Charting the just transition:
Insights from the POWER Initiative to enhance employment amidst coal industry decline

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Abstract

The net-zero transition is going to bring great environmental and economic benefits, but also important policy challenges. One particularly acute challenge could be managing the potential economic and employment impact of the transition on coal-dependent communities. Appalachia provides a key case study to understand the policy implications of phasing out coal. This region has seen an important decline in coal employment, and has experienced consistently high unemployment and poverty rates. As such, it is recipient of federal grants through the Partnerships for Opportunity and Workforce and Economic Revitalization (POWER) Initiative, specifically aimed at revitalizing coal communities. I estimate that unemployment rate decreases on average by 4.2% five years following the announcement of the first POWER project. The cost per job of the POWER Initiative is estimated at USD 16544 implying it is a cost-effective measure for creating jobs. This suggests that the POWER Initiative could be scaled up for additional impact.

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1 Introduction

Phasing out coal is a key lever of climate policy. However, the phase-out of coal could have significant negative impacts on coal-dependent regions. As such, the transition to net-zero emissions is expected to have substantial economic and social impacts. The Appalachian region in the United States provides a pertinent case study of the changing coal economy. Studying it can inform our understanding of the economic adjustments that could result from environmental policy (Weber, 2020). The Appalachian coal industry and coal employment have been declining due to the adoption of less labor-intensive mining practices, decreasing natural gas and renewable energy prices, as well as due to more stringent federal environmental regulation. At the same time, the Appalachian region has some of the most economically vulnerable communities in the United States, with high poverty rates and weak economic growth. Given the persistent economic distress that coal mining communities have been experiencing, the Partnerships for Opportunity and Workforce and Economic Revitalization (POWER) Initiative specifically targets areas hit by the decline in the coal industry. The initiative aims to re-skill workers, to diversify the economy and to develop modern infrastructure, among others. Between 2015 and 2023, the Appalachian Regional Commission has provided USD 420 million through 507 grants within the POWER Initiative (Appalachian Regional Commission, 2023d).

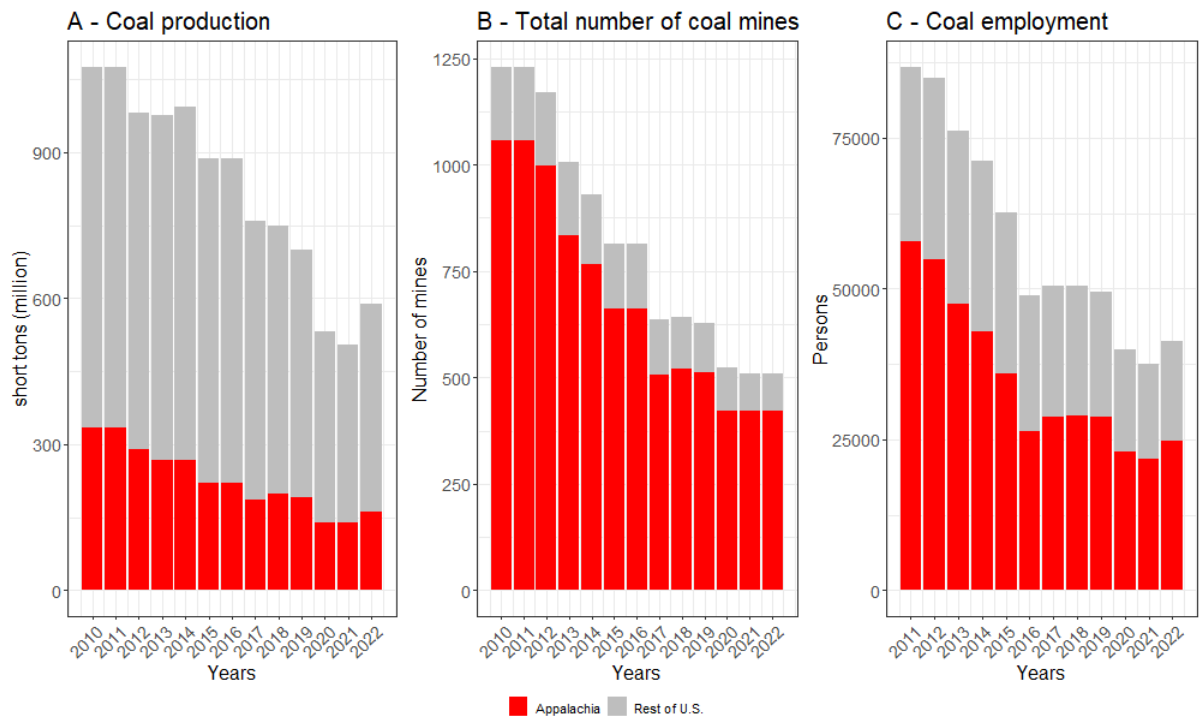
Does the POWER Initiative improve employment outcomes? To investigate this question I employ an estimation method proposed by de Chaisemartin and d'Haultfoeuille (2024), which is a flexible heterogeneity-robust differences-in-differences estimator. I find that unemployment rate decreases on average by 4.2% five years following the announcement of the first POWER project. The negative effect is robust to alternative definitions of the treatment and to an analysis using generalized synthetic control method (Xu, 2017). I also estimate that the cost per job of the POWER Initiative is USD 16544, which is within the range found in the literature for similar programs.

In the current context of announcements for ambitious climate policies and the transition to net-zero emissions by 2050, the just transition concept needs to be revisited. The just transition concept emerged from labor movements in the 1970s as a reaction of industries that struggled with the employment impacts of environmental regulations (Wang and Lo, 2021). In 2015, in the same year when the Paris Agreement was accepted, the International Labour Organization agreed upon the *Guidelines for a just transition towards environmentally sustainable economies and societies for all* which emphasizes that some of the major challenges in the transition to environmentally sustainable economies includes "economic restructuring, resulting in the displacement of workers and possible job losses" (ILO, 2015). Similarly, the OECD argues that climate policies could exert pressure on jobs reliant on fossil fuel extraction as well as carbon-intensive heavy industries, which calls for the re-skilling of workers to improve their transferability across firms and sectors (OECD, 2021). The just transition is also a global issue, with the impact on coal mining jobs felt across several regions, including the European Union, South and Southeast Asia, China as well as the Americas (Galgoczi, 2019; ILO, 2022; Do and Burke, 2023; Wang and Lo, 2022; Feng et al., 2023). However, Konisky and Carley (2021) reports that there is little evidence on which policies work for communities that rely on fossil fuel industries. In the context of the just transition, it is unclear whether policymakers should help regions or individuals (Vona, 2023).

2 Background and Context

In the United States, coal production fell by more than 50% between 2010 and 2022, from almost 1.1 billion short tons to 589 million short tons (see Figure 1, panel A). Appalachia also experienced a decrease in coal production, from 334 million short tons in 2010 to 161 million short tons in 2022. Similar decline can be observed in the total number of mines in the United States, which declined from 1230 mines in 2010 to 510 mines in 2022 (see Figure 1, panel B). The decline is more substantial in Appalachia, the total number of mines decreasing from 1056 in 2010 to 422 in 2022, an approximately 60% decline. There has also been a steep decline in coal mining jobs. In 2011 almost 90,000 workers were employed in the coal mining industry in the United States (see Figure 1, panel C). By 2023, this number has declined to approximately 40,000 workers, a more than 50% drop. In Appalachia, the decrease was more substantial: in 2011 there were almost 60,000 coal workers but this number declined to less than 25,000 by 2022, a 60% decrease. The reasons for this important decline in the coal industry are manifold: significant reductions in the cost of natural gas, the competitiveness of renewable energy at market prices, as well as an increasingly strict regulatory environment[1] have made coal a much less competitive energy source for power generation (Bowen et al., 2021). In addition, there is further competition among the coal producing regions within the United States. Western coal fields, such as the Powder River Basin, produce less polluting coal at a much lower margin compared to the more traditional coal mining facilities found in the Appalachian region (Look et al., 2022).

Figure 1: The coal economy in Appalachia and the United States has seen an important decline in the last decade

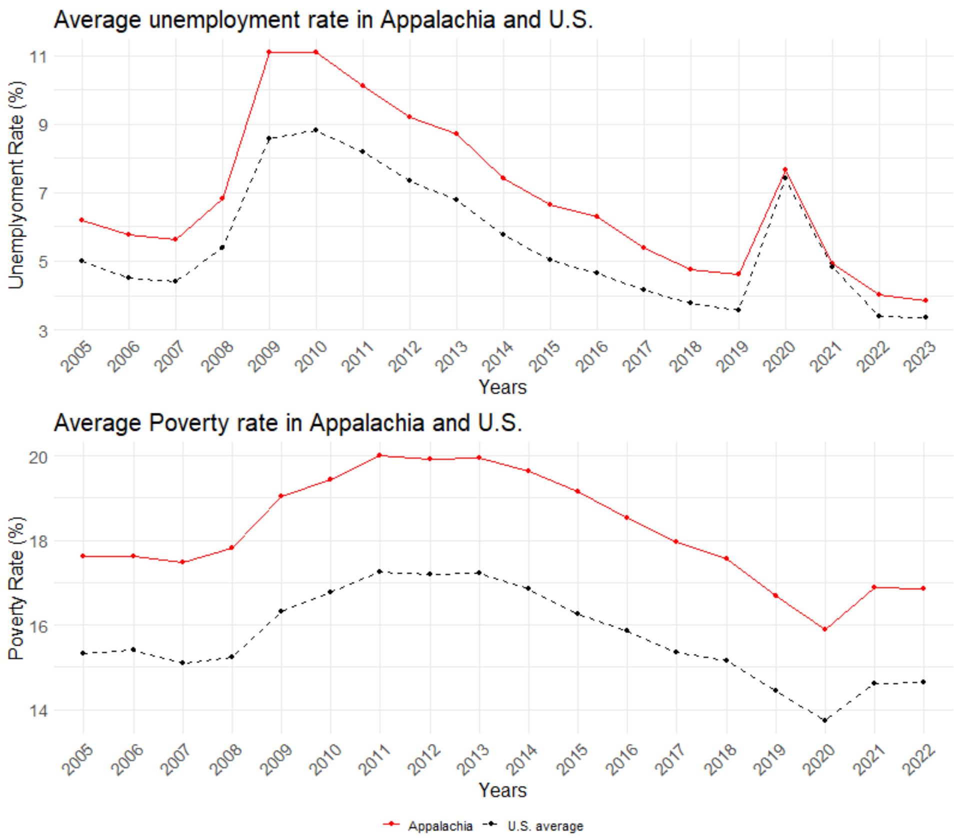


Notes: "Appalachia" corresponds to the 423 counties that are officially served by the Appalachian Regional Commission (ARC). The "Rest of U.S." corresponds to all other U.S. counties that are not part of the ARC region but have positive coal production, coal employment and active coal mines between 2010 and 2022. Data on coal production and the number of coal mines is from the U.S. Energy Information Administration's Annual Coal Reports (2010-2022). Coal employment data is from U.S. Mine Safety and Health Administration's Historical Coal Production Data (2010-2022).

[1] See Van Nostrand (2022) for a discussion on the impact of the EPA's Mercury and Air Toxics Standards (MATS) rule and the Clean Power Plan on the coal economy in general, and West Virginia in particular.

These developments are welcome insofar that they allow the United States, the fourth largest coal producer in the world, to decouple from coal and move towards cleaner energy sources. The energy transition will likely result in net benefits for the United States and for the world. However, such a transition may not be "just," raising questions about equity. The coal industry and coal employment are highly geographically concentrated, meaning that the distributional effects of coal decline would be more acutely felt in coal producing regions, which may often have high levels of poverty and persistently high unemployment rates (Betz et al., 2015). Figure 2 shows that both unemployment rates as well as poverty rates have been consistently above the national average for a considerable time in Appalachia. Furthermore, many workers depend on coal mining for employment and livelihoods, and public authorities may lose key fiscal revenue sources for the provision of public goods such as education and healthcare, among others (International Energy Agency, 2022). For instance, the closure of the Dayton Power & Light coal-fired power plant in Adams county, Ohio has led to the destruction of 1100 jobs and the loss of USD 8.5 million in revenue for the local government (Jolley et al., 2019). Therefore, a just transition concept would need to take into account the need to support workers and regions that directly depend on fossil fuel industries (OECD, 2023).

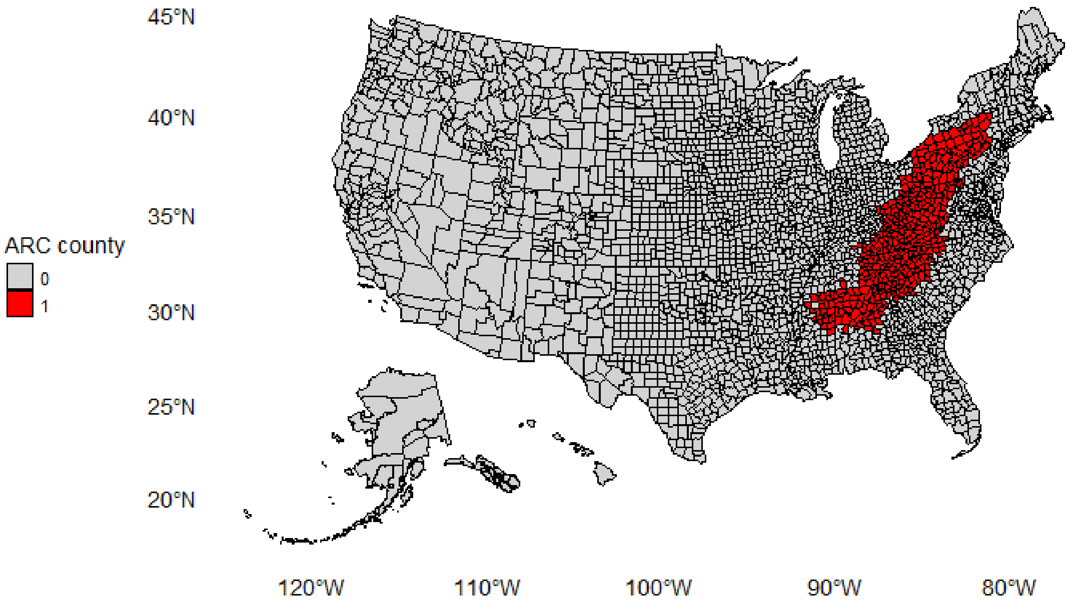
Figure 2: Unemployment and poverty rates are on average higher in Appalachia compared to the national average



Notes: Values for "Appalachia" correspond to the 423 counties that are officially served by the Appalachian Regional Commission (ARC). Unemployment rate for "Appalachia" is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). The "U.S. average" unemployment rate corresponds to the yearly average unemployment rate of all States in the United States. Poverty rate corresponds to the poverty rate for all ages as reported by the U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program: Poverty and Median Household Income Estimates - Counties, States, and National data sets (2005-2022) (U.S. Census Bureau, 2024c).

It is in this context that the federal funding program Partnerships for Opportunity and Workforce and Economic Revitalization (POWER) Initiative was launched in 2015 by the Obama administration, a program that is still on-going (Congressional Research Service, 2022). The initiative aims to support coal communities in transition by providing funding necessary to help workers gain new skills, to build vital infrastructure that can bolster economic development, and to provide healthcare and other welfare services. The Appalachian Regional Commission (ARC) is the main grant administrator in Appalachia. The ARC serves 423 counties across 13 different states[2] and has a key role in the coordination of grants and projects.

Figure 3: The geographic extent of counties served by the Appalachian Regional Commission



Notes: The value "1" corresponds to one of the 423 counties that are officially served by the Appalachian Regional Commission (ARC).

POWER project applicants apply for funding and the ARC makes the final decision to award grants based on the merits of the projects being proposed. Each project must address one of the strategic investment goals of the ARC, such that a project should contribute to economic diversification, build businesses, and improve the workforce ecosystem or infrastructure. Projects are eligible if they are located in, or target, a community which has been impacted or is expected of being impacted by the decline in coal mining and coal power generation (Appalachian Regional Commission, 2023c). The ARC provides grants based on the economic status of the proposed service area. Each Appalachian county is classified into one of five economic status designations based on its position in the national ranking of all United States counties. The five different designations for economic status are distressed (bottom 10%), at-risk (10-25%), transitional (25-75%), competitive (75%-90%) and attainment (90-100%) - see Figure 4. These designations are built based on a composite index of lagged county economic indicators: three-year average unemployment rate, per capita market income, and four-year average poverty rate.

[2]These are Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia, and West Virginia.

ARC funding and matching rates are as follows: for Distressed counties, the match requirement is 20% and maximum ARC share is 80%; for At-risk counties the match requirement is 30% while the maximum ARC share is 70%; for Transitional counties the match requirement is 50% and maximum ARC share is 50%; for Competitive counties the match requirement is 70% while the maximum ARC share is 30% (Appalachian Regional Commission, 2023b). Rules on the maximum ARC share for any given project are included in the text of the Appalachian Regional Development Act and its Amendments.

Figure 4: ARC County Economic Status Designation by National Index Value Rank

Source: Appalachian Regional Commission (2023a)

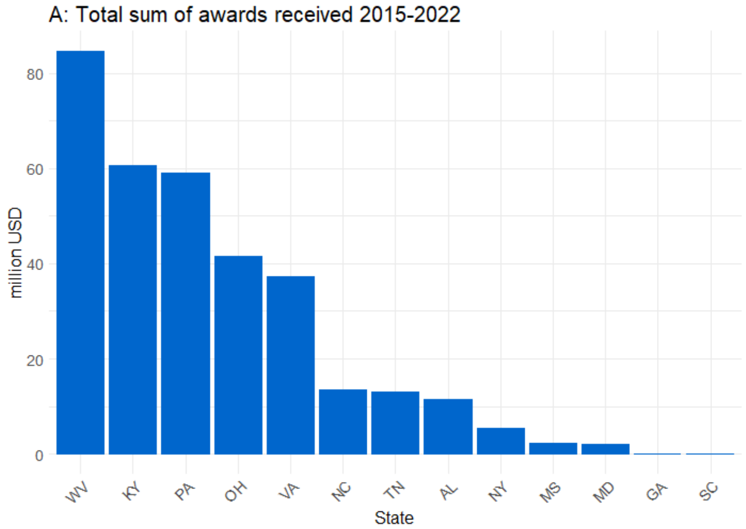
How substantial are these grants under the POWER Initiative? Until 2023, USD 420 million have been disbursed under the initiative. For each project, POWER grants can amount up to USD 2.5 million. Small technical assistance grants can at most be USD 50,000. Larger implementation projects can receive as much as USD 1.5 million. Finally, infrastructure projects, such as broadband development, can receive up to USD 2.5 million. Figure 5 shows that five out of thirteen states, such as West Virginia, Kentucky, Pennsylvania, Ohio and Virginia are the main recipients of POWER funding, capturing 86% of all funding awarded between 2015 and 2022. Importantly, grants are also projected to leverage private investment amounting to USD 1.8 billion (Appalachian Regional Commission, 2022).

Given that the POWER program specifically targets communities that are affected by the declining coal industry, a key metric would be the dollar amount of award per coal mining job.[3] On average, approximately USD 10,000 were awarded per coal mining job, with some important heterogeneities across states (see Panel A of Figure 6): award per coal mining job is more than USD 35,000 in Pennsylvania and almost USD 24,000 in Alabama but much less in other states. Another metric to judge awards by would be award per net destroyed coal mining job. I define net destroyed coal mining job as the number of coal mining jobs that were destroyed net of coal mining job creation.[4] On average, awards per net destroyed coal mining job amounted to USD 23,000. Panel B of Figure 6 shows that award per net destroyed coal mining job is substantial in Alabama, Pennsylvania, Virginia and West Virginia as well as Ohio, but much lower in other states.

[3]Award per coal mining job is calculated as follows: I divide the total amount of awards (in USD) received in a county in a given year by the number of coal mining jobs. If there are no coal mining jobs in a county, I define the value as zero. Then I take the average of the resulting award per coal mining job for each state.

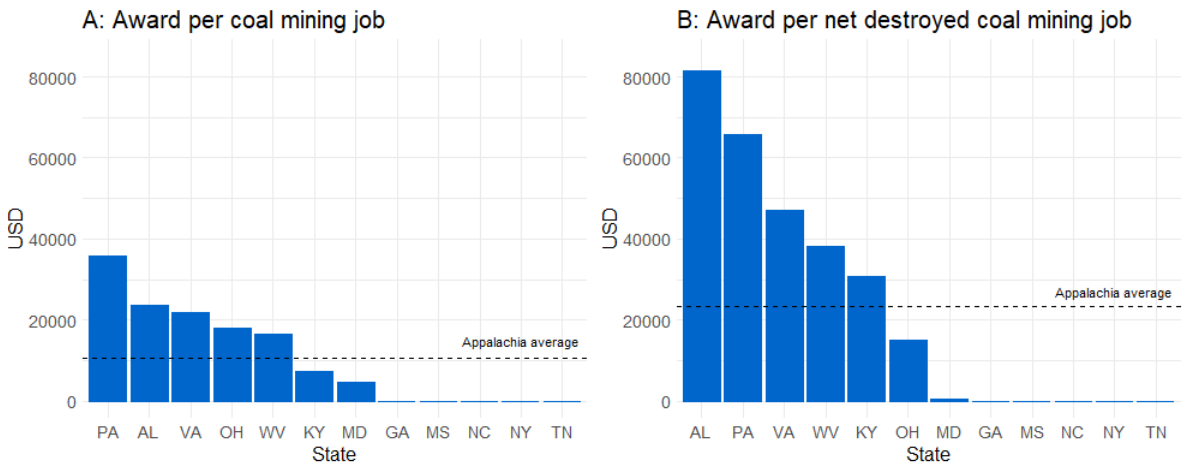
[4]Net destroyed coal mining job is defined as the number of coal mining jobs that were destroyed net of coal mining job creation. Therefore, if for example two mining jobs were destroyed and one created, the net destroyed coal mining job would be one. Meanwhile, if two mining jobs were created and one destroyed, net coal mining job destruction would be zero, as more jobs are created than destroyed. Award per net destroyed coal mining job is calculated as follows: I divide the total amount of awards (in USD) received by net destroyed coal mining job in each county. Then I average the resulting values across states.

Figure 5: ARC POWER awards are heterogeneously distributed across the Appalachian region



Notes: For state abbreviations, "AL" corresponds to Alabama, "GA" corresponds to Georgia, "KY" corresponds to Kentucky, "MD" corresponds to Maryland, "MS" corresponds to Mississippi, "NY" corresponds to New York, "NC" corresponds to North Carolina, "OH" corresponds to Ohio, "PA" corresponds to Pennsylvania, "TN" corresponds to Tennessee, "VA" corresponds to Virginia, "WV" corresponds to West Virginia. Award data is compiled from the Appalachian Regional Commission (2022).

Figure 6: ARC POWER awards could represent important assistance to mining communities



Notes: Net destroyed coal mining job is defined as the number of coal mining jobs that were destroyed net of coal mining job creation. "Appalachia average" corresponds to the mean of the individual state values reported. For state abbreviations, "AL" corresponds to Alabama, "GA" corresponds to Georgia, "KY" corresponds to Kentucky, "MD" corresponds to Maryland, "MS" corresponds to Mississippi, "NY" corresponds to New York, "NC" corresponds to North Carolina, "OH" corresponds to Ohio, "PA" corresponds to Pennsylvania, "TN" corresponds to Tennessee, "VA" corresponds to Virginia, "WV" corresponds to West Virginia. Award data is compiled from the Appalachian Regional Commission (2022). Coal employment data is from U.S. Mine Safety and Health Administration's Historical Coal Production Data (2010-2022).

3 Literature Review

Although there is a rich literature on place-based policies in general, there are few studies that investigate the impact of place-based policies in the context of fossil fuel dependent communities. And while some studies have attempted to investigate the historical impact of ARC, there is much less evidence on the POWER initiative. First, I provide a brief overview of the literature on place-based policies. Then, I look at papers that study the ARC. Finally, I present those few studies that specifically examine the POWER initiative.

Place-based policies are distinguished from other policies by the fact that they target a geographically well-defined area. Place-based policies often provide assistance to businesses to encourage job growth and target under-performing areas where it is suspected that there is a need for government intervention due to market failures (Neumark and Simpson, 2015; Bartik, 2020). The theoretical basis for establishing place-based policies is quite wide (Neumark and Simpson, 2015; Juhász et al., 2023). Reasons why policymakers may wish to enact place-based policies include: the formation of industrial clusters in areas with access to natural resources; spatial mismatches such as labor frictions; positive externalities arising due to knowledge spill-overs; as well as equity motivations, that is the redistribution of the gains and losses arising through economic policies and market forces. The so-called "fly-paper" effect may also provide further motivation, whereby grants to a community result in a stimulus greater than if the equivalent amount were spent by private individuals (Hines Jr and Thaler, 1995; Inman, 2008), pointing to complementarities between public and private investment (or crowding-in).

Other studies have pointed out that place-based policies could have unintended consequences. Kline and Moretti (2013) suggest that under standard spatial equilibrium modeling assumptions, place-based policies may result in deadweight losses as they incentivize working and living in less productive or hospitable places. Similarly, Moretti (2011) argues that despite clear equity considerations, the benefits of place-based policy may not be fully captured by those that are being targeted since the incidence of subsidy will depend on the elasticity of local labor supply and housing supply. Finally, un-monitored discretionary-grants may lead to political capture of the grants, an oft-cited criticism against place-based policies (Juhász et al., 2023).

Thus far, the empirical evidence of place-based policies on employment outcomes seems positive. For instance, Kline and Moretti (2014) studies the Tennessee Valley Authority program's historical impact on employment. They find that both agricultural employment and manufacturing employment increased for the duration of the program but that manufacturing employment continued to intensify after the program ended, evidencing agglomeration economies. Bernini and Pellegrini (2011), using matched differences-in-differences estimation, find evidence that subsidized firms in southern Italy experience higher growth in output, employment and fixed assets, but lower increase in total factor productivity. Criscuolo et al. (2019) also find that among UK firms eligible for the Regional Selective Assistance program, an increase in investment subsidy is associated an increase in manufacturing employment, but find no evidence of effect on wages and total factor productivity. Other research found similar positive effects of place-based policies (Greenstone et al., 2010; Bronzini and De Blasio, 2006), although there are papers that find no effect (Crozet et al., 2004). In addition, studying the French Enterprise Zone program, Briant et al. (2015) show that the effect of place-based policies on employment depend on spatial integration.

Empirical evidence on the impact of the Appalachian Regional Commission's development initiatives is much less robust. The ARC was created in 1965, as an institution with the aim of fostering regional development (see Isserman and Rephann (1995) for a brief overview of ARC's history). Although the impact of ARC programs are evaluated by the ARC itself (for example, see the report *Appalachia then and now* by the Appalachian Regional Commission (2015)), there are few quantitative studies published in academic journals that try to estimate the impact of ARC programs. Possibly the first quantitative study on the subject was by Isserman and Rephann (1995) who find that between 1969 and 1991 total personal income and earnings grew 48 percentage points faster, population grew 5 percentage points faster and per capita income grew 17 percentage points faster in ARC counties than in other US counties with comparable socioeconomic and demographic attributes. In a subsequent paper, Glaeser and Gottlieb (2008) study the time period between 1970 to 2000 and find no evidence that population growth and income per capita growth in ARC counties are significantly different from non-ARC counties. In response to these two papers, using differences-in-differences approach, Ziliak (2012) provides estimates of the effect of ARC investments on poverty rates and per capita incomes, finding that ARC investments between 1960 and 2000 reduced Appalachian poverty rates by 7.6 percentage points relative to the rest of the United States and 4.5 percentage points compared to comparable rural counties. Finally, Sayago-Gomez et al. (2018) find that over a fifty-year period, counties which received ARC funding had higher per capita income and employment growth compared to control counties with similar socio-economic characteristics. Besides these studies, a few more papers investigate the effect of more specific ARC initiatives. Using differences-in-differences method, Grossman et al. (2019) find that ARC investments to expand sewage and waste water treatment improved access to running water in Appalachia. Jaworski and Kitchens (2019) find that the building of the Appalachian Development Highway System has led to welfare gains both in the United States and in Appalachian counties.

According to the ARC, POWER investments are projected to create or retain nearly 40,000 jobs, leverage USD 1.8 billion into the region and prepare 100,000 workers for jobs in technology, manufacturing, entrepreneurship and agriculture, among others (Appalachian Regional Commission, 2022). Despite the importance of supporting coal mining communities in the transition away from coal, research on the impact of the POWER Initiative remains scant. To my knowledge, only a few studies look into this question, none of which are published in academic journals. Closest to the present paper is the junior independent work by Morita (2021). Morita finds no evidence of POWER's impact on unemployment, suggesting that the null-effects could be due to recentness of the program. Therefore, it is worth revisiting the topic now that more time has passed and the program has been extended and use more sophisticated techniques to evaluate POWER's impact. There are four studies commissioned by the ARC which investigate the impact of the POWER Initiative (Chamberlin et al., 2019; Chamberlin and Dunn, 2020, 2021, 2022). While they provide important insight into the achievements and challenges of individual projects, they rely on qualitative methods such as surveys and in-depth interviews. Therefore, they do not constitute the robust quantitative evidence needed to assess the impact of the POWER initiative. Finally, Look et al. (2022) present a descriptive analysis of the POWER grants, providing an analysis of the types of projects, award amounts and their location. However, this study does not attempt to estimate the impact of the POWER program on economic outcomes such as on unemployment. Therefore, the causal effect of POWER grants on economic outcomes is currently not well-understood despite policy relevance.

As such, my study contributes to the literature in three ways. First, it contributes to the literature on place-based policies. Secondly, it contributes to a small literature on impact evaluation of the Appalachian Regional Commission's activity. Finally, it adds to an emerging literature on policies for a just and green transition.

4 Empirical Strategy

Does the POWER initiative reduce unemployment rates? A naive analysis of the effects of grants on unemployment would lead to biased estimates because the receipt of grants could be determined endogenously. There could be unobserved variables affecting both receipt of grants, as well as unemployment, or both grants and unemployment could be determined simultaneously. For instance, counties where the average unemployment rate is higher could receive higher amount of grants - but it is not higher grants that cause unemployment to be high.[5]

Building on the literature, I employ quasi-experimental differences-in-differences methodology, exploiting the temporal variation in treatment across counties. However, unlike the previous literature employing this methodology, I take into consideration recent developments in the differences-in-differences literature. In particular, a causal interpretation of the two-way fixed effects estimates requires that both parallel trends hold and that treatment effects be constant over time (Goodman-Bacon, 2021). This is because the two-way fixed effects estimator is a weighted average of differences-in-differences estimators with possibly negative weights, which could lead to biased estimates (de Chaisemartin and d'Haultfoeuille, 2020). An emerging new literature is proposing alternative estimators which can account for treatment heterogeneity, as well as dynamic effects. In particular, the estimator proposed by de Chaisemartin and d'Haultfoeuille (2024) is a flexible differences-in-differences estimator that is robust to heterogeneous treatment effects. It can be used in applications with binary and non-binary treatment, and when treatment is absorbing or non-absorbing, as well as when lagged treatments may affect outcomes.[6]

Heterogeneous treatment effects are plausible in the context of the POWER Initiative, since grants are given for a variety of different projects which could have different impacts on unemployment rate. Some projects may be more labor-intensive up-front, creating substantial temporary jobs for the duration of the project but which could then be destroyed following project completion. This could be the case for broadband infrastructure projects.[7] Meanwhile, some other projects may have a more long-term impact. For instance, training and re-skilling of coal miners would give them the necessary skills to earn a wage in industries other than coal mining - but the effects of such training may not be as immediately felt on unemployment rates. These are just some examples which show the need to take into account heterogeneous treatment effects.

My unit of analysis is county i in year t. For my main analysis, I assume that treatment is binary, absorbing and that treatment timing is staggered. As such, a county becomes treated once the first POWER project is announced in any given year, and its treatment status cannot be reversed. This specification is the most flexible because it allows for endogenous response of additional funding (including private investments) in subsequent periods. This is also a goal of ARC itself, which says that their funding also leveraged USD 1.8 billion in private investments, thus amplifying the impacts of the POWER grants. Therefore, my estimates for the main specification represent the effect of an initial announcement in a county where a project grantee is located.

My main outcome variable is unemployment rate in county i in year t. I allow for group-specific linear trends, to better capture the unique dynamics of groups' outcome evolution. As such, the outcome

[5] Appendix 10.3 provides additional robustness checks showing naive ordinary least square (OLS) regressions.

[6] Appendix section 10.5 provides a more detailed discussion of the methodology.

[7] Of course, infrastructure development including broadband infrastructure could then help both bring jobs to people and people to jobs with further long-term impact on unemployment. My example is to showcase that there is an initial creation of temporary jobs that are then likely destroyed following project completion.

variable is reported in first differences, that is the difference between unemployment rate between t and $t-1$.

As control variables, I use a number of variables that capture socio-demographic characteristics, as well as the size of the coal economy. I control for the size of the population and the poverty rate at $t-1$. I equally take into account the County Economic Status and Index Value Rank of a county. The former corresponds to the status designations presented previously, which are determined in a given fiscal year and influence the maximum possible ARC-share for a given project. Projects that target counties that have a lower County Economic Status designation are thus eligible for a higher grant amount from the ARC. The Index Value Rank corresponds to the specific position that a county takes in the rank of all U.S. counties from 1 (best) to 3113 (worst). Beyond these covariates, I also control for the size of the coal economy, specifically total coal production, total number of coal mines (including both underground and surface mines) and for average coal employment in a given county at $t-1$. Finally, I control for the total retired coal power plant capacity (in MegaWatts) in a given county in year $t-1$, to again account for the declining economic activity in the coal industry.

Furthermore, I make two identifying assumptions:

Assumption 1 - No Anticipation: I assume that the current outcome is not affected by future treatments.

Assumption 2 - Parallel trends: I assume that groups with the same baseline treatment have the same second-differenced outcome if those are explained by their covariates.[8]

These assumptions can be tested using placebo tests, which I present in subsequent sections. In addition, I conjecture that Assumption 1 should *a priori* hold given the policy setting. My treatment relates not to when POWER grants are paid out but when they are announced. Therefore, it is unlikely that unemployment would change in anticipation of the announcement, given the possible uncertainties associated with the grant awarding process. Indeed, many projects are not accepted by the ARC, which would likely deter project applicants from undertaking substantial project implementation decisions ahead of the announcements.

5 Data and Descriptive Statistics

To investigate whether the POWER Initiative has an impact on unemployment rates, I study a panel of 423 Appalachian Regional Commission counties observed from 2010 to 2022. I compile a variety of publicly available data sources for my study. Data on POWER grants is transcribed from a document titled "POWER Award Summaries by State as of October 2022" (Appalachian Regional Commission, 2022). For each entry, there is also a short description of the project and the grantee, which allows to gain more granular information about each project. It is important to note that the document provides information on the project grantee. Thus a working assumption I make throughout this study is that projects affect primarily the county where the project grantee is found. For unemployment rates, I use data from the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Furthermore, I gather data for covariates. I use county-level data on coal employment

[8] A parallel trends not on the level but for the first-difference of the outcome has been called the parallel growths assumption by Mora and Reggio (2012). See Appendix section 10.5 for the specific parallel trends expression used in my study.

(U.S. Department of Labor: Mine Safety and Health Administration, 2024), on coal production and the number of active coal mines (U.S. Energy Information Administration, 2012, 2013, 2014, 2015, 2016a,b, 2017, 2018, 2019, 2020, 2021, 2022, 2023a), and on the total retired coal power generating capacity (U.S. Energy Information Administration, 2023b). I also use data on socioeconomic and demographic variables of interest, such as county-level data on poverty rates (U.S. Census Bureau, 2024c) and data on the population (U.S. Census Bureau, 2024a,b). Finally, I use data from the ARC on counties' national Index Value Rank and economic status designation through fiscal years 2010 to 2022 (Appalachian Regional Commission, 2023a) to account for specificities in the grant process.

In total 427 projects received a POWER grant from 2015 to 2022. During this period, counties received almost USD 100,000 in grant awards on average. The highest amount of total awards were given to project grantees in Washington County, Virginia, with grants totaling to almost USD 6 million in 2016. Panel A of Table 1 shows key summary statistics for the outcome variable and control variables. In my data set there are 5463 observations, which correspond to 423 unique ARC counties observed between 2010 and 2022. Therefore, each observation corresponds to a county-year observation. The unemployment rate stood at 7% on average, but with a range from 1.8% (Shelby County, Alabama) to 20.6% (Magoffin County, Kentucky), showing that some counties may struggle with persistently high unemployment rates. A similarly stark picture emerges when looking at poverty rates, where the average poverty rate stood at 18.3%, but ranged from 4.1% in Forsyth County, Georgia to 47% in McCreary County, Kentucky. Counties had 60,000 inhabitants on average. Given the rural nature of the Appalachian region, some counties have a very small population (little more than 2000 inhabitants, such as Robertson County in Kentucky or Highland County in Virginia) while others may house larger cities such as Pittsburgh. As per the coal economy, average coal production stood at 540 thousand short tons, with maximum production at 30 million short tons (Greene County, Pennsylvania). Similarly, the average number of coal mines was almost 2 across all counties in the entire study period, with 88 coal mines found in Pike County, Kentucky. Average coal mine employment stood at 87 persons, with Boone County, West Virginia, having more than 4000 coal miners in 2011, at the peak of coal employment. Finally, average retired coal plant capacity reached 87 MegaWatts, with some counties seeing an almost 3000 MegaWatt decrease in coal-power generating capacity (for example Beaver County, Pennsylvania).

Panel B of Table 1 shows the mean and standard deviation of control variables broken down by treatment status, with treated county observations marked with "1" and county observations never-treated or not-yet treated marked with "0." The poverty rates are slightly lower in treated counties compared to non-treated counties, which could be due to the fact that the coal industry is an important employer and hence dampens poverty rates. Similarly, treated counties are more populous, which could again be a consequence of the coal industry being an important economic activity in the region, leading to the formation of agglomerations around coal mines. Equally, coal production is more important among the treated. The number of coal mines is almost three times as large in treated counties than in non-treated ones while the number of mines and coal employment is twice as large. In treated counties the size of retired coal plant capacity is also almost three times that of never-treated counties. These differences in magnitude justify the inclusion of these covariates in my analysis. Finally, the second part of Panel B of Table 1 details the breakdown of county economic status. The share of Transitional, At-Risk and Distressed counties is comparable across treated and non-treated units. Meanwhile the number of Attainment counties is slightly higher among the non-treated. Similarly, there are more Competitive counties among the treated than the non-treated, possibly because the ARC has an incentive to give awards to counties where the matching rate is low and a larger private investment can be leveraged.

Table 1: Key statistics for main variables

Panel A: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Unemployment rate (percent)	5,463	7.0	2.8	1.8	20.6
Poverty rate (percent)	5,463	18.3	5.7	4.1	47.0
Population	5,463	60,787.9	100,724.6	2,108	1,249,524
Total coal production ('000 short ton)	5,463	540.5	2,211.4	0	30,004
Number of coal mines	5,463	1.6	5.5	0	88
Total retired coal plant capacity (MW)	5,463	87.0	308.2	0	4,085
Persons employed in coal industry	5,463	6.1	83.8	0.0	2,741.1

Panel B: Summary statistics by treatment status

		0		1	
		Mean	St. Dev.	Mean	St. Dev.
Poverty rate (percent)		18.4	5.7	17.7	5.7
Population		56 240.4	89 680.3	96 636.0	159 097.5
Total coal production ('000 short ton)		457.2	1992.9	1197.7	3415.3
Number of coal mines		1.4	5.3	3.1	6.4
Total retired coal plant capacity (MW)		5.2	73.0	13.5	142.3
Persons employed in coal industry		75.5	293.1	177.5	397.5
		N	Pct.	N	Pct.
County Economic Status	Attainment	37	0.8	2	0.3
	Competitive	137	2.8	29	4.7
	Transitional	2478	51.1	321	52.2
	At-Risk	1192	24.6	145	23.6
	Distressed	1004	20.7	118	19.2

Notes: The data set corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Poverty rate corresponds to the poverty rate for all ages as reported by the U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program: Poverty and Median Household Income Estimates - Counties, States, and National data sets (2005-2022) (U.S. Census Bureau, 2024c). Population data is from the U.S. Census Bureau's population estimates for 2010-2019 and 2020-2022 (U.S. Census Bureau, 2024a,b). Data on coal production and number of coal mines is from the U.S. Energy Information Administration's Annual Coal Reports (2010-2022). Coal employment data is from U.S. Mine Safety and Health Administration's Historical Coal Production Data (2010-2022). In Panel B a county is treated and denoted with "1" if in a given year a project award is announced and is absorbing such that the county remains treated. Non-treated counties are denoted with "0."

6 Empirical Analysis

Having outlined the motivation, empirical strategy and descriptive statistics for this research, in this section I present the empirical findings of my analysis. I first provide the main results, which is then followed by a number of robustness checks using both alternative treatment definitions, as well as using an alternative method.

I conduct an event study analysis and estimate six post-treatment effects. Given the possibly long-term impacts of projects on unemployment rates, I include as many post-treatment periods as possible. This ensures that I capture the impact of projects which may create temporary jobs, as well as support workers in finding jobs in a longer horizon. I also use three pre-treatment lags to test for parallel trends, coinciding with the idea that economic status designations are decided based on three-year lagged indicators.

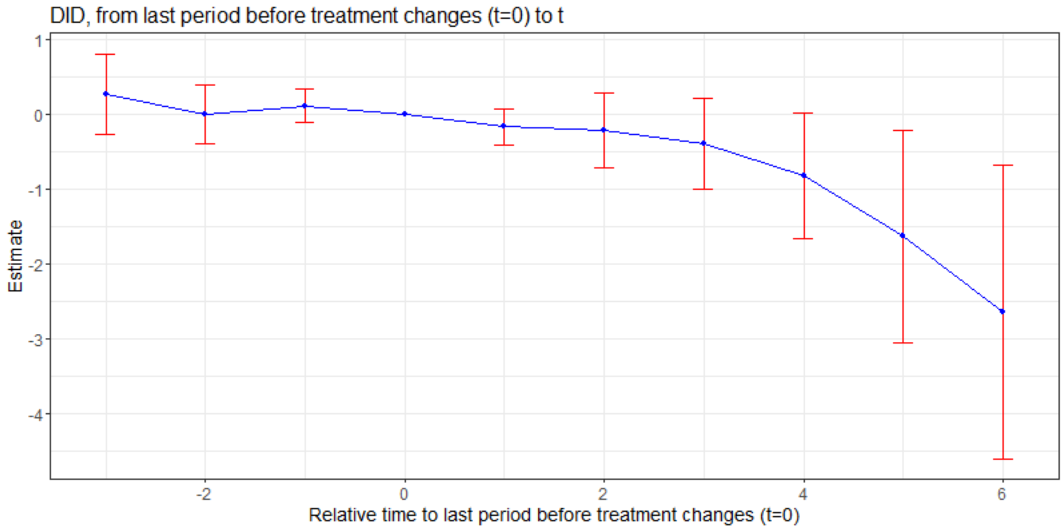
Figure 7 shows that there is a negative impact of POWER awards on the growth of unemployment rate 4-5 years after announcing the first POWER award, which is significant at the 1% significance level.[9] Specifically, the estimated effect on the first difference in unemployment rates are -1.6% four years and -2.6% five year following the first POWER award announcement. The interpretation of this effect is that this is the average effect of having been treated for five and six years rather than non-treated. The negative effect suggests that there could either be a slowdown in unemployment rate increase or an acceleration of the unemployment rate decrease. Since during this period unemployment rates were on average falling from their highs in the aftermath of the global financial crisis, it is likely that POWER projects accelerated this process by providing job opportunities and training for individuals in counties impacted by the decline in the coal industry.

Table 2 presents the estimated effects, the standard errors as well as the lower and upper-bound of the estimates (the 99% confidence interval). Event-study effects 1-4 are not significantly different from zero. This suggests that there could be delays in project implementation and in the impact of these projects on the unemployment rate. As mentioned previously, some projects, such as re-skilling and education may only bear fruit once the first cohorts have been trained and found jobs. Indeed, once sufficient time has passed from treatment onset, there is a decrease in the growth of unemployment rate.

Equally importantly, I find no evidence of violations of the parallel trends (parallel growths). The three placebos are not significantly different from zero. This shows that there is parallel growth in unemployment rates before the announcement of the first POWER project. Therefore, once accounting for group-specific linear trends, as well as for covariates, treated and non-treated countries are on a parallel growth trajectory pre-treatment, meaning that non-treated countries constitute a comparable group for analysis.

[9] Notice that period $t = 0$ corresponds to the last period before treatment changes. Therefore, treatment takes place in $t = 1$. Effects $t = 5$ and $t = 6$ then correspond to 4 to 5 years after the announcement of the first POWER award.

Figure 7: Effect of first POWER award announcements on growth of unemployment rate in ARC counties (treatment absorbing)



Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and is absorbing such that the county remains treated. Otherwise treatment is 0 for not-yet-treated and never-treated counties. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Bars represent the 99% confidence intervals.

Table 2: Estimation of treatment effects - Event-study effects (treatment binary and absorbing)

Effect	Estimate	SE	LB CI	UB CI
Placebo 3	0.272 56	0.210 90	−0.270 69	0.815 81
Placebo 2	0.004 06	0.150 11	−0.382 58	0.390 71
Placebo 1	0.119 54	0.085 93	−0.101 81	0.340 90
Effect 1	−0.162 24	0.095 34	−0.407 82	0.083 35
Effect 2	−0.206 77	0.193 82	−0.706 01	0.292 47
Effect 3	−0.382 80	0.235 95	−0.990 56	0.224 97
Effect 4	−0.819 40	0.326 84	−1.661 28	0.022 49
Effect 5	−1.633 60	0.555 50	−3.064 46	−0.202 74
Effect 6	−2.645 82	0.766 04	−4.619 02	−0.672 62

Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and is absorbing such that the county remains treated. Otherwise treatment is 0 for not-yet-treated and never-treated counties. SE refers to standard errors clustered at the FIPS-level. LB CI refers to the lower-bound of the 99% confidence interval. UB CI refers to the upper-bound of the 99% confidence interval.

I further investigate the robustness of my findings by using the alternative treatment definitions, including to account for treatment intensity. The benefit of alternative treatment definitions is that one can get a more granular overview of the effect of project grant announcements. It allows studying the effects of treatment reversals, and the effect of variable treatment intensity by looking at the number of project announcements or the overall size of the projects announced. I use an additional treatment definition whereby the treatment is binary but not absorbing: there will be some projects announced in some counties in some years but not in others. I equally use a treatment definition whereby treatment defined as a discrete number which corresponds to the number of projects announced in any given year in a given county. Therefore, treatment increases as the number of project announcements increase. Finally, I provide a further definition of treatment as the total amount of award funding (in USD million) announced by the ARC to be given to project grantees located in given county i in year t. This last definition is of interest as one could hypothesize that larger projects and more grants in a given county lead to a more substantial decrease in unemployment rates.

As such, I have three additional treatment definitions besides my preferred one:

1. Treatment is binary taking value 1 in whichever year the first POWER project is announced in a given county, absorbing (preferred definition)
2. Treatment is binary taking value 1 in the year in which any number of projects are announced in a given county, non-absorbing with possible treatment reversals
3. Treatment takes a positive discrete value corresponding to the number of projects announced in a given year in given county, non-absorbing with possible treatment reversals
4. Treatment takes a positive discrete value corresponding to the size of projects announced (in USD million) in a given year in given county, non-absorbing with possible treatment reversals

Using treatment definition 2, Appendix Figure 8 shows that five years following the announcement of any project grant in a given county, there is a negative effect on the growth of unemployment rate. Appendix Table 3 shows that the growth of unemployment rate is negative five years after treatment, estimated at -2%. Again, one finds that placebos are not significantly different from zero, which ensures that the parallel trend holds (see Appendix Table 3). Therefore, I find an effect that is not as large as in the previously presented analysis. This could be because my treatment definition picks up on small projects (for example small implementation projects under USD 50,000) which are unlikely to have an impact on unemployment rates but would still be part of this analysis. This suggests that one should perhaps take into account additional information, including how many projects are announced and the size of the projects (in USD).

Appendix Figure 9 shows the (normalized) effect of POWER award announcements using treatment definition 3, when treatment is defined as the number of projects announced in a given year in a given county (treatment definition 3).[10] The effect of one additional project announcement on unemployment rate growth is estimated at -0.3% 3 years following treatment, -0.5% 4 years following treatment and at -0.6% 5 years following treatment (see Appendix Table 4). This suggests that counties in which multiple projects have been announced are also more likely to see a decrease in the growth of unemployment rate (i.e. a slowdown of increase or an acceleration of the decrease in unemployment rates). Again, the parallel growth holds as the placebo effects estimates are not statistically significant at the 1% significance level.

[10]With normalization, the effect can be interpreted as being that of a one unit increase in treatment, i.e. the announcement of one additional project in a given year in a given county.

Finally, I also present analysis using treatment definition 4, whereby it is defined as the dollar amount announced for a given project in a given county in a specific year, and is non-absorbing. With this treatment definition, I find that the normalized effect of a project announcement of USD 1 million is associated with a decrease in unemployment rate growth by 0.2% in the treatment year, a decrease of 0.2% 2 years following treatment, a decrease of 0.4% 3 years following treatment, a decrease of 0.6% 4 years following treatment and a decrease of 0.7% 5 years following treatment (see Appendix Figure 10 and Appendix Table 5). Thus, the effect is greater, and is statistically significant at earlier periods than those found using the previous treatment definitions. However, one can also notice that the parallel growths does not fully hold, with the $t = -3$ placebo effect being statistically different from zero. This is because projects which receive large awards are likely in counties which have persistently high levels of unemployment. This suggests that there could be selection into treatment based on how quickly unemployment is increasing or how slowly unemployment is decreasing in some counties.

From the previous analysis, one may be worried that the parallel trends may not fully hold when looking at the effect of large project announcements (see Appendix Figure 10). Therefore, I present additional robustness checks for my analysis using synthetic control methods, which have been widely used in cases when parallel trends are not likely to hold. The synthetic control method suggested by Abadie et al. (2010, 2015) was developed for one treated unit with the purpose of bridging the gap between qualitative and quantitative studies (Abadie et al., 2015). However, the synthetic control method can also be extended to estimate the treatment effect in the presence of multiple treated units (Abadie, 2021). For my analysis, I use a "generalized synthetic control method" proposed by Xu (2017), which combines synthetic control methods with linear fixed effect models. This method is a generalization of the synthetic control method to cases with multiple treated units and variable treatment periods, and is robust to heterogeneous treatment effects.[11]

In order to check for the robustness of my results, I estimate the treatment effect of the first large POWER project announcement on unemployment rate. The method can only handle binary treatment that is of an absorbing state, thus it cannot directly estimate the effect of treatment intensity. I define as large award announcements those that are at least USD 1.5 million (i.e. implementation projects). Therefore, a county is considered treated whenever total announcements of at least this value are made, and the county remains treated for the rest of the study period as treatment is an absorbing state. I also use the same set of controls as in the previously presented analysis. Appendix Figure 11 shows that using the generalized synthetic method, the effect of the first POWER award announcement on unemployment rate[12] is negative five and six years following the announcement of the first large POWER award and is statistically significant at the 10% level. The effect is estimated at -0.7% five and six years following the first large POWER award announcement (see Appendix Table 6). This provides further evidence that large award announcements have a significant negative effect on unemployment rates in the five to six year horizon.

[11]I present a discussion of the methodology in Appendix section 10.6
[12]The outcome variable is no longer given in first differences.

7 Discussion and Policy Implications

What are some of the policy implications that emerge from this analysis? One important finding is that the POWER Initiative seems to have a negative effect on the growth of unemployment rate. This may suggest that POWER projects slow down the growth of unemployment in counties where programs are implemented. It could also suggest that the program has an accelerating effect on the fall of unemployment rate. Counties where projects within the POWER Initiative take place see a comparatively faster fall in their unemployment rate compared to control counties. Estimates suggest that unemployment rate decreases on average by 4.2% five years following treatment onset.[13] The relatively large effect could be due to endogenous response of additional funds following the announcement of a POWER initiative project in a given county. Since one of the objective of the ARC is to leverage private investment (which they claim amounted to USD 1.8 billion), findings perhaps also point to the possibility that there could be crowding-in and that public funding could be complementary to private funding.

An important metric to judge the POWER initiative by is how cost-effective it is in terms of creating jobs. I estimate the cost per job of the POWER Initiative to be USD 16544.[14] This figure is in line with cost per job estimates found elsewhere in the literature. For instance, Criscuolo et al. (2019) report that the Regional Selective Assistance program in the UK had a cost per job of USD 3541. Other studies find higher estimates (cf. Criscuolo et al. (2019) Appendix G), including USD 18295 and USD 63100 for grants and hiring credits in Empowerment Zones (Bartik, 2010; Glaeser and Gottlieb, 2008; Busso and Kline, 2008), USD 50820 for capital investment subsidies through the New Markets Tax Credit programme (Freedman, 2012), USD 22781 for guaranteed loans through Small Business Administration loans in the U.S. (Brown and Earle, 2017), USD 42638 to 68409 for capital subsidies in least-developed regions in Italy through Law 488/91 (Pellegrini and Muccigrosso, 2017; Cerqua and Pellegrini, 2014). Thus, the estimated cost per job of the POWER Initiative is on the lower end, implying that it could be a cost-effective measure to create jobs.

A policy implication is that that there could be scope to increase the scale of the POWER Initiative, and that it could be a possible blue-print for place-based policies targeting areas where there is a decline in fossil-fuel based activities. Throughout the years, the amount of project funding requested by project applicants has been at least 2-3 times larger than the budget available to the ARC for the POWER program (Congressional Research Service, 2022). Therefore, there could be scope to meet the increasing demand for project grants.

One caveat, however, is that this analysis is agnostic to the quality of jobs created, including whether they are full-time or part-time jobs or as to the wages associated with these jobs. Therefore, while it was estimated that the POWER initiative reduces unemployment rates in the four to five-year horizon, it remains to be seen whether they allow coal communities in Appalachia to reach comparable welfare levels as during the peak of coal employment.

[13] The effect on the outcome can be calculated as the sum of the effects on the first-differenced outcome. Thus the sum of the estimated -1.6% four years and -2.6% five years following the first project announcement gives a -4.2% effect on unemployment rate five years following treatment.

[14] Appendix Section 10.4 details the exact methodology used to estimate the cost per job of the POWER Initiative.

8 Extensions

This present study found evidence that POWER Initiative may decrease unemployment in the 4-5 year horizon. While this is in and by itself interesting evidence that can be leveraged for further policy analysis and to better design policies for the just transition, there are important extensions that this work could be used for.

The phase-out of coal could have a significant negative impact on coal-dependent regions, which in turn could generate political backlash against ambitious environmental policies. Therefore, despite expert consensus on the need for phasing out coal, policymakers could be constrained by the political feasibility of environmental policy (Millner and Ollivier, 2016). Governments can help build public support for environmental policies by understanding and addressing citizens' concerns (Dechezleprêtre et al., 2022). How the public arrives at its beliefs about environmental problems has not been at the center of environmental policy considerations, with economic studies taking the demand for environmental policy as given (Millner and Ollivier, 2016). This is despite the fact that evidence from large-scale surveys with more than 40000 respondents in 20 countries suggests that fundamental beliefs are a major predictor of support for environmental policy (Dechezleprêtre et al., 2022). These predictors include beliefs about the distributional impacts of policy on lower-income households as well as the perceived economic impact of policy on individuals. Similarly, in an analysis of a representative sample of 2,476 Americans, Bergquist et al. (2020) find that bundling together climate policy with other economic and social reforms, such as affordable housing or minimum wage, increases public support for climate mitigation in the US.

In the case of the POWER initiative, the main motivation for place-based policies is to support workers that lose their livelihoods due to the decline of coal mining, and to ensure that the minimum level of public good provision, such as healthcare and education, is available for these communities. This suggests equity motivations and a strong desire to redistribute. Indeed, Gaikwad et al. (2022) find that coal communities have higher preferences for compensatory measures for coal workers who may lose their jobs due to climate policies, implying a strong taste for redistribution and policies in line with the "just transition." In the United States there is evidence on strong bipartisan support for assisting displaced coal workers (Mayer, 2018, 2022b). Support often includes saving coal mining jobs even at the expense of ratepayers (Van Nostrand, 2022; Mayer, 2022a). These regions could have strong identities tied to fossil fuels (DeWitte, 2023).

Currently the literature suggests that the distributional impact of the decline in the coal industry may lead to political backlash. Egli et al. (2022) report that Appalachian counties that experienced decline in coal industry jobs are also more likely to vote for (pro-coal) Republican candidates. This is in line with the wider literature finding political backlash among white voters following trade liberalization and deindustrialization (Autor et al., 2020; Baccini and Weymouth, 2021). Environmental policies could also lead to similar backlash (Colantone et al., 2022). Could the opposite be true? Could place-based policy with a redistribution component also help curb possible backlash against environmental policies? If policy, such as the POWER program, is successful in reducing unemployment rates in places heavily impacted by the net-zero transition, they may not only provide a blue-print for just transition policies but also alleviate the potential political economy concerns associated with the just transition. As such, it may be of interest to policymakers to consider including a strong redistribution within environmental policy packages.

9 Conclusion

As governments announce ambitious climate policies, and economies shift away from fossil fuels, the livelihoods of hundreds of thousands of people could be affected. Therefore, the coal phase-out could have important distributional consequences, which in turn poses a policy challenge. The present study provides empirical evidence that place-based policies could help reduce unemployment in coal communities.

A traditionally coal-based economy, the Appalachian region in the United States has seen a large decline in coal employment. This has prompted policymakers to support coal communities in transition by providing grants through the POWER Initiative with an aim to diversify the economy and re-skill workers so that they are better prepared for a post-coal economy. I find in my analysis that five years following the first announcement of POWER awards, on average unemployment rate decreases by 4.2%. The cost per job of the POWER Initiative is estimated at USD 16544, which makes it a relatively cost-effective program.

Needless to say, the United States is far from being the only coal-producing country. China, India and Indonesia are also some of the largest coal producers, with possibly much higher coal employment than the United States. Australia and South Africa are similarly important coal producers globally. Countries in Europe, ranging from Germany, Poland and Greece, also have active coal employment or coal production. As governments of these countries devise meaningful climate policies to meet net-zero ambitions, they may also need to think about the distributional consequences of these policies on their respective coal-dependent regions. Place-based policies aiming to re-skill workers and diversify the economy could be a key policy instrument in their toolkit.

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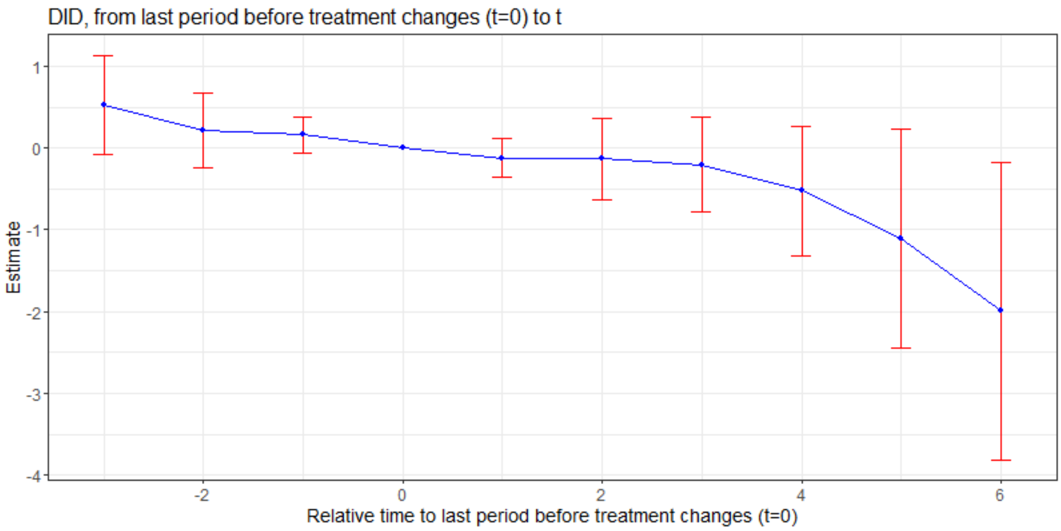
10 Appendix

10.1 Robustness checks using differences-in-differences

Figure 8: Effect of POWER award announcements on growth of unemployment rate in ARC counties (treatment binary and non-absorbing)



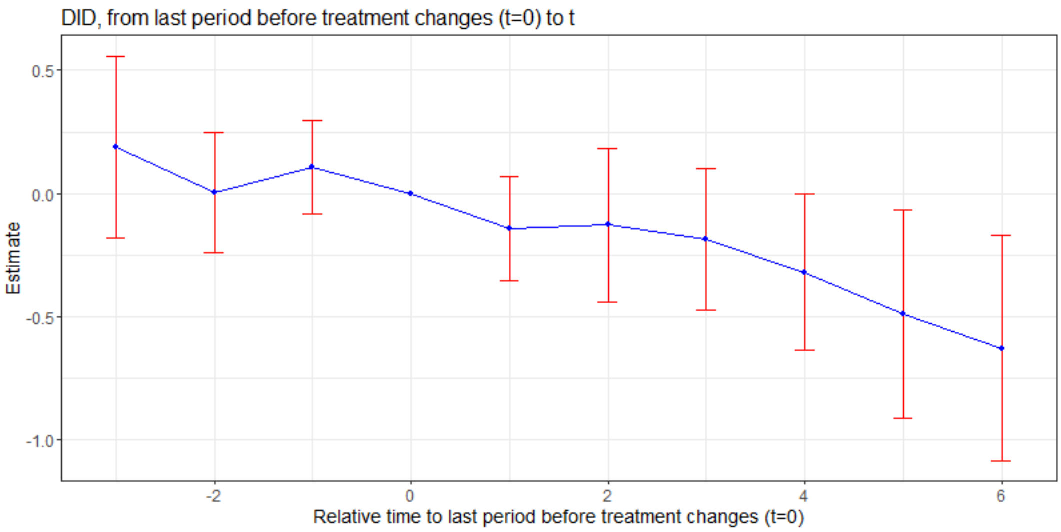
Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and 0 otherwise. Treatment can reverse if no project awards are announced in subsequent years. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Bars represent the 99% confidence intervals.

Table 3: Estimation of treatment effects - Event-study effects (treatment binary and non-absorbing)

Effect	Estimate	SE	LB CI	UB CI
Placebo 3	0.528 42	0.235 12	−0.077 21	1.134 06
Placebo 2	0.212 77	0.176 73	−0.242 45	0.667 98
Placebo 1	0.159 57	0.086 71	−0.063 77	0.382 91
Effect 1	−0.119 90	0.094 58	−0.363 51	0.123 72
Effect 2	−0.129 71	0.193 31	−0.627 64	0.368 21
Effect 3	−0.204 45	0.226 77	−0.788 57	0.379 67
Effect 4	−0.527 05	0.308 81	−1.322 50	0.268 40
Effect 5	−1.109 03	0.518 26	−2.443 98	0.225 92
Effect 6	−1.993 15	0.708 21	−3.817 38	−0.168 91

Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and 0 otherwise. Treatment can reverse if no project awards are announced in subsequent years. SE refers to standard errors clustered at the FIPS-level. LB CI refers to the lower-bound of the 99% confidence interval. UB CI refers to the upper-bound of the 99% confidence interval.

Figure 9: Effect of number of POWER award announcements on growth of unemployment rate in ARC counties (treatment discrete and non-absorbing)



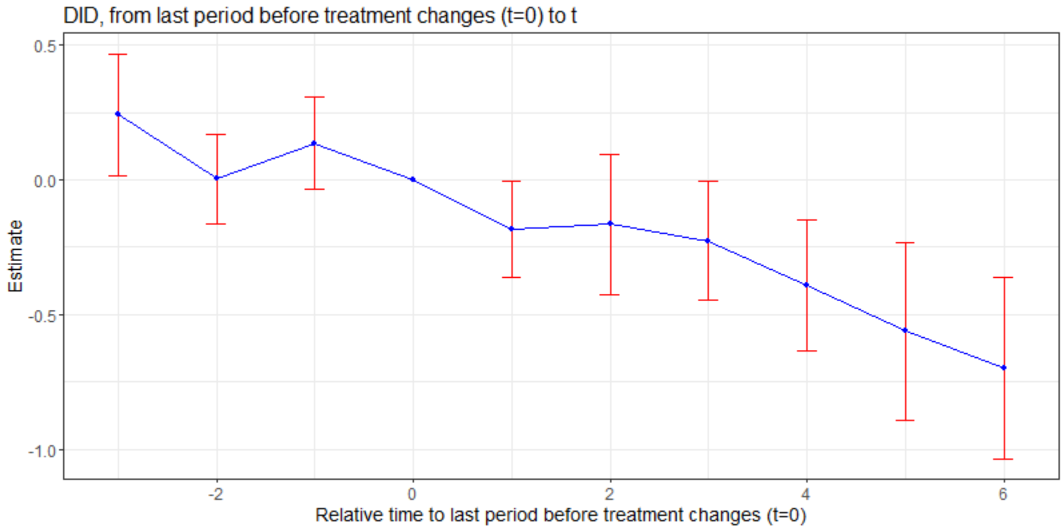
Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. The graph shows the normalized event study effects. Treatment is defined as a discrete variable that takes value equal to the number of project award announcements in a given year in a given county. Treatment can reverse if no project awards are announced in subsequent years. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Bars represent the 99% confidence intervals.

Table 4: Estimation of treatment effects - Event-study effects (treatment discrete and non-absorbing)

Effect	Estimate	SE	LB CI	UB CI
Placebo 3	0.189 41	0.143 25	−0.179 59	0.558 40
Placebo 2	0.002 64	0.094 81	−0.241 58	0.246 85
Placebo 1	0.104 79	0.073 41	−0.084 30	0.293 89
Effect 1	−0.142 22	0.081 45	−0.352 01	0.067 57
Effect 2	−0.129 49	0.120 35	−0.439 50	0.180 52
Effect 3	−0.184 62	0.111 44	−0.471 66	0.102 42
Effect 4	−0.320 49	0.123 49	−0.638 57	−0.002 41
Effect 5	−0.490 85	0.164 02	−0.913 33	−0.068 37
Effect 6	−0.628 83	0.178 08	−1.087 53	−0.170 13

Notes: Sample includes 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as the number of projects announced in a given year in a given county. Treatment can reverse if no project awards are announced in subsequent years. The table shows the estimates after normalization. SE refers to standard errors clustered at the FIPS-level. LB CI refers to the lower-bound of the 99% confidence interval. UB CI refers to the upper-bound of the 99% confidence interval.

Figure 10: Effect of size of POWER award announcements (in million USD) on growth of unemployment rate in ARC counties (treatment discrete and non-absorbing)



Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. The graph shows the normalized event study effects. Treatment is defined as a discrete variable that takes a value equal to the size of project award announcements in a given year in a given county. Treatment can reverse if no project awards are announced in subsequent years. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Bars represent the 99% confidence intervals.

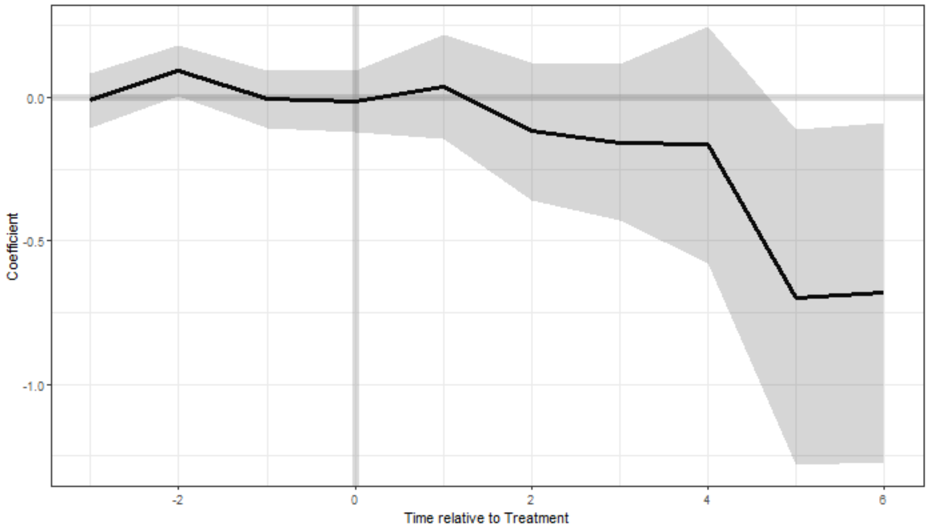
Table 5: Estimation of treatment effects - Event-study effects (treatment discrete and non-absorbing)

Effect	Estimate	SE	LB CI	UB CI
Placebo 3	0.242 42	0.087 47	0.017 11	0.467 73
Placebo 2	0.003 39	0.064 86	−0.163 68	0.170 45
Placebo 1	0.134 62	0.066 43	−0.036 50	0.305 74
Effect 1	−0.182 70	0.069 84	−0.362 60	−0.002 79
Effect 2	−0.165 30	0.100 59	−0.424 41	0.093 81
Effect 3	−0.227 47	0.085 77	−0.448 40	−0.006 53
Effect 4	−0.392 14	0.093 77	−0.633 67	−0.150 61
Effect 5	−0.562 55	0.128 85	−0.894 45	−0.230 66
Effect 6	−0.699 58	0.130 96	−1.036 90	−0.362 26

Notes: Sample includes 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as dollar amount announced for a given project in a given county in a specific year. Treatment can reverse if no project awards are announced in subsequent years. The table shows the estimates after normalization. SE refers to standard errors clustered at the FIPS-level. LB CI refers to the lower-bound of the 99% confidence interval. UB CI refers to the upper-bound of the 99% confidence interval.

10.2 Robustness check using generalized synthetic control method

Figure 11: Effect of large POWER award announcements on unemployment rate (generalized synthetic control method)



Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 whenever a first award announcement of at least USD 1.5 million value takes place in a county. Otherwise treatment is 0 for not-yet-treated and never-treated counties. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). Shaded area represents the 90% confidence intervals.

Table 6: Average treatment effect on the treated by period (including pre-treatment periods)

	ATT	SE	LB CI	UB CI
-3	−0.009 740	0.057 03	−0.103 549	0.084 07
-2	0.092 242	0.054 83	0.002 057	0.182 43
-1	−0.005 579	0.057 61	−0.100 341	0.089 18
0	−0.014 083	0.069 42	−0.128 268	0.100 10
1	0.037 538	0.112 19	−0.146 996	0.222 07
2	−0.117 368	0.139 66	−0.347 090	0.112 35
3	−0.156 224	0.166 05	−0.429 344	0.116 90
4	−0.165 206	0.243 85	−0.566 305	0.235 89
5	−0.697 036	0.358 14	−1.286 127	−0.107 95
6	−0.679 071	0.347 43	−1.250 542	−0.107 60

Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 whenever an award announcement of at least USD 1.5 million takes place in a county. Otherwise treatment is 0 for not-yet-treated and never-treated counties. Unemployment rate is calculated as the yearly average of monthly unemployment rates, as reported by the Local Area Unemployment Statistics (LAUS) program (Bureau of Labor Statistics, 2024). ATT refers to the average treatment on the treated. SE refers to standard errors, clustered at the FIPS-level. LB CI refers to the lower-bound of the 90% confidence interval. UB CI refers to the upper-bound of the 90% confidence interval.

10.3 Analysis using OLS and TWFE estimator

One may want to estimate the following regression:

$$y_{it} = \psi a_{it} + X'_{it}\gamma$$

This is a regression of unemployment rate (y_{it}) in county i at time t on POWER award announcement (a_{it}) announced by ARC for county i at time t,with pre-determined covariates that account for the size of the coal economy and county-level socio-demographic characteristics ($X'_{it}\gamma$). The parameter of interest is (ψ), the effect of the first POWER award announcement on the unemployment rate. Table 7 shows that a simple regression of unemployment rate on award announcement recovers a negative relationship (see column 1 of Table 7). Once I include controls, the coefficient becomes smaller (see column 2 of Table 7). While the estimated effect of POWER award announcement on unemployment rate is negative, this could in fact be due to a generally decreasing unemployment rate throughout this period (See Figure 2). Therefore, one can include county and time fixed effects:

$$y_{it} = \psi a_{it} + X'_{it}\gamma + \delta_i + \tau_t$$

Finally, using the two-way fixed effects estimator indeed reverses the relationship such that there is a positive association between award size and unemployment rate. This could be due to the fact that when treatment effects are heterogeneous, the two-way fixed effects estimation recovers a weighted average of differences-in-differences estimators with possibly negative weights. Tables 8, 9, 10 provide results for a similar regression analysis using treatment definitions 2-4, as defined in Section 6:

1. Treatment is binary taking value 1 in whichever year the first POWER project is announced in a given county, absorbing (preferred definition)
2. Treatment is binary taking value 1 in the year in which any number of projects are announced in a given county, non-absorbing with possible treatment reversals
3. Treatment takes a positive discrete value corresponding to the number of projects announced in a given year in given county, non-absorbing with possible treatment reversals
4. Treatment takes a positive discrete value corresponding to the size of projects announced (in USD million) in a given year in given county, non-absorbing with possible treatment reversals

The estimated effects using the OLS estimator are negative for all treatment definitions, although the magnitudes are lower once one accounts for treatment intensity. This could be because treatment definitions account for treatment reversal. But again, using the two-way fixed effect estimator recovers a positive effect of award on unemployment rate, which could be attributed to the heterogeneity of treatment effects.

Table 7: Regression of unemployment rate on POWER award announcements (binary, absorbing)

Dependent Variable:	Unemployment rate		
Model:	(1)	(2)	(3)
Variables			
Constant	7.156***	3.670***	
	(0.0392)	(0.4188)	
Award (binary, absorbing)	-1.574***	-1.184***	0.7165***
	(0.1168)	(0.1085)	(0.1073)
Number of coal mines in t-1		0.0507***	0.0209
		(0.0117)	(0.0184)
Total coal production (thousand short ton) in t-1		3.71×10^{-5}**	-7.77×10^{-5}
		(1.75×10^{-5})	(4.74×10^{-5})
Total retired coal plant capacity (MegaWatts)		0.0008*	0.0002
		(0.0004)	(0.0002)
Population in t-1		-5.87×10^{-7}	-4.47×10^{-6}
		(5.27×10^{-7})	(5.14×10^{-6})
Poverty (%) in t-1		0.1994***	0.0861***
		(0.0179)	(0.0106)
Index Value Rank		-0.0003*	-0.0004***
		(0.0002)	(0.0001)
County Economic Status: Attainment		-0.2397	-0.0430
		(0.5419)	(0.5298)
County Economic Status: Competitive		-0.1647	0.0753
		(0.3434)	(0.2493)
County Economic Status: Distressed		0.5294***	0.0677
		(0.1657)	(0.1023)
County Economic Status: Transitional		-0.0361	0.0684
		(0.1509)	(0.0853)
Fixed-effects			
FIPS			Yes
Year			Yes
Fit statistics			
Standard-Errors	IID	cluster	
Observations	5,463	5,043	5,043
R^2	0.03218	0.27202	0.87098
Within R^2			0.06441

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and is absorbing such that the county remains treated. Otherwise treatment is 0 for not-yet-treated and never-treated counties. Standard errors (in parenthesis) are clustered at the FIPS-level.

Table 8: Regression of unemployment rate on on POWER award announcements (binary, non-absorbing)

Dependent Variable:	Unemployment rate		
Model:	(1)	(2)	(3)
Variables			
Constant	7.058***	3.606***	
	(0.0384)	(0.4231)	
Award (binary, non-absorbing)	-1.434***	-1.103***	0.5461***
	(0.1631)	(0.1366)	(0.0805)
Number of coal mines in t-1		0.0485***	0.0166
		(0.0117)	(0.0185)
Total coal production (thousand short ton) in t-1		2.89×10^{-5}	-9.11×10^{-5}*
		(1.84×10^{-5})	(4.8×10^{-5})
Total retired coal plant capacity (MegaWatts)		0.0008**	0.0002
		(0.0004)	(0.0003)
Population in t-1		-8.26×10^{-7}	-4.62×10^{-6}
		(5.89×10^{-7})	(4.93×10^{-6})
Poverty (%) in t-1		0.2054***	0.0944***
		(0.0180)	(0.0107)
Index Value Rank		-0.0004**	-0.0004***
		(0.0002)	(0.0001)
County Economic Status: Attainment		-0.2396	-0.0199
		(0.5116)	(0.5999)
County Economic Status: Competitive		-0.1956	0.0293
		(0.3536)	(0.2509)
County Economic Status: Distressed		0.5106***	0.0685
		(0.1678)	(0.1043)
County Economic Status: Transitional		-0.0344	0.0519
		(0.1514)	(0.0851)
Fixed-effects			
FIPS			Yes
Year			Yes
Fit statistics			
Standard-Errors	IID	cluster	
Observations	5,463	5,043	5,043
R^2	0.01395	0.25990	0.86894
Within R^2			0.04964

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and 0 otherwise. Treatment can reverse if no project awards are announced in subsequent years. Standard errors (in parenthesis) are clustered at the FIPS-level.

Table 9: Regression of unemployment rate on number of POWER award announcements

Dependent Variable:	Unemployment rate		
Model:	(1)	(2)	(3)
Variables			
Constant	7.044***	3.557***	
	(0.0381)	(0.4261)	
Number of awards	-0.9185***	-0.7626***	0.3235***
	(0.1105)	(0.0822)	(0.0553)
Number of coal mines in t-1		0.0481***	0.0169
		(0.0117)	(0.0185)
Total coal production (thousand short ton) in t-1		2.86×10^{-5}	-8.97×10^{-5}*
		(1.9×10^{-5})	(4.86×10^{-5})
Total retired coal plant capacity (MegaWatts)		0.0008**	0.0002
		(0.0004)	(0.0003)
Population in t-1		-7.33×10^{-7}	-4.91×10^{-6}
		(6.39×10^{-7})	(4.95×10^{-6})
Poverty (%) in t-1		0.2071***	0.0941***
		(0.0180)	(0.0108)
Index Value Rank		-0.0004**	-0.0004***
		(0.0002)	(0.0001)
County Economic Status: Attainment		-0.2197	-0.0452
		(0.5124)	(0.5970)
County Economic Status: Competitive		-0.1515	0.0076
		(0.3584)	(0.2518)
County Economic Status: Distressed		0.5092***	0.0726
		(0.1683)	(0.1045)
County Economic Status: Transitional		-0.0276	0.0452
		(0.1516)	(0.0858)
Fixed-effects			
FIPS			Yes
Year			Yes
Fit statistics			
Standard-Errors	IID	cluster	
Observations	5,463	5,043	5,043
R^2	0.01248	0.26026	0.86840
Within R^2			0.04571

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Treatment is defined as the number of projects announced in a given year in a given county. Treatment can reverse if no project awards are announced in subsequent years. Standard errors (in parenthesis) are clustered at the FIPS-level.

Table 10: Regression of unemployment rate on size of POWER award announcements

Dependent Variable:	Unemployment rate		
Model:	(1)	(2)	(3)
Variables			
Constant	7.023***	3.532***	
	(0.0379)	(0.4220)	
Award (million USD)	-0.7269***	-0.6604***	0.2151***
	(0.1079)	(0.0654)	(0.0451)
Number of coal mines in t-1		0.0482***	0.0144
		(0.0118)	(0.0189)
Total coal production (thousand short ton) in t-1		2.61×10^{-5}	-8.95×10^{-5}*
		(1.93×10^{-5})	(4.98×10^{-5})
Total retired coal plant capacity (MegaWatts)		0.0009**	0.0001
		(0.0004)	(0.0003)
Population in t-1		-9.02×10^{-7}	-4.98×10^{-6}
		(6.06×10^{-7})	(4.99×10^{-6})
Poverty (%) in t-1		0.2071***	0.0950***
		(0.0180)	(0.0108)
Index Value Rank		-0.0004**	-0.0004***
		(0.0002)	(0.0001)
County Economic Status: Attainment		-0.1656	-0.0432
		(0.5114)	(0.5951)
County Economic Status: Competitive		-0.1383	0.0076
		(0.3550)	(0.2556)
County Economic Status: Distressed		0.5028***	0.0736
		(0.1685)	(0.1050)
County Economic Status: Transitional		-0.0226	0.0448
		(0.1512)	(0.0865)
Fixed-effects			
FIPS			Yes
Year			Yes
Fit statistics			
Standard-Errors	IID	cluster	
Observations	5,463	5,043	5,043
R^2	0.00824	0.25813	0.86775
Within R^2			0.04102

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Treatment is defined as dollar amount announced for a given project in a given county in a specific year. Treatment can reverse if no project awards are announced in subsequent years. Standard errors (in parenthesis) are clustered at the FIPS-level.

10.4 Cost per job methodological note

I provide a summary of the methodology used to calculate the cost per job estimate presented in Section 7. I first calculate the total number of unemployed persons (using LAUS data from the Bureau of Labor Statistics (2024)) in ever-treated counties, i.e. counties where a POWER project announcement takes place between 2015 and 2022. Taking the most recent 6 years as the basis of my calculation, unemployment levels fell by 71383. I then conduct a differences-in-differences analysis using the same specification as in the main analysis (i.e. treatment is binary and absorbing) and using log unemployment as my outcome variable (See Table 11). Using this method I estimate that the first announcement of the POWER Initiative is associated with a 28% decrease in unemployment levels, calculated as $\exp(-0.32178) - 1 = -0.2751$. I interpret this as meaning that the POWER Initiative explains 28% of the fall in unemployment in a six year period, which corresponds to a decrease in unemployment levels by 19987.[15] The cumulative project grant spending in ARC counties by 2022 amounted to USD 330658710, or almost USD 331 million. Dividing this number by the estimated number of persons who exited unemployment due to the POWER initiative gives the following cost per job (j) formula:

$$j = \frac{\text{Total POWER spending}}{\text{Estimated number of persons that exited unemployment due to POWER}} = \frac{330658710}{19987} = 16543.49$$

i.e. the estimated cost per job is approximately USD 16544. As explained in Section 7, this estimate is within the range of cost per job figures reported elsewhere in the literature.

Table 11: Estimation of treatment effects: Event-study effects on log unemployment (treatment binary and absorbing)

Effect	Estimate	SE	LB CI	UB CI
Placebo 3	0.036 05	0.032 70	−0.048 17	0.120 27
Placebo 2	0.022 33	0.023 26	−0.037 58	0.082 25
Placebo 1	0.016 16	0.011 70	−0.013 97	0.046 28
Effect 1	−0.005 27	0.014 00	−0.041 35	0.030 80
Effect 2	0.013 10	0.028 44	−0.060 16	0.086 37
Effect 3	−0.016 77	0.033 50	−0.103 07	0.069 53
Effect 4	−0.069 05	0.045 43	−0.186 07	0.047 98
Effect 5	−0.168 94	0.069 01	−0.346 71	0.008 83
Effect 6	−0.321 78	0.095 53	−0.567 86	−0.075 70

Notes: Sample corresponds to a panel of 423 counties designated as officially served by the Appalachian Regional Commission from year 2010 to 2022. Treatment is defined as a binary variable that takes value 1 if in a given year a project award is announced and is absorbing such that the county remains treated. Otherwise treatment is 0 for not-yet-treated and never-treated counties. SE refers to standard errors clustered at the FIPS-level. LB CI refers to the lower-bound of the 99% confidence interval. UB CI refers to the upper-bound of the 99% confidence interval.

[15] Chamberlin and Dunn (2022) estimates that nearly 21000 jobs were created or retained within the POWER program by 2022, which is very close to my estimate.

10.5 Differences-in-differences methodological description

To further elucidate the method used throughout this study, I present the differences-in-differences estimator proposed by de Chaisemartin and d'Haultfoeuille (2024), closely following the notation presented by the authors.[16] I have a panel of G groups (counties), observed over T periods (from 2010 to 2022). Treatment of group g at time t is denoted by $D_{g,t}$, with $\mathbf{D}_g = (D_{g,1}, ..., D_{g,T})$ being a vector stacking group g's treatments across time. $\mathbf{D}$ stacks treatments of all groups across all periods, and is the design of the study on which analysis is conditioned. Let $Y_{g,t}(d_1, ..., d_t)$ denote the potential outcome of g at t. Let F_g denote the first period when treatment changes for group g. T_g is the last period where there is still a group with the same first period treatment as g that remains not treated. Let $X_{g,t}$ be a vector of covariates.

I make two identifying assumptions:

Assumption 1 - No Anticipation: I assume that the current outcome is not affected by future treatments.

Assumption 2 - Parallel trends: I assume that the following relationship holds:

$$
\begin{aligned}
&E[Y_{gt}(D_{g,1,t}) - Y_{g,t-1}(D_{g,1,t-1}) - (Y_{g,t-1}(D_{g,1,t-1}) - Y_{g,t-2}(D_{g,1,t-2})) \\
&\quad -(X_{g,t} - X_{g,t-1} - (X_{g,t-1} - X_{g,t-2}))'\theta_{D_{g,1}})|\mathbf{D}, \mathbf{X}] \\
&= E[Y_{g',t}(D_{g',1,t}) - Y_{g',t-1}(D_{g',1,t-1}) - (Y_{g',t-1}(D_{g',1,t-1}) - Y_{g',t-2}(D_{g',1,t-2})) \\
&\quad -(X_{g',t} - X_{g',t-1} - (X_{g',t-1} - X_{g',t-2}))'\theta_{D_{g',1}})|\mathbf{D}, \mathbf{X}]
\end{aligned}
$$

Assumption 2 allows for groups to experience differential trends if groups with the same baseline treatment have the same second-differenced outcome and if those "growths" are explained by their covariates.[17]

An estimator of interest is then given by the following expression:

$$
\begin{aligned}
DID^{fd,X}_{g,l} &= Y_{g,F_g-1+l} - Y_{g,F_g-1+l-1} - (Y_{g,F_g-1} - Y_{g,F_g-2}) \\
&\quad -(X_{g,F_g-1+l} - X_{g,F_g-1+l-1} - (X_{g,F_g-1} - X_{g,F_g-2}))'\hat{\theta}_{D_{g1}} \\
-\frac{1}{N^g_{F_g-1+l}} &\sum_{g':D_{g'1}=d, F_{g'}>F_{g-1+l}} [Y_{g',F_g-1+l} - Y_{g',F_g-1+l-1} - (Y_{g',F_g-1} - Y_{g',F_g-2}) \\
&\quad -(X_{g',F_g-1+l} - X_{g',F_g-1+l-1} - (X_{g',F_g-1} - X_{g',F_g-2}))'\hat{\theta}_{D_{g1}}]
\end{aligned}
$$

If Assumptions 1 and 2 hold, then:

$$E[DID^{fd,X}_{g,l}] = \delta_{g,l} - \delta_{g,l-1}$$

where $\delta_{g,l} = E(Y_{g,F_g-1+l} - Y_{g,F_g-1+l}(D_{g,1}, ..., D_{g,1}))$ and $\delta_{g,l-1} = E(Y_{g,F_g-1+l-1} - Y_{g,F_g-1+l-1}(D_{g,1}, ..., D_{g,1}))$, which are the expected difference between group g's actual outcome and the counterfactual outcome in

[16] The complete and detailed treatment of the proposed estimator is found in de Chaisemartin and d'Haultfoeuille (2024), here I only present the essentials necessary to motivate the empirical strategy used in this study. For my analysis I use the R package `DIDmultiplegtDYN` developed to implement the estimator (Ciccia et al., 2024).

[17] This parallel trends assumption is based on a combination of Assumption 7 and Assumption 8 of the Web Appendix of de Chaisemartin and d'Haultfoeuille (2024). A parallel trends not on the level but for the first-difference of the outcome has been called the parallel growths assumption by Mora and Reggio (2012)

the absence of treatment. Then it follows that:[18]

$$DID_{l,l'}^{fd,X} = \frac{1}{N_l^{fd,X}} \sum_{g:F_g \geq 3, F_g - 1 + l \leq T_g} S_g DID_{g,l'}^{fd,X}$$

where l is all possible l that can be estimated and $l' \in \{1, ..., l\}$, and where $N_l^{fd,X} = \#g : F_g \geq 3, F_g - 1 + l \leq T_g$ and $S_g = 1\{D_{g,F_g} > D_{g,1}\} - 1\{D_{g,F_g} < D_{g,1}\}$. Then it is implied that:

$$E[DID_{l,l'}^{fd,X}] = \frac{1}{N_l^{fd,X}} \sum_{g:F_g \geq 3, F_g - 1 + l \leq T_g} S_g(\delta_{g,l'} - \delta_{g,l'-1})$$

which in turn leads us to:

$$\sum_{l'=1}^{l} DID_{l,l'}^{fd,X} = \frac{1}{N_l^{fd,X}} \sum_{g:F_g \geq 3, F_g - 1 + l \leq T_g} S_g \delta_{g,l} = \delta_l^{fd,X}$$

which is the non-normalized event-study effect in a model allowing group-specific linear trends and controlling for covariates. The $\delta_l^{fd,X}$ estimated are objects of interest in this study.

In addition to the non-normalized event-study effect, I am also interested in understanding the normalized event-study effect whereby:

$$\delta_{g,l}^n = \frac{\delta_{g,l}}{\sum_{k=0}^{l-1}(D_{g,F_g+k} - D_{g,1})}$$

that is one divides the treatment effect of interest by the total size of the treatment. Thus $\delta_{g,l}^n$ is a weighted average of current effect and $l-1$ treatment lags. The normalized event-study effect is then given by:

$$\delta_l^n = \frac{\delta_l}{\delta_l^D}$$

Estimating the normalized event-study effects is important for an easier interpretation of treatment effects, whereby through the normalization, the effects can be interpreted as the marginal change in the outcome variable due to a unit increase in the treatment.

[18] Here I follow Lemma 5 from Web Appendix of de Chaisemartin and d'Haultfoeuille (2024), taking into account covariates.

10.6 Generalized synthetic control method methodological description

I present the method proposed by Xu (2017), and I follow his notation. Y_{it} is the outcome of interest (unemployment rate) for county i at time t. I assume that the problem takes the following functional form:

$$Y_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it}$$

where D_{it} is a binary treatment indicator, δ_{it} is the heterogeneous treatment effect, x_{it} is a vector of control variables and β is a vector of unknown parameters. λ'_i is a vector of unknown factor loadings and f_t is a vector of unobserved common factors. It is assumed that the factor component model takes a linear, additive form $\lambda'_i f_t = \lambda_{i1} f_{1t} + ... + \lambda_{ir} f_{rt}$, where r corresponds to the number of factors to be included in the model. Letting:

$$Y_{it}(0) = x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it} \quad Y_{it}(1) = \delta_{it} + x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it}$$

it follows that $Y_{it}(1) - Y_{it}(0) = \delta_{it}$. Of interest is the average treatment effect on the treated at time t when $t > T_{0,i}$ the period when unit i is first treated:

$$ATT_{t,t>T_{0,i}} = \frac{1}{N_{tr}} \sum_{i \in T} [Y_{it}(1) - Y_{it}(0)] = \frac{1}{N_{tr}} \sum \delta_{it}$$

where N_{tr} is the number of treated. The estimation of the model happens in three steps, where in the first step the interactive fixed effects model is estimated using only the control group to obtain estimates $\hat{\beta}$, the matrix of factors $\hat{F}$ and the matrix of factor loadings $\hat{\Lambda}_{N_{co}}$ where N_{co} corresponds to the number of control units. In a second step the factor loadings of each treated unit are estimated by minimizing the mean squared error of the predicted treated outcome before treatment onset. In the final step the counterfactuals are estimated: $\hat{Y}_{it}(0) = x'_{it}\hat{\beta} + \hat{\lambda}'_i \hat{f}_t$. Thus, the estimator of the average treatment effect is given by:

$$A\hat{T}T_t = \frac{1}{N_{tr}} \sum_{i \in T} [Y_{it}(1) - \hat{Y}_{it}(0)]$$

Finally, the uncertainty estimates of the generalized synthetic control method are obtained via parametric bootstrap, allowing inference.