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Updated CARES Act Program Evaluation Methods, Insights, and Future Directions

National Economic Research and Resilience Center
Decision and Infrastructure Sciences Division

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Maturing the CARES Act Effectiveness Framework

Updated CARES Act Program Evaluation Methods, Insights, and Future Directions

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Table of Contents

Acronyms and Abbreviations

ACS	American Community Survey
Argonne	Argonne National Laboratory
BDS	Business Dynamics Statistics
BEA	U.S. Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
CARES Act	Coronavirus Aid, Relief, and Economic Security Act
CEII	County Economic Impact Index
CEW	Census of Employment and Wages
DiD	Difference in Differences
EDA	U.S. Economic Development Administration
EDD	Economic Development District
FEMA	Federal Emergency Management Agency
FIPS	Federal Information Processing System
FY	Fiscal Year
GDP	Gross Domestic Product
JHU	Johns Hopkins University
km	kilometer
MSA	Metropolitan Statistical Area
NAICS	North American Industry Classification Standard
NERRC	National Economic Research and Resilience Center
NTA	National Technical Assistance
OMB	Office of Management and Budget
PSM	Propensity score matching
QWI	Quarterly Workforce Indicator
R&D	Research and Development
RLF	Revolving Loan Fund
SBIR	Small Business Innovation Research

Maturing the CARES Act Effectiveness Network

Executive Summary

In October 2022, U.S. Economic Development Administration (EDA) provided Argonne National Laboratory (Argonne) with grant award ED22HDQ3120191 to establish the National Economic Research and Resilience Center (NERRC). One core component of NERRC's scope of work is to further mature the Coronavirus Aid, Relief, and Economic Security (CARES) Act Effectiveness Framework (Effectiveness Framework), originally developed under a previous award, and to update any associated analysis of impacts from CARES Act non-infrastructure investments. The Effectiveness Framework is an integrated, multi-objective approach to evaluating impact from EDA investments using methods consistent with the EDA Logic Model and the Foundations of Evidence Based Policymaking Act of 2018.

This report documents NERRC's efforts to validate existing Effectiveness Framework methods and the incorporation of synthetic control as a new impact analysis method. Next, the report documents three central analytical challenges that make it difficult to detect impact from CARES Act non-infrastructure awards using publicly available data. Finally, the report provides suggested enhancements to the Effectiveness Framework and EDA program evaluation efforts, emphasizing the need for a more nuanced understanding of grant success theories, more accurate data collection, and a refined approach to measuring economic development capacity and grant effectiveness. Each of these enhancements can assist in overcoming the identified challenges and improving future assessments of EDA programs.

Analytical Challenges

While it is NERRC's assessment that Propensity Score Matching (PSM) and synthetic control are appropriate causal inference methods for analyzing impact from EDA investments, three key challenges make it difficult to detect impact from EDA's CARES Act non-infrastructure investments at this time:

> **Data granularity:** Publicly available data do not capture sufficient geographic granularity given the scope of typical EDA-funded activities;
>
> **Time since award:** It is too soon after the disbursement of CARES Act grants to observe impact using publicly available data; and
>
> **Relative size of award:** Given that the majority of publicly available data suitable for this analysis is constrained to the county-level, most EDA investments are too small relative to county-level economies to be able to detect impact using county-wide economic data.

Possible Future Directions

Based on its findings, NERRC has identified the following recommendations to enhance future EDA program evaluation efforts.

Develop more specific theories of program and activity success: This analysis mapped proxy indicators to grant activities using the EDA Logic Model. However, additional evolution to the EDA Logic Model could help to create stronger and more logical connections between grant activities, expected outcomes, and measures of success, which in turn can help generate more specific testable hypotheses.

Clearly distinguish program impact vs. effectiveness: For EDA, program impact is considered a measurable change in a community's capacity to engage in economic development or overall level of economic development. A different set of questions focusing on program effectiveness might seek to answer questions such as "Did the program reach its targeted population?" "Were grant awards disbursed in a timely and equitable manner?" or "Did the grant activities cover the most urgent needs of the target population?" These types of program effectiveness analyses are more concerned with internal processes and the implementation of grant activities as opposed to whether a desired outcome was measurably achieved. Studies into EDA grant program effectiveness would complement impact analyses such as those conducted here.

Capture more precise county-level and industry-specific grant data: Although each grant has a county Federal Information Processing System (FIPS) code associated with it, work performed through many of the CARES Act non-infrastructure grants took place in counties other than the one listed EDA's grants management system data. Given that this field is the primary means of understanding where grant-funded activities take place, it is important that this data be as accurate as possible. Similarly, while the ED-916 project reporting form allows for the use of North American Industry Classification System (NAICS) codes to identify industries of interest, it is often left blank. More systematic reporting would allow for additional levels of analysis.

Explore additional analytic methods: To further enhance the broader program evaluation effort, NERRC suggests exploring additional analytic methods, particularly employing case studies and exploring modeling as impact estimation approach in the early years after a grant award. These methods could offer valuable insights into the effectiveness and impact of EDA grant programs. Incorporating both case studies and modeling approaches into the program evaluation framework will enrich the analysis and provide complementary perspectives on the effectiveness and impact of EDA grant programs. By employing a broad range of methods, EDA can generate robust evidence to inform program design, decision-making, and resource allocation, ultimately enhancing the agency's capacity to promote economic development and prosperity across communities nationwide.

Background

The emergence of COVID-19 in early 2020 and its ongoing repercussions on both the national and global economies led to a significant increase in the resources available to the U.S. Economic Development Administration (EDA) to assist communities in strategically revitalizing and reinvigorating their local and regional economies. In March 2020, the passage of the Coronavirus Aid, Relief, and Economic Security (CARES) Act allocated approximately $1.5 billion in economic adjustment assistance to the EDA. This funding was specifically aimed at aiding communities in preventing, preparing for, and responding to the economic impacts of the COVID-19 pandemic.

To gain a deeper insight into the overall effectiveness and impact of these allocated funds and to establish a replicable methodology for future investments, the EDA partnered with Argonne from 2021 to 2022 to create the CARES Act (Effectiveness Framework) as a tool to conduct ongoing evaluation of EDA's CARES Act non-infrastructure awards. Drawing from established EDA practices, economic development literature, statute, and Office of Management and Budget (OMB) guidelines, the Effectiveness Framework equips EDA program officers with the tools to estimate the impacts of discretionary and competitive grants across a range of eligible non-infrastructure activities. This Effectiveness Framework is designed as an evaluation guide, forming the basis for future assessments of the long-term impacts of programs and investments at both the community and regional levels.

The Foundations of Evidence-Based Policy Making Act of 2018 and subsequent guidance from the OMB define impact assessments as an evaluation of "the causal impact of a program, policy, or organization, or aspect thereof, on outcomes relative to those of a counterfactual."[1] Answering causal questions is best done by employing methodologies from causal inference.[2] Argonne therefore undertook a causal inference approach in the Effectiveness Framework. Specifically, the research team employed Propensity Score Matching (PSM) as its primary counterfactual method.

The Effectiveness Framework also introduced the use of new data sources in EDA's program evaluation efforts. Specifically, Argonne and EDA sought third-party data that is openly accessible, routinely updated, and well validated at a nation-wide scale to provide a clear, consistent measure of programmatic impact across the country. The research team grounded the measure of impact in the EDA Logic Model and its associated 'realized outcomes.'[3]

Because publicly available third-party data was a required input of the Effectiveness Framework, and because most indicators that would relate to the EDA Logic Model's realized outcomes are produced at the county level (e.g., Local Area Unemployment Statistics), the primary unit of analysis is counties. Ideally, researchers could take the same county in the same economic conditions and observe that county's economic development capacity and outcomes with the assistance of EDA grants and without. However, multiple constraints, discussed later in this report, make it challenging to detect impact from

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[1] Office of Management and Budget. (2020, March 10). *Phase 4 Implementation of the Foundations for Evidence-Based Policymaking Act of 2018: Program Evaluation Standards and Practices.* Retrieved from https://www.whitehouse.gov/wp-content/uploads/2020/03/M-20-12.pdf.

[2] Abadie, A., & Cattaneo, M. D. (2018, August 2). "Econometric Methods for Program Evaluation." *Annual Review of Economics, 10* (1), 465–503. https://doi.org/10.1146/annurev-economics-080217-053402.

[3] Economic Development Administration and SRI International. (2021). *Building and Using a New Economic Development Evaluation System: A Toolkit for Practitioners.* Retrieved from https://www.eda.gov/archives/2021/files/performance/ED-Evaluation-Toolkit.pdf.

EDA non-infrastructure investments at a county level. Ultimately, the initial round of Effectiveness Framework provided a methodical approach for evaluating non-infrastructure awards. However, the assessment did not yet yield statistically significant results.

Report Purpose and Overview

In October 2022, EDA provided Argonne with a grant to establish the National Economic Research and Resilience Center (NERRC) under award ED22HDQ3120191. One key component of NERRC's scope of work is to further mature the Effectiveness Framework and to update any associated analysis of impacts from CARES Act non-infrastructure investments. The intent of NERRC's program evaluation activities is to grow and mature the Effectiveness Framework, introduce new methods and approaches, and to attempt to detect impacts from EDA's CARES Act non-infrastructure investments. This report specifically documents the following:

- Effectiveness Framework validation efforts through historical analysis of 2012 Disaster Supplemental awards;
- Refinement of the PSM model;
- Reanalysis of both the 2012 Disaster Supplemental and CARES Act program impacts; and
- The introduction of a synthetic control as an additional analytical method.

In addition, the report includes analysis of three central non-infrastructure grant impact analysis challenges, which include the following:

> **Data granularity:** Publicly available data do not capture sufficient geographic granularity given the scope of typical EDA-funded activities;
>
> **Time since award:** It is too soon after the disbursement of CARES Act grants to observe impact using publicly available data; and
>
> **Relative size of award:** Given that the majority of data suitable for this analysis is constrained to the county-level, the size of EDA investments too small relative to county-level economies to be able to detect impact using county-wide economic data.

Finally, the report outlines possible future research directions that, if taken, may enhance the ability for future evaluations to lead to the detection of impact from non-infrastructure grant awards.

Evolving and Maturing the EDA Program Effectiveness Framework

The Effectiveness Framework builds upon existing EDA practice and program evaluation efforts by taking a layered approach to understanding impact across several timescales and at different geographies. It introduces multiple third-party data sources to help estimate and validate program impact and build a more robust data-informed narrative for evaluating ongoing program investments. Importantly, third-party data can be used to supplement existing self-reported program performance data, to verify assumptions about investment outcomes, and deepen understanding of impact at local, regional, and national levels.

The Effectiveness Framework currently comprises three interlinked components, each with its own data sources and methods that individually characterize various temporal and spatial aspects of programmatic impact. When taken together, the coupled data sources allow users to understand a strong and nuanced causal relationship from initial baseline conditions to EDA program investment through to activity and, finally, to capturing investment outcomes and impacts.

The three component parts of the framework are outlined below and summarized in Table 1. A more detailed documentation is available in Argonne's previous report, *Developing an Approach for Measuring EDA Program Effectiveness for CARES Act COVID-19 Recovery Efforts*.

1. Self-Reported Program Evaluation Analysis (Outputs): This component of the Effectiveness Framework is closely aligned with existing EDA program evaluation practices. It involves analysis of operational data that EDA generated to characterize award data and associated programmatic elements, such as special initiative coding, as well as grantee self-reported data from the ED 916, 917, and 918 project performance surveys as they become available. The reporting frequency—semi-annually for ED 916 and annual for the ED 917 and 918—provides a short to medium timeframe for understanding which activities and subsequent outcomes are occurring where and when. Longer-term realized outcomes are also self-reported at 3-, 6- and 9-year intervals, but reporting is inconsistent and largely unverified in the test dataset.

2. Capacity Change Analysis (Capacity Outcomes): This component of the Effectiveness Framework involves analysis of the Economic Development Capacity Index (EDCI), which characterizes community capacity at the county-level across five core capacity areas, each of which is defined by multiple indicators reported through reputable third-party open data sources.[4] The EDCI does not directly report on EDA program effectiveness. However, as indicators of local capacity change over time, EDCI changes for county or region of interest can be paired with other parts of the framework, notably the Self-Reported Program Evaluation Analysis, to determine whether EDA funding and activity can be reasonably inferred to have made the observed difference. As of the time of this report, NERRC is finalizing results for the first new timestep of the EDCI. As such, this component of the Effectiveness Framework has not yet been applied.

3. Long-Term Impact Analysis (Realized Outcomes): The Long-Term Impact Analysis component of the Effectiveness Framework uses third-party data from open and credible sources, such as the American Community Survey (ACS) from the U.S. Census Bureau, to understand how EDA funding and activity as a whole is impacting community equity, recovery, and resilience nationally. Given the timescale on which economic development and local capacity building occur, as additional data are reported and available over time, greater fidelity can be achieved. Because of the scale of analysis, definitively determining cause and effect at the individual community level is not possible; however, coupling self-reported data with the EDCI change over time analysis and long-term impact analysis can generate new insights on program outcomes and impacts.

[4] National Economic Research & Resilience Center. (n.d.). "Economic Development Capacity Index (EDCI)." Argonne National Laboratory. Retrieved from https://www.anl.gov/dis/economic-development-capacity-index.

Table 1: Summary of CARES Act Effectiveness Framework Components

	Data Type	General Scale of Analysis	General Geographic Scale
Self-Reported Program Evaluation Analysis	Self-reported through a customer management system	By project and activity, aggregated to activities by program and geography	Recipient county[5]
EDCI Change-Over-Time Analysis	Third-party, freely available and open source, reported as an index	Community capacity aggregation as an index	County, region, nationwide
Long-Term Impact Analysis	Third-party, freely available and open source	Total EDA funding or activity type	National

Although the Effectiveness Framework does not currently rely on explicit, measurable program goals or broader organizational metrics, it is grounded in the EDA's theory of change articulated through its Logic Model. The Effectiveness Framework measures effectiveness primarily through the lens of community impact.

PSM Methodology

The initial design of the Effectiveness Framework used PSM as the primary method to conduct long-term impact analysis. PSM is used to gauge program effectiveness when the use of a control group is not possible.[6] Instead, treatment cases are paired with non-treated comparison cases with similar characteristics (covariates) to control for confounding variables. The initial PSM analysis included a set of 24 covariate indicators from openly available, third-party data sources (see Appendix A for details). Matches are identified by developing propensity scores that aggregate a series of covariates. These scores allow analysts to find a population of non-funded (control) counties to compare to the funded (treatment) population and to determine program effectiveness. As a part of this framework, PSM allowed for comparison of outcomes in funded communities in relationship to outcomes in communities that did not receive funding to determine if measurable changes exist. Figure 1 shows the steps in a standard PSM matching process.

[5] Because this question in the survey allows for free-text responses, grantees choose to report at the tract level in a limited number of cases.

[6] Austin, P.C. (2011). "An introduction to propensity score methods for reducing the effects of confounding in observational studies." *Multivariate behavioral research*, *46*(3), 399–424. https://doi.org/10.1080%2F00273171.2011.568786.

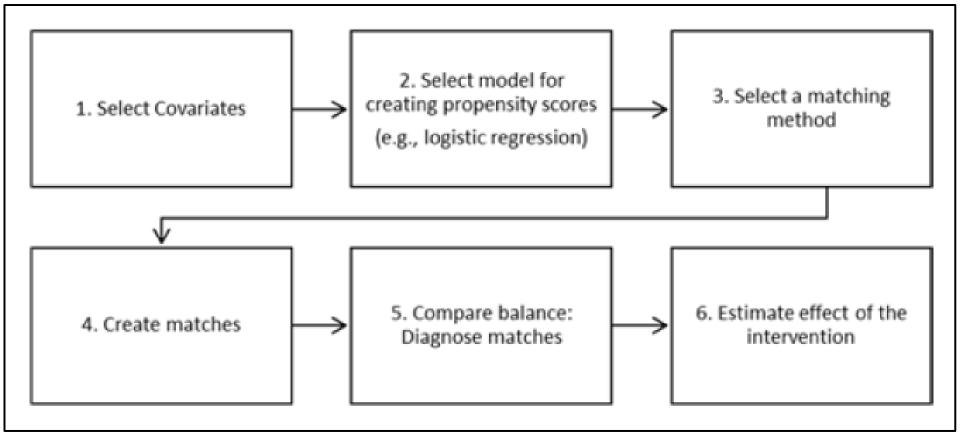

Figure 1: Steps in a PSM process, from Harris and Horst (2016)

Through its first round of analysis, NERRC used several analytical approaches, including a test case and evaluation for equity, recovery, and resilience analyses based on EDA's Investment Priorities. Several preliminary conclusions were drawn. First, based on the research questions and dependent variables selected for this analysis, it was not yet feasible to detect local economy-wide impacts—positive or negative—from EDA CARES Act investments using publicly available data. NERRC identified several key reasons for the lack of detectable impact:

- The size of EDA investments compared to the size of the local economy. On average, EDA investments made up .06% of the size of the local economy as measured by Gross Domestic Product (GDP).
- Not enough time has elapsed since the injury or the treatment to accurately quantify impact from the EDA investment. As of the time of the initial analysis, there were approximately two years-worth of GDP and employment data since the onset of the COVID-19 pandemic. Economic literature supports the notion that it can take years to recover from significant economic shocks or natural disasters.[7,8]
- Currently available third-party economic data, which are most commonly reported at the county level, are not sufficiently granular to detect change at a scale that is commensurate with the EDA investment.
- EDA program data does not provide comprehensive reporting on project activity location or industry activity.

Second, the analysis preliminarily showed that industry-specific impacts from EDA funding may exist. Given the size and purpose of EDA investments, future analysis should, as feasible, focus on more granular analysis that captures the targeted impact of EDA investments.

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[7] Pfeffer, F. T., Danziger, S., & Schoeni, R. F. (2013). "Wealth Disparities Before and After the Great Recession," *The ANNALS of the American Academy of Political and Social Science, 650*(1), 98–123. https://doi.org/10.1177/0002716213497452.

[8] Chang, S. E., & Rose, A. Z. (2021). "Towards a Theory of Economic Recovery from Disasters," *International Journal of Mass Emergencies & Disasters, 30*(2), 171–81. https://doi.org/10.1177/028072701203000202.

Framework Evolution Step 1: 2012 Disaster Supplemental Program Evaluation

EDA's 2012 Disaster Supplemental program data provided an additional opportunity to interrogate, validate, and potentially resolve the lack of sufficient time for impacts to reveal themselves and be recorded by lagging third-party data. To conduct this analysis, NERRC compiled a list of eligible counties using disaster declaration data from the Federal Emergency Management Agency (FEMA) into a dataset of all eligible counties that could have received funding for the 2012 Disaster Supplemental. Disasters declared in Fiscal Year (FY) 2011 (October 1, 2010, through September 30, 2011) were eligible under this appropriation. Based on the available data, 769 individual counties, parishes, or cities across 24 different states were eligible for funding.

NERRC and EDA chose the 2012 Disaster Supplemental awards for several reasons. Although other EDA program data sets with long-term time horizons could have been used to measure impact, the 2012 Disaster Supplemental data allowed for a targeted and manageable test analysis. In addition, the type and nature of the harm that disaster-impacted communities experienced allowed for the possibility of a more detectable measure of injury and potential recovery than other EDA economic assistance programs.

To conduct an analysis that would both validate the PSM methodology for future uses and identify programmatic impact, NERRC collected an additional 10 years of third-party data to contextualize the period of performance of the 2012 Disaster Supplemental (2010–2022) program activities. Third-party data were available for most of the 24 variables used in the initial PSM analysis of the CARES Act, as outlined in Appendix A.

Extending the timeline for evaluation included several important new challenges imposed by data limitations as outlined below.

Designated Coal Communities: While most historical measures were easy to capture, identifying designated coal communities dating back to 2012 was more challenging. For the original Effectiveness Framework analysis, NERRC derived Coal Community designations from the White House's *The Interagency Working Group on Coal and Power Plant Communities and Economic Revitalization* report, published in January 2021. However, no published data source exists that aggregates coal plant retirements and coal mine abandonments at the county level dating back to 2012. In an effort to replicate the coal community methodology, NERRC developed a procedure using geospatial analysis to take third-party data on recorded instances of coal plant closures or retirements and coal mine abandonments and determine a county's coal community designation status. More details on this procedure are outlined in Appendix B. Coal community designation is a composite metric including two factors:

- Direct coal-sector jobs / total employment, and
- A distance less than 200 kilometers (km) from a coal mine or coal power plant.

County Economic Impact Index (CEII): Argonne's CEII, which measures change in county GDP and industry value added, posed similar timeframe challenges. The CEII, originally designed to estimate the change in overall county-level economic activity during the COVID-19 pandemic relative to a January 2020 baseline, did not have results that pre-dated the pandemic. Rather than recreating the CEII and setting a new baseline for this analysis, NERRC used Bureau of Economic Analysis (BEA) data to estimate change in county GDP year-over-year.

Internet Access Index: The Argonne-developed Internet Access Index is derived from 2019 and 2020 data. Due to lack of long-term data availability, NERRC removed this metric as a variable.

NERRC added some measures to the matching variables due to their incorporation of time considerations within their measurements. These included new growth rate variables from the BEA that incorporate inflation and compounding into their calculations, such as Five-year % Growth of the Population, Five-Year % Growth Per Capita Income, and Five-Year % Growth of Real GDP.

Across all measures, the analysis of the 2012 Disaster Supplemental awards produced similar results to the initial Effectiveness Framework PSM analysis. Specifically, NERRC was unable to detect impact from EDA disaster supplemental awards using third-party data. Although this analysis sought to understand whether longer time horizons for impact signals to emerge in the data, the two other confounding factors remained:

- The size of the award relative to the totality of economic activity makes discerning a specific effect using these measures unlikely; and
- The geographic scale of the publicly available economic data is well aligned with the scale and scope of the traditional EDA investment.

Results of the 2012 Disaster Supplemental analysis are in Appendix C.

Framework Evolution Step 2: Reduced PSM Model Matching Variables

After evaluating the results of the 2012 Disaster Supplemental analysis, NERRC implemented several revisions to the PSM methodology. The motivation behind this process was to reduce potential noise from the variables and to streamline the PSM, more directly weighing key features the stakeholders were interested in to define matched counties. The initial PSM analysis used a list of 24 covariates to match the initial counties. The set of variables included population demographics, geographical indicators, and other economic indicators. Although the PSM successfully found matches using this method and set of covariates, upon manually reviewing paired matches, the NERRC team assessed that paired counties were not adequate for further analysis and required refinement. NERRC implemented a more focused selection of covariates to match counties that could be considered more reasonable matches for stakeholders.

NERRC iteratively reduced the list of covariates until the resulting matches appeared to return comparable communities closer to expectation.

The final list of variables is detailed in Table 2 and Appendix A.

Table 2: Final List of Covariates Selected for PSM Analysis

Variable	Description	Data Source	Dataset Year
5-Year % Growth Population	Compound annual growth rate of population from 2007-2011.	BEA	2007-2011
5-Year % Growth Real GDP	Compound annual growth rate of real GDP from 2007 to 2011.	BEA	2007-2011
Log of GDP Per Capita	Log transformed real GDP in chained 2012 dollars per person in a county.	BEA	2007-2011
Population	Number of persons in a county.	2007-2011 Census ACS	2007-2011
Log of Per Capita Income	Log transformed per capita income for the county.	2007-2011 Census ACS	2007-2011
% Between Age 18 and 64	Number of persons between the age of 18 and 64 as a percentage of total persons in a county.	2007-2011 Census ACS	2007-2011
% Minority	The sum of percent Hispanic of any race, percent Black/African American non-Hispanic, percent Native Hawaiian/Other Pacific Islander non-Hispanic, percent American Indian/Alaskan Native non-Hispanic, percent Asian non-Hispanic, percent some other race non-Hispanic, percent two or more races non-Hispanic.	2007-2011 Census ACS	2007-2011
% Greater than High School Education	The sum of the number of persons with at least some college education (associate degree, bachelor's degree, or a graduate or professional degree) as a percentage of the population.	2007-2011 Census ACS	2007-2011
Average Local 24-Month Unemployment Rate	The average unemployment rate for the civilian population 16 and greater years old over the past two years.	Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics	2007-2011
Population Density (2010)	The total population or number of housing units within a geographic entity divided by the land area of that entity in square miles.	U.S. Census Bureau	2010

NERRC analyzed the CARES Act and the 2012 Disaster Supplemental award data using revised PSM methodology with reduced variables. In both cases, across all outcome metrics, NERRC was unable to detect impacts from EDA investments using third-party data.

Framework Evolution Step 3: Incorporating New Methods

NERRC evaluated several additional causal inference methods for possible incorporation into the Effectiveness Framework. Ultimately, NERRC selected synthetic control as the most appropriate method to compliment PSM, as well as other elements of the framework. Synthetic control was first introduced into the economic research domain 2003. Since then, it has become an applied econometrics and program evaluation staple in cases where randomized controlled trials are not possible and observational data must be used instead.[9,10] When working with observational data, one must adjust for

[9] Abadie, A., & Gardeazabal, J. (2003, March). "The Economic Costs of Conflict: A Case Study of the Basque Country." *American Economic Review, 93*(1), 113–32. https://doi.org/10.1257/000282803321455188.
[10] Abadie, A., & Cattaneo, M. D. (2018). "Econometric Methods for Program Evaluation." *Annual Review of Economics, 10.* https://doi.org/10.1146/annurev-economics-080217-053402.

differences in the units of analysis that might account for their different outcomes. With a proper set of statistical adjustments, making causal claims from observational data is possible.

Synthetic control specifically enables researchers to create counterfactual scenarios by combining statistical adjustment with weights assigned to a group of units that were not given the treatment or policy under study.[11] This weighting approach is one of the key differences between synthetic control and PSM, which treats each of the covariates as equal. For a given dependent variable (i.e., outcome indicator), the synthetic control aims to reproduce that outcome indicator's trend, prior to the onset of treatment or change in policy, for each unit that was subjected to the treatment or policy. This goal is accomplished by using statistical adjustments as in traditional regression analysis, in combination with a unique weighting of the untreated units. The result of this approach is a "synthetic" (or weighted) control unit, for each treated unit, that consists of a unique weighting of untreated units and the statistical adjustments of covariate data. Ultimately, this results in one counterfactual "synthetic" control scenario for each treated unit that consists of a weighted average of the untreated units. Finally, the causal impact of the treatment or policy under study is the difference between the treated unit's post-treatment trajectory and the "synthetic" control's post-unit trajectory, averaged across all treated units. This difference is an estimate of what would have happened to the treated units in the absence of treatment.

The structure of synthetic control approach allows researchers to detect causality as either a positive outcome that would otherwise not have occurred, or the avoidance of a negative outcome that otherwise would have occurred. The case where a treatment caused a positive outcome that otherwise would not have occurred might look like the notional results in Figure 2. The post-treatment trajectory (after 20 time-units) of the synthetic control shows that, in the absence of treatment and as denoted by the "synthetic control" unit, the treated unit would have maintained pre-treatment levels. However, the treated unit experience significant growth after the onset of treatment, and the difference between the treated unit's outcome and the untreated unit's outcome is large and positive.

[11] Abadie, A., Diamond, A., & Hainmueller, J. (2010). "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association 105*(490), 493–505. https://doi.org/10.1198/jasa.2009.ap08746.

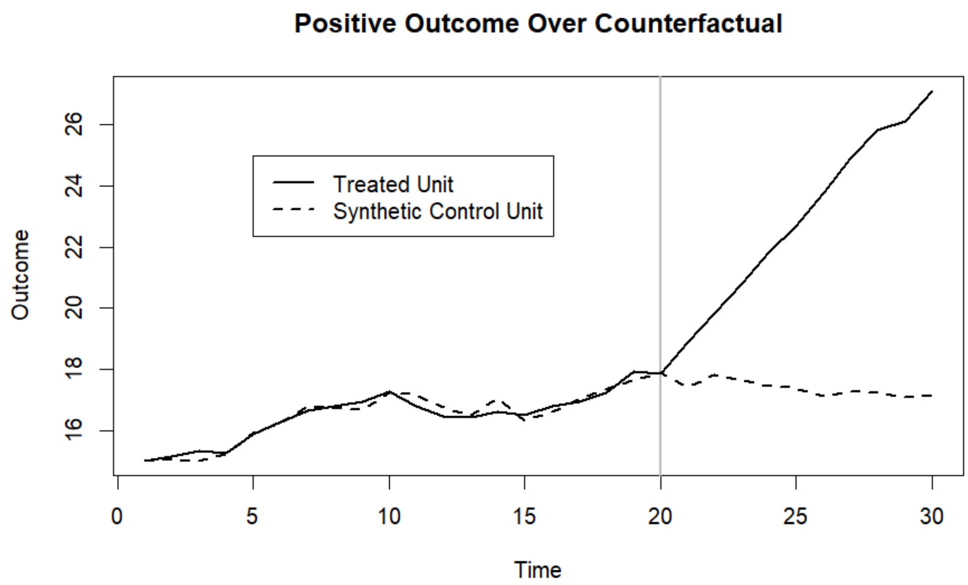


Figure 2: Example positive outcome over a counterfactual using synthetic control

A different situation might occur where the treatment prevents a negative outcome that otherwise might occur. A graph visualizing this case might look like Figure 3.

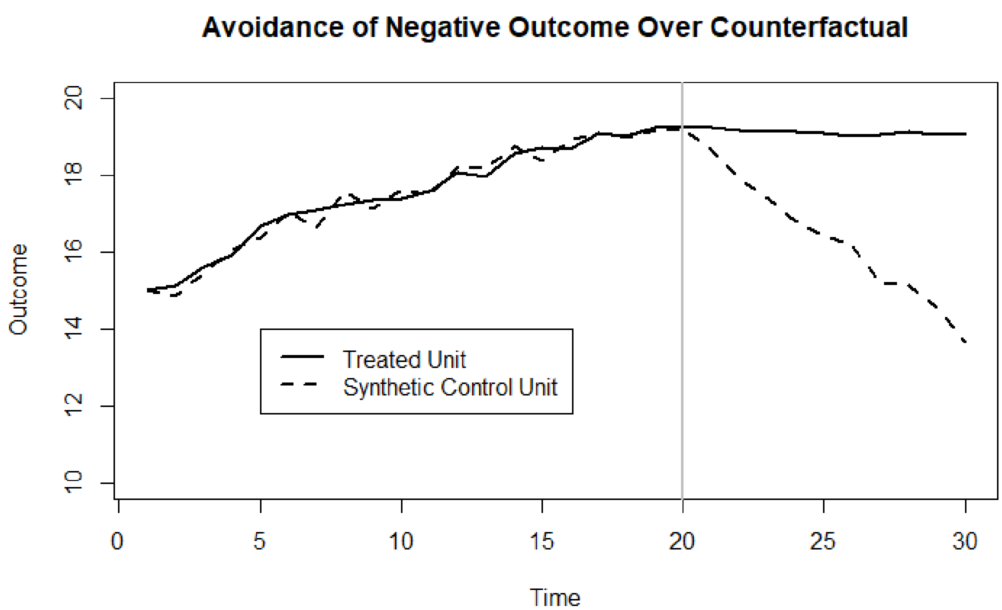


Figure 3: An example of an avoided negative outcome over a counterfactual

Here, the post-treatment trajectory of the synthetic control unit indicates that in the absence of treatment, the treated unit would have experienced a negative outcome. However, the treated unit maintained its pre-treatment level of the outcome indicator, and so the difference between the treated and untreated unit is, again, large and positive. Because the synthetic control estimates the difference between the treated and untreated units, the two cases presented above would both appear as a positive difference between the treated unit and its counterfactual.

Synthetic Control, PSM, and Other Methods

Synthetic control is similar to other causal inference techniques such as PSM and difference-in-differences (DiD), which both seek to establish valid counterfactuals and allow for causal interpretations of results. PSM is a static approach that estimates each unit of analysis's probability of receiving treatment to identify pairs of units that are most similar. If each treated unit can be matched to a similar (but untreated) unit, then comparing treated units to their matched counterparts can approximate the randomization that occurs in a randomized controlled trial. Drawing conclusions on the causal impact of a treatment or policy would then be valid.

PSM has several key limitations, which inform the types of analytical questions that it is most appropriately suited for. First, application of PSM to generic program evaluation questions may result in biased estimates of causal impact.[12] Second, PSM may be most helpful in situations where a large degree of imbalance, or difference in covariates, exists between the treated and untreated units. Well-balanced datasets are typical of large, randomized control trials, and can allow for simpler statistical comparisons because baseline conditions are already similar, or balanced, between the treatment and control groups. In these cases, using PSM to match treatment and control groups is likely unnecessary and may introduce statistical bias into the model. On the other hand, in observational studies such as this analysis, baseline conditions in treatment and control groups are likely to be systematically different from one another, causing imbalance in the data. In such cases, PSM can effectively reduce the imbalance between the treatment and control groups, allowing analysts to combine PSM with techniques such as regression modeling to generate valid causal estimates.

In the context for the CARES Act non-infrastructure awards, counties that received EDA grants are systematically different from those that do not. As such, the research team determined that PSM is one useful methodology for the Effectiveness Framework. However, even in cases where imbalance in the covariates exists, there is no guarantee that PSM will be able to find valid matches for some or all treated units, in which case the model may return poor estimates of the causal impact. Finally, PSM is not designed to detect causal impact over time, which limits its usefulness in contexts that involve longer timeframes. To address PSM's shortcomings in detecting impact over time, NERRC employed the DiD technique in combination with PSM for the 2012 Disaster Supplemental analysis.

DiD offers a dynamic framework for estimating causal impacts. The DiD approach estimates the average change in the difference between treated and untreated units' outcome indicator over a period of time. Much like the PSM, DiD can adjust for pre-treatment (i.e., baseline) differences between the treated and untreated units, but DiD can also adjust for pre-treatment differences in the outcome indicator. By combining PSM and DiD, NERRC was able to compare trends in outcome indicators over time between

[12] King, G., & Nielsen, R. (2019, October). "Why Propensity Scores Should Not Be Used for Matching." *Political Analysis, 27*(4), 435–54. https://doi.org/10.1017/pan.2019.11.

counties matched through the PSM. However, for DiD to produce valid causal estimates, researchers must assume that the pre-treatment difference between the outcome indicator for the treated and control units would remain the same had no treatment been administered. In the econometrics literature, this supposition is called the "parallel trends assumption" because it assumes that outcome trends for treated and untreated units would be parallel in the absence of treatment.[13] In cases where the PSM produced reliable matches between counties, the parallel trends assumption may be plausible. However, when the matches are not reliable, the assumption becomes increasingly suspect.

Like PSM and DiD, synthetic control adjusts for pre-treatment differences in the covariates of treated and untreated units. And like DiD, the synthetic control also adjusts for pre-treatment differences in the outcome variable between the treated and untreated units. Unlike DiD, synthetic control does not require the "parallel trends assumption" and can adjust for post-treatment differences through the weighting scheme.[14]

Synthetic Control Analysis Outcome

Through the application of the synthetic control methodology to the CARES Act non-infrastructure awards, NERRC was unable to detect impact from EDA programmatic activity across any of the metrics used. While the synthetic control approach can serve as a robust methodology for causal inference, it cannot solve or mitigate the identified data challenges due to limited geographic granularity, short post-award durations to detect impact, and the small size of grant awards relative to county-level economies. Moreover, the EDA Logic Model specifically focuses on economic development and development capacity, which are multi-faceted phenomena and can be difficult to quantify. Because directly measuring a community's level of economic development capacity is challenging with publicly available data, NERRC used proxy indicators. While not direct measures, these proxy indicators are representative of possible outcomes in the capacity areas outlined in the EDA Logic Model.

The use of the additional, robust methodology further demonstrated that a mismatch likely exists between the types of non-infrastructure awards EDA makes, and the county-level, nationally available, open, and accessible data that were used to estimate the impact of those awards.

Detailed results of the synthetic control analysis are outlined in Appendix D.

Grant Intensity Analysis

Detecting a causal impact from EDA grants on a community's economic development or development capacity requires considering what size of an effect might be expected. Expected impact is, in part, a function of the grant size relative to the county's baseline economic activity. Table 3 describes different quantiles of EDA grant award size compared to a county's GDP in the year of the award, broken out by EDA grant activity type.

[13] Angrist, J. D., and Pischke, J. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press. Pp. 227-43.
[14] Abadie, A. (2021, June 1). "Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects." *Journal of Economic Literature, 59*(2), 391–425. https://doi.org/10.1257/jel.20191450.

Table 3: Grant Intensity by Outcome Category

Outcome Category	Percentile	50th (median)	75th	90th	99th
Markets and Networks	Total Grant $ / GDP (%)	0.016%	0.055%	0.131%	0.387%
Innovation, Technology Transfer, and Commercialization	Total Grant $ / GDP (%)	0.016%	0.051%	0.116%	0.376%
Product, Production and Business	Total Grant $ / GDP (%)	0.016%	0.058%	0.118%	0.513%
Financing and Investment	Total Grant $ / GDP (%)	0.016%	0.055%	0.131%	0.387%
Human Capital and Workforce	Total Grant $ / GDP (%)	0.017%	0.046%	0.132%	0.470%
Organizational Capacity	Total Grant $ / GDP (%)	0.018%	0.061%	0.149%	0.485%

For most activity types, approximately 90% EDA grant awards totaled less than 0.1% of a county's GDP. Given such small investments relative to a county's baseline economic activity, even large relative impacts will be small in absolute terms and therefore difficult to detect. For instance, if an EDA grant has a five-fold positive impact relative to grant award, and the grant award is 0.1% of county GDP, the impact would be a 0.5% increase in a county's GDP. However, in any given year a county's GDP might change by 2% or more, making it difficult to detect a grant-induced impact given the inherent variation in the outcome indicator.[15]

Analytical Challenges and Limitations

The goal of NERRC's program evaluation effort is to use third-party, openly available data that are consistently reported to detect a measurable impact from EDA CARES Act non-construction awards in communities across the county. While using third-party, openly available data has several advantages, such as reproducibility and transparency, the data also have a limited viable geographic scope due to many economic indicators being reported at county level. While the government does collect similar data at the tract, firm, or even household level, those data are suppressed or restricted to protect privacy, meaning that researchers must have approved use cases and cannot share raw data. Specific methodological challenges are discussed in detail below.

Data Granularity

Compounding the issue of low grant intensity relative to a county's baseline level of economic activity is the generally low geographic fidelity of publicly available economic data. For the statistical methods NERRC employed to detect impact, data are required on a consistent and regular basis. Most continuously available open-source government data sets are available at the county level or at higher geographic aggregations. For example, the ACS only publishes a subset of indicators at the census tract level alongside the county-level data in the five-year estimates. In addition, the five-year estimates

[15] Derived from Bureau of Economic Analysis Regional Dataset: Bureau of Economic Analysis, "Regional Dataset - CAGDP1 Table," Retrieved from https://apps.bea.gov/API/.

themselves are running five-year averages as opposed to single-year estimates. Some of the indicators NERRC used as outcome variables, such as patents, are available at the address level and can easily be mapped to counties, while others such as Small Business Administration loans are available at the ZIP code level and are subsequently cross-walked to the county level. ZIP code to counties crosswalks exist, but they are not perfect: ZIP codes do not always align cleanly with county boundaries, highlighting some challenges in using open-source government data.

While the analyses presented here use counties as the unit of analysis, counties are highly variable in size and composition. For instance, the largest county in the United States is Los Angeles County, California, which has a population of 10 million people and a GDP of more than $600 billion. The smallest county in the United States is Kalawao County, Hawaii, with a population of fewer than 100 residents. The disparities in size, economic diversity, and industry composition between these two counties illustrate the challenges of treating all U.S. counties as similar units from the same underlying population.

Moreover, the economies of larger counties such as Los Angeles County or New York County are large, diverse, and highly connected to international markets and networks. This has several consequences when building statistical models to detect impact. First, the covariates that adjust for baseline economic conditions in large and diverse counties are systematically different from smaller counties. Second, counties such as Los Angeles County or New York County will require significantly larger EDA investments to result in statistically significant results due to their baseline level of economic activity. As an example, consider New York County, with a GDP of nearly $900 billion, much of which is connected to international real estate and financial markets. The entirety of EDA's CARES Act funding, $1.5 billion, is less than 0.2% of New York County's GDP.

Finally, the EDA ED-916 form, which provided the data on individual grant awards used in this analysis, records only a single Project County. This is typically the administrative location of the grant recipient. However, the form does not include details about the specific geographic area where the project work is actually performed. In some cases, grantees might report the county where the work is being conducted, but the provided data do not allow for a distinction between the administrative location and the performance location, nor do they reveal the full geographic scope of the work. While more geographic specificity in the ED-916 would help, a comprehensive statistical analysis of the impact of EDA grants would require that all variables be on the same geographic scale, including the data sourced from the ACS, BLS, BEA, and other open-source government data sets.

Several potential long-term opportunities are available to address these limitations. First, improved geographic and industry-specific EDA grant data may help researchers to pinpoint what areas and aspects of the economy are most likely to be addressed. Second, this challenge may be partially remedied by leveraging data sources such as U.S. Census Bureau microdata. However, using microdata would require specific approvals and would have limit the ability to publish reproducible results.

Time Since Award

The short duration since EDA awarded CARES Act grants and the varying time frames on which impact could be expected present additional analytic challenges.[16] Many of the outcome indicators NERRC used in this analysis are published with a two-year lag. For example, the firm exit rate, published as part of the Census Bureau's Business Dynamic Statistics is published at a near two-year lag. As a result, data for this specific indicator was only available through 2021. Figure 4 displays the timeline of cumulative grant awards for the subset of grants considered in this study.

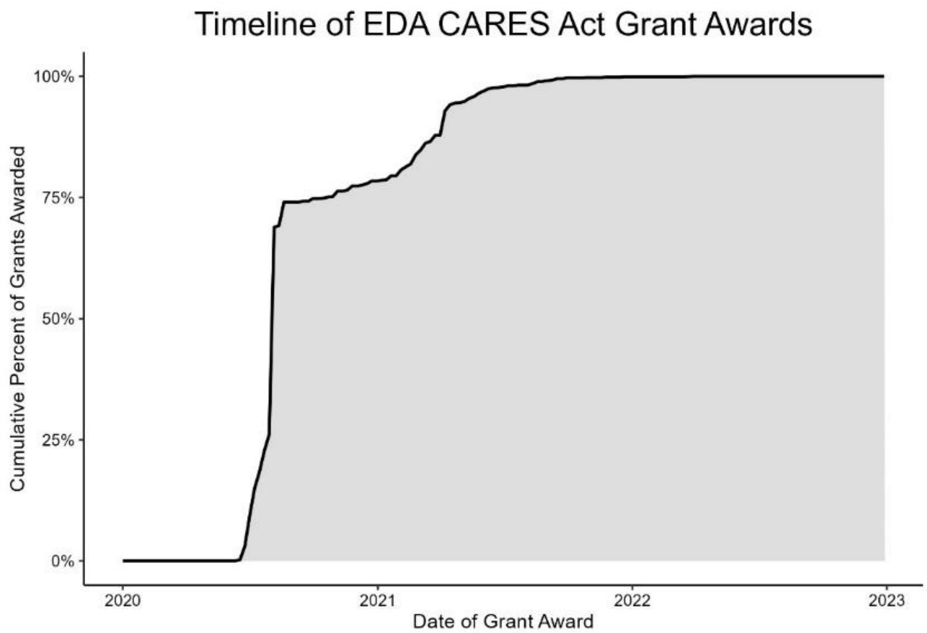


Figure 4: Cumulative percent of grants awarded over time

For some grants, additional timing issues may be present related to when the grant work occurs. Many grants fund work that takes months to plan, such as networking events with industry partners in a local community. Other types of grant work might consist of work that continues for months or years, and for which the full impact of the grant may only materialize toward the end of the work performance period. In other cases, the grant work may be accomplished quickly but the effect does not materialize for some time. One example of such a phenomenon is commercialization support for acquiring patents, where the average wait-time for a patent to be issued is nearly three years.[17]

This specific limitation could potentially be mitigated in several ways. First, more in-depth engagement with grantees to understand and document how specific grant-funded activities translate into on-the-

[16] For example, Grant et al (1995) study supply-side economic development policies over a 15-year period, from 1970-1985: Don Sherman Grant, D. S., Wallace, M., & Pitney, W. D. (1995). "Measuring State-Level Economic Development Programs, 1970-1992," *Economic Development Quarterly, 9*(2), 134–45. https://doi.org/10.1177/089124249500900203.

[17] Gergen, J. (2022, January 10). "How Long Is the Patent Process (From Start to Finish)?" *Gerben.* Retrieved from https://www.gerbenlaw.com/blog/how-long-is-the-patent-process-from-start-to-finish/.

ground outcomes could better inform what outcome indicators are selected in future evaluations. Furthermore, careful study of outcomes of specific grants could help to determine modeling approaches that could be used in tandem with observational techniques to assess impact in the period immediately after award.

Low CARES Act Grant Intensity Relative to County-level Economic Activity

Many EDA grants are a small fraction of a county's economic activity. In these cases, it is not feasible to anticipate a grant totaling less than 0.1% of a county's GDP will be able to measurably influence county-wide macro-economic outcomes. Smaller grants are still likely to have an impact at a microeconomic level; however, detecting impact will require more granular data and a more precise understanding of how and where the funds are directed (e.g., sub-county geography, specific industries addressed).

Conclusion and Possible Future Directions

Conducting impact assessments for EDA non-infrastructure grants, in line with standards outlined in the Foundations of Evidence-Based Policymaking Act of 2018, presents a series of methodological challenges as outlined in this report. Generally, non-infrastructure grants are small relative to the size of the local economy in which they are directed. Publicly available data that can be used to assess impact is most commonly available at the county level, further compounding the issue of low grant intensity relative to the economy. Finally, for awards that have been made in recent years, it may take time for the impact of the grant to be observable in data.

Through two rounds of evaluation, NERRC has employed three different causal inference methods to attempt to detect impact from EDA CARES Act non-infrastructure investments. To date, however, NERRC has been unable to detect an impact. This result does not indicate that EDA investments have had no impact. Rather, the statistical methods and publicly available data currently available are not yet sufficient to detect impact. Based on these findings, NERRC has identified several additional pathways that can be taken to mitigate some of these challenges and better position EDA to conduct future impact assessments for its non-infrastructure grant programs.

Develop More Specific Theories of Program and Activity Success

The theoretical framework underpinning the statistical analysis is the EDA Logic Model. Further refinement of the logic model, to include more explicit connections between allowable grant activities and capacity outcomes, will allow researchers to generate additional specific and testable hypotheses. Tighter logical connections between grant activities and capacity outcome indicators can help the program evaluation framework by moving away from testing proxy variables, which are inherently more noisy and therefore more difficult to attribute causal impact to. As EDA develops new grant programs and new grant activities, further evolution of the logic model to incorporate those new programs and activities is an important first step to measuring their impact.

A community's state of economic development or capacity to engage in economic development is multi-faceted and difficult to directly observe. This analysis mapped proxy indicators to grant activities using the Logic Model as a starting point. Further development of the Logic Model could tighten the logical connections between grant activities and expected outcomes and measures of success, which in turn can help generate specific testable hypotheses.

Accurate and reliable measurements of outcomes are the single most important aspect of any statistical analysis. But the outcomes studied in this study are typically proxies; they are intended to represent potential outcomes from EDA's programs, rather than measuring the outcomes directly. Proxies, by nature, are subjected to additional factors other than the underlying outcome that they represent. This means that proxy data are likely to be noisy, and any statistical methodology will struggle to reliably detect impact with that level of noise. As an example, consider the establishment exit rates, which can be used a proxy indicator for Product, Production, and Business outcomes. A county's aggregate firm exit rate is influenced by many factors, from global financial conditions to regional economic cluster interactions to seasonal affects. These systemic factors can exert significant influence over an establishment's choice to exit the market, and they may vary significantly over time.

Distinguish Between Program Impact and Effectiveness

This study focused on measuring the impact from EDA grants on county-level economic development indicators. A second but equally important subject to study would be program effectiveness. If impact is determined as the ultimate effect of a grant program, effectiveness is focused on the program successfully achieving its stated objectives. Impact is often included in program effectiveness, but effectiveness includes topics beyond impact. For example, program effectiveness analysis might seek to answer questions such as,

- Did the program reach its targeted population?
- Were grant awards disbursed in a timely and equitable manner?
- Did the grant activities cover the most urgent needs of the target population?

Studies that dive more deeply into EDA grant program effectiveness would complement impact analyses such as those conducted here. For effectiveness studies to be successful, it will also require a clear articulation of program objectives—beyond EDA's investment priorities—that informed the design, award, and implementation of those programs.

Capture More Precise Geographic and Industry-level Grant Data

One data quality challenge highlighted in this report is how the ED-916 survey attributes a grant to a geographic location. Although each grant has county FIPS code associated with it, feedback from EDA subject matter experts suggested that location is most commonly attributed to where the awarded organization is based. However, grantees frequently perform work in counties other than the one listed on the ED-916 form, or the grantee performs work in multiple counties.

To produce accurate impact assessments, ensuring that project location data be as accurate and comprehensive as possible is critical. EDA has already begun implementing new technology to improve the grant data-collection process. Ensuring that precise geographic information is being entered by grantees moving forward is crucial to future program evaluation work. Similarly, collecting more comprehensive data on the industries that each grant award covered, for example using the NAICS codes, would add a second dimension of granularity that is currently unavailable.

Explore Additional Analytic Methods

To further enhance the broader program evaluation effort, additional analytic methods, including case studies approach and modeling could supplement existing observational techniques. These methods offer valuable potential insights into the effectiveness and impact of EDA grant programs.

A case study approach would involve in-depth examination of specific instances or cases where EDA grant programs have been implemented. This method allows for a detailed exploration of the context, processes, and outcomes associated with individual grants or projects. By selecting a diverse range of case studies representing various program types, geographic regions, and economic contexts, EDA can gain a comprehensive understanding of program implementation and its effects on local economic development. Case studies provide rich qualitative data, enabling researchers to identify patterns, success factors, and challenges associated with different grant initiatives. Moreover, they offer opportunities for stakeholder engagement and capturing perspectives from grant recipients, local communities, and other relevant actors involved in program implementation. Case studies can inform and improve statistical analyses, such as those undertaken in this work, by providing qualitative information not captured in numerical data.

Modeling techniques can complement traditional statistical analysis by providing a systematic framework for simulating and analyzing the complex relationships between grant activities, economic indicators, and capacity outcomes. Building on the existing EDA Logic Model, modeling, and simulation approaches such as structural equation modeling or agent-based modeling can help elucidate the causal pathways and mechanisms through which grant interventions influence economic development outcomes. By formalizing the underlying assumptions and pathways within the Logic Model into quantitative models, researchers can test hypotheses, predict outcomes, and assess the relative importance of different program components. Furthermore, modeling approaches allow for scenario analysis and sensitivity testing, facilitating a deeper understanding of the potential impacts of alternative policy interventions or program designs. Modeling can also help to estimate impacts in the immediate years after a grant award, when causal inference methods may be more challenging.

Incorporating both case study and modeling approaches into the program evaluation framework will enrich the analysis and provide complementary perspectives on the effectiveness and impact of EDA grant programs. By triangulating findings from diverse methods, EDA can generate robust evidence to inform program design, decision-making, and resource allocation, ultimately enhancing the agency's capacity to promote economic development and prosperity across communities nationwide.

Appendix A: Propensity Score Matching Variables

Appendix A provides the list of original PSM matching variables used in the first CARES Act Effectiveness Framework report (September 2022) as well as the list of reduced variables used in this report.

Table 4: Original Effectiveness Framework PSM Matching Variables

Metric	Metric Description	Data Source	Dataset Year
Log of Population	Log transformed number of persons in a county.	2015–2019 American Community Survey (ACS)	2015–2019
Log of Per Capita Income	Log transformed per capita income for the county.	2015–2019 ACS	2015–2019
Log of Gross Domestic Product (GDP) Per Capita	Log transformed real GDP in chained[90] 2012[91] dollars per person in a county.	U.S. Bureau of Economic Analysis (BEA)	2015–2019
Percent Between Age 18-64	Number of persons between the age of 18 and 64 as a percentage of total persons in a county.	2015–2019 ACS	2015–2019
Percent Minority	The sum of percent Hispanic of any race, percent Black/African American non-Hispanic, percent Native Hawaiian/Other Pacific Islander non-Hispanic, percent American Indian/Alaskan Native non-Hispanic, percent Asian non-Hispanic, percent some other race non-Hispanic, percent two or more races non-Hispanic.	2015–2019 ACS	2015–2019
Percent with Greater Than a High School Education	The sum of the number of persons with at least some college education (associates degree, bachelor's degree, or a graduate or professional degree) as a percentage of the population.	2015–2019 ACS	2015–2019
Percent without Health Insurance	The number of persons without health insurance as a percentage of the population.	2015–2019 ACS	2015–2019
Average Local 24-Month Unemployment	The average unemployment rate for the civilian population 16 and greater years old over the past two years.	Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics	2017–2019
Average Internet Access Index Value	The average of the household internet access value across census tract level within a county.	Argonne Internet Access Index	2019
Population Density	The total population or number of housing units within a geographic entity divided by the land area of that entity.	U.S. Census Bureau	2010
Percent Rural	Number of persons not included within an urban area of 50,000 or more people as a percentage of total population.	U.S. Census Bureau	2010
Percent Employed by Farm Sector	Number of persons full-time or part-time employed in the farm sector as a percentage of total employment.	BEA	2019
Percent Employed by Military Sector	Number of persons full-time or part-time employed in the military sector as a percentage of total employment.	BEA	2019

Metric	Metric Description	Data Source	Dataset Year
Designated Coal Community	Designation by the White House interagency group report as a coal community. Coal communities are those identified hard-hit by declines in coal production and consumption. These geographies are vulnerable to economic distress as coal power plants and coal mines close within their areas.	Initial Report to the President on Empowering Workers Through Revitalizing Energy Communities, National Energy Technology Laboratory, April 2021	2019
Nuclear Power Plant Present	An indicator of whether a nuclear power plant is located within a county.	Nuclear Decommissioning Collaborative	2019
Tribal Land Adjacent	An indicator of whether the county is located adjacent to any federally recognized tribal lands.	U.S. Census Bureau	2019
Persistent Poverty Indicator	An indicator of whether the county is in a persistent state of poverty. A persistent state of poverty is calculated as counties that have had poverty rates of 20% or greater for at least 30 years.	U.S. Economic Development Administration (EDA)	2019
Miles to Closest Metropolitan Statistical Area (MSA) (Any)	The number of miles a county is located from a MSA of any population size.	National Bureau of Economic Research County Distance Database	2019
Miles to Closest MSA (250,000 Population)	The number of miles a county is located from a MSA of population size 250,000.	National Bureau of Economic Research County Distance Database	2019
Miles to Closest MSA (500,000 Population)	The number of miles a county is located from a MSA of population size 500,000.	National Bureau of Economic Research County Distance Database	2019
Number of Disasters from five Years Prior	The total number of major disaster declarations by the Federal Emergency Management Agency (FEMA) in the past five years.	FEMA	2014–2019
Amount of Federal Grant Dollars per Capita	The total amount of federal grant funding dollars excluding EDA grant funding per person within a county.	USASpending.gov	2019

Table 5: Revised PSM Matching Variables

Variable	Description	Data Source	Dataset Year
5-Year % Growth Population	Compound annual growth rate of population from 2007-2011.	BEA	2007–2011
5-Year % Growth Real GDP	Compound annual growth rate of real GDP from 2007-2011.	BEA	2007–2011
Log of GDP Per Capita	Log transformed real GDP in chained 2012 dollars per person in a county.	BEA	2007–2011
Population	Number of persons in a county.	2007–2011 Census ACS	2007–2011
Log of Per Capita Income	Log transformed per capita income for the county.	2007–2011 Census ACS	2007–2011

Variable	Description	Data Source	Dataset Year
% Between Age 18 and 64	Number of persons between the age of 18 and 64 as a percentage of total persons in a county.	2007–2011 Census ACS	2007–2011
% Minority	The sum of percent Hispanic of any race, percent Black/African American non-Hispanic, percent Native Hawaiian/Other Pacific Islander non-Hispanic, percent American Indian/Alaskan Native non-Hispanic, percent Asian non-Hispanic, percent some other race non-Hispanic, percent two or more races non-Hispanic.	2007–2011 Census ACS	2007–2011
% Greater than High School Education	The sum of the number of persons with at least some college education (associate degree, bachelor's degree, or a graduate or professional degree) as a percentage of the population.	2007–2011 Census ACS	2007–2011
Average Local 24-Month Unemployment Rate	The average unemployment rate for the civilian population 16 and greater years old over the past two years.	BLS Local Area Unemployment Statistics	2007–2011
Population Density (2010)	The total population or number of housing units within a geographic entity divided by the land area of that entity in square miles.	U.S. Census Bureau	2010

Appendix B: Coal Communities Methodology

This appendix outlines the specific steps the National Economic Research and Resilience Center used to identify coal communities in the 2012 disaster supplemental analysis.

Step 1: Data Collection

1.1. Begin by accessing the provided data. Ensure you have the following files:

Excel table named "coal_communities_2011.xlsx"
Crosswalk named "MSA_NonMSA_County_2011_nodups"
Shapefile: coal_mines_abandoned_2005_2020.shp
Shapefile: coal_PP_retired_2005_2020.shp

1.2. These datasets were downloaded on 4/14/2023 via NHGIS and include the following:

2010 county boundary
2010 places boundary
2011 CBSA MSA boundary

Step 2: Prerequisites Check

2.1. Ensure that the "coal_communities_2011.xlsx" contains 298 records.

2.2. Note that these records consist of both Metropolitan Statistical Area (MSA) boundary records and non-MSA boundary records.

2.3. Pay attention to two specific fields:

"area_title" – a text-based name of the area
"area" – a numeric identifier

2.4. Verify that when joining by the "area" field, 247 records precisely match the 2011 MSA Boundary files, while 151 records do not match and require further investigation.

Step 3: Methodology Execution

3.1. Use the crosswalk spreadsheet to handle non-MSA boundary records within the "coal_communities_2011" spreadsheet.

3.2. Note that it contains a field named "NewGeo," representing the county, city, village, town, parish, etc., most aligned with the non-MSA boundary.

3.3. Recognize the one-to-many relationship between the non-MSA boundary record and the various counties, cities, etc., it aligns with.

3.4. Understand that the crosswalk contains 5,165 unique records.

3.5. Create primary keys to match non-MSA boundary records with their corresponding "NewGeo" entries.

3.6. Remove records corresponding to MSA areas already matched, leaving 3,471 unique records.

3.7. Compare the crosswalk with the 2010 county file, creating a new field "concat" and matching 1,691 records, representing 124 of the initially non-matched 151 records.

3.8. Dissolve matched records on the primary key, leaving 27 unmatched records from the initial spreadsheet.

3.9. Compare the crosswalk with the 2010 place file, creating a new field "concat" and matching 133 records, representing 22 of the initially non-matched 151 records.

3.10. Dissolve matched records on the primary key, leaving eight unmatched records from the initial spreadsheet.

Step 4: Coal Communities Buffer

4.1. Create a 200-kilometer (km) buffer around the provided shapefiles:

coal_mines_abandoned_2005_2020.shp
coal_PP_retired_2005_2020.shp

4.2. Use the "select by location" tool to identify places, counties, or MSAs intersecting with the buffers.

4.3. Assign values:

Within 200km of a CoalMine: 0 = no, 1 = yes
Within 200 km of a CoalPP: 0 = no, 1 = yes

Appendix C: 2012 Disaster Supplemental Results

This appendix describes the outcome of National Economic Research and Resilience Center's (NERRC's) analysis of U.S. Economic Development Administration's (EDA's) 2012 Disaster Supplemental awards. For this analysis, NERRC propensity score matching (PSM) to estimate impacts from 2012 Disaster Supplemental awards. NERRC used the following outcome indicators to evaluate impact from 2012 Supplemental investments:

Indicator	Source
Gross Domestic Product (GDP) Indexed to 2010	Bureau of Economic Analysis CAGDP9 Table
Job gain rate	Census Bureau Quarterly Workforce Indicators (QWI)
Job Loss Rate	Census Bureau QWI
Employment growth	Census Bureau QWI
Earnings growth	Census Bureau QWI

NERRC used two regression models for each matching method: one without variables and one with. Across the five outcome variables, one showed a negative statistically significant result to the 95% confidence level. This was removed after including covariates.

All Industries Regression Results for 2012 Disaster Supplemental

	Generalized - NN	Generalized - NN Covariates	Generalized - Full	Generalized - Full Covariates
GDP Index	-0.0097 *(0.0059)*	-0.0006 *(0.0057)*	-0.0091 *(0.0057)*	-0.0007 (0.0067)
Job Gain Rate	-0.0004 *(0.0009)*	-0.0004 *(0.0009)*	-0.0009 *(0.0009)*	-0.0008 (0.0009)
Job Loss Rate	-0.0012 *(0.0008)*	-0.0011 *(0.0008)*	-0.0016. *(0.0009)*	-0.0005 (0.0008)
Employment Growth	0.0005 *(0.0008)*	0.0006 *(0.0008)*	-0.0005 *(0.0007)*	-0.0002 (0.0007)
Earnings Growth	0.0003 *(0.0014)*	0.0005 *(0.0013)*	0.0010 *(0.0011)*	0.0013 (0.0176)
Covariates Included:	No	Yes	No	Yes
Fixed Effects:				
Year	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes
S.E Clustered	County	County	County	County

Note:
Significance codes: '***' 0.001; '**' 0.01; '*' 0.05; '.' 0.1

Across all outcome metrics under two different regression methods, NERRC was unable to detect a statistically significant impact of EDA funding.

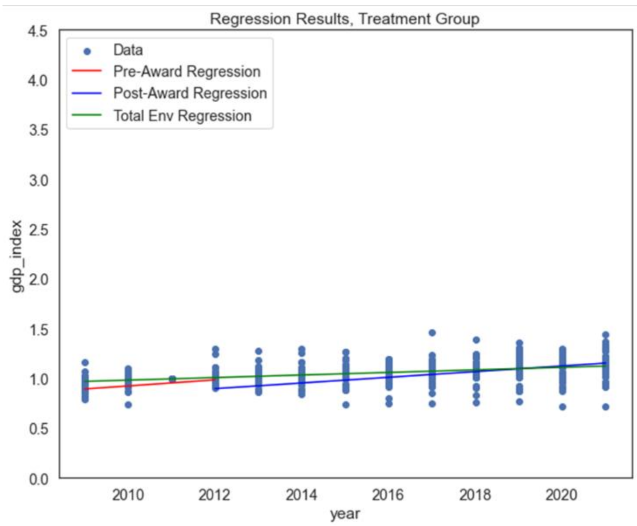
NERRC observed similar limitations from this analysis to the previous Coronavirus Aid, Relief, and Economic Security Act (CARES Act) analysis, including the following:

- **Data granularity:** Publicly available data are not sufficiently granular given the scope of EDA-funded activities under the 2012 Disaster Supplemental.
- **Data specificity:** EDA project reporting data for non-construction projects does not include sufficient activity or program service area.
- **Size of investment:** Given the constraint of data availability to the county level, the size of EDA investments is likely too small to be able to detect impact using county-wide economic data.

Because this analysis sought specifically to determine whether longer timeframes might surface measurable impacts over time, one must note that no effect was detected when longer timeframes are introduced. It is likely that the scale of the investment and the granularity of the data most significantly contribute to obscuring an impact. Program funds were disbursed to eligible communities over six fiscal years, significantly reducing the overall number of treated counties in any single time period. Ultimately this rolling disbursement only culminating in a full representation of funded counties in 2018, far less time for impacts to be observed than the total period since the qualifying events in 2011.

Regression Analysis

NERRC's next analytical step was to perform a regression analysis looking at the treatment group (the group of counties which received funding) and the control group (the matched counties that did not receive funding) to determine if any noticeable change exists in the communities as a result of the funding. For this step, NERRC used the gdp_index variable to measure the economic conditions over the time period of analysis. The plots below show the GDP Index over time with an overlay of the linear trend among all counties in the analysis. The red line represents the pre-award regression, and the blue line represents the post-award regression. The regression lines were also included with the control group for comparison between the two, despite the control group counties not receiving an award. The green line displays the overall regression line for the entire span.



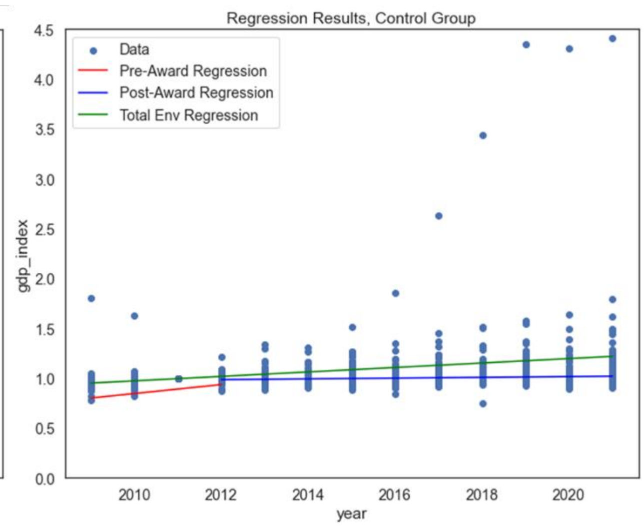


Figure 5: Initial regression plots of treatment and control counties

The initial results with the 2012 supplemental data found a general return of the treatment group to the national mean of GDP growth after a noticeable shift in 2012. NERRC performed a second PSM regression analysis on CARES Act data in an attempt to find any noticeable effect. This technique followed the same matching technique, with eligible counties and award flags determined with the updated ED-916 awards data. Figure 6 shows the regression results.

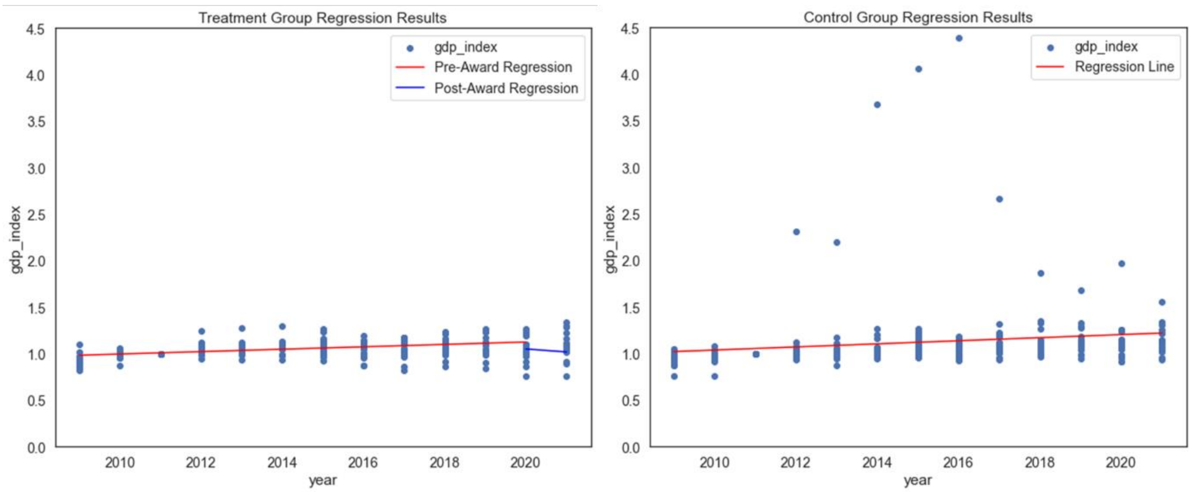


Figure 6: Initial regression plots of treatment and control counties

Reanalysis with Updated PSM Matching Variables

The reevaluation of both the 2012 Disaster Supplemental and the CARES Act program data with the reduced number of matching variables did not return statistically significant results. As seen in the results of both Figure 6 and 7, multiple treatment counties were matched with control counties with significant GDP Index values above those observed in the treatment groups. This is seen in the Control Group Regression plots; the GDP Index values significantly greater than the values in the Treatment Group Regression plots.

These results further suggest the foundational challenges with the investment size and the geographic scale render the impact of EDA investment impact undetectable using currently available third-party economic data.

Appendix D: Synthetic Control Analysis

This appendix describes National Economic Research and Resilience Center's (NERRC's) design and application of synthetic control in the analysis of Coronavirus Aid, Relief, and Economic Security Act (CARES Act) non-infrastructure awards. In order to apply the synthetic control in a targeted way, NERRC explicitly tailored the methodology and questions to U.S. Economic Development Administration's (EDA's) non-construction grant programs and theory of change.

The theoretical underpinnings of EDA's non-construction grants are grounded in the EDA Logic Model (Logic Model), created in partnership between EDA and SRI International in 2017. The Logic Model is visualized in Figure 7. EDA's Logic Model connects a community's baseline capacity for economic development to grant activities (outputs), which in turn are connected to specific short-term capacity outcomes and long-term realized outcomes. Each grant activity is logically connected to a distinct set of one or more capacity outcomes, which allow the generation of specific and testable hypotheses.

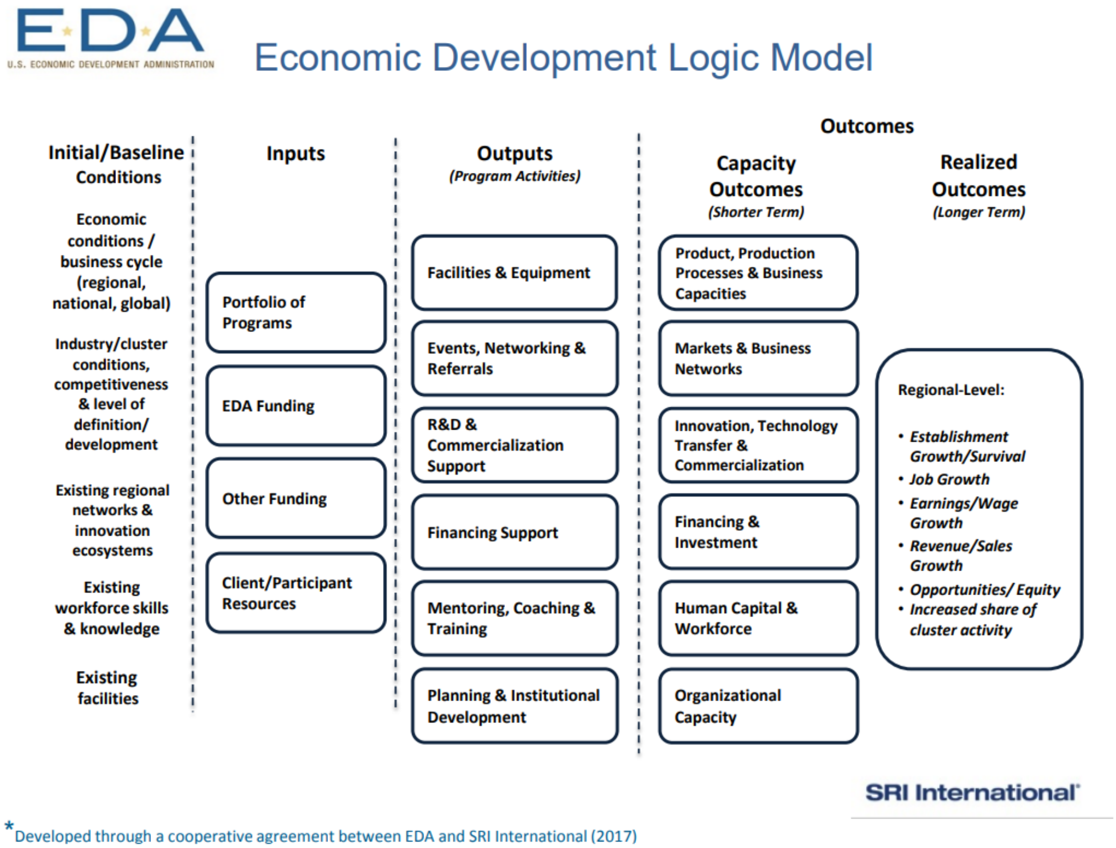


Figure 7: EDA Logic Model

As a first step, NERRC mapped eligible grant activities listed in EDA self-reported grant data (ED-916) to capacity outcomes and realized outcomes defined in the Logic Model, shown in Figure 8.

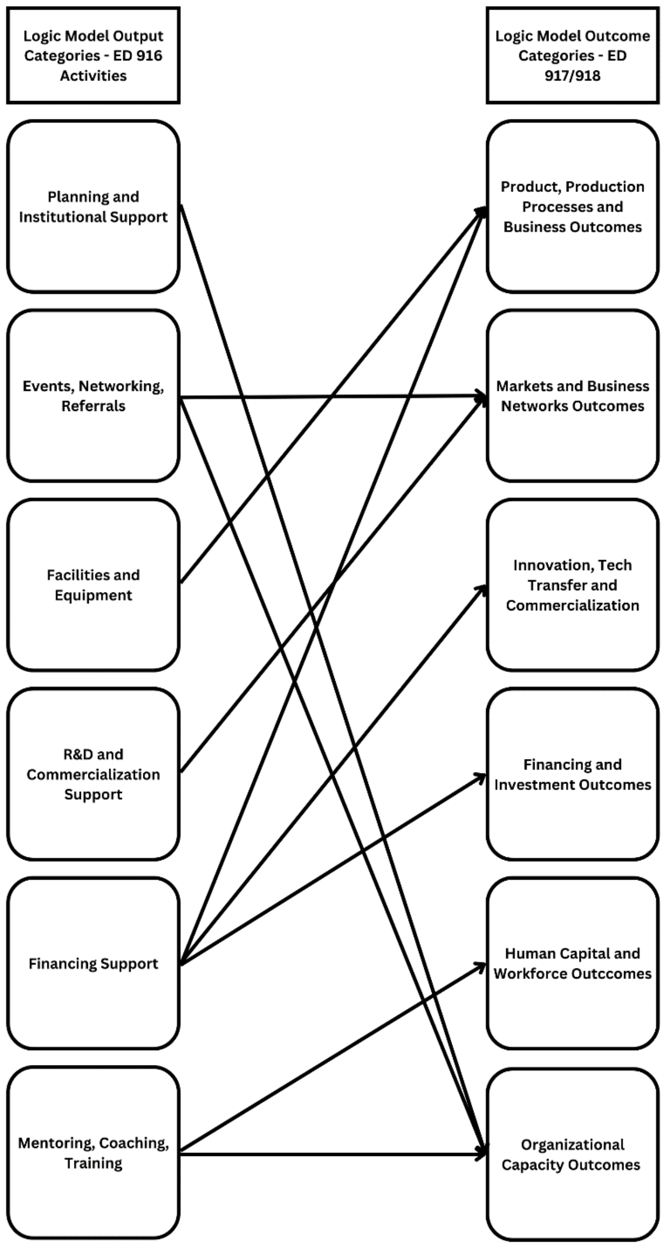


Figure 8: Activity-Outcome Mapping of ED-916 Activities to Logic Model

NERRC did not evaluate every possible eligible activity and every possible outcome; rather, the mapping consisted of those activities most frequently included in EDA grantee self-reported data. Therefore, a lack of connection between a grant activity and outcome category does not imply that it is impossible for that grant activity to affect that outcome category. Rather, the connections in the above diagram indicate the relationships that are *most likely* to hold, and therefore are *most likely* to be observable in data. The relative strength of these relationships was determined through consultation with EDA staff and not through statistical likelihood analysis. Additionally, an outcome category may be connected to several different grant activities.

Hypothesis Generation

Using the activity-outcome mapping, NERRC generated a list of potential outcome indicators associated with each outcome category. The research team selected outcome indicators based on their likelihood of being influenced by EDA grants as judged by subject matter experts at EDA, NERRC, and through the initial development of the logic model by SRI. Selected outcome indicators associated with each capacity outcome are listed in Table 6.

Table 6: Activity-Outcome Mapping and Outcome Indicators

Input	Activity	Capacity Outcome	Capacity Outcome Indicators	Realized Long-Term Outcomes (examples)
EDA Grant	• Facilities & Equipment • R&D / Commercialization • Financing Support	Product, Production, and Business Outcomes	• Profit • Firm turnover rate	• Gross Domestic Product (GDP) growth • Job growth • Equality (GINI Index)
EDA Grant	• Events, Networking, and Referrals • Financing Support	Market and Network Outcomes	• Civic and social organizations per capita • Website traffic, google page rank (unobserved) • Inter/Intra-state trade	• GDP growth • Job growth • Equality (GINI)
EDA Grant	• Events, Networking, and Referrals • Research and Development (R&D) / Commercialization • Financing Support	Innovation, Technology Transfer, and Commercialization	• No. of patents • % inventive class • U.S. Food and Drug Administration approvals, copyrights (grantee-specific)	• GDP growth • Job growth • Equality (GINI)
EDA Grant	• Events, Networking, and Referrals • Financing Support	Financing and Investment	• Small Business Administration loans • Small Business Innovation Research (SBIR) third-party loans • Foreign Direct Investment	• GDP growth • Job growth • Equality (GINI)
EDA Grant	• Mentoring, Coaching, and Training	Human Capital and Workforce	• New hires • Apprenticeships • Demographics of workforce	• GDP growth • Job growth • Equality (GINI)

Input	Activity	Capacity Outcome	Capacity Outcome Indicators	Realized Long-Term Outcomes (examples)
EDA Grant	• Mentoring, Coaching, and Training • Events, Networking, and Referrals • Planning and Institutional Support	Organizational Capacity	• Non-profits per capita • Membership organizations per Capita Workforce Training Establishment Ratio	• GDP growth • Job growth • Equality (GINI)

Not all listed outcome indicators are observable or available from open-source data. For example, the Product, Production, and Business outcome group is closely linked to firm profit, but the profit of grantees who received EDA support associated with those activities is unavailable. Other indicators are observable but lack quality open-source data, such as the number of apprenticeships in a given county. The capacity outcome indicators italicized in bold were ultimately those where open-source data were available and deemed to be of sufficient quality.

Using these capacity outcome indicators, we defined formal hypotheses that could be tested with open-source data and the synthetic control methodology. Below are a series of hypotheses that NERRC developed in consultation with the EDA program evaluation team, along with additional background about how the research team applied hypothesis in this analysis.

Product, Production, and Business Outcomes

Hypothesis: Counties that received EDA CARES Act grants targeted to Financing, R&D and Commercialization, or Facilities & Equipment activities have lower firm exit rates (on average) compared to control counties that did not receive any EDA CARES Act grants.

Market and Network Outcomes

Hypothesis: Counties that received EDA CARES Act grants targeted to Events, Networking, & Referrals or Financing Support activities have higher civic organization per capita ratios (on average) compared to control counties that did not receive any EDA CARES Act grants.

After discussions with subject matter experts at EDA, it was determined that civic organizations, normalized by total population, can serve as a proxy for social capital and therefore a plausible indicator of a community’s market and network structure.

Innovation, Technology Transfer, and Commercialization Outcomes

Hypothesis: Counties that received EDA CARES Act grants targeted to Events, Networking, & Referrals, R&D and Commercialization, or Financing Support activities have higher issued patents per $M of GDP ratios (on average) compared to control counties that did not receive any EDA CARES Act grants.

NERRC normalized the raw number of patents issued by the GDP of the county to account for different levels of economic production across counties.

Financing and Investment Outcomes

Hypothesis: Counties that received EDA CARES Act grants targeted to Events, Networking, & Referrals or Financing Support activities have higher SBIR grant per capita ratios (on average) compared to control counties that did not receive any EDA CARES Act grants.

The decision to normalize SBIR grants by total population was done to account for the total population of a county and is in line with how Argonne National Laboratory's Economic Development Capacity Index (EDCI) incorporates SBIR grant data.

Organizational Capacity Outcomes

Hypothesis: Counties that received EDA CARES Act grants targeted to Mentoring, Coaching & Training, or Events, Networking, & Referrals, or Planning & Institutional Support activities have higher non-profit establishment per capita ratios (on average) compared to control counties that did not receive any EDA CARES Act grants.

After discussions with subject matter experts at EDA, NERRC determined that non-profit establishments, normalized by total population, are one possible proxy metric for a community's organizational capacity.

Realized Long-Term Outcomes

Hypothesis: Counties that received EDA CARES Act grants of any activity type have higher job creation rates (on average) compared to valid control counties that did not receive any EDA CARES Act grants.

Although several human capital and workforce outcome indicators were proposed, such as the number of apprenticeships, we were unable to find an open-source data set of sufficient data quality to be tested.

Job creation and other general metrics of economic development are realized long-term outcomes for all grant activity types, as outlined in the logic model. Further refining the logic model and theory of program impact for the specific grant program under study may lead to different hypotheses, and therefore different results. This subject is discussed in more detail in the conclusion.

Synthetic Control Data Selection

NERRC's synthetic control analysis used two types of data to build the model: open-source data sets from various federal government agencies and proprietary EDA program reporting data on grant awards. NERRC collected open-source data was pulled from five major sources: the U.S. Census American Community Survey (ACS) 5-year estimates, the Census Business Dynamics Statistics (BDS), the Bureau of Labor Statistics (BLS) Census of Employment and Wages (CEW), the Federal Emergency Management Agency (FEMA) Disaster Declarations database, and the Johns Hopkins University (JHU) Coronavirus Resource Center county-level COVID-19 case data. Argonne used annual data for each county from 2009-2021. Overall, the data quality of these sources is high, but important limitations are still present.

First, the Census Bureau generally recommends against using the five-year ACS estimates for analysis that involves change over time, as the five-year estimates are an average over a five-year period. However, the ACS one-year estimates only cover geographic regions that exceed a total population of 65,000, and many counties that received EDA non-construction grants fall below that threshold and are therefore not included in the one-year estimates. Because no other comprehensive county-level demographic data set beginning in 2009 exists, NERRC determined that the five-year estimates were the most appropriate despite the limitations of using five-year averages.

Second, not all counties were present in each data set. Occasionally states define new counties or aggregate two existing counties into one new county. In those cases, a complete historical data set is not available for the affected counties. Five counties in Alaska, each created in 2013, were removed because they were not in the ACS five-year estimates prior to their creation. An additional 22 counties were not present in all ACS 5-year estimates for various reasons and were therefore removed. Another 59 counties were removed from the data set because they were missing either BLS CEW or Census BDS economic indicators that we used as dependent variables. Lastly, 78 municipalities in Puerto Rico were removed for substantial amounts of missing data across the ACS five-year estimates, the BLS CEW, and the Census BDS. The complete list of counties removed, and their reason for removal, is in Appendix E.

It is important to note that counties that the research team removed for missing data are likely to be systematically different from counties not missing data. For example, they are more likely to have lower economic capacity and are less likely to engage with the federal government. For that reason, the results presented here cannot be interpreted as applying to all U.S. counties and must be restricted to the set of counties studied in this specific assessment.

The EDA form ED-916 was used to collect information on the number of non-construction grants awarded in each county, the total dollar amount of non-construction grant awards in each county, and the activity types of the non-construction grants in each county. ED 916 data contains both EDA programmatic information such as grant number and amount and self-reported survey information about specific program activities from EDA grantees for non-construction grants.

Because the ED-916 data are self-reported, they have several inherent limitations. First, data on the outcomes of the grants are frequently missing. When available, corroborating their accuracy is difficult. For example, if a grant is targeted toward Innovation, Technology Transfer, and Commercialization outcomes, a grantee might report assisting 10 firms in commercializing their technology. Ideally, those numbers could be corroborated with independent, third-party, open-source data, or a quality control verification, to better demonstrate impact.

A second limitation of the self-reported ED-916 data concerns the geographic information they contain. For each grant, the grantee enters one county FIPS code associated with that grant. This entry is the determinant of where grant activity occurred. An additional 18 grant awards were listed as “Multi-County” and were removed from the analysis because of the effort involved in determining exactly which counties were covered under those grants, which is required to properly code a county as treated or untreated. However, even for grants that list a single county FIPS code, it is likely that the impact of that grant extends beyond that county. For many of these grants, the work associated with the grant is spread across multiple counties (i.e., throughout a regional Economic Development District). In these cases, NERRC assessed that the county FIPS code associated with the grant is likely to be the county FIPS where the grantee is physically located. Without more accurate data, however, NERRC chose to use the county FIPS codes listed in the ED-916 data as the locations where each grant was awarded.

The ED-916 data initially contained 4,525 projects across 703 counties and 35 sub-programs, over the fiscal years 2020 to 2022. We then filtered to sub-programs linked to the CARES Act, which resulted in 3,281 grants across 606 counties and 9 sub-programs over FY20-FY22. Of the 9 remaining sub-programs, the following 5 were deemed to be outside the scope of this analysis:

- CARES Act - Competitive Revolving Loan Fund (RLF) (94 projects)

- CARES Act – Innovation and Research and National Technical Assistance (7 projects)
- CARES Act – Non-Competitive RLF (1,003 projects)
- CARES Act – Non-Competitive University Center (211 projects)
- CARES Act – RLF (18 projects)

This left four sub-programs remaining to be included in this analysis:

- CARES Act – FY2020 Scaling Pandemic Resilience Through Innovation and Technology (SPRINT) Challenge (100 projects)
- CARES Act – Non-Competitive EDD (1,297 projects)
- CARES Act – Non-Competitive Tribal Planning (150 projects)
- CARES Act – Non-Construction (401 projects)

Prior to merging the ED-916 data with the open-source data to construct the final dataset, a total of 456 counties remained in the data. The breakdown by grant activity type is shown in Table 7.

Table 7: Breakdown of Counties by Grant Activity Type

ED-916 Activity Type	Number of Counties or County Equivalents
Facilities & Equipment	187
Events, Networking, & Referrals	335
R&D and Commercialization	105
Financing Support	236
Mentoring, Coaching, & Training	289
Planning and Institutional Support	416
Any Activity Types	456

Due to the data quality issues mentioned previously, NERRC was unable to include all counties that received EDA CARES Act grants in the analysis. Table 8 summarizes, by grant activity type, the number of counties that remained in the final data set.

Table 8: Number of counties included in the final analysis by grant activity type.

ED-916 Activity Type	Number of Counties or County Equivalents
Facilities & Equipment	167
Events, Networking, & Referrals	283
R&D and Commercialization	79
Financing Support	207
Mentoring, Coaching, & Training	240
Planning and Institutional Support	307

ED-916 Activity Type	Number of Counties or County Equivalents
Any Activity Types	382

In total, 382 counties received at least one EDA CARES Act grant included in the analysis. Many counties received multiple grants across multiple different activity types. NERRC removed 74 counties that received EDA CARES Act grants because the research team was unable to compile covariate data on those counties from available open-source data sets. Many grant awards cover multiple activities, and any county can receive multiple grants with each grant covering multiple activity types.

Counties that NERRC removed from the analysis are likely to be systematically different than those that remained in the data set. This has two important implications. First, the results from the synthetic control models cannot be universally applied to all counties; rather, the validity of the conclusions on EDA CARES Act grants only applies to the 382 counties that NERRC included in the final analysis. Second, and more relevant to the Effectiveness Framework, it is possible that the counties that were dropped for missing data may be places where EDA CARES Act grants had the largest impact. For example, if the removed counties have lower overall capacity, then it is plausible that EDA grants would be most beneficial to these counties. However, without acquiring data on these counties it is not possible to determine the impact of EDA grants on their economic development capacity.

In the final synthetic control models, NERRC used the following covariates for each outcome indicator (sources in parenthesis):

- Annual COVID deaths per 100k (John's Hopkins University)
- Total population (ACS 5-year estimates)
- Median gross rent (ACS 5-year estimates)
- Percent of population with gross rent > 35% of income (ACS 5-year estimates)
- Percent of population < 18 years old (ACS 5-year estimates)
- Percent of population > 65 years old (ACS 5-year estimates)
- Percent Race = White alone (ACS 5-year estimates)
- Percent born in current state (geographic mobility; ACS 5-year estimates)
- Percent of population above 150% of poverty level
- Number of health diagnosing practitioners per capita (ACS 5-year estimates)
- GDP $M (BLS CEW)
- Unemployment Rate (BLS CEW)
- # of FEMA-declared disasters (FEMA Disaster Declaration Database)
- Annual COVID Cases (JHU Coronavirus Resource Center)
- Year fixed effect (controls for remaining uniqueness of each year across all counties)
- County-level fixed effect (controls for remaining uniqueness of each county across all years)

The last two covariates are part of the enhanced synthetic control approach and can account for unobserved county-level and year-specific characteristics. [18]

Synthetic Control Analysis Results

This section includes two different sets of analysis. First, one set of synthetic control models includes all counties that received EDA CARES Act grants. Second, another group of models includes counties where the EDA grant amount (in dollars) to GDP ratio was in the top 10% of all counties for each capacity outcome group. The second iteration of models focuses the analysis on counties where EDA CARES Act grants were a larger portion of the economy, and therefore were more likely to have a detectable effect. As stated previously, these graphs report the estimated treatment effect averaged across all counties that received EDA non-construction CARES Act grants.

Model Results with All Counties

Product, Production, and Business Outcomes

Figure 9 shows the synthetic control model output for the Product, Production, and Business outcomes hypothesis.

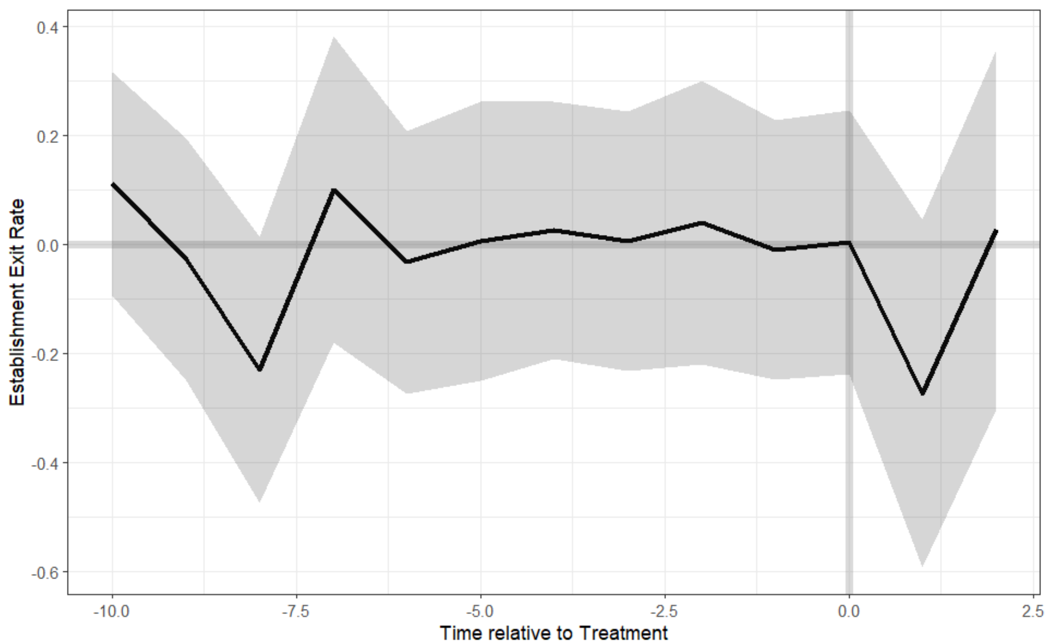


Figure 9: Establishment Exit Rate Difference Between Treated and Untreated Counties

The synthetic control is able to reproduce historical establishment exit rate trends, which suggests that a valid counterfactual synthetic control unit exists. Looking at the post-treatment window, the time to the right of vertical 0.0 line, it appears that the average establishment exit rate for treated counties drops in

[18] Xu, Y. (2017, January). "Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models." *Political Analysis 25*(1), 57–76. https://doi.org/10.1017/pan.2016.2.

2020, but the confidence bands continue to contain 0. Therefore, this model is unable to currently detect impact, given the challenges outlined above.

Market and Network Outcomes

The model output for the Market and Networks outcomes is presented in Figure 10. As before, the synthetic control is able to accurately match historical trends for membership organizations per capita. The post-treatment windows show the average difference post-grant award is close to zero, and the confidence bands indicate no detectable effect.

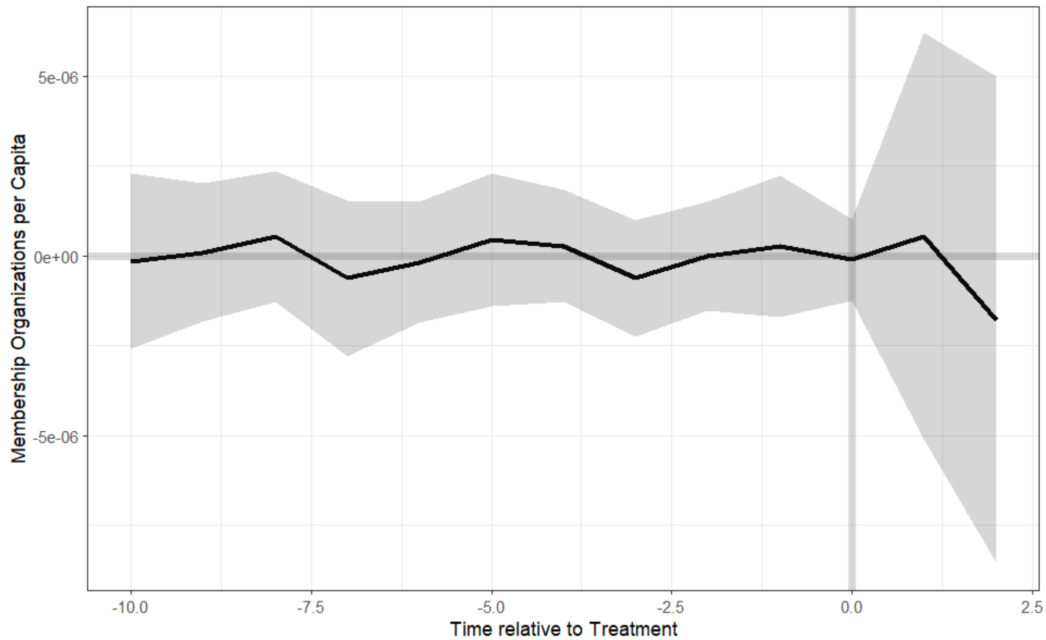


Figure 10: Membership Organizations per Capita Difference Between Treated and Untreated Counties

Innovation, Technology Transfer, and Commercialization Outcomes

Figure 11 visualizes the output of the Innovation, Technology Transfer, and Commercialization outcomes hypothesis. Once again, the synthetic control accurately reproduces the pre-2020 trend of issued patents per millions of dollars of GDP, indicating that the model is creating a valid counterfactual. Because the post-treatment average gap between treated and untreated units is close to 0, and the confidence bands contain 0, this model is also unable to currently detect impact.

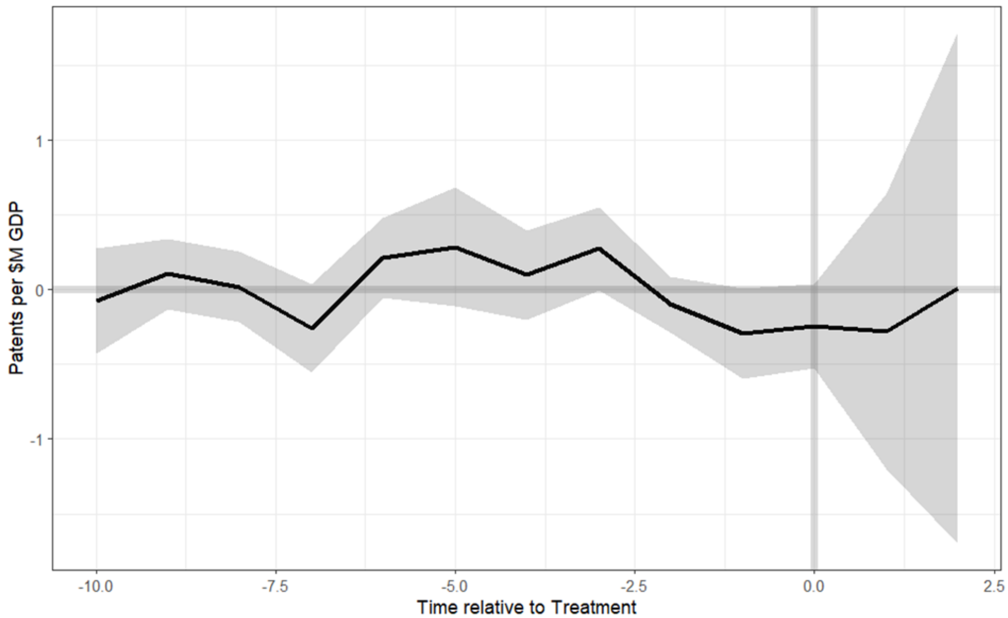


Figure 11: Patents per $M GDP Difference Between Treated and Untreated Counties

Financing and Investment Outcomes

Figure 12 shows the results of the model testing the Financing and Investment outcome hypothesis. This model is not able to accurately reproduce historical SBIR grant ward trends and therefore is unlikely to serve as a valid counterfactual against which causal comparisons can be made. The pre-treatment window confidence bands and the average difference between treated and untreated counties dip below the horizontal 0 line in 2012. Further, the post-treatment window again indicates that this model is unable to currently detect impact. However, as currently constructed, the model is likely not a valid counterfactual, so the post-treatment impact should not be trusted as an accurate estimate of the causal impact from EDA non-construction CARES Act grants on the number of SBIR grant awards per capita in a county.

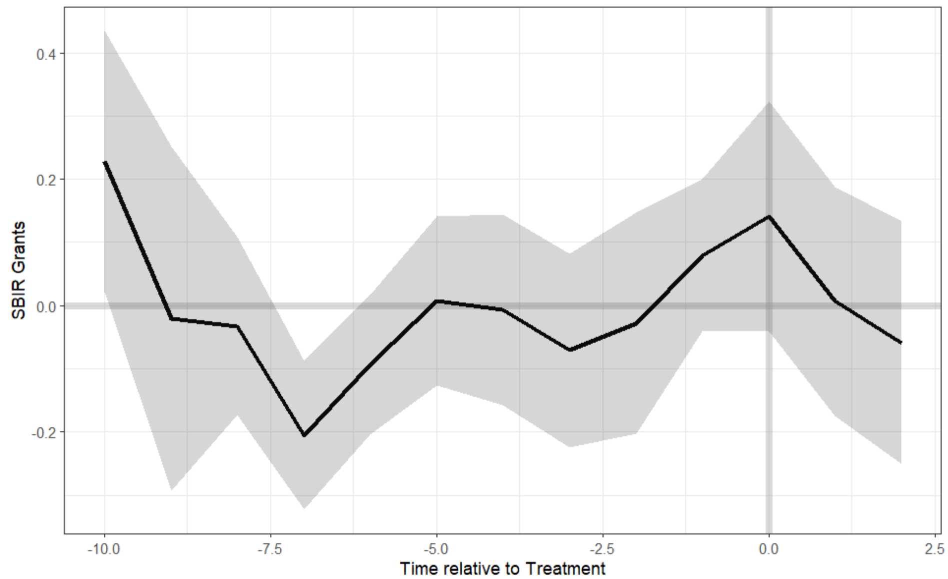


Figure 12: Number of SBIR Grants Awarded per Capital Difference Between Treated and Untreated Counties

Organizational Capacity Outcomes

Figure 13 shows the output of the model that tested the Organizational Capacity outcome hypothesis. Here, the synthetic control is able to reproduce historical non-profit establishments per capita trends, and the post-treatment window suggests that this model is unable to currently detect impact.

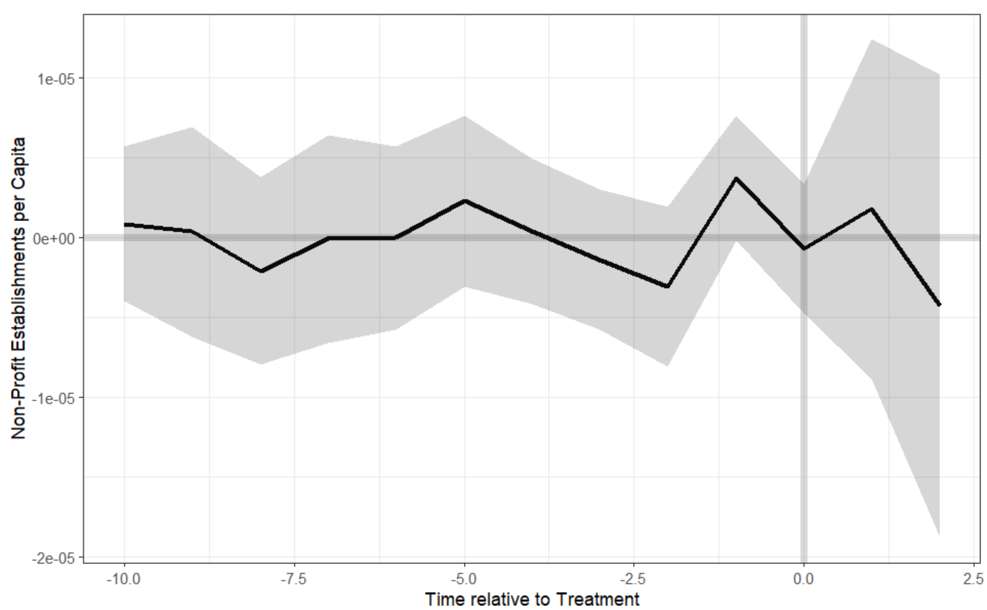


Figure 13: Non-profit Establishments per Capita Difference Between Treated and Untreated Counties

Realized Long-Term Outcomes

Figure 14 visualizes the results from testing the net job creation rate against all ED-916 activity types. The synthetic control can generate a valid counterfactual, as indicated by its ability to reproduce historical net job creation rate trends. The post-treatment window shows that in 2021, the net job creation rate for counties that received EDA CARES Act grants was statistically different (lower) than the net job creation rate of counties that did not receive EDA CARES Act grants. However, the confidence bands are very close to 0; in practice, because these confidence bands are simulated numerically, a small but statistically significant difference such as this is not of practical significance. Although counties that received EDA CARES Act grants appear to have slightly lower net job creation rates than those that did not, this should not be interpreted as a negative impact on job creation due to EDA CARES Act grants.

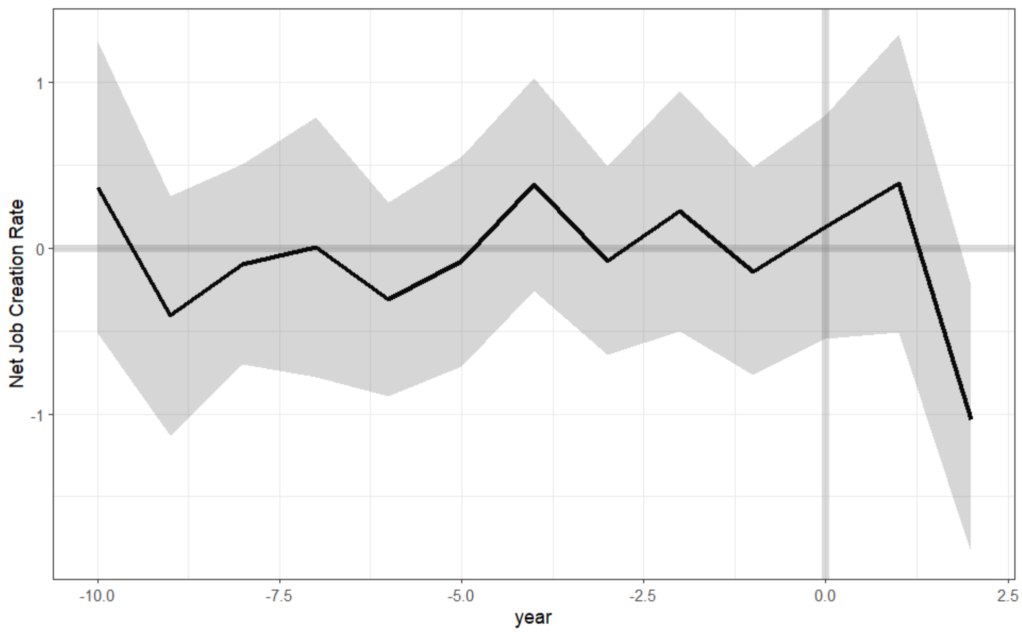


Figure 14: Net Job Creation Rate Difference Between Treated and Untreated Counties

Model Results for Higher Intensity Grants

Model results that focused on the 10% highest intensity grants, where intensity was measured as the total EDA Grant amount for the appropriate capacity outcome group as a percent of the county's GDP are presented below. In cases where a county received one grant across several different grant activities, it was assumed that the dollar value of the grant was evenly distributed across all grant activities. While this assumption is likely to be untrue in many cases, without more granular data on each grant this was the most plausible approach.

Product, Production, and Business Outcomes

Figure 15 shows the synthetic control model output for the Product, Production, and Business outcomes hypothesis. The synthetic control is able to create a valid counterfactual judging by the pre-treatment fit. Looking at the post-treatment window, the confidence bands continue to contain 0 indicating that this model is unable to currently detect impact.

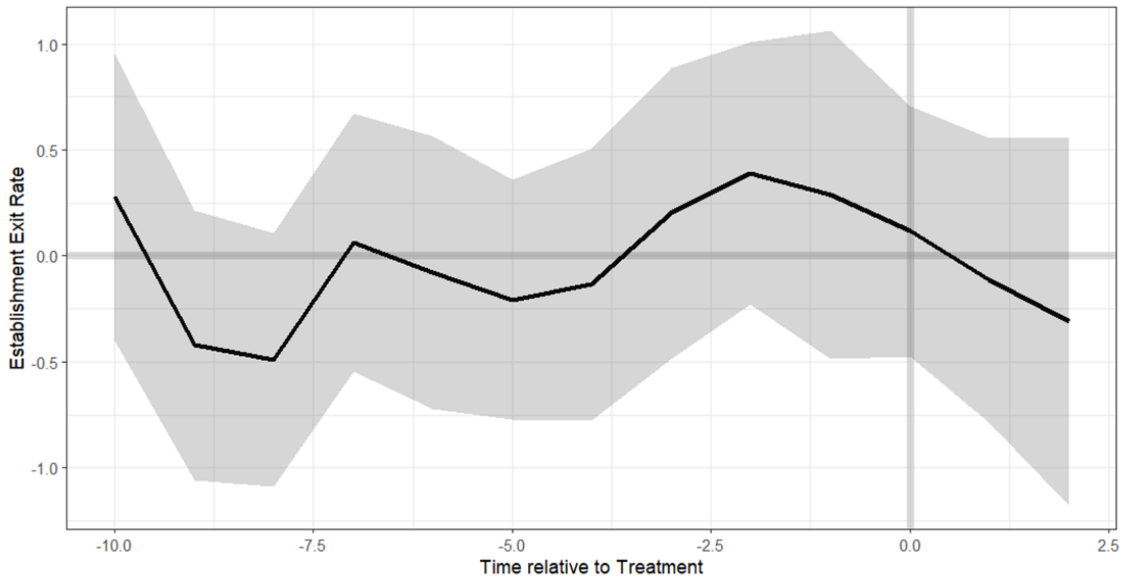


Figure 15: Establishment Exit Rate Top 10% of Grantees by Grant $ / GDP

Market and Network Outcomes

Figure 16 shows the model output for Market and Networks outcomes . Unlike the Market and Networks model that included all counties, here the synthetic control is not serving as a valid counterfactual based off the pre-treatment fit. The post-treatment window shows the average difference post-grant award is close to zero, and the confidence bands contain no effect. However, given the poor pre-treatment fit, this conclusion is likely not justified. Additional and more accurate and granular data, both for explanatory variables or outcome indicators, could allow for increased validity in the statistical model.

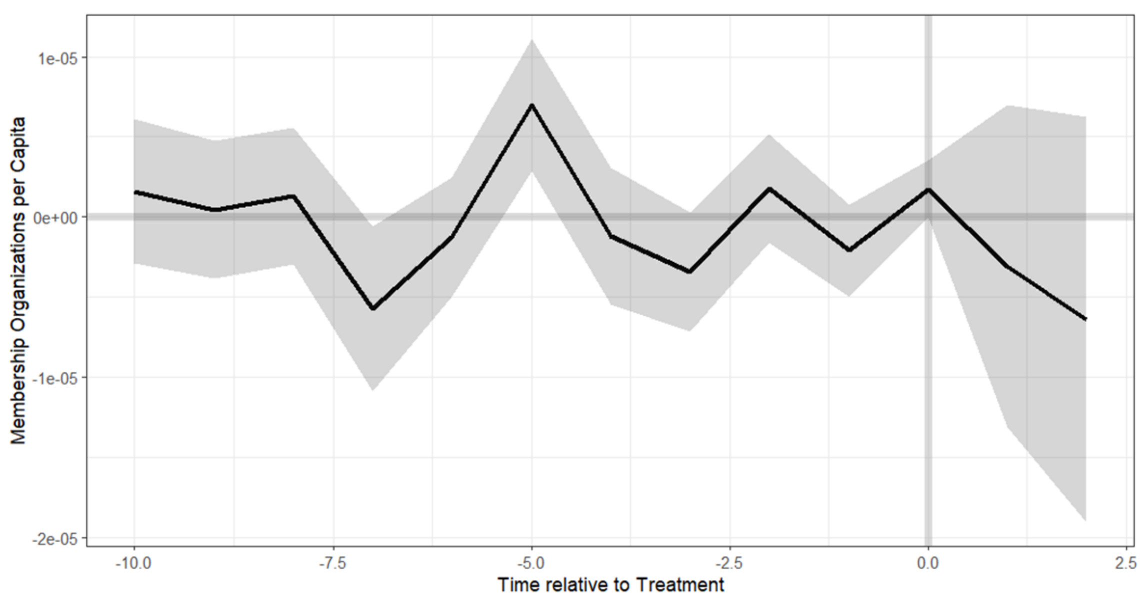


Figure 16: Number of Membership Organizations per Capita Top 10% of Grantees by Grant $ / GDP

Innovation, Technology Transfer, and Commercialization Outcomes

Figure 17 visualizes the output of the Innovation, Technology Transfer, and Commercialization outcomes hypothesis. The synthetic control appears to be generating a valid counterfactual based on the pre-treatment fit. Post-treatment, the confidence bands continue to contain the horizontal line at 0, indicating that this model is unable to currently detect impact.

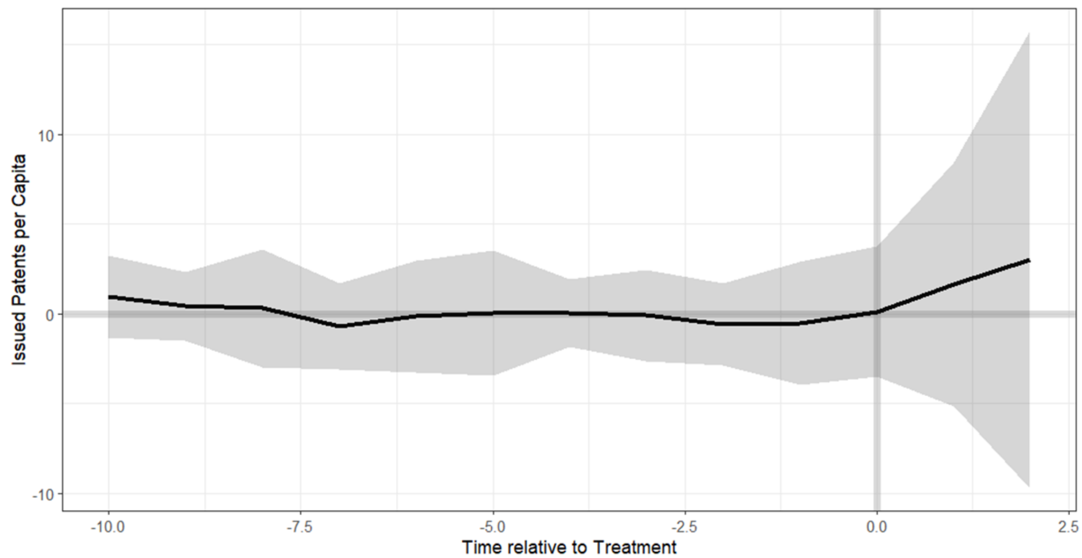


Figure 17: Number of Issued Patents per Capita Top 10% of Grantees by Grant $ / GDP

Financing and Investment Outcomes

Figure 18 shows the results of the model testing the Financing and Investment outcome hypothesis. Unlike the full Financing and Investment outcomes model, here the synthetic control is able to produce a valid counterfactual as judged by the pre-treatment fit. However, the post-treatment window again indicates that this model is unable to currently detect impact.

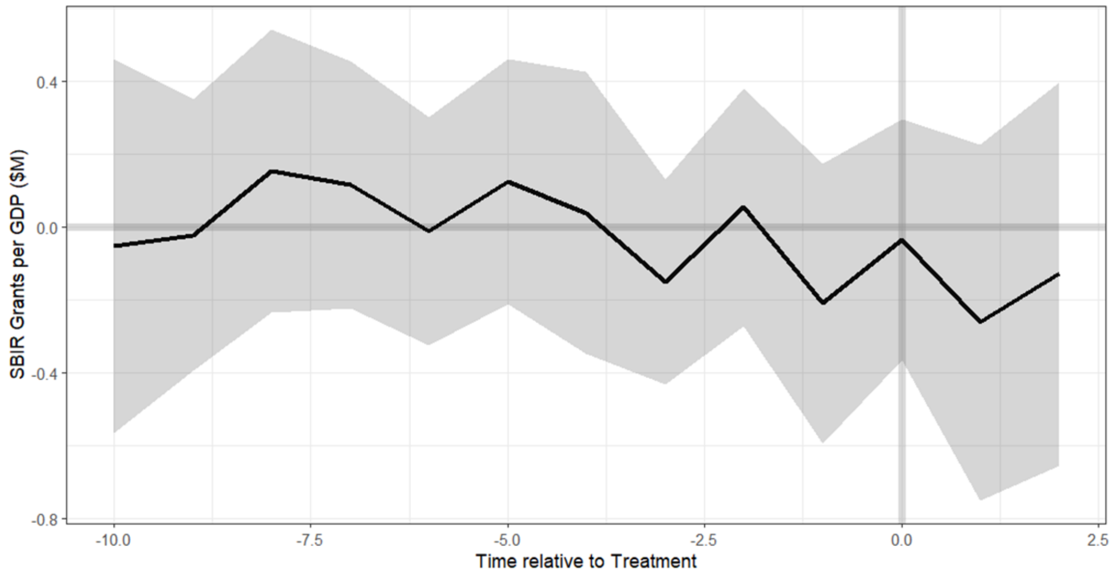


Figure 18: Number of SBIR Grants Awarded / GDP ($M) Top 10% of Grantees by Grant $ / GDP

Organizational Capacity Outcomes

Figure 19 shows the output of the model that tested the Organizational Capacity outcome hypothesis. Unlike the full Organizational Capacity outcomes model, the synthetic control is unable to produce a valid counterfactual based on the pre-treatment divergence from the horizontal 0 line. Although the post-treatment window suggests that no evidence of effect exists from EDA CARES Act grants on county-level non-profit establishments, due to the model's inability to produce a valid counterfactual the results of the model should not be considered valid.

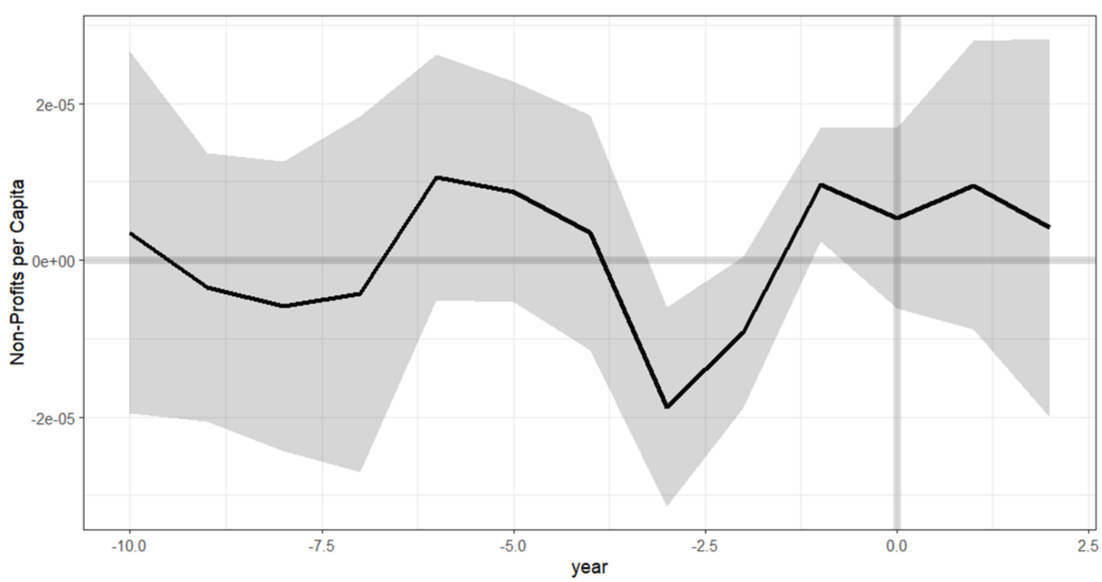


Figure 19: Number of Non-Profit Establishments per Capita Top 10% of Grantees by Grant $ / GDP

Realized Long-Term Outcomes

Figure 20 below visualizes the results from testing the net job creation rate against all ED-916 activity types. Here, the synthetic control's validity as a counterfactual is questionable given the confidence interval's exclusion of the horizontal zero line in 2014. Unlike before, the post-treatment affect appears close to zero and the confidence bands contain the horizontal zero line throughout, and we conclude that no evidence of effect from EDA CARES Act grants exists on county-level net job creation rates. However, given the questionable validity of the synthetic control as a counterfactual, the model results are themselves subject to uncertainty.

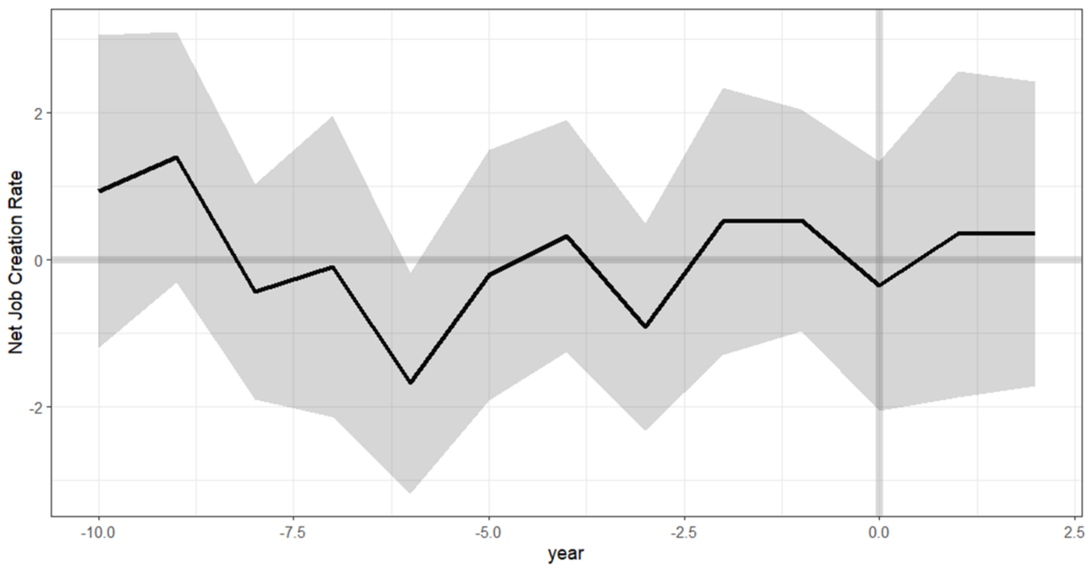


Figure 20: Net Job Creation Rate Top 10% of Grantees by Grant $ / GDP

Summary

The results of the synthetic control models presented above consistently showed that in light of the data challenges outlined in the body of this report, the synthetic control models are not currently able to detect impact. As previously stated, a takeaway from this analysis is that the analytic challenges outlined throughout this report affect the ability to detect impact using synthetic control.

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