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Impact Evaluation of Investments in the Appalachian Region: A Reappraisal

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Abstract

We evaluate the impact of the Appalachian Regional Commission's investments on its members counties over almost fifty years. We apply different propensity score methods to find the most appropriate matching and to identify the effect of policy implementation in the most accurate way possible.

The general evidence is that counties that received ARC funding had higher per-capita income growth compared to the control counties. Per-capita income growth rate in ARC counties grew an average of 5.5 percent over the entire study time period compared to the control counties. Employment grew significantly faster in ARC counties compared to the control counties for most of the study period. The average difference in growth rates between the counties that obtained ARC investments and those matched counties that did not receive ARC investments was approximately 4.2 percent.

Keywords: Quasi Experimental Methods, Matching Algorithms, Appalachian Regional Commission, Regional Economic Development

JEL Classification: O1, O18, C00, C01

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1 Introduction

The present paper aims at evaluating the impact of public investments made from the Appalachian Regional Commission (henceforth ARC) in the counties of Appalachia over a fifty year period. Assessing this impact can be challenging since one should posit an alternative scenario as if the investments did not take place. Although this seems like a daunting task, the methodology outlined in Isserman and Rephann (1995) can be used to assess the effectiveness of these investments and answer the counterfactual question posed above.

In line with previous literature (e.g., Isserman and Rephann, 1995; Pender and Reeder, 2010), we use Quasi-Experimental methods (hereafter QEM) to determine the effectiveness of these investments. In a nutshell, QEM attempt to replicate the case-control group framework most commonly associated with clinical trials and other forms of scientific experiments (Rosenbaum, 2010; Guo and Fraser, 2009). They use matching techniques to assign to each "treated" entity one (or more) "control(s)" and then use statistical tests to see if outcomes significantly differ between the cases and the controls. If the matching is done accurately and the differences between treatments and controls are significant, we can be confident that the divergence is due to the experimental intervention.

Among the pioneering studies using QEM methods to evaluate regional development programs is Isserman and Rephann's 1995 study of the economic impacts of the ARC. Their paper constructed a counterfactual by matching counties in Appalachia that received ARC funding (i.e. the "treated" group) to counties outside of Appalachia that did not receive any ARC funding (i.e. the "control" group) but were otherwise similar to funded counties in terms of demographic, socioeconomic, and other characteristics.

The present paper could be considered a "follow-up" study of Isserman and Rephann (1995) in that we use a generally similar methodology to evaluate the impact of the ARC over fifty years. There are, however, three main differences from the original paper. First, while the original study used 24 variables to match the treated and control counties, this study uses 29 indicators. The added variables, whose omission was questioned by Feser (2013), include important starting conditions such as poverty rates, racial composition, and farming employment. These additional variables in the matching algorithm help to ensure that we are obtaining a match that is as good as (or even better than) that of Isserman and Rephann (1995). Second, building on recent advances in the field (Caliendo and Kopeinig, 2008), we use a more sophisticated econometric technique to implement the matching.[1] Last but not least, we study a longer period of analysis for which we have developed smaller sub-periods to observe the empirical effects of ARC policy in these sub-periods.

Our findings can be summarized as follows: Depending on the periods under investigation, the Mahalanobis distance and Nearest Neighbors methods are the best strategies to match treated counties with the most appropriate controls. For the analysis on the entire periods, counties that received ARC funding had higher per-capita income growth compared to the control control counties. Per-capita income growth rate in ARC counties grew an average of 5.5 percent over the entire study time period compared to the control counties. Employment grew significantly faster in ARC counties compared to the control counties for most of the study period. The average difference in growth rates between the counties that obtained ARC investments and those matched counties that did not receive ARC investments was approximately 4.2 percent.

In Section 2, we provide a summary of the relevant literature. Section 3 describes the data employed in our empirical analysis. Section 4 contains details on the methodological aspects and Section 5 discusses the main results. Finally, we draw some conclusions and indications for further research.

2 QEM and regional economic analysis

QEM have a long tradition in regional economic analysis and the extant literature is voluminous. In this section we put the emphasis on the variety of topics that have been analyzed with QEM methods.

One of the most popular practices of QEM in regional economics consists of measuring the effect of development policies (such as highway construction) on various regional economic indicators (such as, for example, employment or economic growth). This is generally achieved by comparing the effects on the treated region(s) with one (or more) matching region(s) (see e.g., Isserman and Beaumont, 1989; Isserman and Merrifield, 1982; Ham and LaLonde, 2005, among others). An early example is represented by Rephann and Isserman (1994). They study the effect of highway construction over the period 1963–75 on regional economic development for counties that had in-

[1] Detailed explanation of these techniques are given in a later section.

terstate highway mileage in 1987 across the United States. They found that the effects of highways on economic development of a region highly depend on the spatial characteristics of the region. They suggest counties that had some levels of urbanization enjoyed the economic growth brought by development of highways. This is not the case for isolated areas.

Rogers and Marshment (2000) tackle a similar issue. They study the impact of a highway bypass on a small town business district in Oklahoma by examining changes in retail sales over time. The analysis is conducted by employing standard difference-in-differences methods incorporating cross sectional time series data. To test the robustness of the results, three different control groups were considered as well as several post-bypass periods. Although the theory seems to suggest a competitive advantage leading to economic growth, none of the estimated impacts were found to be statistically significant.

Somewhat mixed evidence is found by Funderburg et al. (2010) which integrates a regional growth model with the quasi experimental approach to evaluate the effects of new highway investments in three counties in California (Merced, Orange, and Santa Clara). The three counties experienced substantial highway improvements during the 1990s. They examine temporal changes in population and employment growth before and after a substantive highway improvement and they use quasi-experimental techniques to understand what would have happened if the investment had not been made. They find a statistically significant effect on employment in the case of the exurban region in Orange County where new toll roads were constructed, but no effect on population or employment growth that can be attributed to the new highway investments near the urban center of Santa Clara County.

Similarly, Broder et al. (1992) find mixed results that the development of highways itself is not sufficient to boost economic development. They use a regression discontinuity design (RDD) to evaluate the effects of six highways on regional economic development in rural Georgia over the period 1975–1981.[2] They measure regional economic development in terms of population, per-capita income, and taxable sales.

Although highways are a major theme in the QEM literature, these methodologies are not limited to examining the effects of highways on vari-

[2] In regression discontinuity methods (Bhutta, 2009) regions are assigned to control and treatment group based on a threshold value (i.e. a cutoff point) of the selected assignment variable (Lee and Lemieux, 2010). Cases and controls closer to the threshold are assumed to be more similar, allowing the estimation of local treatment effects. Additional information regarding the use of RDD techniques is contained in Angrist and Pischke (2008).

ous outcomes. Here, we now illustrate the use of these techniques to other empirical questions of interest.

Aleseyed et al. (1998) employs quasi-experimental control group methods to examine the effects of large dam reservoirs on county income, earnings, population, and employment growth for dams opened in the U.S. during the period 1975-1984. This paper shows that large dam reservoirs have some statistically significant positive effects and tend to stimulate growth. Almus and Czarnitzki (2003) analyzes the effects of public R&D policy schemes on the innovation activities of firms in Eastern Germany. Compared to the case in which no public financial means are provided, it turns out that firms increase their innovation activities by about four percentage points. Artz et al. (2007) investigates the effects of this industry on social and economic outcomes in non–metropolitan counties of 23 Midwestern and Southern states from 1990 to 2000. Results suggest that as the meat packing industry's share of a county's total employment and wage bill rises, total employment growth increases. However, employment growth in other sectors slows, as does local wage growth. Galiani et al. (2005) examined the question of whether or not there was an effect of water privatization in Argentina on child mortality. Using the variation in ownership of water provision across time and space generated by the privatization process, the study found that child mortality fell 8 percent in the areas that privatized their water services and that the effect was largest (26 percent) in the poorest areas. Glasmeier and Farrigan (2007) studied the effect of prison construction on rural economic development. The study uses a quasi–experimental control group method to examine the effect of state-run prisons constructed in rural counties between 1985 and 1995 on county earnings by employment sector, population, poverty rate, and degree of economic health. Analysis suggests a limited economic effect on rural places in general, but may have a positive impact on poverty rates in persistently poor rural counties, as measured by diminishing transfer payments and increasing state and local government earnings in places with relatively good economic health. Goldstein and Renault (2004) use a quasi–experimental methodology to assess whether or not universities contribute to regional development and the authors conclude that the research and technology creation functions generate significant knowledge spillovers that result in enhanced regional economic development that otherwise would not occur.

Isserman and Merrifield (1987) take a quasi-experimental approach to evaluate the effect of energy booms on different income categories over the period ranging from 1967 to 1981. Isserman and Rephann (1995) analyzes the effect of the Appalachian Regional Commission programs on various counties in Appalachia. Greenberg et al. (1998) explore the effects of the Savannah River nuclear weapon site on four adjacent counties. Johnson (2009) investigates the effect of the U.S. Department of Agriculture's Business and Industry (B&I) Guaranteed Loan Program on employment. DeVuyst et al. (2003) evaluate the effect of different agricultural and non-agricultural policies in North Dakota. Wenz (2007) analyzes the effect of casino gambling on regional economic development, and Rogers and Tao (2004) and O'Keefe (2004) investigate the effect of implementing community redevelopment areas (CRAs) and enterprise zone (EZs) policies in cities in Florida. Hicks (2007) explores the effect of entrance of a large retail store in regional employment, while Card and Krueger (1994) quantify the effect of an increase in the minimum wage on employment growth in fast-food restaurants in New Jersey. Ona et al. (2007) examine the effects of hospital closure on rural counties in the three southern states of Georgia, Tennessee, and Texas. Kahsai and Jackson (2015) is an annotated bibliography devoted to all aspects of quasi–experimental methods and the interested reader is encouraged to consult this source.

3 Data

The data used in the present analysis were collected from different sources. The investment data were provided to us by the Appalachian Regional Commission. The variables used for the matching as well as the outcome variables were collected from different sources including Bureau of Economics Analysis (BEA), Bureau of Labor Statistics (BLS), and the United States Census Bureau.

Table 1 summarizes the investment data. In particular, it shows the number of counties by state and time period that received their first grant from the Appalachian Regional Commission (ARC). The last row of the table refers to the total number of counties in the Appalachian region. By 1970, more than 300 counties (corresponding to 72% of the total number of counties that nowadays are part of the Appalachian region) had received an initial investment, and 94% of the counties received their first investment before 1980. While the table only shows the time of the initial investment, many of these counties kept receiving financial aid over multiple time periods. The average amount of the ARC investments per county over the entire period is slightly above $600,000.[3]

[3] In many cases these investments are associated with other local or state funds, making the overall investment even larger.

Figure 1 present a time series for each state with the annual amount received by the ARC. The series are pretty steady, thus implying that the amount of funds distributed to each state has been stable over the entire period. There are, however, some exceptions to this general evidence. The time series of investments in Pennsylvania decreases around the 80's and after a few years starts again to be stable. This is not very surprising though since Pennsylvania is one of the most developed regions among the Appalachia. Interestingly, in later years the level of investments has been increased for states as Kentucky, Mississippi, Tennessee, and West Virginia.

The original data provided were separated by investment type.[4] However, we decided not to perform the analysis by type of investment but rather by creating a set of outcomes variables (described below) to evaluate the investments. The rationale behind this is that it would have been very difficult to disentangle the effect of each type of investment (even with a small number of categories) since different types of investments were allocated during the same year and within the same county.

Ideally, one would like to estimate the effect of only a single program in a particular year (i.e. only one investment in each county in a specific year). This is to avoid any sorts of spillover effects, either spatial as well as coming from some sort of combination of different investments. The ARC investments were made over a long period of time, therefore our empirical problem was far from being an ideal situation. To cope with this issue, we decided to break up the overall period into sub-periods. Of course, this implied finding controls at the beginning of each time interval (see below for details).

The variables used for the matching include the economic structure of the county, the level of economic development, other socioeconomic factors and demographic characteristics. The variables included for each classification are listed in Table 2. As we mentioned in the introduction, the original variables used by Isserman and Rephann (1995) totaled 24 and in the analysis presented here, five additional variables were used to bring the number of variables used in the matching exercise to 29. These five variables are: the percentage of the population on poverty in 1959; the percentage of the population under 17 years of age in 1959; the percentage of the population

[4]The investments were classified in Asset-Based Development, Business Development, Child Development,Civic Entrepreneurship, Community Development, Education and Work Force Development, Education and Job Training, Environment and Natural Resources, Health, Housing, Leadership and Civic Capacity, Local Development District Planning and Administration, Research and Evaluation, Research and Technical Assistance, and State and LDD Administration.

over the age of 65 in 1959; the percentage of the population that was black in 1959; and the population living on farms or the rural population, when available. These additional variables are important to include in the analysis because they enable the matching algorithms to provide better matches between control and treatment counties and thus can provide for a more accurate assessment of the effects of ARC investments.

We excluded counties located within 60 miles of the closest ARC county to avoid issues related to spatial spillovers. The 60 miles distance is important because as Plane and Rogerson (1994) explain, this distance accounts for a local labor market that could obtain benefits from the jobs created in the ARC counties.[5]

The variables included in Table 2 are designed to capture various aspects of the counties under study. For example, the economic characteristics of counties such as the variables measuring earnings and income measure the overall economic strength of the counties. The variables that measure the various industry shares are designed to measure the industrial mix of the various counties, while the demographic variables measure the population characteristics.

In the empirical analysis undertaken in this study, we concentrate on two important metrics to evaluate the impact of the ARC investments: the growth in per-capita income and the growth in employment. Income growth is one economic indicator that is important to many stake holders. Although there are potentially a number of variables that could be used to measure "well–being" in a region we adhere to the idea that per–capita income growth is one of the most important variables to consider. Growth in per–capita income is used in a number of studies to measure economic well–being and our use of the measure allows us to situate the current study in the broader literature on the effects of economic policy. Another potentially crucial measure of economic well–being is the growth in employment. Job growth is an economic outcome that many individuals and policy makers strive to increase using various policy measures. Employment growth is usually seen as a catalyst to overall economic growth, as employment growth can lead to growth in other areas of economic activity. Individuals also benefit from increased job growth and the associated agglomeration economies that can potentially result from an increase in jobs. Given the importance of job growth, we

[5]Of course, by excluding all the counties within 60 miles, the total number of counties varies among the subperiods. For example, in the first subperiod we have a total of 2,604 counties. Of those, 265 are treatment and 2,339 are the potential controls. The numbers for the other sub-periods as well as for the entire sample are quite similar.

utilize growth in employment as another measure of economic well–being.

In order to test the effect of the policy, we need to compare the effect of the investment in the treated group with a comparable group of counties that did not receive the investment. This control group should be similar to the treated group before the treatment (pre-test) and this similarity is measured by how closely counties match in terms of selected variables. The similarity of these groups is ensured by an accurate matching, described in the next section.[6]

4 Methodological Aspects

Before outlining the matching procedure, we discuss the definition of our control counties. Let us first consider the entire period from 1965–2012. The first step was to isolate all the counties that received investments from the ARC (between 1965 and 1969). Then, we calculated the distance of all other counties in the US (but not in the Appalachian region) from the closest Appalachian county identified in the previous step and excluded those that were less than 60 miles away. Then, we defined a dummy variable (D) equal to one for the counties identified in the first step, and zero for the counties identified in the second step.[7]

For the various sub-period analyses we use the same definition for the dummy variable. Specifically, for the period from 1975 to 1984, the treatments are all the countries in the Appalachian region that received funds between 1972 and 1974, while the potential controls are identified among the US counties at least 60 miles away from the treatment. The periods of study are: (1) from 1965 to 1974; (2) from 1975 to 1984; (3) from 1985 to 1994; (4) from 1995 to 2002; and (5) from 2003 to 2012. The sub-period analysis is included to determine if the effects of ARC investments differs over time.

Several matching methods have been used in the literature: propensity score matching using kernel matching, nearest neighbor matching, radius

[6] A result from this analysis done by different periods show that the counties selected to match the ARC is changing due to the faster development registered by the ARC counties. This is explained by the fact that posterior matches will find counties that are matched to the ARC counties in their improved conditions. Therefore the subsequently matched counties have better conditions and than the matched counties on the first matches.

[7] To avoid endogeneity problems, the variables used for the matching are collected for periods before the investments took place. In particular, for the entire period we used data for 1959 since later years where not available.

matching, stratification, and the Mahalanobis distance metric, among others (Caliendo and Kopeinig, 2008; Rosenbaum, 1989). In this study we examin matches based on three criteria: nearest neighbors, kernel matching and Mahalanobis distance. Both nearest neighbor matching and kernel matching are based on fitted values of a probit model (propensity scores) to determine similar cases and controls. We now review those three methods in detail.

For the two methods based on the propensity scores, the starting point is to estimate a probit model with D as the dependent variable, and x as the matrix of explanatory variables:

$$p(x) = \Pr(D = 1|x) = E(D|x) \tag{1}$$

The fitted values of the probit model (i.e. the propensity scores) provides the probability over which the matching is calculated.

The nearest neighbor approach matches each treated observation i with one of the control observations j that has the closest propensity score using the formula

$$\min ||p_i - p_j||.$$

The procedure can be employed either with or without replacement. For our estimation purposes we use without replacement since we have a large number of candidate counties to be selected for the control group, and to avoid the situation where a single county was selected to match a large group of treated counties.

The kernel matching estimator does not find a county to be the closest match to each treated observation but rather calculates a combination of control counties that provide a closer comparison group. The controls are weighted by their degree of similarity to the treated observation. The weights used in the matching algorithm are defined as follows:

$$w(i, j) = \frac{K(\frac{p_j - p_i}{h})}{\sum_{j=1}^{n_0} K(\frac{p_j - p_i}{h})} \tag{2}$$

Where p measures the propensity score of each i (treated) and j (not treated) counties, K is the kernel function, h is the bandwidth in the kernel density function, and the kernel function used in the matching is the Epanechnikov kernel. The bandwidth choice implies a trade-off between a high bandwidth obtains a smoother density estimation and decreasing variance, but can smooth important characteristics and obtaining a biased estimation Caliendo and Kopeinig (2008). The function creates weights for each of the j counties.[8]

The Mahalanobis Distance metric is not a propensity score method per se, although it can be used with the propensity scores as well.[9] This approach measures the distance between the treated county and other counties weighted by the inverse of the variance-covariance matrix of the variables. Mathematically it can be represented as:

$$d^2(X_T, X_C) = (X_T - X_C)'\Sigma^{-1}(X_T - X_C) \tag{3}$$

where X_T is the matrix containing the variables in the treated county, X_C is the matrix containing the variables of a possible control county, d is the distance between the two vectors, and Σ^{-1} is the inverse of the variance-covariance matrix.

The decision of which matching algorithm to choose is a problematic one since different criteria can point towards different models. Therefore, to determine the most appropriate matching method for our set of data, we follow the suggestions given in Caliendo and Kopeinig (2008).

They recommend looking at different criteria rather then to a single one. In particular, we consider the standardized bias for each variable, which measures the differences in the variables between the treated and control groups (Rosenbaum and Rubin, 1985). Such result compares the overall match between cases and controls variables "as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups" (Caliendo and Kopeinig, 2008, 15). The best matching algorithm (between Mahalanobis distance, nearest neighbors, and Kernel) is the one with the lowest pseudo R^2 and likelihood ratio test statistic values (estimated after treated and control groups were selected), the least number of variables with significant biases, and lowest bias values (Caliendo and Kopeinig, 2008). First we identify variables used in the model that are significantly different between treated and matched controls, and focus on the percentage difference between treated and control (bias), and how many variables in the matched counties have large and significant differences. We then look for low values among pseudo R^2 and the likelihood ratio test statistics, because low values on these tests

[8]We also experienced with different bandwidth obtaining consistent results.

[9]However we decided to use the entire set of variables. We also experimented to add the propensity scores but the results were similar.

indicate that the explanatory variables will predict a lower difference in the propensity score between treated and untreated matched counties.

The next step in the analysis is to use a difference-in-difference model (DID). It measures the difference-in-differences average treatment effect on the treated (ATET) and is specified as:

$$\begin{aligned} ATET &= E(\delta_a - \delta_b | D = 1) = E(y_{1a} - y_{0a}) - (y_{1b} - y_{0b} | x, D = 1) \\ &= E(y_{1a} - y_{1b} | x, D = 1) - (y_{0a} - y_{0b} | x, D = 1) \end{aligned} \tag{4}$$

where the first term in the equation refers to the differences in outcomes (y) before and after the treatment for the treated group. The before and after differences alone may be biased if there are time trends. The second term in the equation measures the before and after change in the control groups. Together they are used to eliminate this bias under the assumption that both groups experience the same time trend.

5 Results

In this section we present the results of our empirical analysis. We start with the results for the full period (1965–1970), and later we present results for the various sub-periods.

5.1 Full Period Matching Results

As we pointed out in the previous section, the matching was performed using data from 1959.[10] The dependent variable of the probit model is a dummy variable equal to one for countries that received grant from the Appalachian Regional Commission over the period 1965–1969.

By looking at Table 3, the matching from the three procedures generates control counties that are very similar to the treated ones. The first column

[10]Some of the variables, however, are taken from the 1960 census. In particular, those variables are the percentage of population under 17, the percentage of population over 65, the percentage of black population, distance to the closest city with population larger than 25,000, distance to the closest city with population larger than 100,000, distance to the closest city with population larger than 250,000, distance to the closest city with population larger than 500,000. and distance to the closest city with population larger than 1,000,000.

of Table 3 lists all the variables used for the matching, while the second column displays the average of that particular variable for the treated counties. The remaining columns refer to the three different matching methodology: Mahalanobis distance, nearest neighbors (without replacement), and kernel matching. For each matching method, the first column report the average value of the variables in the controls (identify by using that specific method); while the second column displays the percentage bias (i.e. a hundred times the average of the treated minus the average of the controls again divided by the average of the controls). The last column is a t-test of the difference in mean. Since the better model is the one that finds a control group that is closer to the treated we are looking for the methods that, among other things, has the least number of significant t-tests. A significant value for the t-test for a particular variable shows a difference in the average of that particular variable between the treated and control. Therefore, an higher number of significant t-tests mean a “worse" matching. There are, however, other criteria to judge the “best" fit. Table 4 reports, for each methods, some of the criteria suggested in the literature. For example, a lower pseudo R^2 and likelihood ratio test statistic will point towards the better fitted model, as well as a lower number of significantly different variables and a lower value for the average bias. An additional evidence that points toward a good matching is shown in Table 5. In Table 5 we calculated the average of one of the two output variables (i.e. the per-capita income)[11] over the treated and the control counties and we perform a test to determine whether they are statistically different at the time of the matching. While the t-test is significant when using the Kernel matching algorithm, both the nearest neighbors and the Mahalanobis are not. These results indicate that the nearest neighbor matching procedure is the better algorithm for matching our treatment and controls. Figure 4 is a map of the matched counties for the entire period. There are two interesting aspects when looking at Figure 4. On the one hand, there are very few controls in the western part of the United States. This is, in a sense, reinsuring because we know as a fact that the western counties are generally different from those belonging to our samples of controls. On the other hand, there is evidence that the matching algorithm is selecting counties relatively “closer" to the treatments although far enough to avoid problems of spatial spillovers effects.

Table 6 contains information regarding the results of Equation 4 estimated on per-capita income growth. The first column is the year, where

[11]We only consider per capita income because could not find data for employment growth in 1959.

the estimates correspond to each year reported (i.e. the growth rate from the original year to the year in question), followed by the growth rate in per-capita income for the treated counties, i.e. those that received ARC investment funds. The third column is the growth rate for the matched control counties, i.e. those that did not receive ARC investment funds, while the fourth column is the difference in the growth rate in per-capita income between the treated and control counties. The final column is the t-statistic which is a metric used to determine if the difference in the growth rate in per-capita income between the treated and control counties is statistically significant. These results are also illustrated in Figure 2 entitled "Per-Capita Income Growth Rates Between Treated and Control Counties".

Over most of the study period, counties that received ARC funding had higher per-capita income growth compared to the control control counties. Per-capita income growth rate in ARC counties grew an average of 5.5 percent over the entire study time period compared to the control counties. The differences in per-capita income growth between the treated and control counties are positive and statistically significant for nearly every year, meaning that it is unlikely that the growth in ARC counties are simply due to random chance. The only exception is in 1973, where there was no difference in per-capita income growth between the ARC counties and the comparison group. Historically speaking, 1973 was a year that was plagued by various economic woes, including the Arab Oil embargo and the 1973-1974 stock market crash. Overall, these results paint a very positive picture for the counties that are located in Appalachia and provide evidence that these investments undertaken by the ARC led to higher growth in per-capita income over the time period 1970-2012.

Employment growth is another important metric that can be used to measure the economic vitality of a region. Table 7 contains information regarding the results of the QEM analysis regarding employment growth.

Employment grew significantly faster in ARC counties compared to the control counties for most of the study period. The average difference in growth rates between the counties that obtained ARC investments and those matched counties that did not receive ARC investments was approximately 4.2 percent. This is shown in Graph 3, which shows that ARC counties had higher employment growth than the matched counties for nearly every year. This gap narrowed after 1995, but the difference remained statistically significant at the 90 percent confidence threshold. The difference in employment growth was rather small and insignificant at first (1970 to about 1972), but the groups began to quickly diverge throughout most of the seventies and eighties. As mentioned earlier, the early seventies was an atypical period for the United States economy, and it is reasonable to expect that ARC investments would take some time to manifest themselves especially when it comes to employment growth. Again, these findings strongly suggest that ARC investments had a positive influence on the employment prospects for residents of the region.

5.2 Sub-period 1965-1974

The data for the sub-period from 1965 to 1974 comes from the economic structure for the year 1965, defined as the share of the income by sector and the rest of the variables are measured from the 1960 U.S. Census. The treatment group includes only those counties that received investments in the years 1966 to 1968. The control group, as usual, excludes those counties within 60 miles to counties that are members of the ARC and this exclusion is repeated for all sub-periods hereafter. The rates of growth use 1965 per capita income as base year and 1969 employment as base year to measure the change in the periods.

To determine the matching algorithm we proceeded in the same way as for the entire sample period and to save space we only show the tables on the output variables.[12]

The results from the fitted models highlight that per capita income in the treated counties (Table 8) and employment in the treated counties (Table 9) have a higher rate of growth and that the difference between the two groups of counties is positive and significant (except for a few years).[13]

5.3 Sub-period 1975-1984

The data for the sub-period from 1975 to 1984 comes from the economic structure for the year 1974, as explained in the last sub-period and the rest of the variables are calculated from the 1970 U.S. Census. The treatment group includes only those counties that received ARC investments in the

[12] The detailed results can be obtained by writing to the corresponding author.

[13] Data on employment is only available from 1969, we use this year as base for the change analysis, while income is available for periods before 1969 and use information for year 1965.

years 1975 to 1978. The measured rates of growth for per-capita income and employment use 1974 as the base year in this sub-period analysis.

The observed results in Table 10 show that the per capita income has a higher and significant growth rate for treated counties than for the control counties. However, the growth rate of employment is lower for treated counties than the control counties (see Table 11), and this result is only statistically significant for the years 1983 and 1984.

5.4 Sub-period 1985-1994

The data for the sub-period from 1985 to 1994 comes from the economic structure for the year 1984 and other variables are measured from the 1980 U.S. Census. The treatment group includes as treated only those counties that received ARC investments in the years 1985 to 1988. The year 1984 is used as the base year in calculating the growth rate in per-capita income and employment for this sub-period.

The observed results in Table 12 show that the per capita income has a higher and significant growth rate for treated counties than the control counties. However the growth rate of employment is lower and not significant for treated counties compared to the control counties (see Table 13).

5.5 Sub-period 1995-2002

The data for the sub-period from 1995 to 2002 comes from the economic structure for the year 1994 and the rest of the variables are measured from the 1990 U.S. Census. The treatment group includes as treated only those counties that received investments in the years 1995 to 1997. The growth rates for per-capita income and employment use 1994 as the base year in the calculations for this sub-period.

The results in Table 14 show that per capita income has a lower and for most years not statistically significant (it is only statistically significant for 2001) growth rate for treated counties relative to the control counties. However the growth rate of employment is negative and decreases for treated counties relative to control counties (see Table 15), but these results are not statistically significantly different from zero.

5.6 Sub-period 2003-2012

The data for the sub-period from 2004 to 2012 comes from 2002 and the rest of the variables are measured from the 2000 U.S. Census. The treatment group includes as treated only those counties that received investments in 2003 because from the year 2003 onward all counties in the Appalachian Region received investments. The growth rate for per-capita income and employment use 2001 as the base year in this sub-period analysis.

One noteworthy aspect of Table 16 is that the per capita income has a negative difference that is not significantly different from zero and from Table 18 employment has a positive and significant difference that shows that employment grows faster in the ARC counties.

5.7 Regression Results

Table 18 shows the regression models to determine if higher rates of growth of per capita income and employment are correlated to ARC investments and total investment from ARC projects and other sources. The four columns represent different specifications that were utilized in the empirical analysis. In each specification, 16 different control variables that represent such things as e.g. the presence of a highway, population measures, and other demographic characteristics, were used as were two variables related to ARC investments. The top number next to each variables name is the coefficient estimate with the bottom number in parentheses being the p-value.

The main variables of interest are the two different ARC investment variables. The first ARC investment variable consists of just funds from ARC alone, while the other variable is ARC funds plus funds from other sources such as local and state government spending on programs such as job training, education, and water treatment to name just a few examples. The sample of counties used in the regression results consist of only those counties that are contained in the ARC region and thus the sample size is 421 counties. The reason for this choice is twofold. First, we do not have data on investments for counties that are not part of the ARC region and second, the sample needs to be restricted to ARC counties to determine if the investments that are specifically targeted to ARC counties are effective.

The results indicate that counties that received ARC funds alone experienced a positive and statistically significant increase in both per-capita income growth and employment growth over the period 1965 to 2005. Counties that received a combination of ARC and other local government funds experienced a positive and statistically significant increase in employment over this same period. The only exception to this pattern is that counties that received a combination of ARC and other government funds experienced a positive increase in per-capita income growth over this time period, although this result was not statistically significant.

6 Summary

The paper was an evaluation of the impact of public investments made from the ARC in the counties of Appalachia over a fifty year period. We used matching techniques to assign to each treated county one control and then use statistical tests to see if the outcomes from the two groups were significantly different.

Our findings can be summarized as follows: We show that employment growth and per-capita income growth over the period 1970-2012 was higher in Appalachian counties that received ARC investments compared to a control group of counties that did not receive ARC investments.
On average, counties that received ARC investments experienced employment growth of 4.2 percent and per-capita income growth of 5.5 percent higher than the control counties that did not receive ARC funding. The results indicate the effectiveness of ARC investments for these counties located in Appalachia.

We also performed the analysis over shorter time periods. Per-capita income in the treated counties has a higher rate of growth for early sub-periods (1965-1974, 1975-1984, and 1985-1994). In these sub-periods, the difference between the treatments and controls is positive and significant. The evidence for the employment follows a different pattern: in early sub-periods there is no significantly difference between the two groups of counties. However, for the sub-period 2003-2012, employment has a positive and significant difference.

Overall, these results paint a very positive picture for the counties that are located in Appalachia and provide evidence that these investments undertaken by the ARC led to higher growth both in per-capita income and employment.

References

Aleseyed, M., Rephann, T., and Isserman, A. (1998). The local effects of large dam reservoirs: U.s. experience, 1975 – 1995. *Review of Urban & Regional Development Studies*, 10(2):91–108.

Almus, M. and Czarnitzki, D. (2003). The effects of public R&D subsidies on firms' innovation activities: the case of Eastern Germany. *Journal of Business & Economic Statistics*, 21(2):226–236.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Artz, G. M., Orazem, P. F., and Otto, D. M. (2007). Measuring the impact of meat packing and processing facilities in nonmetropolitan counties: A difference-in-differences approach. *American Journal of Agricultural Economics*, 89(3):557–570.

Bhutta, N. (2009). Regression discontinuity estimates of the effects of the GSE act of 1992. Finance and Economics Discussion Series 2009-03, Board of Governors of the Federal Reserve System (U.S.).

Broder, J. M., Taylor, T. D., and McNamara, K. T. (1992). Quasi-Experimental Designs For Measuring Impacts Of Developmental Highways In Rural Areas. *Southern Journal of Agricultural Economics*, 24(01).

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.

Card, D. and Krueger, A. B. (1994). Minimum wages and employment: A case study of the fast-food industry in new jersey and pennsylvania. *American Economic Review*, 84(4):772–93.

DeVuyst, C. S., Leistritz, F. L., and Schepp, A. (2003). Economic development initiatives in rural north dakota communities: Socioeconomic impacts. Agribusiness & Applied Economics Report 23577, North Dakota State University, Department of Agribusiness and Applied Economics.

Feser, E. (2013). Isserman's impact: Quasi-experimental comparison group designs in regional research. *International Regional Science Review*, 36(1):44–68.

Funderburg, R. G., Nixon, H., Boarnet, M. G., and Ferguson, G. (2010). New highways and land use change: Results from a quasi-experimental research design. *Transportation Research Part A: Policy and Practice*, 44(2):76 – 98.

Galiani, S., Gertler, P., and Schargrodsky, E. (2005). Water for life: The impact of the privatization of water services on child mortality. *Journal of political economy*, 113(1):83–120.

Glasmeier, A. K. and Farrigan, T. (2007). The economic impacts of the prison development boom on persistently poor rural places. *International Regional Science Review*, 30(3):274–299.

Goldstein, H. and Renault, C. (2004). Contributions of universities to regional economic development: A quasi-experimental approach. *Regional Studies*, 38(7):733–746.

Greenberg, M., Isserman, A., Krueckeberg, D., Lowrie, K., Mayer, H., Simon, D., and Sorenson, D. (1998). Socioeconomic impacts of US nuclear weapons facilities: A local-scale analysis of Savannah River, 1950–1993 . *Applied Geography*, 18(2):101 – 116.

Guo, S. and Fraser, M. (2009). *Propensity Score Analysis: Statistical Methods and Applications*. Advanced Quantitative Techniques in the Social Sciences. SAGE Publications.

Ham, J. C. and LaLonde, R. J. (2005). Special issue on Experimental and non-experimental evaluation of economic policy and models. *Journal of Econometrics*, 125(1-2):1–13.

Hicks, M. J. (2007). A quasi-experimental test of large retail stores' impacts on regional labor markets: The case of cabela retail outlets. *Journal of Regional Analysis and Policy*, 37(2):116–122.

Isserman, A. and Rephann, T. (1995). The economic effects of the appalachian regional commission: An empirical assessment of 26 years of regional development planning. *Journal of the American Planning Association*, 61(3):345–364.

Isserman, A. M. and Beaumont, P. M. (1989). New directions in quasi-experimental control group methods for project evaluation. *Socio-Economic Planning Sciences*, 23(1–2):39 – 53.

Isserman, A. M. and Merrifield, J. (1982). The use of control groups in evaluating regional economic policy. *Regional Science and Urban Economics*, 12(1):43 – 58.

Isserman, A. M. and Merrifield, J. D. (1987). Quasi-experimental control group methods for regional analysis: An application to an energy boomtown and growth pole theory. *Economic Geography*, pages 3–19.

Johnson, J. (2009). Rural economic development in the united states: An evaluation of the u.s. department of agriculture's business and industry guaranteed loan program. *Economic Development Quarterly*, 23(3):229–241.

Kahsai, M. S. and Jackson, R. (2015). Quasi–experimental methods: An annotated bibliography. Technical report, Regional Research Institute West Virginia University.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2):281–355.

O'Keefe, S. (2004). Job creation in California's enterprise zones: a comparison using a propensity score matching model. *Journal of Urban Economics*, 55(1):131–150.

Ona, L. Y., Hudoyo, A., and Freshwater, D. (2007). Economic Impact of Hospital Closure on Rural Communities in Three Southern States: A Quasi-Experimental Approach. *Journal of Regional Analysis and Policy*, 37(2).

Pender, J. L. and Reeder, R. J. (2010). Economic Impacts of Regional Approaches to Rural Development: Initial Evidence on the Delta Regional Authority. 2010 Annual Meeting, July 25-27, 2010, Denver, Colorado 60909, Agricultural and Applied Economics Association.

Plane, D. and Rogerson, P. (1994). *The Geographical Analysis of Population: With Applications to Planning and Business*. Wiley.

Rephann, T. and Isserman, A. (1994). New highways as economic development tools: An evaluation using quasi-experimental matching methods. *Regional Science and Urban Economics*, 24(6):723–751.

Rogers, C. L. and Marshment, R. (2000). Measuring highway bypass impacts on small town business districts. *Review of Urban & Regional Development Studies*, 12(3):250–265.

Rogers, C. L. and Tao, J. L. (2004). Quasi-Experimental Analysis of Targeted Economic Development Programs: Lessons from Florida. *Economic Development Quarterly*, 18(3):269–285.

Rosenbaum, P. R. (1989). Optimal matching for observational studies. *Journal of the American Statistical Association*, 84(408):1024–1032.

Rosenbaum, P. R. (2010). Design Sensitivity and Efficiency in Observational Studies. *Journal of the American Statistical Association*, 105(490):692–702.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38.

Wenz, M. (2007). The Impact of Casino Gambling on Housing Markets: A Hedonic Approach. *Journal of Gambling Business and Economics*, 1(2):101–120.

Table 1: Number of Counties by State and time period that received their first investment from the ARC

	Time periods				
State	1968–1970	1971–1980	1981–1990	1991–2000	2000–2015
Alabama	22	13	0	2	0
Georgia	25	10	0	2	0
Kentucky	34	15	0	0	5
Maryland	3	0	0	0	0
Mississippi	15	5	0	2	2
New York	12	2	0	0	0
North Carolina	27	2	0	0	0
Ohio	18	10	0	1	3
Pennsylvania	39	12	1	0	0
South Carolina	6	0	0	0	0
Tennessee	45	5	0	0	2
Virginia	16	3	0	4	2
West Virginia	39	16	0	0	0
Total ARC	301	93	1	11	14

Variable	Explanation
Freeway	binary variable for presence of highway equal to 1 if present
lpop	log of population for a given year
spc	state and local per capita earnings for a given year
rtot	rate of growth of total income for a specific period
rpop	population growth rate for period for a specific period
dens	population density for a given year
city25	distance to the closest city with 25,000 population for a given year
city100	distance to the closest city with 100,000 population for a given year
city250	distance to the closest city with 250,000 population for a given year
city500	distance to the closest city with 500,000 population for a given year
city1000	distance to the closest city with 1'000,000 population for a given year
psvc	share of income from services
prtl	share of income from retail
ptpu	share of income from transportation
pmfg	share of income from manufactures
pcon	share of income from construction
pfar	share of income from farming
ptrf	share of income from transfers
pdir	share of income from dividends and rents
pres	residential adjustment share
pmil	share income from of military earnings
pfed	share income from of federal earnings
pstl	share income from of state and local earnings
pwhl	share income from of wholesale earnings
pov	pct of population in poverty for a given year
pc17	pct population under the age of 17 for a given year
pc65	pct population over the age of 65 for a given year
Black	pct of black population for a given year
Nfarms/rural	pct population in farms or rural population when available

Table 2: List of Variables

Table 3: Comparison of averages variables in treated and control counties obtained with the three different matching procedures.

Variable	Mean	Mahalanobis Distance			Nearest Neighbors Without replacement			Kernel Matching		
	Treated	Mean Control	%Bias	t–test	Mean Control	%Bias	t–test	Mean Control	% Bias	t–test
freeway	0.44	0.41	5.6	0.79	0.47	-7.7	-1.1	0.42	2.5	0.4
lpop59	10.15	10.18	-2.7	-0.44	10.22	-6.2	-0.9	9.70	41.3	5.5
spc59	0.09	0.10	-3.9	-3.93	0.10	-3.8	-4.6	0.11	-7.1	-3.8
rtot59	59.62	56.21	6.7	1.43	56.89	5.4	0.8	129.04	-137.2	-5.4
rpop59	-2.04	1.10	-13.2	-2.97	2.82	-20.4	-4.3	1.12	-13.2	-2.5
dens59	90.05	86.18	0.7	0.36	114.62	-4.6	-1.8	85.44	0.9	0.3
pov59	19.01	16.63	26.2	2.98	14.70	47.5	6	21.14	-23.5	-2.3
pc1760	37.93	36.57	34.1	5.67	37.20	18.1	2.8	37.35	14.4	1.8
pc6560	9.80	11.19	-48.3	-9.06	10.55	-26.2	-4.4	9.18	21.3	3.6
black60	6.17	6.33	-1.2	-0.21	9.21	-23.1	-3.5	9.03	-21.7	-3.7
city2560	32.32	33.48	-3.8	-0.75	34.26	-6.4	-1.1	32.49	-0.6	-0.1
city10060	67.60	67.31	0.4	0.12	64.06	5.4	1.3	59.85	11.8	2.6
city25060	105.72	105.47	0.3	0.07	100.27	6.5	1.4	94.89	12.9	2.5
city50060	185.85	172.24	8.8	1.97	172.02	8.9	1.7	210.19	-15.7	-2.3
city100060	355.90	366.06	-4.5	-0.77	327.34	12.5	2.1	385.37	-12.9	-1.7
psvc59	0.06	0.07	-6.3	-0.94	0.07	-5.5	-0.8	0.06	19.2	2.7
prtl59	0.09	0.10	-32.5	-5.49	0.09	-16	-2.5	0.08	24.9	3.7
ptpu59	0.05	0.05	1.3	0.19	0.04	6.5	1	0.03	43.8	6.8
pmfg59	0.22	0.22	1.6	0.2	0.23	-5.6	-0.7	0.19	19.7	2.4
pcon59	0.03	0.04	-10	-2.02	0.04	-7.4	-1.4	0.04	-3.8	-0.7
pfar59	0.10	0.11	-3.4	-0.61	0.11	-4.4	-0.7	0.18	-66.1	-7.4
ptrf59	0.12	0.12	10.5	1.37	0.11	28.3	3.5	0.10	48.3	6.4
pdir59	0.08	0.09	-38.1	-7.44	0.09	-32.4	-6.5	0.08	1.5	0.3
pres59	0.06	0.06	4.3	0.6	0.06	1.7	0.2	0.06	2.4	0.3
pmil59	0.01	0.01	0	-0.01	0.01	-5.5	-1.6	0.01	1.3	0.5
pfed59	0.02	0.02	5.1	1.1	0.02	2.7	0.5	0.03	-25.1	-3.6
pstl59	0.07	0.07	14.6	2.68	0.07	8.2	1.3	0.08	-42.4	-4
pwhl59	0.02	0.02	-11.3	-1.74	0.02	-13.8	-2.1	0.02	23.2	3.5

Table 4: Tests of fitting between matching procedures for full period matching

Procedure	Pseudo–R^2	LR χ^2	Average Bias	Variables Significantly Different
Mahalanobis Distance	0.393	430.31	-2.107	10
Nearest Neighbors without replacement	0.229	251.22	-1.332	11
Kernel Matching	0.184	201.54	-2.854	19

Table 5: Comparison of average in growth per-capita income for treatment and control counties at the time of the matching.

Procedure	Variable	Treated	Control	% Bias	t–test
Mahalanobis distance	GPCI 1959–62	0.181	0.183	-1.4	-0.22
Nearest Neighbors	GPCI 1959–62	0.181	0.182	-0.8	-0.12
Kernel Matching	GPCI 1959–62	0.181	0.149	37.2	4.380

Table 6: Per-Capita Income Growth Rate Results and significance levels for full period matching.

year	Per capita income Growth rate			
	Treated	Controls	Difference	t-stat
1970	0.079	0.058	0.020	4.65
1971	0.150	0.134	0.016	3.36
1972	0.247	0.228	0.019	3.68
1973	0.365	0.364	0.001	0.09
1974	0.460	0.438	0.021	3.22
1975	0.546	0.518	0.029	3.82
1976	0.650	0.614	0.036	4.93
1977	0.741	0.698	0.044	5.78
1978	0.852	0.806	0.046	5.78
1979	0.958	0.911	0.047	5.55
1980	1.051	0.990	0.061	7.21
1981	1.148	1.098	0.050	5.70
1982	1.206	1.150	0.056	6.35
1983	1.254	1.204	0.050	5.97
1984	1.357	1.313	0.044	5.29
1985	1.409	1.363	0.045	5.30
1986	1.454	1.406	0.048	5.58
1987	1.501	1.449	0.052	6.33
1988	1.562	1.504	0.058	6.71
1989	1.634	1.578	0.056	6.40
1990	1.688	1.616	0.072	8.09
1991	1.727	1.651	0.077	8.12
1992	1.789	1.709	0.080	8.35
1993	1.821	1.743	0.078	8.03
1994	1.863	1.791	0.071	7.24
1995	1.896	1.822	0.073	7.29
1996	1.938	1.869	0.069	6.73
1997	1.987	1.916	0.071	6.96
1998	2.033	1.959	0.074	7.25
1999	2.065	1.991	0.074	7.20
2000	2.116	2.042	0.073	7.07
2001	2.181	2.117	0.064	5.91
2002	2.195	2.127	0.069	6.42
2003	2.221	2.163	0.059	5.43
2004	2.272	2.214	0.058	5.15
2005	2.307	2.246	0.062	5.29
2006	2.350	2.286	0.065	5.47
2007	2.394	2.333	0.062	5.2
2008	2.435	2.378	0.057	4.65
2009	2.433	2.367	0.067	5.28
2010	2.455	2.387	0.067	5.36
2011	2.501	2.439	0.062	5.00
2012	2.538	2.475	0.063	5.00
Average			0.055	

Table 7: Employment Growth Rate Results and significance levels for full period matching.

year	Employment Growth Rate			
	Treated	Controls	Difference	T-stat
1970	0.004	0.003	0.001	0.36
1971	0.022	0.014	0.005	1.62
1972	0.06	0.047	0.013	2.13
1973	0.104	0.087	0.017	2.36
1974	0.118	0.1	0.018	2.19
1975	0.111	0.083	0.028	3.03
1976	0.152	0.119	0.033	3.32
1977	0.187	0.148	0.039	3.58
1978	0.225	0.178	0.046	3.95
1979	0.243	0.195	0.048	3.88
1980	0.238	0.185	0.053	4.10
1981	0.236	0.188	0.048	3.50
1982	0.218	0.169	0.049	3.28
1983	0.227	0.185	0.042	2.67
1984	0.261	0.217	0.043	2.64
1985	0.272	0.227	0.045	2.62
1986	0.288	0.24	0.048	2.64
1987	0.315	0.266	0.048	2.54
1988	0.335	0.284	0.051	2.65
1989	0.354	0.302	0.052	2.61
1990	0.375	0.32	0.055	2.71
1991	0.371	0.32	0.051	2.45
1992	0.389	0.333	0.056	2.59
1993	0.413	0.357	0.056	2.53
1994	0.435	0.386	0.049	2.13
1995	0.46	0.413	0.046	1.96
1996	0.469	0.425	0.044	1.79
1997	0.489	0.445	0.044	1.75
1998	0.505	0.46	0.045	1.73
1999	0.516	0.473	0.043	1.61
2000	0.529	0.488	0.041	1.48
2001	0.522	0.48	0.041	1.45
2002	0.516	0.473	0.042	1.46
2003	0.519	0.476	0.042	1.43
2004	0.533	0.487	0.046	1.52
2005	0.551	0.5	0.051	1.62
2006	0.565	0.511	0.053	1.68
2007	0.577	0.525	0.053	1.62
2008	0.567	0.518	0.049	1.52
2009	0.531	0.486	0.045	1.37
2010	0.527	0.483	0.044	1.38
2011	0.544	0.498	0.046	1.41
2012	0.554	0.51	0.044	1.36
Average			0.042	

Table 8: PSM Nearest neighbors without replacement results for growth rate of per capita income for sub-period 1969 to 1974 with respect to the base year 1965.

Year	Treated	Controls	Difference	T-stat
1969	0.389	0.382	0.008	0.86
1970	0.469	0.442	0.027	2.56
1971	0.541	0.517	0.024	2.24
1972	0.637	0.61	0.027	2.27
1973	0.752	0.734	0.018	1.42
1974	0.848	0.811	0.037	2.83

Table 9: PSM-Nearest Neighbors results for growth rate of employment for sub-period 1969 to 1974 with respect to the base year 1969.

Year	Treated	Controls	Difference	T-stat
1970	0.0069	0.0019	0.005	1.36
1971	0.8729	0.7084	0.1645	1.58
1972	0.0665	0.0493	0.0171	2.41
1973	0.1115	0.0886	0.0229	2.65
1974	0.1247	0.1018	0.0228	2.43

Table 10: PSM-Nearest Neighbors matching results for growth rate of per capita income for sub-period 1979 to 1984 with respect to the base year 1974.

Year	Treated	Controls	Difference	T-stat
1979	0.499	0.473	0.026	4.02
1980	0.594	0.556	0.038	5.39
1981	0.693	0.663	0.03	3.97
1982	0.751	0.712	0.038	4.99
1983	0.799	0.768	0.03	3.99
1984	0.897	0.872	0.025	3.25

Table 11: PSM- Nearest Neighbors matching results for growth rate of employment for sub-period 1979 to 1984 with respect to the base year 1974.

Year	Treated	Controls	Difference	T-stat
1979	0.123	0.125	-0.002	-0.24
1980	0.117	0.121	-0.004	-0.39
1981	0.116	0.127	-0.011	-1.05
1982	0.096	0.11	-0.015	-1.23
1983	0.104	0.132	-0.028	-2.13
1984	0.138	0.17	-0.032	-2.31

Table 12: PSM Nearest neighbors Without replacement matching results for growth rate of per capita income for sub-period 1989 to 1994 with respect to the base year 1984.

Year	Treated	Controls	Difference	T-stat
1989	0.276	0.261	0.014	2.56
1990	0.33	0.301	0.029	4.81
1991	0.369	0.341	0.028	4.56
1992	0.43	0.401	0.029	4.72
1993	0.463	0.433	0.03	4.52
1994	0.506	0.481	0.024	3.53

Table 13: PSM Nearest neighbors Without replacement matching results for growth rate of employment for sub-period 1989 to 1994 with respect to the base year 1984.

Year	Treated	Controls	Difference	T-stat
1989	0.094	0.095	-0.001	-0.06
1990	0.115	0.111	0.004	0.38
1991	0.11	0.113	-0.002	-0.21
1992	0.127	0.134	-0.007	-0.52
1993	0.153	0.162	-0.01	-0.7
1994	0.173	0.194	-0.02	-1.34

Table 14: PSM-Kernel matching results for growth rate of per capita income for sub-period 1998 to 2002 with respect to the base year 1994.

Year	Treated	Controls	Difference	T-stat
1998	0.17	0.173	-0.003	-0.25
1999	0.202	0.209	-0.007	-0.49
2000	0.252	0.266	-0.014	-0.84
2001	0.318	0.343	-0.025	-1.41
2002	0.333	0.353	-0.02	-1.04

Table 15: PSM-Kernel matching results for growth rate of employment for sub-period 1998 to 2002 with respect to the base year 1994.

Year	Treated	Controls	Difference	T-stat
1998	0.07	0.077	-0.007	-0.41
1999	0.081	0.09	-0.009	-0.43
2000	0.094	0.102	-0.008	-0.36
2001	0.086	0.087	-0.001	-0.04
2002	0.08	0.084	-0.004	-0.15

Table 16: PSM-Kernel matching results for growth rate of per capita income for sub-period 2004 to 2012 with respect to the base year 2001.

Year	Treated	Controls	Difference	T-stat
2004	0.075	0.087	-0.012	-1.77
2005	0.111	0.114	-0.004	-0.45
2006	0.155	0.155	0	0
2007	0.2	0.203	-0.004	-0.37
2008	0.24	0.252	-0.012	-0.92
2009	0.238	0.247	-0.01	-0.74
2010	0.259	0.27	-0.011	-0.78
2011	0.307	0.32	-0.013	-0.73
2012	0.344	0.357	-0.013	-0.69

Table 17: PSM-Kernel matching results for growth rate of employment for sub-period 2004 to 2012 with respect to the base year 2001.

Year	Treated	Controls	Difference	T-stat
2004	0.017	0.004	0.012	2.47
2005	0.034	0.009	0.025	3.57
2006	0.048	0.019	0.029	3.23
2007	0.063	0.033	0.03	2.81
2008	0.054	0.03	0.024	2.02
2009	0.02	0.002	0.018	1.44
2010	0.017	0.002	0.015	1.16
2011	0.034	0.019	0.015	0.98
2012	0.044	0.029	0.015	0.93

Table 18: Regression results for the rate of growth of the per capita income and the employment. The regression results include coefficients and the p-values in parentheses. * = 10%, ** = 5%, and *** = 1%.

Variable	Per capita income	Per capita income	Employment	Employment
(Intercept)	2.984	3.164	-0.569	-0.483
	(0.000)	(0.000)	(0.340)	(0.413)
freeway	-0.015	-0.013	0.083	0.081
	(0.420)	(0.465)	(0.055)	(0.062)
city2560	0.002	0.002	0.004	0.004
	(0.000)	(0.000)	(0.005)	(0.007)
city10060	0.000	0.000	-0.001	-0.001
	(0.521)	(0.577)	(0.076)	(0.074)
city25060	0.001	0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.039)	(0.053)
dens59	0.000	0.000	0.000	0.000
	(0.176)	(0.157)	(0.037)	(0.032)
rpop59	-0.003	-0.003	0.010	0.010
	(0.001)	(0.001)	(0.000)	(0.000)
black60	0.002	0.002	-0.005	-0.004
	(0.037)	(0.027)	(0.009)	(0.016)
pov59	0.001	0.001	-0.004	-0.004
	(0.162)	(0.118)	(0.039)	(0.048)
pfed65	0.514	0.486	1.874	1.879
	(0.050)	(0.065)	(0.003)	(0.003)
pmfg65	-0.109	-0.119	-0.373	-0.362
	(0.218)	(0.184)	(0.076)	(0.087)
pres65	-0.296	-0.296	1.432	1.446
	(0.197)	(0.199)	(0.009)	(0.008)
pwhl65	-0.685	-0.638	1.341	1.392
	(0.168)	(0.200)	(0.255)	(0.238)
perw65	-0.590	-0.575	0.148	0.163
	(0.012)	(0.015)	(0.791)	(0.771)
pmil65	0.627	0.737	-2.405	-2.233
	(0.484)	(0.412)	(0.259)	(0.293)
pfar65	0.708	0.685	0.617	0.616
	(0.000)	(0.000)	(0.042)	(0.043)
pstl65	1.533	1.517	1.810	1.823
	(0.000)	(0.000)	(0.005)	(0.005)
log(investment from ARC)	0.024		0.058	
	(0.038)		(0.031)	
log(Total Investment ARC projects)		0.010		0.047
		(0.304)		(0.046)
R2	0.569	0.566	0.369	0.368
N	421	421	421	421
Fstat	31.220	30.780	13.810	13.740

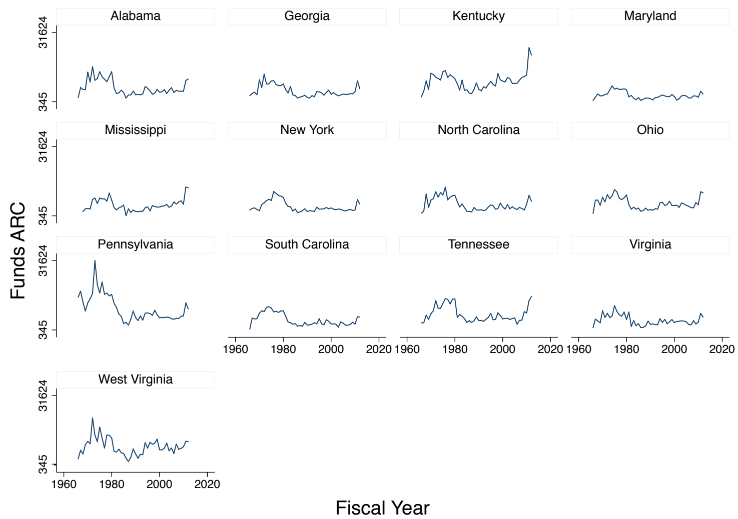

Figure 1: ARC investments by state and fiscal year (thousand of $US)

Figure 2: Comparison of Per Capita Income growth rates between treated and control. Base year 1969

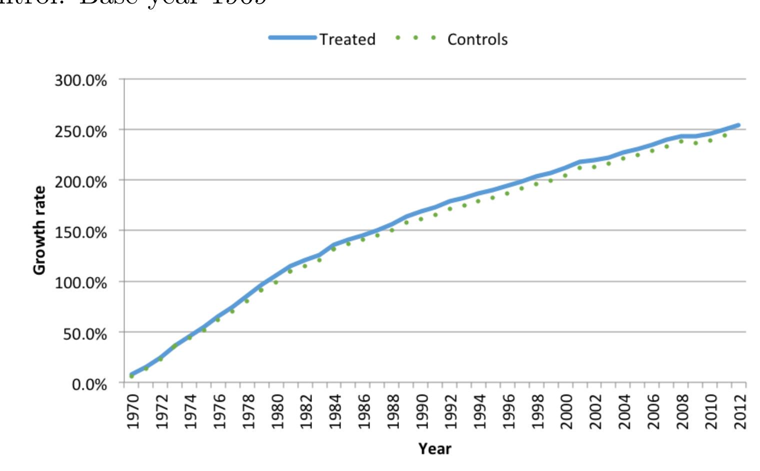

Figure 3: Comparison of Employment growth rates between treated and control. Base year 1969

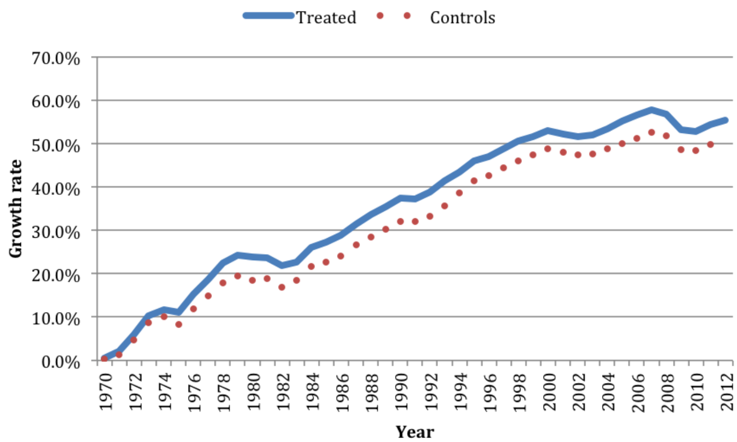

Figure 4: Map of matched counties for full period matching from data for 1959 (Full Period Matching)