Energy Transition and Mental Health*

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Abstract

We provide quasi-experimental estimates of the impact of coal and natural gas power plant retirements on the mental health of local residents in the United States. Combining data on power plant retirements and restricted mental health data, we employ a difference-in-differences approach and find that coal-fired power plant retirements have a significant negative impact on mental health, while natural gas retirements have a positive effect. We explore potential mechanisms and find evidence suggesting that economic impacts and local amenity improvements drive these divergent effects. Our findings highlight the importance of considering mental health implications in energy transition policies and strategies.

JEL Classifications: Q40, Q52, Q51, R11

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*All remaining errors are our own.

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1 Introduction

The United States has witnessed a significant retirement of fossil-fuel power plants in the past decade. This trend is likely to continue in the United States and expand to developing countries due to the energy transition towards renewable energy sources and the increasing regulatory pressure targeting carbon neutrality. While the retirement of fossil-fuel power plants has environmental benefits, it also has significant socioeconomic implications for local communities. On the one hand, fossil fuel power plant retirements lead to reduced jobs, household financial conditions, migration stagnation (Colmer et al., 2023; Liu, 2023; Blonz et al., 2023; Krause, 2024). On the other hand, these retirements are associated with amenity improvements, better air quality, and mortality improvements (Currie et al., 2015; Komisarow and Pakhtigian, 2021, 2022; Fraenkel et al., 2024). Despite the growing literature on the economic and environmental impacts of power plant retirements, little is known about their effects on the mental health of local residents.

This study aims to bridge this knowledge gap by investigating the mental health effects of coal and natural gas generator retirements. Mental health is a crucial aspect of overall well-being, and the prevalence of mental illness in the United States is a growing concern. According to the 2021 National Survey on Drug Use and Health, approximately one-fifth of US adults, equivalent to 57.8 million individuals, reported experiencing mental illness in 2021, which is more than three times the number reported in 2011 (Peng et al., 2016). The prevalence of mental illness in the U.S. is notably higher than in other developed nations, such as England, Switzerland, and France (Hämmig et al., 2009; Leray et al., 2011; McManus et al., 2016).

Mental illness not only affects individuals' quality of life but also has significant economic consequences. It can harm educational outcomes for children and lead to substantial productivity and earning penalties for adults (Cornaglia et al., 2015; Biasi et al., 2021), impacting social mobility (Goodman et al., 2011) and imposing a multi-billion dollar burden on the economy every year (Rice and Miller, 1998). By considering the economic repercussions and environmental amenity changes following fossil-fuel power plant retirements, we aim to document evidence of local residents' mental health responses, thereby enhancing our understanding of the local impacts of energy transition and providing policy insights for social planners during the forthcoming energy transition period.

This paper presents the first evidence on the impact of fossil-fuel power plant retirements on residents' mental health. We utilize a unique dataset that combines information on power plant retirements from the Energy Information Administration (EIA) with restricted mental health data from the National Cancer Institute's Health Information National Trends Survey (HINTS). By leveraging the quasi-experimental variation in the timing and location of power plant retirements, we employ a difference-in-differences approach to compare the mental health outcomes of individuals living within 50 kilometers of retired coal and natural gas generators to those living near active generators. We also explore the effects of power plant retirement status under different scenarios based on the capacity (measured in megawatts, MW) and number of generators retired, with a particular focus on the effects of the complete retirement of coal-fired or natural gas generators for power plants.

Our analysis reveals that the retirement of coal-fired power plants has a significant negative impact on the mental health of local residents, as measured by the PHQ-4 score. We find that the full retirement of coal-fired generators leads to a 0.098 standard deviation increase in the mental health index, indicating a worsening of mental health. This effect is robust across various specifications and persists after controlling for individual and plant-level characteristics. The negative impact is also associated with the retirement progress of coal-fired generators. By using different distance buffer areas from 30 km, 50km, and 100km, we find that closer proximity to power plants with full retirement of coal-fired generators is associated with worse mental health outcomes, while more distant locations exhibit no significant effects. We also find white residents appear to be more negatively affected, while older residents experience a small improvement in mental health post-retirement via heterogeneity analysis.

Contrary to the effects of coal retirements, the retirement of natural gas power plants yields positive mental health outcomes. We find that full retirement leads to a 0.123 standard deviation improvement in the mental health index. Notably, the effects of natural gas retirements are significant only in cases of complete retirement, with more than 50% half retirement or retirement status progress showing no significant impact on mental health.

To shed light on the potential mechanisms driving these divergent effects, we explore the channel of income effects. Our results suggest that the negative mental health effects of coal retirements are primarily driven by the adverse economic impacts, such as reduced income, which are not offset by the potential benefits of improved local amenities. On the other hand, the positive mental health effects of natural gas retirements can be attributed to the improvement in local amenities, such as better air quality and reduced noise pollution, in the absence of significant negative economic impacts.

Our findings contribute to the growing body of literature on the social and economic consequences of energy transitions. While previous studies have examined the effects of climate change and directed innovation (Acemoglu, Aghion, Barrage, and Hémous, 2023), local labor markets (Hanson, 2023; Chan and Zhou, 2023; Curtis, O'Kane, and Park, 2024), household financial dynamics (Blonz et al., 2023), migration (Liu, 2023), and health and education outcomes (Komisarow and Pakhtigian, 2021, 2022; Fraenkel et al., 2024), this study underscores the importance of considering mental health implications in the context of power plant retirements.

Our work also connects to the rich literature documenting numerous factors linked to poor mental health outcomes, encompassing genetic markers and social determinants such as economic opportunities, living conditions, and various nonmedical influences (Gatt et al., 2015; Alegría et al., 2018; Braghieri et al., 2022). The economics literature has further identified links between demographic factors, education, unemployment, retirement, migration effects, and mental health (Bartel and Taubman, 1986; Kennedy and McDonald, 2006; Dave et al., 2008; Farré et al., 2018; Jiang et al., 2020; Picchio and Ours, 2020). By examining the interplay between amenity improvements and economic disruptions, our study provides novel evidence on the factors shaping mental health outcomes in the context of energy transitions.

In addition, we contribute to the growing body of literature that seeks to identify causal relationships between environmental factors and mental health outcomes. Previous research has examined the impact of chronic air pollution exposure on dementia (Bishop, Ketcham, and Kuminoff, 2023), which is closely related to mental illness (Regan, 2016). Chen, Oliva, and Zhang (2024) quantify the causal relationship and short-run effects of air pollution on mental health in the context of China, while Wen and Khanna (2024) investigate the impact of traffic noise on mental health. Our study offers a unique contribution by examining the effects of the removal of cumulative exposure to environmental disamenities, such as the retirement of fossil fuel power plants, on mental health. This perspective is particularly important as it sheds light on the potential mental health benefits of environmental improvements resulting from the energy transition.

More broadly, our findings offer valuable insights for policymakers and stakeholders involved in the energy transition process, informing the development of effective strategies to support affected communities and individuals during this transformative period.

2 Data

We exploit data that measure the surrounding power plant at the residential location of approximately 14,000 individuals in the continental US over 5 years (2014, 2017-2020). A unique feature of our data is that we can link individual mental health outcomes to the retirement status of local power plants through relatively precise residential addresses.

2.1 Mental Health Data

Under a data use agreement, we have access to the restricted version of the National Cancer Institute's Health Information National Trend Survey (HINTS) for five years (2014, 2017, 2018, 2019, 2020). This dataset provides detailed information on individual respondents' demographic characteristics, physical and mental health conditions, and the 9-digit zip code for their residence. HINTS collects nationally representative data to evaluate the American public's knowledge of, attitudes toward, and use of cancer- and health-related information.[1] This dataset is well-suited to our analysis, as it provides both physical and mental health information for each respondent along with a relatively precise residential location. Moreover, the information is gathered without reference to the local coal retirement process, mitigating potential bias in responses.

Our key outcome variable is a summary of the mental health index (PHQ-4[2]) for each respondent in the HINTS data. This summary index is based on the answers to four separate mental health-related questions: over the past 2 weeks, how often have you been bothered by any of the following problems: 1. Little interest or pleasure in doing things; 2. Feeling down, depressed or hopeless; 3. Feeling nervous, anxious, or on edge; 4. Not being able to stop or control worrying. The index ranges from 0 to 12, with a larger number indicating worse mental health.[3] While nearly half the respondents don't report any mental health issues in the two weeks immediately preceding the survey (an index value of zero), nearly 25% report experiencing symptoms of anxiety or depression on some days (an index value between 1 and 4). Since our sample includes respondents from multiple waves of the HINTS survey, we follow the recommendation from the NCI (Richard Moser, personal communication, September 21st, 2022) and standardize this index by year. This standardization accounts for systemic trends across the years and facilitates comparison across survey years.

[1] HINTS uses survey weights to allow researchers to generalize their analysis to the national US population. The first step in creating these weights is to adjust them to reflect the selection probabilities. To compensate for non-response and coverage error, the selection weights are calibrated using data from the American Community Survey conducted by the US Census Bureau. For more details about the sampling and weighting process, see https://hints.cancer.gov/about-hints/frequently-asked-questions.aspx.

[2] The Patient Health Questionnaire-4 (PHQ-4) was developed and validated by Löwe et al. (2010) to address the fact that anxiety and depression are two of the most prevalent illnesses among the general population.

[3] For each mental health-related question, the answers "not at all"; "several days"; "more than half the days"; "nearly every day" are assigned to values from 0 to 3, respectively. For example, respondents who report having all four mental health issues nearly every day will get an index of $3 \times 4 = 12$, indicating the worst case of mental health. If a respondent reports "several days" for one of the questions and "not at all" for all the other questions, the corresponding index value will be $1+0+0+0=1$.

One of the most valuable characteristics of the restricted version of HINTS is that it offers geographic and detailed demographic and health information for each respondent. The geographic information includes residential location, such as rural/urban designation, county FIPS code, and 9-digit zip code. We utilize the 9-digit zip code to locate respondents on the power plant map. The 9-digit zip code information is available for HINTS waves starting from 2014; consequently, our analysis is restricted to the respondents from the following five waves: 2014 and 2017-2020.

2.2 Power Plant Data

We source monthly power plant retirement details from the Preliminary Monthly Electric Generator Inventory, based on the Energy Information Association (EIA) Form EIA-860M, spanning from 2014 to 2020. This dataset includes information on the current status (operating, retired, and proposed) of power plant generators, alongside retirement dates, geographical coordinates, nameplate capacity, and primary energy sources.[4]

To access the impact of power plant retirement, we construct a retirement status measure for each i by energy type e in year t, where $e \in \{\text{coal}, \text{natural gas}\}$, as follows:

$$\text{Retirement Status}_{it}(\%) = \frac{\sum \text{Retired Generators }_{eit}}{\sum \text{Total Generators }_{eit}} \tag{1}$$

which reflects the percentage of retired generators of type e for power plant i in year t. For instance, if power plant A has 5 coal-fired generators in 2014 ($\sum \text{Total Generators}_{ie} = 5$) and 3 of these are retired ($\sum \text{Retired Generators}_{ie} = 3$), the retirement status is 60% based on the number of generators. Should all 5 coal-fired generators at power plant A retire in 2015 ($\sum \text{Retired Generators}_{ie} = 5$), the retirement status reaches 100%, which we define as "full retirement". A retirement status exceeding 50% is termed "half retirement".

In addition to the number of generators, we also consider the retired capacity as an alternative measure for retirement status. Appendix Figure A1 illustrates the distribution of retirement status calculated using both the number of retired generators and retired capacity. The figure presents histograms and kernel density distributions for capacity (MW) retired and the number of generator retirements for all types, fossil fuel, coal, and natural gas generators. While the general retirement status follows similar trends for capacity and

[4]We selectively include operating and retired generators in our analysis based on their generator status codes and descriptions, while proposed generators are omitted from our sample. The selected categories account for 90% of the power plants within the dataset, with proposed generators comprising approximately 20% of the total.

number of generators, there are some differences in the patterns for coal-fired generators.

Our primary focus is to examine the effects of the full retirement of coal-fired or natural gas generators within each power plant. To this end, we initially narrowed down our dataset from 10,982 power plants to 10,611 by excluding plants that had fully retired their coal-fired generators before 2014. This ensures that our analysis captures the impact of retirements that occurred during the study period. In the resulting sample, 104 power plants experienced the full retirement of coal-fired generators, while 100 plants experienced the full retirement of natural gas generators. To provide a more comprehensive understanding of the retirement process and its effects, we also explore the outcomes of half retirement based on capacity and scrutinize the retirement status (percentage).

After constructing the retirement status, we merge the dataset with the HINTS data from 2014 and 2017-2020. After dropping power plants that had new generators after full retirement, we have 9,613 power plants in the sample. Among these, 76 power plants experienced full retirement of coal-fired generators, and 78 power plants experienced more than 50% retirement of coal-fired generators (referred to as "half retirement"). For the analysis of natural gas generator retirement effects, there are 9,482 power plants left in the sample after dropping those with full retirement of natural gas generators before 2014 or those that added new generators after full retirement. In this subset, 79 power plants experienced full retirement of natural gas generators, and 84 power plants experienced half retirement. Ultimately, we are able to evaluate the mental health impacts of complete retirements by focusing on the 76 power plants with full coal retirements and the 79 plants with full natural gas retirements.

2.3 Descriptive Statistics

Table 1 presents a summary of the characteristics of survey respondents located within a 50km buffer of power plants with full retirement of coal-fired generators. These statistics include respondent characteristics such as age, race (percentage identifying with specific racial groups), college graduation rates, gender (percentage identifying as female), low-income status (percentage identifying as low income), and mental health assessed by the standardized PHQ-4 index. The first two columns display the mean and standard deviation values of these characteristics in the pre-retirement period, while the third and fourth columns show the corresponding values for the post-retirement period. P-values are calculated based on t-tests comparing each demographic characteristic between the two periods.

The main demographic variables, such as age, gender, and education level, do not ex-

Table 1: Summary Statistics

	Pre Coal Retirement		Post Coal Retirement		
	Mean	SD	Mean	SD	p-value
Age (years)	56.310	9.613	56.969	8.085	0.484
White (percentage)	0.778	0.240	0.790	0.223	0.645
Black (percentage)	0.142	0.204	0.122	0.183	0.339
Hispanic (percentage)	0.042	0.091	0.046	0.106	0.661
Other race (percentage)	0.038	0.075	0.042	0.088	0.687
College graduate (percentage)	0.254	0.259	0.251	0.233	0.918
Female (percentage)	0.592	0.298	0.601	0.276	0.756
Low Income Rate	0.117	0.166	0.145	0.227	0.208
PHQ-4 (standardized)	-0.064	0.541	0.068	0.631	0.041
N	143		216		359

Notes: This table presents summary statistics for survey respondents living within a 50km buffer of power plants, comparing demographic characteristics and mental health outcomes between the pre- and post-retirement periods of coal-fired generators. The demographic variables include age, race, education level, gender, and low-income status. The mental health outcome is measured using the standardized PHQ-4 score. P-values are calculated using t-tests to compare the means of each variable between the two periods. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

hibit significant differences between the pre-retirement and post-retirement periods for areas surrounding power plants with full retirement of coal-fired generators. However, there is a significant mean difference in the standardized PHQ-4 index (mental health measure). The post-coal retirement pattern shows an increase in the PHQ-4 index, indicating a worsened average mental health situation after the full retirement of coal-fired generators in power plants within their 50 km buffer areas. Additionally, there is a slight increase in the average low-income rate, though the p-value is not statistically significant.

3 Empirical Strategy

The goal of this paper is to estimate the effects of power plant retirements on mental health. By constructing the retirement status and identifying full retirements, we can exploit the quasi-experimental variation in retirement status across power plants and time to estimate the causal impact of such retirements on the mental health of nearby residents. In this approach, we compare the differences in HINTS respondents' mental health (PHQ-4) before and after the full retirement of generators between power plants with and without full retirement.

We begin our empirical analysis using the buffer approach. We create a buffer with a radius of 50 km surrounding each power plant and assign HINTS respondents to buffers based on the geographic coordinates of their zip-9 centroids. This approach allows us to match 85% of power plants to corresponding local HINTS respondents and capture the effect of power plant retirements. We then aggregate the HINTS respondents within each power plant buffer to obtain average individual characteristics (e.g., mental health, demographic information). The analysis is conducted at the within-buffer power plant level.

The baseline specification considers a two-way fixed effects (TWFE) model:

$$Y_{it} = \alpha + \beta D_{it} + \gamma \mathbf{X}_{it} + \lambda_i + \theta_t + \delta_{st} + \epsilon_{it} \tag{2}$$

where Y_{it} represents the average mental health of HINTS respondents within the matched power plant i's impact area (50 km buffer as the baseline) in year t. D_{it} is a binary variable equal to one for the full retirement of coal-fired generators for power plant i in year t. $\mathbf{X}_{it}$ are average demographic controls for all respondents matched with power plant i in year t, including gender, race, age, and education level. Note that income is not included here since we are interested in the effects of coal-fired generator retirement on income. λ_i controls for power plant fixed effects, while θ_t is the year fixed effect and δ_{st} is a state-year fixed effect. In all specifications, we cluster standard errors at the power plant level to match the level of treatment variation (Abadie et al., 2023).

It is important to acknowledge that the retirement of power plants may not be entirely random. Factors such as the age of the generators, environmental regulations, and energy input costs could influence the decision to retire a power plant. However, the current specification is designed to mitigate potential biases arising from non-random retirements. First, the inclusion of power plant fixed effect (λ_i) controls for any time-invariant characteristics of power plants that may be correlated with both the likelihood of retirement and mental health outcomes. This accounts for factors such as the location, size, and age of the power plants. Second, the year fixed effect (θ_t) captures any common time trends or shocks that affect all power plants and mental health outcomes uniformly across the sample. This helps to control for broader economic, social, or policy changes that may coincide with power plant retirements.

Third, the state-year fixed effects (δ_{st}) control for any time-varying unobservables at the state level that could be correlated with both power plant retirements and mental health outcomes. This accounts for state-specific policies, regulations, or economic conditions that may influence the likelihood of retirements and mental health. Furthermore, the decision to retire a power plant is typically made by the utility company or the plant owner, based on a variety of factors that are likely to be exogenous to the mental health of the local population. The timing of retirements is often determined by long-term planning processes, regulatory requirements, or market conditions, rather than being directly influenced by the mental health status of nearby residents.

Given these considerations, the current specification, with its set of fixed effects and controls, helps to mitigate potential biases arising from non-random power plant retirements. While it may not completely eliminate all sources of bias, the approach taken in this study represents a robust attempt to estimate the causal impact of retirements on mental health outcomes.

3.1 Dynamic Effects

To capture the dynamic effects of generator retirements on mental health outcomes, we estimate a panel event study (Clarke and Tapia-Schythe, 2021). This approach allows us to examine the temporal impact of retirements on mental health and test for parallel trends prior to treatment.

The panel event study specification is as follows:

$$Y_{it} = \alpha + \sum_{k=-5}^{5} \beta_k D_{it}^{(k)} + \lambda_i + \theta_t + \delta_{ct} + \epsilon_{it} \tag{3}$$

where $D_{it}^{(k)}$ captures the effect of retirement at each period k relative to the retirement event. We estimate a separate coefficient, β_k, for each year leading up to ($k < 0$) and following ($k > 0$) the retirement, spanning a window from 5 years before to 5 years after the event. The reference period (omitted category) is the period right before the power plant retirement.

Traditional TWFE estimators as the one used in equation 2, have been widely employed to estimate the average treatment effect in the presence of staggered treatment adoption. However, recent studies have highlighted several issues with this approach when treatment effects are heterogeneous across time and/or treated units (De Chaisemartin and d'Haultfoeuille, 2020; Borusyak, Jaravel, and Spiess, 2021; Callaway and Sant'Anna, 2021). These issues include the negative weighting problem, bias in the presence of dynamic treatment effects, and difficulty in interpreting the average treatment effect (Roth, Sant'Anna, Bilinski, and Poe, 2023).

To address these concerns, we implement heterogeneity-robust estimators for staggered treatment timing, as proposed by De Chaisemartin and d'Haultfoeuille (2020), Borusyak et al. (2021), and Callaway and Sant'Anna (2021). These estimators are designed to provide consistent estimates of the average treatment effect even in the presence of heterogeneous treatment effects. The estimator developed by De Chaisemartin and d'Haultfoeuille (2020) isolates the comparisons between treated and never-treated units, avoiding the negative weighting problem. However, it requires a balanced panel for the analysis, limiting the output to a range of 3 years before and after treatment in our case. The estimator proposed by Borusyak et al. (2021) models the treatment effect as a linear combination of "cohort-specific" effects, where cohorts are defined by the time of treatment adoption. This approach is robust to heterogeneous treatment effects and can be applied to unbalanced panels. The estimator introduced by Callaway and Sant'Anna (2021) allows for dynamic treatment effects and is robust to heterogeneity across time and treated units. It is based on a generalized difference-in-differences framework and can accommodate unbalanced panels.

By employing these heterogeneity-robust estimators, we aim to mitigate potential biases arising from heterogeneous treatment effects across power plants and time periods. Given the discontinuities in our panel, we primarily utilize the dynamic effects to assess the overarching trend rather than specific point estimates. They should be interpreted with caution due to the limitations imposed by the available data.

3.2 Individual Level Analysis

To refine our understanding of the localized effects of power plant retirements, we conduct an individual-level analysis. This approach addresses the potential issue of multiple-counting individuals affected by several power plants within overlapping 50 km buffer zones. By matching each individual to their nearest power plant within this radius, we ensure that our analysis reflects the influence of the closest power plant, despite the possibility of additional impacts from other neighboring plants.

This methodology allows for the incorporation of individual-level controls and facilitates the exploration of heterogeneity at the individual level. However, it is important to note that this approach may lead to an underestimation of average effects, as individuals could be subject to influences from multiple power plants. By using this approach, we are able to match 3,037 power plants (approximately 30% of all power plants) to 13,477 corresponding local HINTS respondents. Among these power plants, 19 experienced a full retirement of coal-fired generators, and 18 experienced a half retirement.

The specification for the individual-level analysis is as follows:

$$Y_{jit} = \alpha + \beta D_{it} + \gamma \mathbf{X}_j + \lambda_i + \theta_t + \delta_{st} + \epsilon_{jit} \tag{4}$$

where Y_{jit} represents the mental health of HINTS respondent j within the impact area (50 km buffer as the baseline) of the matched coal power plant i in year t. D_{it} is a binary variable equal to one for the full retirement of coal-fired generators for power plant i in year t. $\mathbf{X}_j$ are demographic controls for respondent j matched with power plant i in year t, including gender, race, age, education level, physical health condition, and environmental factors, which have been documented to influence mental health in the literature (Wen and Khanna, 2024). Fixed effects for power plants, years, and state-years are represented by λ_i, θ_t, and δ_{st}, respectively. We also cluster standard errors at the power plant level.

Due to the one-to-one matching of individuals to power plants, our sample size is significantly smaller. Consequently, this analysis is primarily utilized to investigate potential heterogeneity effects at the individual level rather than to provide definitive average treatment effects.

4 Results

4.1 Baseline Results

Table 2 presents the main two-way fixed effects (TWFE) estimates of the impact of coal-fired generator retirements on mental health using the sample of HINTS-matched power plant buffers. Panel (a) focuses on the effects of full retirement, while Panel (b) examines the effects of half retirement.

In Panel (a), Column (1) shows that a power plant with full retirement of coal-fired generators increases the standardized mental health index by 0.124, indicating that respondents' mental health worsens by 0.124 standard deviations after the full retirement. In Column (2), we include control variables specified in Eq.2 and get similar estimates, confirming the significant negative effect of coal retirement on mental health. Columns (3) and (4) present the results with state-year fixed effects, demonstrating the consistency of the estimates across different specifications. In the most stringent specification, which includes both control variables and state-year fixed effects, the effect size is 0.098 standard deviation units. This effect is comparable to, albeit slightly larger (by approximately 15%) than, the impact of Facebook introduction on students' mental health (Braghieri et al., 2022). Moreover, the impact of full retirement of coal-fired generators on residents' mental health is around 27% of the effect of direct job loss due to factory closures and mass layoffs (Paul and Moser, 2009). It is worth noting that this effect can be considered a lower bound of the retirement impact on residents' mental health, as the effects may have begun since the first coal-fired generator retirement. These results also suggest that the negative effects on mental health persist among residents even after the completion of the retirement process.

Table 2: The Effects of Coal Retirement on Mental Health

(a) Full Retirement

	(1)	(2)	(3)	(4)
Coal Retirement	0.124*	0.106*	0.110*	0.098+
	(0.065)	(0.064)	(0.063)	(0.061)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,899	31,899	31,899	31,899
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Half Retirement

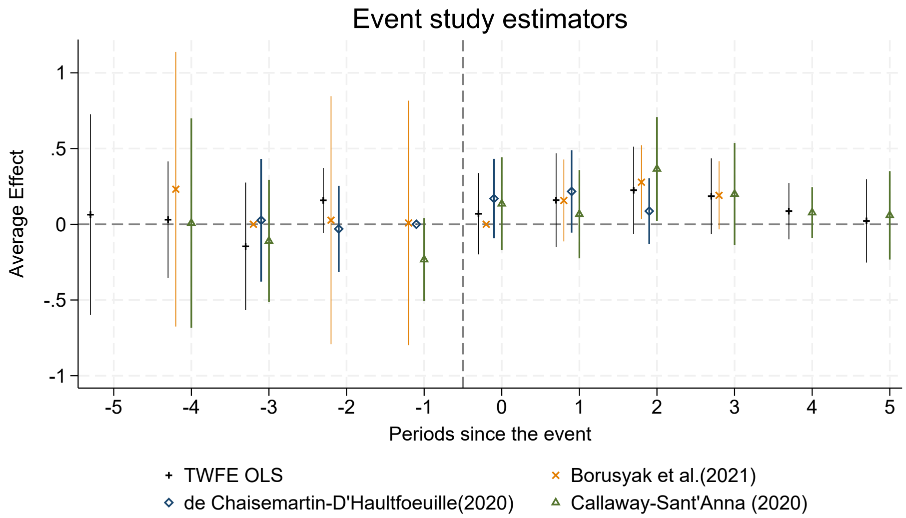
	(1)	(2)	(3)	(4)
Coal Retirement	0.159**	0.139**	0.139**	0.125**
	(0.066)	(0.065)	(0.064)	(0.062)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,879	31,879	31,879	31,879
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents the TWFE estimates of the impact of coal-fired generator retirements on mental health using the sample of HINTS-matched power plant 50km buffers. Panel (a) focuses on the effects of full retirement, and Panel (b) examines the effects of half retirement. The standardized mental health index is the dependent variable, with higher values indicating worse mental health. All standard errors are clustered at the power plant level. +p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

Panel (b) in Table 2 presents the estimates of the impact of half coal retirement on mental health. Overall, we find stronger effects of coal retirement for power plants with more than half of their coal-fired generators retired. This finding could be attributed to the slightly larger treated sample for half retirement and the longer treatment duration for residents. The estimate in Column (1) indicates that respondents' mental health worsens by 0.159 standard deviations if more than half of the coal-fired generators are retired for each power plant. The estimates remain consistently significant across different specifications, as reported in Columns (2)-(4).

To further investigate the role of retirement status calculated by capacity (MW) and number of generators in driving the effects on mental health, we present additional results in Appendix Table A1. The findings align with our intuition, revealing that retirements with larger power plant capacity (i.e., higher MW levels) tend to have more substantial negative effects on mental health. Panel (a) reports these results, which are consistently significant across different specifications. Similarly, we find that a higher percentage of retired generators leads to worse mental health, as shown in Panel (b). The estimates remain consistently significant in all specifications. As these retirement status variables are discrete

Figure 1: Effects of Coal Full Retirement on Mental Health

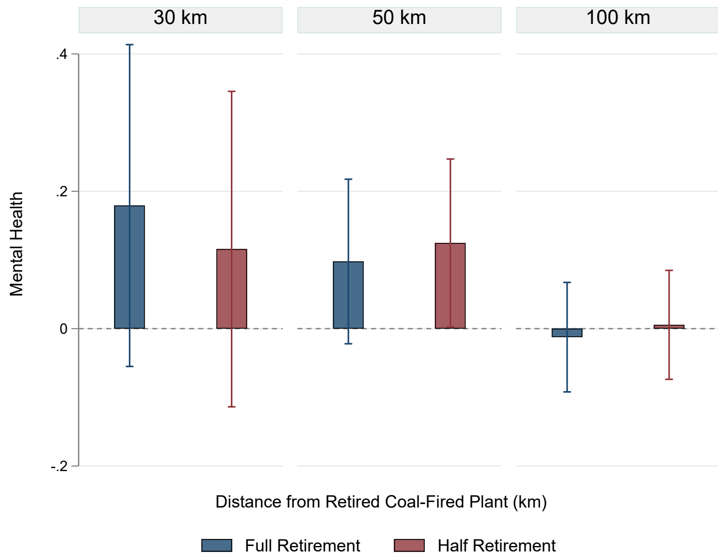


Notes: This figure presents event-study analyses utilizing heterogeneity-robust estimators for staggered treatment timing (De Chaisemartin and d'Haultfoeuille, 2020; Borusyak et al., 2021; Callaway and Sant'Anna, 2021) alongside the two-way fixed effects (TWFE) specification. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. The estimates are based on data with a two-year gap, and the bars represent 95 percent confidence intervals. Standard errors are clustered at the power plant level.

values based on the calculation of each year's retirement capacity and number of generators, we use these results as a robustness check for Table 1 and verify the causal relationship between retirement and mental health. We do not directly attribute a specific magnitude change in mental health to a single degree of retirement.

Figure 1 presents event-study figures using a set of heterogeneity-robust estimators for staggered treatment timing proposed by De Chaisemartin and d'Haultfoeuille (2020); Borusyak et al. (2021); Callaway and Sant'Anna (2021). The estimates are consistent with the parallel trends assumption, as the coefficients for the years preceding the full retirement of coal-fired generators for power plants hover around zero. This supports the notion that any observed post-retirement effects are not due to pre-existing trends. Additionally, the event study illustrates the dynamic nature of treatment effects, with the most substantial impacts of full retirement occurring within one to three years post-retirement. This finding suggests a worsening trend in mental health outcomes following the full retirement of coal-fired generators. Given the year gap present in the sample units used for this analysis, we interpret the event study as providing suggestive evidence for worsening mental health outcomes post-retirement.

Figure 2: Effects of Coal Full Retirement on Mental Health by Distances



Notes: This figure presents the effects of full retirement and half retirement of coal-fired generators on mental health across different buffer area distances: 30 km, 50 km, and 100 km. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. All estimates include year and plant fixed effects, demographic controls, and state-year fixed effects. The bars represent 95 percent confidence intervals. Standard errors are clustered at the power plant level.

4.2 Distance Effects

In our baseline results, we consider the average effects on residents within a 50 km buffer around the power plants, as specified in equation 2. To further explore how the effects change based on the distance between residents and power plants, we also examine 30 km and 100 km buffer areas.

Figure 2 presents the effects of full retirement and half retirement of coal-fired generators on mental health across different buffer area distances: 30 km, 50 km, and 100 km. The results show that at a closer distance (30 km), the average effects and confidence interval ranges are larger compared to the 50 km buffer. This finding is consistent with our intuition that residents experiencing full retirement in closer proximity to the power plant will have worse mental health outcomes and larger effect sizes. However, the coefficients for full retirement within the 30 km buffer are only significant at the 0.15 level, which could be attributed to the relatively smaller sample size when matching HINTS respondents to the 30 km buffer areas (12,078 respondents matched with 6,288 power plants, of which 43 power plants have full retirement of coal-fired generators). On the other hand, when considering the effects of full retirement and half retirement within 100 km buffers, we find nearly zero impact on mental health. This result aligns with our intuition that a 100 km range is too

Table 3: The Effects of Coal Retirement on Mental Health

	(1)	(2)	(3)	(4)
Coal Retirement	-0.176	-0.431***	0.028	-0.091
	(0.108)	(0.123)	(0.203)	(0.256)
White× 1(post)		0.425**		0.483***
		(0.168)		(0.170)
Age × 1(post)			-0.004	-0.007**
			(0.003)	(0.003)
Female× 1(post)				0.107
				(0.155)
Outcome mean	-0.005	-0.005	-0.005	-0.005
Observations	12,154	12,154	12,154	12,154
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
State-Year FE FE	✓	✓	✓	✓

Notes: This table presents the effects of full retirement of coal-fired generators on mental health, incorporating interaction terms between the post-retirement indicator and demographic characteristics (race, age, and gender). The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level. $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

large to identify localized effects.

Overall, Figure 2 demonstrates the effects from different buffer areas and reveals a general trend: closer proximity to power plants with full retirement of coal-fired generators is associated with worse mental health, while more distant locations exhibit no significant effects. This pattern holds even though the closer distance of 30 km includes fewer power plants with corresponding HINTS respondents.

4.3 Heterogeneity

Using the individual-level analysis specification from equation 4, we can control for more individual-level characteristics such as physical health conditions and environmental factors to measure the effects of power plant retirement on individual-level mental health outcomes. Additionally, we can identify the interaction effects between power plant retirement and time-invariant demographic variables such as age, gender, and race.

Table 3 presents the effects of full retirement of coal-fired generators on mental health, incorporating interaction terms. Column (1) shows the baseline effect of coal retirement on mental health, which is negative but not statistically significant. In Column (2), the interaction between the white dummy and the post-retirement indicator reveals that white residents experience significantly worse mental health after power plant retirement.

Column (3) introduces the interaction between age and the post-retirement indicator, but the coefficient is not statistically significant. However, when all interaction terms are included in Column (4), the age interaction becomes significant at the 5% level, with a coefficient of -0.007. This suggests that older residents experience a slight improvement in mental health post-retirement, although the magnitude of the effect is small. The interaction between the female dummy and the post-retirement indicator in Column (4) indicates that females experience worse mental health post-retirement, but this effect is not statistically significant.

Overall, the heterogeneity analysis in Table 3 reveals that the effects of coal-fired generator retirement on mental health vary across different demographic groups. White residents appear to be more negatively affected, while older residents may experience a small improvement in mental health post-retirement. The findings highlight the potential heterogeneity in mental health outcomes related to coal-fired generator retirement across different demographic groups.

4.4 Natural Gas Effects

To provide a comprehensive understanding of energy transitions' mental health implications, we conducted a parallel analysis comparing the effects of natural gas generator retirements to those of coal generator retirements. Utilizing the retirement status of natural gas generators as a treatment indicator within the framework of Equation 2, we assessed the associated mental health outcomes. Table 4 presents the results of this analysis, with Panel A focusing on the effects of full retirement and Panel B on the effects of half retirement.

Table 4 highlights the differential effects of natural gas generator retirements on mental health. Notably, the negative coefficients indicate an improvement in mental health, presenting a contrast to the adverse effects observed in coal retirement scenarios. In Panel A, we find a significant improvement in mental health following the complete retirement of natural gas generators across all four specifications. The coefficients range from -0.102 to -0.128, indicating that the full retirement of natural gas generators leads to an improvement in mental health by 0.102 to 0.128 standard deviations.

In contrast, Panel B shows an insignificant impact of partial natural gas generator retirement (with a smaller magnitude), implying that mental health improvements materialize mainly after complete retirement. This observation contrasts with the coal retirement scenario, where adverse mental health effects emerge during the half-retirement phase.

The effects of natural gas retirement on mental health are the opposite of those found for coal retirement. While the retirement of coal-fired generators leads to a worsening of mental health, with significant positive coefficients, the retirement of natural gas generators

Table 4: The Effects of Natural Gas Retirement on Mental Health

(a) Full Retirement

	(1)	(2)	(3)	(4)
Natural Gas Retirement	-0.106*	-0.128**	-0.102*	-0.123**
	(0.063)	(0.061)	(0.060)	(0.059)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,422	31,422	31,422	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Half Retirement

	(1)	(2)	(3)	(4)
Natural Gas Retirement	-0.051	-0.066	-0.039	-0.057
	(0.061)	(0.059)	(0.059)	(0.057)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,282	31,282	31,282	31,282
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents the effects of full and half retirement of natural gas generators on mental health, using a sample of HINTS respondents matched to power plants within 50km buffers. Panel (a) focuses on the impact of full retirement, while Panel (b) examines the effects of half retirement. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level. $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

improves mental health, as indicated by the significant negative coefficients. Moreover, the timing of the mental health effects differs between the two energy sources. For coal retirement, significant effects on mental health are observed starting from half retirement. In contrast, for natural gas retirement, the effects only become significant after complete retirement.

We also present the results of the retirement status calculated by capacity (MW) and number of generators on mental health in Appendix Table A2. The findings are consistent with the results presented in Table 4. The retirement status considering larger power plant capacity or higher percentage of retired generator numbers improved mental health with negative coefficients. However, the coefficients across all specifications are not significant and have a smaller magnitude compared to the effects of full retirement of natural gas generators. This is in contrast with the coal retirement status effects, where larger capacity and higher percentage of retired generators lead to a significant worsening of mental health (Appendix Table A1).

In conclusion, the comparative analysis demonstrates that natural gas and coal generator retirements have divergent implications for mental health. While coal retirements lead to worsening mental health, natural gas retirements result in improved mental health following complete generator shutdowns.

5 Mechanisms

Power plants influence local residents through the following main channels documented by recent literature: economic impacts, amenity changes, and social factors. We present suggestive evidence and discussion related to these mechanisms in turn and discuss the different mental health outcomes lead by both coal retirement and natural gas retirement.

Economic Impacts The coal industry has historically been a significant employer in many regions, and the retirement of coal-fired generators may lead to job losses and economic disruption in these communities (Colmer et al., 2023; Krause, 2024). The loss of employment and income could contribute to the worsening of mental health observed after coal retirements. To illustrate this process, we apply the average low-income rate to equation 2 and observe the effects of retirement on respondents' incomes.

Table 5 presents the estimates, showing an average increase in the low-income population within the 50 km buffer of full retirement and half retirement of coal-fired generators. Appendix Table A3 presents the retirement status on the average low-income rate, providing consistent evidence that coal retirement increases the amount of low-income populations.

In contrast, natural gas generators may have a less concentrated economic impact, and the retirement of natural gas generators may not lead to the same level of job losses and economic disruption. This could explain the lack of significant negative effects on mental health after natural gas retirements. Appendix Table A4 presents the effects of natural gas retirement on low income, showing no significant effects across all specifications for full retirement, half retirement, and retirement status based on capacity and number of generators.

Furthermore, we investigate the heterogeneous effects of full coal retirement on income by interacting the full coal retirement indicator with respondents' race, gender, and age. The Appendix Table A5 presents these findings, offering suggestive evidence that the percentage of low-income individuals increases among the white population post-retirement, as seen in columns (2) and (4) of Panel (a). However, the income range for the white population decreases, as shown in columns (2) and (4) of Panel (b). Although these estimates are not statistically significant, this opposite trend, combined with the increased mental health evidence from Table 3, suggests that income is a potential channel for worsening mental

Table 5: The Effects of Coal Retirement on Low Income Group

(a) Full Retirement

	(1)	(2)	(3)	(4)
Coal Retirement	0.056**	0.045*	0.051**	0.039+
	(0.025)	(0.025)	(0.025)	(0.024)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,899	31,899	31,899	31,899
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Half Retirement

	(1)	(2)	(3)	(4)
Coal Retirement	0.054**	0.045*	0.049**	0.039*
	(0.025)	(0.024)	(0.024)	(0.024)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,879	31,879	31,879	31,879
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents the TWFE estimates of the impact of coal-fired generator retirements on the average low-income rate using the sample of HINTS-matched power plant 50km buffers. Panel (a) focuses on the effects of full retirement, and Panel (b) examines the effects of half retirement. The standardized mental health index is the dependent variable, with higher values indicating worse mental health. All standard errors are clustered at the power plant level. $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

health post-retirement.

These results indicate that there is an economic impact following coal retirement, particularly on income for specific groups, leading to worse mental health outcomes. For power plants with natural gas retirement, given that they have no significant effects on income and lead to improved mental health post-full retirement, the economic impact channel appears to be less prominent.

Amenity Changes: The retirement of power plants can lead to changes in local amenities, such as improved air quality and reduced noise pollution (Burney, 2020; Komisarow and Pakhtigian, 2022; Fraenkel, Zivin, and Krumholz, 2022). Coal-fired power plants are known to emit higher levels of air pollutants compared to natural gas plants. The retirement of coal-fired generators may result in a more significant reduction in air pollution, which could potentially contribute to improved mental health outcomes, as air quality has been associated with mental well-being (Chen et al., 2024).

However, the observed worsening of mental health across all retirement statuses for coal-fired power plants suggests that the potential benefits of improved amenities may be overshadowed by the negative economic impacts, such as lower or reduced income, as discussed earlier. The economic disruption and job losses associated with coal retirements may have a more dominant effect on mental health, counteracting any positive influence from enhanced local amenities (Liu, 2023).

In contrast, the retirement of natural gas generators, particularly full retirement, leads to improved mental health outcomes. Although the amenity improvements from natural gas retirements may not be as substantial as those from coal retirements, they appear to have a more pronounced effect on mental health. This could be attributed to the absence of significant negative income effects associated with natural gas retirements, as shown in Appendix Table A4.

Interestingly, the positive mental health effects are only observed for the full retirement of natural gas generators, rather than for half retirement or retirement status based on capacity or number of generators. This finding suggests that the amenity channel may only be effective when there is a complete shutdown of natural gas generators. Full retirement is more likely to result in significant improvements in air quality, reduced noise pollution, and other environmental benefits, which could contribute to the observed improvement in mental health.

The difference in the mental health outcomes between coal and natural gas retirements highlights the complex interaction between the economic and amenity channels. For coal retirements, the negative economic impacts seem to dominate, overshadowing any potential positive effects from improved amenities. In the case of natural gas retirements, the absence of significant negative income effects allows the amenity channel to manifest, particularly when there is a complete retirement of the power plant.

Social factors Coal mining and coal-fired power plants have often been deeply embedded in the social and cultural fabric of local communities, particularly in regions with a long history of coal production (Carley et al., 2018). These communities may have developed a strong sense of identity and pride associated with the coal industry, which has provided employment, economic stability, and a way of life for generations.

The retirement of coal-fired generators can lead to a profound sense of loss and disruption to this community identity and cohesion. The closure of coal-fired power plants and the associated decline in coal mining activities may be perceived as a threat to the traditional way of life and the social networks that have been built around the coal industry (Della Bosca and Gillespie, 2018). This loss of identity and social support can contribute to the worsening of mental health observed in communities affected by coal retirements. Moreover, the transition away from coal may be met with resistance and anxiety in these communities, as it represents a significant shift in the social and economic landscape (Lewin, 2019). The uncertainty and fear associated with this transition can further exacerbate the mental health challenges faced by individuals in coal-dependent communities.

In contrast, natural gas extraction and power generation may not have the same level of cultural and social significance in local communities. The development of the natural gas industry is often more recent and may not have the same deep-rooted history and identity associated with it. As a result, the retirement of natural gas generators may not trigger the same sense of loss and disruption to community cohesion. Furthermore, the transition away from natural gas may be perceived as a less dramatic shift compared to the transition away from coal. Natural gas has been viewed as a "bridge fuel" in the transition to cleaner energy sources (Levi, 2013), and its retirement may be seen as a more gradual and expected step in the energy transition process. This perception could contribute to the different mental health effects observed after natural gas retirements.

It is important to note that the social and cultural significance of coal and natural gas may vary across different regions and communities. Some natural gas-dependent communities may also have a strong sense of identity and attachment to the industry (Mayer, 2018), and the retirement of natural gas generators could have similar social and mental health implications as those observed in coal-dependent communities. However, on average, the social and cultural attachment to coal tends to be more prevalent and deeply rooted.

6 Discussion and Conclusion

This study provides novel evidence on the mental health implications of fossil-fuel power plant retirements in the United States. By exploiting the quasi-experimental variation in the timing and location of coal and natural gas generator retirements, we find that the retirement of coal-fired power plants has a significant negative impact on the mental health of local residents, while the retirement of natural gas power plants has a positive effect. These divergent outcomes are driven by the interplay between the economic consequences and environmental amenity changes associated with power plant retirements.

Our findings contribute to the growing literature on the social and economic impacts of energy transitions. We highlight the importance of considering mental health as a critical dimension in evaluating the local effects of power plant retirements, alongside the well-documented economic and environmental consequences (Colmer et al., 2023; Liu, 2023; Blonz et al., 2023; Krause, 2024; Currie et al., 2015; Komisarow and Pakhtigian, 2021, 2022). Our work also adds to the understanding of the complex factors influencing mental health outcomes, particularly in the context of significant economic and environmental changes.

The results of this study have important policy implications. As the energy transition progresses and more fossil-fuel power plants are retired, policymakers and stakeholders should consider the potential mental health impacts on local communities. Developing targeted interventions and support mechanisms to mitigate the negative mental health effects of coal-fired power plant retirements, such as job training programs, financial assistance, and mental health support services, can help ensure a more equitable and sustainable transition. Additionally, recognizing the positive mental health effects of natural gas power plant retirements can inform decisions about the phasing out of different types of fossil-fuel generators and the prioritization of clean energy alternatives.

While this study provides valuable insights, it is important to acknowledge its limitations. First, our analysis is based on HINTS respondents with an unbalanced panel spanning five years, which restricts our ability to accurately assess the dynamic effects of power plant retirements on mental health. Moreover, the relatively short time frame of the data only allows us to study the short-term mental health effects of power plant retirements. Investigating the long-term mental health consequences and the potential adaptation and resilience of communities over time would provide a more comprehensive understanding of the issue.

In addition, the relatively small sample size after matching individuals with the closest power plants leads to reduced statistical power for conducting individual-level analyses. Future research with larger mental health samples, such as data from other countries, could explore the mental health effects of power plant retirements at a more accurate level using individual-level analyses. This would allow for a more precise estimation of the effects on individuals rather than relying on average effects. Cross-country comparisons can also provide valuable insights into how different institutional, social, and economic contexts shape the mental health impacts of energy transitions.

Moreover, further research can document and provide evidence on channels other than economic factors that may influence the mental health effects of power plant retirements. For example, social factors, such as community cohesion, social support networks, and sense of place attachment, can play a significant role in shaping mental health outcomes. Exploring the role of these potential mediating factors can help identify protective mechanisms and strategies to support communities affected by power plant retirements.

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics 138*(1), 1–35.

Acemoglu, D., P. Aghion, L. Barrage, and D. Hémous (2023). Climate change, directed innovation, and energy transition: The long-run consequences of the shale gas revolution. Technical report, National Bureau of Economic Research.

Alegría, M., A. NeMoyer, I. Falgàs Bagué, Y. Wang, and K. Alvarez (2018). Social determinants of mental health: where we are and where we need to go. *Current psychiatry reports 20*, 1–13.

Bartel, A. and P. Taubman (1986). Some economic and demographic consequences of mental illness. *Journal of Labor Economics 4*(2), 243–256.

Biasi, B., M. S. Dahl, and P. Moser (2021). Career effects of mental health (no. w29031). Technical report, National Bureau of Economic Research.

Bishop, K. C., J. D. Ketcham, and N. V. Kuminoff (2023). Hazed and confused: the effect of air pollution on dementia. *Review of Economic Studies 90*(5), 2188–2214.

Blonz, J., B. R. Tran, and E. E. Troland (2023). The canary in the coal decline: Appalachian household finance and the transition from fossil fuels. Technical report, National Bureau of Economic Research.

Borusyak, K., X. Jaravel, and J. Spiess (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.

Braghieri, L., R. Levy, and A. Makarin (2022). Social media and mental health. *American Economic Review 112*(11), 3660–3693.

Burney, J. A. (2020). The downstream air pollution impacts of the transition from coal to natural gas in the united states. *Nature Sustainability 3*(2), 152–160.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Carley, S., T. P. Evans, and D. M. Konisky (2018). Adaptation, culture, and the energy transition in american coal country. *Energy Research & Social Science 37*, 133–139.

Chan, H. R. and C. Zhou (2023). Charged up? distributional impacts of green energy on local labor markets. *Working Paper*.

Chen, S., P. Oliva, and P. Zhang (2024). Air pollution and mental health: evidence from china. In *AEA Papers and Proceedings*, Volume 114, pp. 423–428. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Clarke, D. and K. Tapia-Schythe (2021). Implementing the panel event study. *The Stata Journal 21*(4), 853–884.

Colmer, J., E. Krause, E. Lyubich, and J. Voorheis (2023). Transitional costs and the decline of coal: Worker-level evidence. Technical report, Working Paper.

Cornaglia, F., E. Crivellaro, and S. McNally (2015). Mental health and education decisions. *Labour Economics 33*, 1–12.

Currie, J., L. Davis, M. Greenstone, and R. Walker (2015). Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. *American Economic Review 105*(2), 678–709.

Curtis, E. M., L. O'Kane, and R. J. Park (2024). Workers and the green-energy transition: Evidence from 300 million job transitions. *Environmental and Energy Policy and the Economy 5*(1), 127–161.

Dave, D., I. Rashad, and J. Spasojevic (2008). The effects of retirement on physical and mental health outcomes. *Southern Economic Journal 75*(2), 497–523.

De Chaisemartin, C. and X. d'Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review 110*(9), 2964–2996.

Della Bosca, H. and J. Gillespie (2018). The coal story: Generational coal mining communities and strategies of energy transition in australia. *Energy Policy 120*, 734–740.

Farré, L., F. Fasani, and H. Mueller (2018). Feeling useless: the effect of unemployment on mental health in the great recession. *IZA Journal of Labor Economics 7*(1), 1–34.

Fraenkel, R., J. G. Zivin, and S. Krumholz (2024). The coal transition and its implications for health and housing values. *Land Economics 100*(1), 51–65.

Fraenkel, R., J. S. G. Zivin, and S. D. Krumholz (2022). The coal transition and its implications for health and housing values. Technical report, National Bureau of Economic Research.

Gatt, J. M., K. L. Burton, L. M. Williams, and P. R. Schofield (2015). Specific and common genes implicated across major mental disorders: a review of meta-analysis studies. *Journal of psychiatric research 60*, 1–13.

Goodman, A., R. Joyce, and J. P. Smith (2011). The long shadow cast by childhood physical and mental problems on adult life. *Proceedings of the National Academy of Sciences 108*(15), 6032–6037.

Hämmig, O., F. Gutzwiller, and G. Bauer (2009). Work-life conflict and associations with work-and nonwork-related factors and with physical and mental health outcomes: a nationally representative cross-sectional study in switzerland. *BMC Public Health 9*(1), 1–15.

Hanson, G. H. (2023). Local labor market impacts of the energy transition: Prospects and policies. Technical report, National Bureau of Economic Research.

Jiang, W., Y. Lu, and H. Xie (2020). Education and mental health: Evidence and mechanisms. *Journal of Economic Behavior & Organization 180*, 407–437.

Kennedy, S. and J. T. McDonald (2006). Immigrant mental health and unemployment. *Economic Record 82*(259), 445–459.

Komisarow, S. and E. L. Pakhtigian (2021). The effect of coal-fired power plant closures on emergency department visits for asthma-related conditions among 0-to 4-year-old children in chicago, 2009–2017. *American journal of public health 111*(5), 881–889.

Komisarow, S. and E. L. Pakhtigian (2022). Are power plant closures a breath of fresh air? local air quality and school absences. *Journal of Environmental Economics and Management 112*, 102569.

Krause, E. (2024). Selective migration and regional decline: Evidence from coal country.

Leray, E., A. Camara, D. Drapier, F. Riou, N. Bougeant, A. Pelissolo, K. Lloyd, V. Bellamy, J. Roelandt, and B. Millet (2011). Prevalence, characteristics and comorbidities of anxiety disorders in france: results from the “mental health in general population” survey (mhgp). *European Psychiatry 26*(6), 339–345.

Levi, M. (2013). Climate consequences of natural gas as a bridge fuel. *Climatic change 118*, 609–623.

Lewin, P. G. (2019). “coal is not just a job, it’sa way of life”: The cultural politics of coal production in central appalachia. *Social Problems 66*(1), 51–68.

Liu, J. L. (2023). Powering down and moving on? energy transition, gentrification, and local impacts.

Löwe, B., I. Wahl, M. Rose, C. Spitzer, H. Glaesmer, K. Wingenfeld, A. Schneider, and E. Brähler (2010). A 4-item measure of depression and anxiety: validation and standardization of the patient health questionnaire-4 (phq-4) in the general population. *Journal of affective disorders 122*(1-2), 86–95.

Mayer, A. (2018). Community economic identity and colliding treadmills in oil and gas governance. *Journal of Environmental Studies and Sciences 8*, 1–12.

McManus, S., P. E. Bebbington, R. Jenkins, and T. Brugha (2016). *Mental health and wellbeing in England: the adult psychiatric morbidity survey 2014*. NHS digital.

Paul, K. I. and K. Moser (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational behavior 74*(3), 264–282.

Peng, L., C. D. Meyerhoefer, and S. H. Zuvekas (2016). The short-term effect of depressive symptoms on labor market outcomes. *Health Economics 25*(10), 1223–1238.

Picchio, M. and J. C. v. Ours (2020). Mental health effects of retirement. *De Economist 168*(3), 419–452.

Regan, M. (2016). The interface between dementia and mental health: an evidence review.

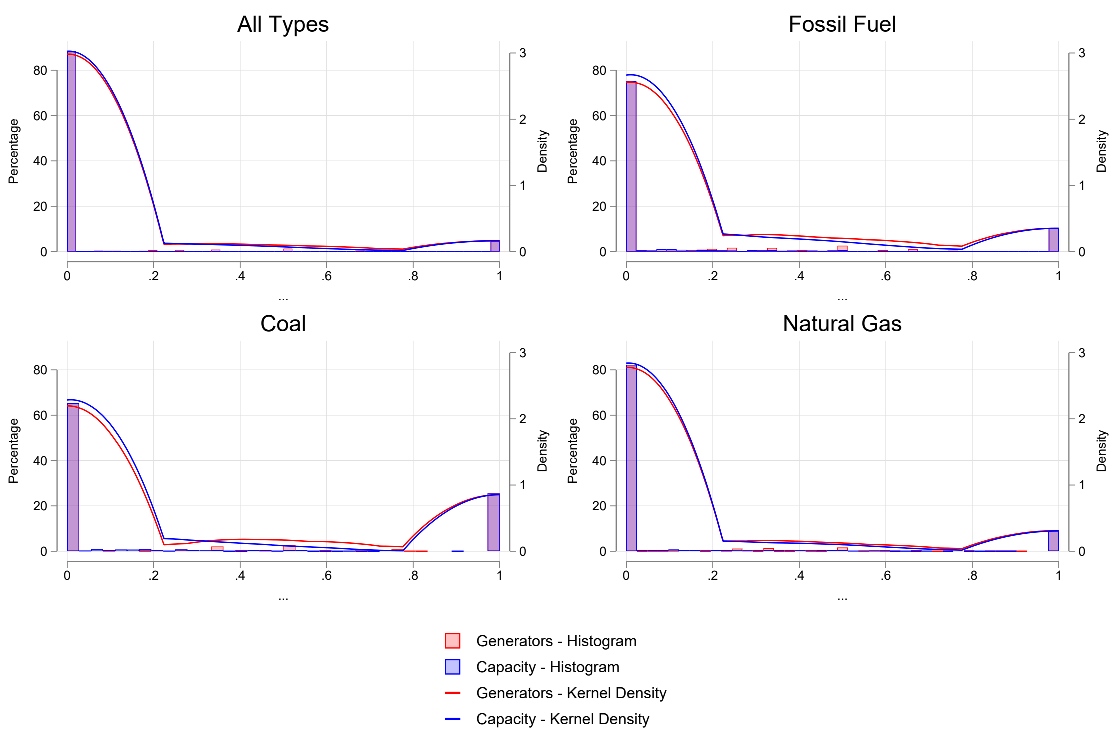
Rice, D. P. and L. S. Miller (1998). Health economics and cost implications of anxiety and other mental disorders in the united states. *The British Journal of Psychiatry 173*(S34), 4–9.

Roth, J., P. H. Sant’Anna, A. Bilinski, and J. Poe (2023). What’s trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*.

Wen, K. and N. Khanna (2024). Beyond the haze of air pollution: Traffic noise and mental health.

Appendix: Figures and Tables

Figure A1: Example of Treatment Indicator for Power Plant Retirement



Notes: The figure shows the distribution of retirement status based on two different metrics: the number of generators retired and the total capacity (in megawatts, MW) retired. It includes histograms and kernel density plots for each measurement, covering all generator types as well as specific categories for fossil fuel, coal, and natural gas generators. While the distributions generally follow similar patterns for both measurement types, notable differences are observed in the retirement patterns of coal-fired generators.

Table A1: Coal Retirement Status on Mental Health

(a) Capacity (MW) Retirement on Mental Health

	(1)	(2)	(3)	(4)
Coal Retirement	0.143^{**}	0.126^{*}	0.127^{*}	0.113^{*}
	(0.068)	(0.066)	(0.065)	(0.063)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,899	31,899	31,899	31,899
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Number of Generators Retirement on Mental Health

	(1)	(2)	(3)	(4)
Coal Retirement	0.139^{**}	0.126^{*}	0.123^{*}	0.113^{*}
	(0.068)	(0.067)	(0.065)	(0.063)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,899	31,899	31,899	31,899
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents results on the role of retirement status, calculated by capacity (MW) and number of generators, on mental health. Retirement status variables are discrete values derived from the calculation of each year's retirement capacity and number of generators. Panel (a) focuses on the impact of retirement status based on capacity retried, while Panel (b) explores the effects of retirement status based on the number of generators retried. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

Table A2: Natural Gas Retirement Status on Mental Health

(a) Capacity (MW) Retirement on Mental Health

	(1)	(2)	(3)	(4)
Natural Gas Retirement	-0.059	-0.074	-0.052	-0.069
	(0.064)	(0.063)	(0.063)	(0.061)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,422	31,422	31,422	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Number of Generators Retirement on Mental Health

	(1)	(2)	(3)	(4)
Natural Gas Retirement	-0.061	-0.074	-0.050	-0.066
	(0.066)	(0.065)	(0.065)	(0.064)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,422	31,422	31,422	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents the effects of retirement status of natural gas generators on mental health, using a sample of HINTS respondents matched to power plants within 50km buffers. Retirement status is calculated based on the capacity (MW) and number of generators retired. Panel (a) focuses on the impact of retirement status based on retired capacity, while Panel (b) explores the effects of retirement status based on the number of retired generators. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level. $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Coal Retirement Status on Low Income Rate

(a) Capacity (MW) Retirement on Low Income

	(1)	(2)	(3)	(4)
Coal Retirement	0.054**	0.043*	0.048*	0.036+
	(0.026)	(0.025)	(0.025)	(0.024)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,899	31,899	31,899	31,899
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Number of Generators Retirement on Low Income

	(1)	(2)	(3)	(4)
Coal Retirement	0.056**	0.047*	0.049*	0.039+
	(0.026)	(0.025)	(0.025)	(0.024)
Outcome mean	-0.012	-0.012	-0.012	-0.012
Observations	31,899	31,899	31,899	31,899
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents the effects of the retirement status of coal-fired generators on the average low-income rate, using a sample of HINTS respondents matched to power plants within 50km buffers. Retirement status is calculated based on the capacity (MW) and number of generators retired. Panel (a) focuses on the impact of retirement status based on retired capacity, while Panel (b) explores the effects of retirement status based on the number of retired generators. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level. +p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Natural Gas Retirement Status on Low Income Rate

(a) Full Retirement on Low Income

	(1)	(2)	(3)	(4)
Natural Gas Retirement	0.011	0.008	0.011	0.009
	(0.020)	(0.019)	(0.020)	(0.019)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,422	31,422	31,422	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(b) Half Retirement on Low Income

	(1)	(2)	(3)	(4)
Natural Gas Retirement	0.009	-0.066	-0.039	0.022
	(0.015)	(0.059)	(0.059)	(0.016)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,282	31,282	31,282	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(c) Capacity (MW) Retirement on Low Income

	(1)	(2)	(3)	(4)
Natural Gas Retirement	0.012	0.013	0.012	0.013
	(0.018)	(0.017)	(0.018)	(0.017)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,422	31,422	31,422	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

(d) Number of Generators Retirement on Low Income

	(1)	(2)	(3)	(4)
Natural Gas Retirement	0.012	0.014	0.012	0.015
	(0.017)	(0.017)	(0.017)	(0.017)
Outcome mean	-0.013	-0.013	-0.013	-0.013
Observations	31,422	31,422	31,422	31,422
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls		✓		✓
State-Year FE			✓	✓

Notes: This table presents the effects of the retirement status of natural gas generators on the average low-income rate, using a sample of HINTS respondents matched to power plants within 50km buffers. Retirement status is calculated based on the capacity (MW) and number of generators retired. Panel (a) focuses on the effects of full retirement, and Panel (b) examines the effects of half retirement. Panel (c) focuses on the impact of retirement status based on retired capacity, while Panel (d) explores the effects of retirement status based on the number of retired generators. The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level. $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.

Table A5: Coal Retirement on Income By Demographic Characteristics

(a) Full Retirement on Low Income

	(1)	(2)	(3)	(4)
Coal Retirement	-0.039	-0.052	-0.105*	-0.055
	(0.042)	(0.048)	(0.062)	(0.087)
White× 1(post)		0.022		0.017
		(0.062)		(0.070)
Age × 1(post)			0.001	0.001
			(0.001)	(0.001)
Female× 1(post)				-0.068
				(0.067)
Outcome mean	-0.005	-0.005	-0.005	-0.005
Observations	12,154	12,154	12,154	12,154
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
State-Year FE FE	✓	✓	✓	✓

(b) Full Retirement on Income Range

	(1)	(2)	(3)	(4)
Coal Retirement	0.296	0.364	-0.311	-0.481
	(0.228)	(0.231)	(0.630)	(0.652)
White× 1(post)		-0.112		-0.144
		(0.243)		(0.261)
Age × 1(post)			0.011	0.012
			(0.012)	(0.011)
Female× 1(post)				0.480
				(0.304)
Outcome mean	-0.005	-0.005	-0.005	-0.005
Observations	12,154	12,154	12,154	12,154
Year FE	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
State-Year FE FE	✓	✓	✓	✓

Notes: This table presents the effects of full retirement of coal-fired generators on low-income rate and income range, incorporating interaction terms between the post-retirement indicator and demographic characteristics (race, age, and gender). The standardized mental health index serves as the outcome variable, with higher values indicating worse mental health. Standard errors are clustered at the power plant level. $^{+}$p<0.15, * p<0.1, ** p<0.05, *** p<0.01.