.73	60.30	57.45
	(8.73)	(8.37)	(9.70)
N	31,093	24,861	6,232
Panel B: *Appalachia*			
Unemployment Rate	8.19	8.11	8.47
	(2.80)	(2.75)	(2.93)
Labor Force Participation Rate	54.39	54.18	55.76
	(6.85)	(6.85)	(6.66)
N	4,200	3,649	551

Standard deviations in parenthesis. There is information missing for seven counties for the US, all in the state of Louisiana in the year 2006.

Table 2: Descriptive Statistics

Statistic	Mean	St. Dev.	Min	Max
Demographic: (Obs. = 4,200)				
Population	59,688	97,312	2,138	1,231,527
Percent Female	0.505	0.017	0.325	0.564
Percent Asian	0.006	0.010	0.000	0.118
Percent Black	0.065	0.111	0.0001	0.826
Percent Other Race	0.002	0.007	0.000	0.151
Percent Two or more Races	0.011	0.005	0.002	0.046
Percent American Indian	0.004	0.015	0.0001	0.280
Percent Latin	0.027	0.032	0.002	0.339
Percent White	0.911	0.114	0.154	0.993
Percent $<$ 15yo	0.178	0.022	0.035	0.288
Percent 15–64yo	0.655	0.026	0.548	0.780
Percent $>$ 64 yo	0.167	0.032	0.059	0.334
Industry/Employment: (Obs. = 4,200)				
Avg. Weekly Wage for Total Manufacturing ($100s)	7.787	2.153	0.000	21.427
Avg. Weekly Wage for Total Services ($100s)	5.279	1.073	0.000	11.853
Unemployment	2,070	3,347	36	48,202
Labor Force	28,366	49,901	796	653,196
Library: (Obs. = 3,649)				
Avg. Adult Participation (1000s)	2.290	4.867	0.000	67.848
Avg. Number of Adult Programs	134.985	270.552	0.000	3,988
Avg. Children's Participation (1000s)	7.169	13.461	0.000	181,539
Avg. Number of Children's programs	276.558	479.011	0.000	5,480
Avg. Number of Print Materials (1000s)	86.509	126.933	3.375	1,204.317
Avg. Number of Computers	31.714	48.729	0.000	498.000
Avg. Number of Librarians without M.A.	2.740	4.700	0.000	47.880
Unduplicated Served Population (1000s)	41.481	72.675	910.000	894.928

Note: Other Race Population includes non-white, non-black, non-american indian/alaska native, non-asian and, in in this paper the native hawaiian and other pacific islander individuals; Two or more Races include individuals who provided multiple races listed.

Table 3: Results for Library Programs on Unemployment Rate and Labor Force Participation Rate

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	OLS	IV	OLS	IV
Adults	−0.001	−0.091	0.021	−0.358
	(0.009)	(0.079)	(0.023)	(0.273)
Children	−0.006	−0.015	0.056**	−0.126
	(0.004)	(0.069)	(0.026)	(0.210)
R-Squared	0.883	0.873	0.910	0.884
Wu-Hausman		1.429		4.827***

First Stage:	Adult Program	Children Program
Non Masters Librarian	−4417.500	6539.300*
	(3773.900)	(3341.200)
Computers	0.739***	0.834**
	(0.276)	(0.347)
F-test (1st stage)	18.3***	20.3***

Clustered standard errors in parentheses at county level. *p<0.1; **p<0.05; ***p<0.01. *Note:* Obs.=3,649 in all regressions (Unbalanced Panel: T=10, N=420). Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, national unemployment rate and time-lagged national unemployment rate, and county fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population.

Table 4: Results for Library Participation on Unemployment Rate and Labor Force Participation Rate

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	OLS	IV	OLS	IV
Adults	0.000	−0.009	0.001	−0.031
	(0.001)	(0.009)	(0.001)	(0.027)
Children	−0.000	0.001	0.002*	0.001
	(0.000)	(0.003)	(0.001)	(0.007)
R-Squared	0.883	0.856	0.910	0.860
Wu-Hausman		1.539		4.389**
First Stage:				
		Adult Part.		Children Part.
Non Masters Librarian		−16779.400		193423.000**
		(35632.600)		(77479.900)
Computers		10.0899**		18.720**
		(4.222)		(8.407)
F-test (1st stage)		7.947***		45.3***

Clustered standard errors in parentheses at county level. *p<0.1; **p<0.05; ***p<0.01. *Note:* Obs.=3,649 in all regressions (Unbalanced Panel: T=10, N=420). Controls: ppercent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, national unemployment rate and time-lagged national unemployment rate, and county fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population.

Table 5: Moran's I Stastiics for Unemployment Rate and Labor Force Participation Rate

k	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Panel A: 420 Appalachian Counties										
Unemployment Rate										
1	0.552	0.601	0.551	0.523	0.502	0.487	0.451	0.552	0.575	0.587
2	0.557	0.600	0.552	0.536	0.507	0.497	0.481	0.578	0.550	0.567
3	0.535	0.559	0.523	0.509	0.491	0.506	0.497	0.574	0.539	0.546
4	0.511	0.531	0.503	0.486	0.473	0.486	0.466	0.551	0.511	0.512
5	0.493	0.516	0.479	0.455	0.449	0.460	0.435	0.530	0.492	0.500
6	0.488	0.514	0.462	0.431	0.428	0.443	0.423	0.531	0.492	0.501
7	0.472	0.496	0.447	0.410	0.403	0.421	0.396	0.510	0.470	0.478
8	0.473	0.497	0.457	0.416	0.404	0.424	0.391	0.503	0.466	0.468
9	0.456	0.479	0.444	0.405	0.394	0.413	0.374	0.483	0.445	0.445
10	0.448	0.474	0.435	0.398	0.382	0.400	0.360	0.469	0.436	0.433
Labor Force Participation Rate										
1	0.558	0.519	0.537	0.498	0.595	0.576	0.570	0.584	0.604	0.631
2	0.565	0.542	0.556	0.518	0.565	0.544	0.536	0.549	0.570	0.594
3	0.537	0.521	0.528	0.491	0.540	0.525	0.514	0.523	0.542	0.568
4	0.529	0.516	0.520	0.485	0.515	0.499	0.486	0.495	0.520	0.544
5	0.513	0.502	0.505	0.468	0.493	0.478	0.468	0.476	0.500	0.526
6	0.513	0.503	0.506	0.470	0.489	0.474	0.461	0.472	0.497	0.524
7	0.491	0.484	0.484	0.448	0.474	0.457	0.446	0.454	0.482	0.509
8	0.485	0.480	0.483	0.446	0.468	0.452	0.442	0.450	0.477	0.501
9	0.470	0.467	0.470	0.431	0.452	0.437	0.428	0.437	0.463	0.486
10	0.459	0.458	0.460	0.421	0.442	0.426	0.417	0.425	0.452	0.475
Panel B: 360 Counties with Public Library										
Unemployment Rate										
1	0.498	0.538	0.514	0.501	0.490	0.444	0.445	0.593	0.559	0.582
2	0.478	0.501	0.501	0.519	0.491	0.457	0.449	0.572	0.521	0.552
3	0.475	0.500	0.502	0.517	0.496	0.480	0.481	0.592	0.540	0.550
4	0.459	0.492	0.494	0.497	0.484	0.473	0.459	0.571	0.524	0.518
5	0.433	0.469	0.466	0.466	0.459	0.450	0.428	0.548	0.503	0.509
6	0.422	0.448	0.441	0.431	0.438	0.439	0.421	0.543	0.497	0.505
7	0.406	0.427	0.426	0.417	0.417	0.422	0.403	0.527	0.476	0.480
8	0.395	0.411	0.425	0.413	0.411	0.420	0.398	0.520	0.466	0.464
9	0.385	0.400	0.417	0.400	0.393	0.401	0.375	0.499	0.442	0.438
10	0.377	0.393	0.404	0.395	0.385	0.392	0.364	0.488	0.433	0.428
Labor Force Participation Rate										
1	0.564	0.548	0.562	0.523	0.612	0.579	0.553	0.557	0.581	0.616
2	0.535	0.528	0.540	0.498	0.535	0.518	0.506	0.517	0.537	0.567
3	0.523	0.520	0.529	0.496	0.529	0.511	0.496	0.510	0.531	0.561
4	0.508	0.505	0.513	0.480	0.504	0.486	0.472	0.483	0.507	0.537
5	0.493	0.492	0.500	0.465	0.481	0.464	0.453	0.465	0.487	0.516
6	0.487	0.487	0.492	0.459	0.476	0.458	0.445	0.460	0.483	0.512
7	0.465	0.464	0.470	0.439	0.460	0.442	0.430	0.441	0.466	0.494
8	0.452	0.450	0.459	0.429	0.449	0.432	0.422	0.434	0.459	0.484
9	0.441	0.441	0.450	0.420	0.430	0.413	0.405	0.418	0.442	0.465
10	0.434	0.436	0.445	0.417	0.424	0.409	0.400	0.412	0.437	0.459

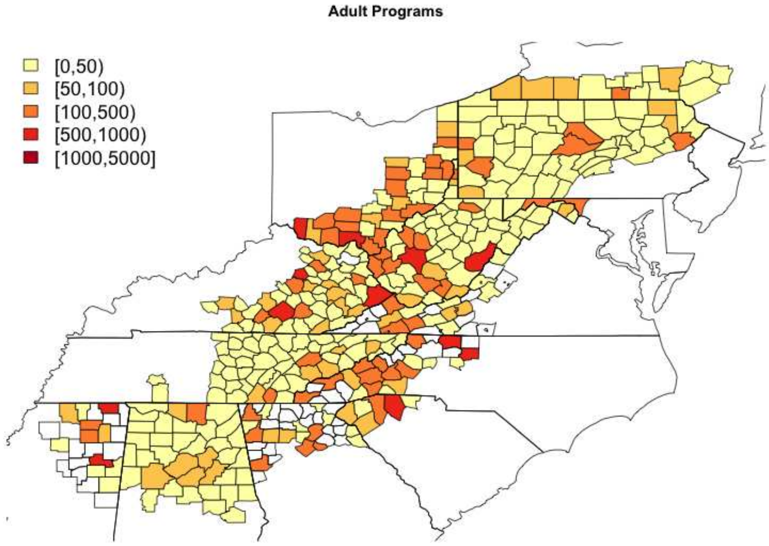
All Moran's I statistics are statistically significant at the 1% level.

Table 6: Spatial Dependence and Spillovers of Library Program and Participation

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	SLX-IV	SDEM-IV	SLX-IV	SDEM-IV
Panel A: *Programs*				
Adults	-0.064	-0.050	-0.276^{**}	-0.278^{*}
	(0.057)	(0.063)	(0.138)	(0.142)
Children	-0.009	-0.029	-0.086	-0.074
	(0.040)	(0.031)	(0.099)	(0.096)
Spatially Lagged Adults	0.001	-0.025	-0.091^{***}	-0.120^{***}
	(0.007)	(0.032)	(0.016)	(0.026)
Spatially Lagged Children	-0.001	-0.010	0.016	0.001
	(0.0086)	(0.015)	(0.016)	(0.009)
λ		0.344		0.065
Pesaran CD	19.481^{***}	19.952^{***}	10.018^{***}	11.095^{***}
Panel B: *Participation*				
Adults	-0.007	-0.005	-0.028^{*}	-0.027^{*}
	(0.006)	(0.006)	(0.015)	(0.015)
Children	0.001	-0.000	0.001	0.001
	(0.001)	(0.002)	(0.004)	(0.004)
Spatially Lagged Adults	-0.000	-0.003	-0.003^{***}	-0.005^{***}
	(0.0000)	(0.003)	(0.001)	(0.002)
Spatially Lagged Children	-0.000	0.000	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
λ		0.316		0.059
Pesaran CD	18.479^{***}	19.979^{***}	10.476^{***}	10.849^{***}

Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. *Note:* Obs.=3,600 in all regressions (Balanced Panel: T=10, N=360). Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, national unemployment rate and time-lagged national unemployment rate, spatially-lagged independent variables, and county fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population. Models are estimated using the spgm function in R which does not provide information for statistical inference on the spatial error parameter, not allows for dealing with multiple outcome correlation inference, to the best of my knowledge.

Figure 1: Number of Adults and Children Program in 2006



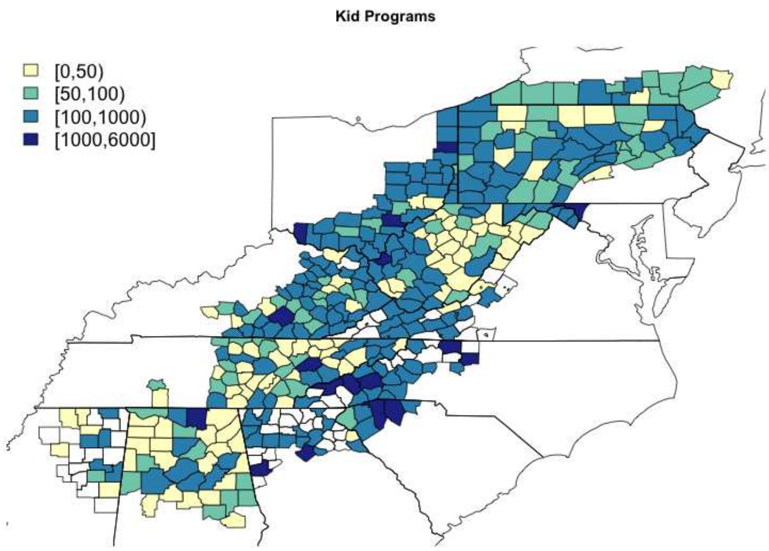
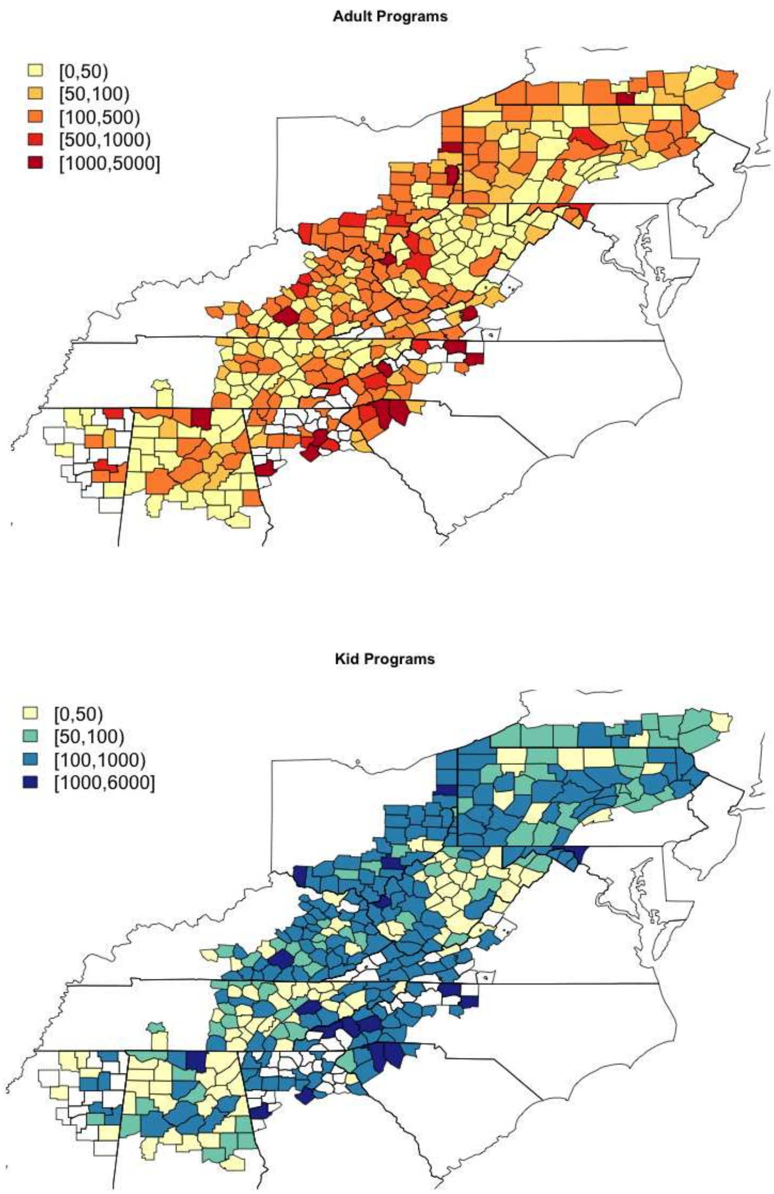


Figure 2: Number of Adults and Children Program in 2015



A Year Fixed Effects

Halleck Vega and Elhorst (2016) notes that time fixed effects only partially accounts for common factors, and that the inclusion of these common factors precludes the use of time fixed effects. Table A1 provides the results for the use of time fixed effects in lieu of the common factors and are similar to those in the main analysis.

Table A1: IV Regressions with Year Fixed and No Common Factor

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	SLX-IV	SDEM-IV	SLX-IV	SDEM-IV
Panel A: *Programs*				
Adults	−0.065	−0.064	−0.085	0.088
	(0.066)	(0.077)	(0.145)	(0.153)
Children	−0.007	−0.035	0.003	0.011
	(0.042)	(0.040)	(0.093)	(0.093)
Spatially Lagged Adults	−0.000	−0.032	−0.070***	−0.081***
	(0.007)	(0.039)	(0.015)	(0.028)
Spatially Lagged Children	−0.001	−0.008	−0.001	0.002
	(0.007)	(0.015)	(0.014)	(0.008)
λ		0.337		0.066
Pesaran CD	1.922*	3.527***	−1.100	−1.012
Panel B: *Participation*				
Adults	−0.006	−0.006	−0.006	−0.005
	(0.006)	(0.006)	(0.014)	(0.014)
Children	0.001	−0.000	0.001	0.2002
	(0.002)	(0.001)	(0.004)	(0.004)
Spatially Lagged Adults	−0.000	−0.003	−0.002	−0.002
	(0.000)	(0.003)	(0.001)	(0.001)
Spatially Lagged Children	0.000	0.000	0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)
λ		0.314		0.065
Pesaran CD	2.232**	3.249***	−1.416	−1.356

Robust standard errors in parentheses for spatial models. *p<0.1; **p<0.05; ***p<0.01. *Note:* Obs.=3,600 in all regressions (Balanced Panel: T=10, N=420). Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, spatially-lagged independent variables, and county and year fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population. Models are estimated using the spgm function in R which does not provide information for statistical inference on the spatial error parameter, not allows for dealing with multiple outcome correlation inference, to the best of my knowledge.

B Adult and Children as Separate Regressions

In this appendix I provide the results for the spatial analysis when considering adults and children's program and attendance in separate regressions. The results are similar to those in the main analysis.

Table B1: IV Regressions for Adults Only

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	SLX-IV	SDEM-IV	SLX-IV	SDEM-IV
Panel A: *Programs*				
Adults	−0.008	−0.095	−0.301	−0.293
	(0.009)	(0.090)	(0.200)	(0.207)
Spatially Lagged Adults	−0.000	−0.047	−0.092***	−0.129***
	(0.001)	(0.045)	(0.017)	(0.037)
λ		0.336		0.079
Pesaran CD	19.403***	16.863***	7.878***	8.679***
Panel B: *Participation*				
Adults	−0.001	−0.005	−0.018	−0.017
	(0.001)	(0.005)	(0.012)	(0.013)
Spatially Lagged Adults	−0.000	−0.003	−0.002***	−0.004**
	(0.000)	(0.002)	(0.001)	(0.002)
λ		0.331		0.082
Pesaran CD	18.795**	20.064***	9.087***	10.212***

Robust standard errors in parentheses for spatial models. *p<0.1; **p<0.05; ***p<0.01.
Note: Obs.=3,600 in all regressions (Balanced Panel: T=10, N=420). Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, spatially-lagged independent variables, and county and year fixed effects. Instruments: average number of computers for public use per served population. Models are estimated using the spgm function in R which does not provide information for statistical inference on the spatial error parameter, not allows for dealing with multiple outcome correlation inference, to the best of my knowledge.

Table B2: IV Regressions for Children Only

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	SLX-IV	SDEM-IV	SLX-IV	SDEM-IV
Panel A: *Programs*				
Children	−0.054	−0.061	−0.191	−0.173
	(0.058)	(0.057)	(0.139)	(0.013)
Spatially Lagged Children	−0.005	−0.021	0.035*	0.006
	(0.008)	(0.021)	(0.020)	(0.009)
λ		0.331		0.079
Pesaran CD	17.092***	16.963***	13.028***	14.509***
Panel B: *Participation*				
Children	−0.002	−0.003	−0.010	−0.009
	(0.003)	(0.002)	(0.007)	(0.006)
Spatially Lagged Children	−0.000	−0.001	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
λ		0.342		0.076
Pesaran CD	18.046***	18.108***	13.386***	14.939***

Robust standard errors in parentheses for spatial models. *p<0.1; **p<0.05; ***p<0.01. *Note:* Obs.=3,600 in all regressions (Balanced Panel: T=10, N=420). Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, spatially-lagged independent variables, and county and year fixed effects. Instruments: average number of computers for public use per served population. Models are estimated using the spgm function in R which does not provide information for statistical inference on the spatial error parameter, not allows for dealing with multiple outcome correlation inference, to the best of my knowledge.

C No Libraries as Zeroes

The estimation of spatial panel models rely on balanced panels only. In this appendix I consider all non-available (NA) library information as zeroes, thus including all 420 counties in Appalachia. The results are largely consistent with the main analysis in terms of sign, magnitude and statistical significance. While the results in the main analysis show negative direct and indirect effect on the labor force participation, the results in this appendix shows indirect negative effect on unemployment rate. Increasing in neighboring library programs is associated with smaller local unemployment rate, suggesting counties internalize the benefits from other library programs.

Table B1: Spatial Models Considering all Counties

	Dependent variable:			
	Unemployment Rate		Labor Force Participation Rate	
	SLX-IV	SDEM-IV	SLX-IV	SDEM-IV
Panel A: *Programs*				
Adults	−0.056	−0.030	−0.012	−0.137
	(0.045)	(0.043)	(0.109)	(0.112)
Children	−0.012	−0.030	0.009	−0.024
	(0.033)	(0.032)	(0.080)	(0.080)
Spatially Lagged Adults	−0.011**	−0.021	−0.011	−0.004
	(0.005)	(0.021)	(0.013)	(0.026)
Spatially Lagged Children	0.003	−0.011	0.005	−0.003
	(0.004)	(0.015)	(0.009)	(0.013)
λ		0.348		0.122
Pesaran CD	16.193***	13.38***	13.425***	13.936***
Panel B: *Participation*				
Adults	−0.005	−0.003	−0.010	−0.012
	(0.004)	(0.004)	(0.009)	(0.010)
Children	0.000	−0.000	0.002	0.002
	(0.002)	(0.001)	(0.004)	(0.004)
Spatially Lagged Adults	−0.001***	−0.002	−0.001	−0.003
	(0.000)	(0.002)	(0.001)	(0.002)
Spatially Lagged Children	0.000	−0.000	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
λ		0.330		0.117
Pesaran CD	15.664***	16.8667***	13.262***	13.815***

Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. *Note:* Obs.=4,200 in all regressions (Balanced Panel: T=10, N=420). Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, time-lagged dependent variable, time-lagged average weekly wage on manufacturing and service, national unemployment rate and time-lagged national unemployment rate, spatially-lagged independent variables, and county fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population. Models are estimated using the spgm function in R which does not provide information for statistical inference on the spatial error parameter, not allows for dealing with multiple outcome correlation inference, to the best of my knowledge.

D Quantile Regression

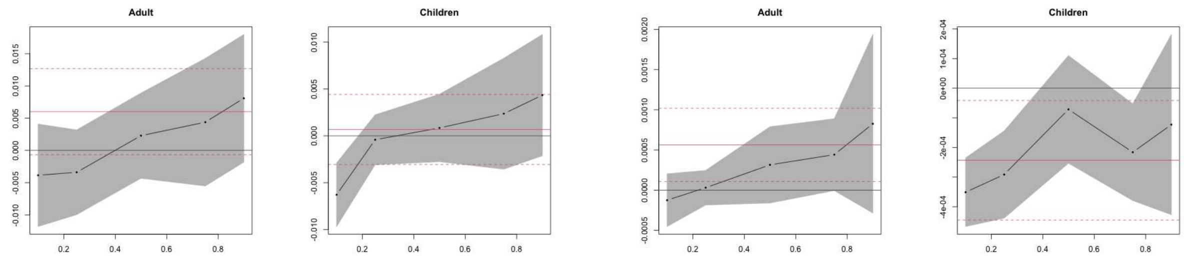
One possible concern is that the cost associated with joining the labor market and/or finding a job varies along the distribution of labor force participation and unemployment. In other words, it may be less costly to join the labor market in areas with higher labor force participation and easier to find a job in areas with low unemployment. To test this hypothesis, I use quantile regression as described in Koenker and Bassett (1978), and re-estimate the empirical model without the spatial dependence for different quantiles of the dependent variable. Particularly, I focus on the 10th, 25th, 50th, 75th and 90th quantiles.

Figure C1 summarizes the results using for the OLS estimates and Figure C2 summarizes the results using the predicted value of the first stage instead. The results in both cases show that the estimates along the distribution are not statistically different from the OLS ones, which corroborates the main results. Because the predicted values are used in Figure C2 in lieu of observable values, one can expect larger confidence intervals for the quantile estimates. Complete results are available upon request.

Figure C1: Quantile Regression Results using OLS

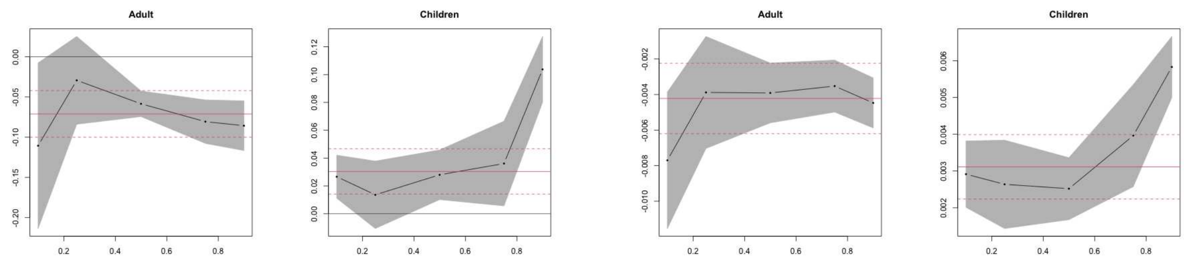
Panel A: Unemployment Rate

A1: Number of Programs A2: Participation



Panel B: Labor Force Participation Rate

B1: Number of Programs B2: Participation

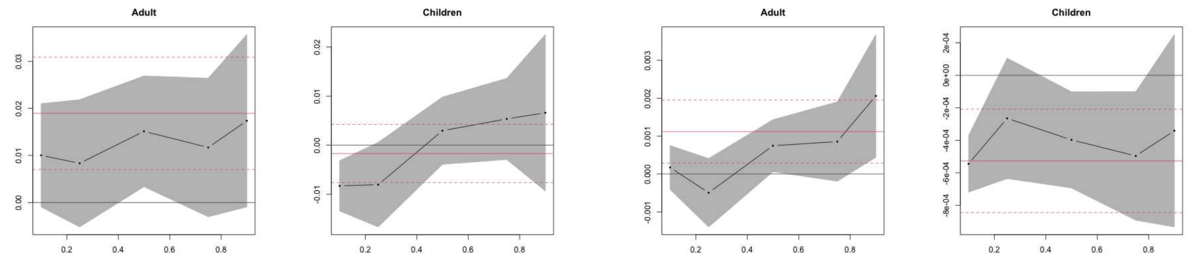


Note: Black dots are the slope coefficients for the each estimated quantile. The solid red line is the least squares estimate, and red dashed line is its confidence interval. Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, 2-year time-lagged unemployment rate, time-lagged average weekly wage on manufacturing and service, national unemployment rate and time-lagged national unemployment rate, and state fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population.

Figure C2: Quantile Regression Results using Predicted Values

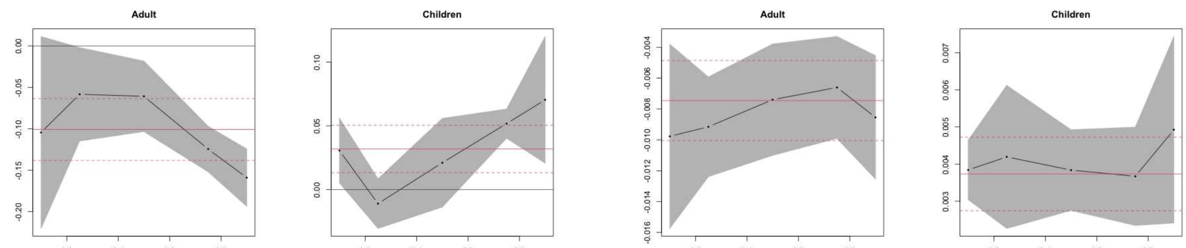
Panel A: Unemployment Rate

A1: Number of Programs A2: Participation



Panel B: Labor Force Participation Rate

B1: Number of Programs B2: Participation



Note: Black dots are the slope coefficients for the each estimated quantile. The solid red line is the least squares estimate, and red dashed line is its confidence interval. Controls: percent population asian, black, american indian, other race, latin, and two or more races, percent female, percent population between 15 and 64 years old, 2-year time-lagged unemployment rate, time-lagged average weekly wage on manufacturing and service, national unemployment rate and time-lagged national unemployment rate, and state fixed effects. Instruments: average librarians without masters degree per served population and average number of computers for public use per served population.